

Smart Animal Production 2

Ilias Kyriazakis *Editor*

Smart Livestock Nutrition

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Smart Animal Production

Volume 2

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Daniel Berckmans, M3-BIORES Department of BioSystems, Katholieke
Universiteit Leuven, Leuven, Belgium

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This new book series wishes to contribute to the discussion by looking at various aspects of modern livestock production. This includes the acceptability of how this is done in relation to the ethics and animal welfare, the practicality of the role of technology and the economics of animal-based food production.

The increasing demand for cheap animal products, for higher animal welfare and healthier animals while heavily reducing environmental load and energy use with an ever smaller suitable workforce is putting livestock farming world-wide under pressure. Previous research has shown that modern technology has a high potential to address these issues by using sensors and sensing systems to automatically capture quantitative information directly from the animal; this is referred to as Precision Livestock Farming (PLF).

However, it has also been shown that important issues remain to be solved: (i) lack of cooperation between animal scientists, veterinarians, bio- and other engineers and economists, (ii) lack of implementable systems which relate sensors, image and sound analysis to key indicators on farms, (iii) lack of understanding how PLF creates value for the different stakeholders and (iv) suitable business models to further adoption of PLF. Furthermore, the divide between consumer understanding and the reality of modern livestock production is widening with the urbanisation of the population and the increased use of intensive farming systems.

Ilias Kyriazakis
Editor

Smart Livestock Nutrition

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Editor

Ilias Kyriazakis
Institute for Global Food Security
School of Biological Sciences
Queen's University Belfast
Belfast, UK

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Preface

There is an increased requirement to solve accurately the animal nutritionist's problem of what will happen if a particular animal is fed in a particular way whilst kept in a specific environment at a specific point in time. The pressure arises from the need to develop more efficient livestock systems that reduce their impacts to the environment and enhance food security whilst at the same time provide improved animal welfare. It is associated with the fact that novel feedstuffs that meet the above criteria are entering the supply chains, whilst at the same time supply chains of traditional feedstuffs are being disrupted due to conflict, climate change and changes in human dietary habits, among other factors. The solution to the nutritionist's problem is compounded by the fact that there is a change in the way we manage livestock, including the move towards large-scale units that rely less and less on human input in order to improve system efficiency and reduce labour shortages and costs.

Technological advances may enable the move towards such livestock systems whilst facilitating more accurate solutions to the way we feed and manage animals. Such technologies involve automation and capture of information that can be communicated to devices or networks that may allow decision-making in real or near-real time. One class of these technologies are the smart technologies, which are based on sensors operating on electronic technologies and are capable of capturing information about the various components of livestock systems. Their utility to the livestock sector is being enhanced by rapid advancements in the fields of computer and electronics, and their adaptation to provide tailor-made solutions.

It is within the context of this background that this book was developed. The principle of smart nutrition involves the utilisation of smart technologies in feeding and managing livestock. As an idea it is not a new one, but technological developments now enable the application of its principles to livestock systems where it was previously thought impossible. This is the case of feeding extensively kept ruminants in environments that may be challenging, due, for example, to their spatial heterogeneity. In addition, technological developments also enable data capture, transmissibility and storage, which are the usual bottlenecks in the application of such technologies on farm. It is, therefore, likely that we will be increasingly relying on such technologies in the future.

This book is essentially divided in two parts, although this distinction is not made explicitly. In the *first part*, we deal with advances in technologies that enhance or enable the capture of relevant information. At the same time advancements in fields of biology, such as in molecular agriculture, now enable the characterisation of animal and plant genomes to enable genotype selection in a faster and more targeted manner. The *second part* of the book deals with the applications of smart nutrition to a variety of livestock systems, ranging from intensively, indoor-managed systems for broilers and dairy cows to more extensively, outdoor-managed systems for beef cattle and sheep. Most of the book chapters have heuristic value as their authors were given the remit to consider how these systems may look in the future and how this can be achieved through the application of smart nutrition. The book concludes by considering the consequences of smart nutrition on the environmental impact of livestock systems, due to the current global focus on this issue. It is possible that the application of smart nutrition will confer other benefits in the future.

Like all multi-author endeavours, the book took a bit longer to be completed than desired. Because of this, several chapter authors expressed their concerns that their chapters may become outdated during the editing process, especially because new information in the field arises almost on daily basis. Given the heuristic value of the chapters I do not have similar concerns about outdateness. I am obviously grateful for the patience shown by my collaborators, but also for their rising to my challenge of writing chapters that were developing principles, so that will not be overtaken rapidly. I particularly enjoyed our collaboration and I hope that they also enjoyed it in return. I expect that some of the enjoyment of this interaction is reflected in the quality of the book and appreciated by its readership.

Belfast, UK

Ilias Kyriazakis

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Putting Smart into Nutrition

1

Ilias Kyriazakis

Abstract

The solution to the central problem of nutritionists, of what will happen if a particular animal is fed in a particular way whilst kept in a specific environment at a specific point in time, relies on *sufficient* and *accurate* descriptions of animal genotype and phenotype, feeding regime, and other dimensions of the environment. Such descriptions are the main focus of this chapter. Due to scientific advances, we are becoming aware of descriptions of these components and their consequences in ways we have not previously thought of. Examples include: (1) description of animal resilience, i.e., its ability to maintain high health and/or performance when it is challenged by a perturbation; (2) measurements of emissions, such as greenhouse gases, indicative of feed digestion and utilisation; and (3) descriptions of an animal's social and infectious environment that have the potential to affect animal performance. Some of these measurements are now made possible through smart technologies, i.e., technologies that rely on electronic devices, that automatically capture information and, through communication with other devices or networks, generate information in real time. In this chapter, I also consider additional descriptions of the animal, its feed, and its environment that, although desirable, are currently not able to be captured by (smart) technologies. In this respect, the chapter has a heuristic value and may guide future developments in the field. The final part of the chapter addresses the issue of granularity in the descriptions. The topics of frequency and resolution are considered; in the extreme, smart technologies will make it possible to collect information on a continuous, real-time basis. As far as animal phenotype resolution is concerned, the focus may be not on the individual phenotype, leading to

I. Kyriazakis (✉)

Institute for Global Food Security, School of Biological Sciences, Queen's University Belfast, Belfast, UK

e-mail: ilias.kyriazakis@qub.ac.uk

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precision nutrition, but on (small) groups of animals that may require a specific management intervention at a point in time, leading to targeted nutrition, or on herd or flock ‘phenotype’. This will depend on the type of livestock we are dealing with and what we aim to achieve through their production system.

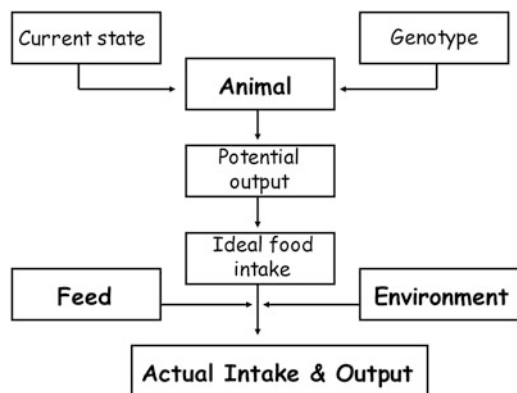
Keywords

Animal nutrition · Genotype · Environment · Environmental sensors · Feed composition · Individual nutrient requirements · Infectious environment · Livestock · Near-infrared reflectance spectroscopy · NIRS · Nutrient requirements · Nutrient excretion · Phenotype · Precision feeding · Smart technologies · Smart nutrition · Targeted nutrition · Social environment · Sustainable feed · Sustainable livestock

1.1 Introduction

Animal nutritionists are challenged with what will happen if a particular animal is fed in a particular way, whilst kept in a specific environment at a specific point in time. By definition, the challenge is in three parts: (1) What is the kind of animal in terms of its potential (e.g., the maximum growth it can achieve, or quantity of milk it can yield), and what is its state at this specific point in time (e.g., has it been previously affected by disease or how has it been fed up to the particular point in time)? (2) What knowledge about the feeding regime, including the properties of the feed(s) offered to the animal is required? Please note that the prediction of what amount of the feed will be consumed is part of the nutritionists’ problem, although in some instances the amount of a particular feed offered may be known *a priori*, such as in the cases of restricted feeding. (3) What are the necessary and adequate dimensions of the environment that need to be known in order to make the predictions? A schematic description of the challenge and the interactions of its parts are given in Fig. 1.1.

Fig. 1.1 A schematic description of the challenge faced by nutritionists when predicting the output of an animal: how is this particular animal going to perform, whilst given access to a particular feed, whilst kept in a certain environment?



Clearly, the dimensions of the feed and the environment that can be used to describe them may be numerous, but the emphasis here is on the *necessary* and *adequate*. It has been argued that increasing unnecessarily the complexity of inputs, such as phenotype or environmental descriptions, to a predictive (nutritional) system would lead to a poor predictive performance (Emmans & Kyriazakis, 2001). However, increasingly we recognise ‘novel’ nutritional and environmental dimensions that may be of relevance and have not been previously considered as part of the challenge. A case in point is the social environment where the animal is kept in, as the interaction of an animal with its conspecifics may affect its performance in ways not previously considered (Wellock et al., 2003a). The same applies to a certain extent to the assessment of genotype and phenotype, especially as interest in novel traits may apply. The increased interest in animal resilience, i.e., its ability to maintain high health and/or performance when it is challenged by a perturbation, as a novel trait is a good case in point (Doeschl-Wilson & Kyriazakis, 2012).

Quantitative assessments of the above dimensions have been limited in the past by being laborious, time-consuming and frequently imprecise. They may also cause animal disturbance and therefore affect animal welfare. For example, measurements of liveweight and conformation, or body composition have not always been straightforward, been associated with inaccuracy as, for example, the animal moves within the weighing crate, and frequently required separation of the animal from its group. The same applies to the assessment of the chemical composition of a feed, which has been based on wet chemistry and therefore its assessment needed some time to yield outcomes. The move towards livestock units with a larger number of animals and higher animal-to-staff ratios, and the need to operate efficiently in order to minimise undesirable impacts, such as environmental ones, will exaggerate these limitations. It is the thesis of this book that there are now novel technologies, such as Smart Technologies, that may help us to overcome such limitations and thus lead to a more efficient or even *precise* management of livestock systems.

Smart Technologies are technologies that rely on electronic devices, such as sensors, to capture automatically information, and through communication with other devices or networks and the use of data analytics and artificial intelligence, are able to generate outputs that can be used, for example, for the management of a livestock system (Berckmans, 2017). *Smart Nutrition* is defined here as the method of feeding animals that involves the utilisation of smart devices. Subsequent chapters in this book will focus upon such technologies and their current or potential use in livestock systems in the context of smart nutrition. The overall aim of this chapter is to focus upon the *necessary* and *adequate* descriptions of the animal, its feed, and its environment. By doing so, it will effectively generate a wish list; smart technologies may or may not be able to generate such information on all their dimensions. In this respect, the chapter will also have a heuristic value and may guide future developments in the field. The final part of the chapter addresses the issue of granularity in these descriptions. The topics of their frequency and resolution are considered here.

1.2 Animal Genotype and Phenotype Assessment

The respective questions of *where an animal wants to be* and *at what state it currently is*, can be two simple definitions of the terms *genotype* and *phenotype*. Whether an animal will achieve its ‘potential’, i.e., where it wants to be, will depend on the environment it is kept in, including its nutritional environment, which will define how the animal performs at a specific point in time.

In principle, the genome of an animal, i.e., its DNA sequence, is finite and can be characterised fully for an individual. Through very rapid advancements in genetics and genomics, there are currently several different types of genetic markers used for the purposes of animal genotyping (Schlötterer, 2004). The current preferred genomic markers of choice are the single nucleotide polymorphisms (SNPs), which are now widely used, due to the development of relatively low cost to generate information on thousands of SNPs simultaneously in an automated process. Such genomic tools are used now for a variety of purposes in livestock management, ranging from genomic evaluations, to monitoring of major genes, and congenital defects to ultimately facilitating more precise management decisions. Given their wide availability and applicability, they will not be considered any further here. The emphasis of this section is on traits that can be used for phenotype assessment; in a later section, the desired frequency of measuring them is discussed.

1.2.1 Phenotype Assessment

A list of phenotypic traits that may be of interest in the context of a nutritionist’s challenge is in Table 1.1. The list is not meant to be exhaustive, but indicative. Many of these traits essentially relate to animal life history, as they define its state and how

Table 1.1 Phenotypic traits that may be of relevance in describing current animal state

Morphological traits	Physiological traits	Behavioural traits
Body size (weight)	Reproductive traits	Activity
Body length	Body temperature	Posture
	Temperature of a body component	Feeding behaviour
Body width	Gastrointestinal function & capacity	Drinking behaviour
Body height	Heart rate	Coping reactivity
Body condition	Respiratory rate	
Udder size	Secretions (incl. composition)	
	Including composition with e.g. Milk	
	Excretions (incl. composition)	
	Faeces	
	Urine	
	Respiratory emissions	
	Immunological status	
	Infectious status	

this has been reached at a particular point in time. Some of these traits may be highly correlated, for example, animal body weight may correlate with animal length or height, and the duration an animal spends visiting a feeder is highly correlated with the amount of feed it will consume. In such cases, such correlations should be considered, especially when redundancy in the phenotypic assessments may be desirable, due to the sheer numbers of animals and records involved.

At a first glance, there might be some glaring omissions from the list in Table 1.1. However, this is because the rule of method used for the Table was not to include traits that are composite and therefore can be deduced from other traits. This included one of the central traits in animal management, that of feed utilisation efficiency. Again, the example of the trait *resilience* is a good case in point. Resilience is a combination of *resistance*, i.e., the ability to limit pathogen replication within the body, and *tolerance*, which is the ability to limit the impact of a perturbation on health and performance (Doeschl-Wilson & Kyriazakis, 2012). In the case of an infection, the former can be assessed by the immunological or infectious status of the animal, whereas the latter can be assessed through a time series of measurements of performance.

Morphological Traits The traditional morphological traits of interest relate to body size at a particular point in time. There has been a lot of progress in assessing and recording body liveweight automatically, for obvious reasons. This trait is of course composite and does not tell us much about, for example, body composition or how the chemical components of the body are distributed within its tissues. Two animals may have an identical liveweight, but very different weights of fat and protein in their body, which is likely to affect their response to feeding and nutrition (Kyriazakis & Emmans, 1990). However, this trait has been included on the list, because, currently at least, is one of the most frequently used assessments of animal performance.

Additional body size traits of interest may include linear measurements such as body length, body width, and body height. In certain respects, these were also used in the past, especially for animals of breeding value, but they may now have additional value in the context of smart nutrition, as they may combine and provide composite or novel traits, as indicated above. For example, a combination of these traits captured automatically via 3D cameras may lead to estimates of liveweight without the need to weigh an individual animal.

Physiological Traits The obvious traits of interest may relate to the reproductive state of the animal, such as whether it has attained puberty, whether it is pregnant, how many foetuses it carries, its parity, the stage of lactation or egg production, etc. There has been a long-standing interest in quantifying these traits in a non-invasive and accurate manner.

There is an increasing interest in assessing non-invasively and/or remotely the current physiological state and function of an animal, in terms of, for example, body

temperature, gastrointestinal function, heart, and respiratory rate. This includes the assessment of the temperature of a particular body part as it will relate to the function of specific organs or the presence of inflammation (Greenwood et al., 2016). Valuable information may be obtained by assessing the composition of secretions or excretions by the animal, such as its milk, urine, faeces, and respiratory emissions. The latter is of particular interest in the context of assessing the environmental impact of livestock systems (FAO, 2017). All these traits may provide the necessary or desired information about how the animal has reached this point in time, including whether it is or has been under physiological stress, and information on how the animal may cope with its current environment.

Some of the above measurements may also relate to the assessment of the state of animals in relation to a past or present infection. There is an increased recognition that experience with an infectious challenge may affect the amount an animal will eat, how fast it will grow and how it will partition in its body nutrient resources (Sandberg et al., 2007). For example, infection is usually accompanied by a reduction in voluntary feed intake (pathogen-induced anorexia), which may or may not be compensated once the animal has recovered. In Sect. 1.4.1, I detail novel developments in the assessment of the infectious environment. Some of these developments also apply to assessing the immunological or infectious status of the animal as a phenotypic state.

Finally, I have included here feed intake consumed over a certain period of time as a physiological trait. Please note that whilst the prediction of the feed intake *to be* consumed by a particular animal is part of the nutritionist's challenge, the amount of feed and nutrients that has been consumed up to the point of interest should be viewed as phenotypic traits. This is because these intakes can affect the capacity of the animal to consume a subsequent feed, its body composition, and its capacity to grow beyond this point (Whittemore et al., 2003).

Behavioural Traits It is now widely appreciated that animal behaviour can tell us a lot about animal state and behavioural traits can be exploited for the benefit of managing modern livestock systems. Some of these traits, such as activity-related ones (e.g., locomotion and posture), relate to how the animal performs, as higher activity is associated, for example, with increased maintenance energy requirements. Some other traits may be related to the coping reactivity of the animal in challenging environments (Matthews et al., 2016). Such traits may include strategies individual animals adopt in the face of competition for feed and water resources, increased environmental temperature, or even avoidance of pathogens (Sandberg et al., 2006). Although currently coping-related traits are not well defined, coping reactivity has been included in Table 1.1, due to the increased interest in this trait in relation to animal health and welfare, and even production efficiency (Rauw et al., 2017).

There has been a widespread interest in the quantification of the feeding and drinking behaviour traits of livestock. Such traits include the number of visits to the feeding or drinking source, duration and frequency of visits, number of visits clustered within a meal, etc. The interest arises from the significance these traits may have in the

control and regulation of feed and water intake (Emmans & Kyriazakis, 2001). Although it is suggested that such behavioural traits are a means to an end, it is possible that some of these traits may actually play a role in how a feed is utilised once consumed, or that they may be of significance in challenging environments, such as those with high competition at the feeding sources.

1.3 Assessment of the Nutritional Environment

The interest in the assessment of the chemical composition of a feedstuff and the utilisation of the feed consumed by the animal has been *the* central problem of animal nutritionists. Formally the former is a property *only* of the feedstuff, whereas the latter is a function of *both* the feedstuff and the animal, as there is variation in how individual animals digest and utilise different feedstuffs and feeds. Therefore, no single value for a feed can be ascribed to these. Traditionally, however, animal nutritionists have dealt with the latter as being a function of only the feedstuff and the resultant feed consumed by the animal; this is the principle upon which Nutrient Composition tables are based, when they provide values, for example, for the Digestible Energy or a digestible amino acid content of a feed. This is also the assumption made here, but the issue has also been raised in the previous section, regarding the previous experience of an animal on a feed potentially affecting its capacity to accommodate or digest it (Whittemore et al., 2003).

The challenge of assessing the nutritional environment is different for animals kept indoors, which are usually offered a homogeneous feed, and animals kept outdoors which are faced with a more complex nutritional environment whilst foraging; for this reason, these two problems of assessing the nutritional environment are dealt with separately here.

1.3.1 Indoor-Managed Livestock

Although ultimately the animal may be offered a feed of a particular ingredient composition at a particular point in time, there are considerable sources of variation that may result in uncertainty over its chemical composition. Feed ingredients may vary substantially in nutrient composition, due to growing conditions, hybrid or variety differences, planting and harvest dates, and storage and feed out conditions (Symeou et al., 2016). In addition, variation in feed composition may arise from the feed manufacturing process, such as mixing and processing, including, for example, the drying process in the production of distillers' dry grain solubles (DDGS; Pedersen et al., 2007).

Traditionally, feed ingredient and feed composition were assessed by wet chemistry, but this has gradually been replaced by methods, such as spectroscopy (e.g., near-infrared reflectance spectroscopy (NIRS)), which enable rapid assessment of their chemical composition. Due to the rapidity of these methods, they have the potential to be incorporated in various points in the feed production system. The

challenge would be to ensure that they operate in real time if they are to be used in the context of smart animal nutrition.

A significantly greater challenge is the assessment of the properties of the feed that relate to its digestion and utilisation within the animal. The traditional approach to achieve this has been reliant on *in vitro* methods validated on a wide range of feedstuffs to measure the potential digestibility of a feed. As this approach is also reliant on wet chemistry, it is also characterised by the limitations mentioned above. Research efforts should and are being directed towards the development of rapid assessment methods that can be incorporated into smart animal nutrition processes. The challenge of these approaches would be their validation on a wide range of feedstuffs. With increasing incorporation of alternative feedstuffs, co-products, and by-products into livestock feeds, the challenge increases in its complexity.

In theory, rapid assessment of the nutritional properties of feeds once consumed may be based on the non-digested residues of nutrients excreted in the faces. The rationale behind this approach is that these assessments may contain information on feed characteristics and nutrient digestibility, even though the feed had been transformed as it passes through the gastrointestinal tract of the animal. The challenge of assessing the properties of the feed which relate to their amino acid digestibility is even greater, given the issues associated with the conversion of amino acids lower down in the digestive tract (Moughan et al., 2018).

One particular issue is the description of the heterogeneous feeds offered to indoor-kept livestock. This is the case of the Total Mixed Ration (TMR) offered to cows which may consist of forage (e.g., silage) and a concentrate mix. In these cases, the animal may select within its feed and consume more or less nutrients from its theoretical composition. This selection may matter in the longer term, both on the basis of imbalanced nutrition and excretion of nutrients. An (incomplete) solution to this problem would require knowledge of the composition of what has been left in the feeding trough. As far as I am aware this challenge does not seem to have been considered thus far.

1.3.2 Outdoor-Managed Livestock

When dealing with pasture properties, one is interested in pasture biomass and composition, and plant growth rate. All these properties are highly dependent on weather, soil, and pasture management. There are now monitoring tools that are able to predict the effects of these variables on grass growth and availability (<https://www.grasscheckgb.co.uk/>). Even when these variables can be accounted for, it is challenging to account for plant and species distribution, even when the desired pasture is meant to be a monoculture. Different plant species may establish their own microenvironments within a pasture and therefore would not be evenly distributed.

The complexity of assessing pasture availability and nutritional quality has been a long-standing challenge for animal and forage scientists (Harmoney et al., 1997). The ability to accurately measure pasture biomass would estimate forage availability and determine livestock management, such as stocking rates for grazing to achieve a

certain output. Pasture available biomass is a function of plant growth and offtake due to animal grazing. Neither of these processes are linear, as plant growth can vary spatially within a pasture, and animals would be expected to select at various scales (e.g., between different plants and within different parts of the same plant). Previous methods to determine these properties have been either tedious (e.g., clip samples) or inaccurate, especially when measured by mechanical means (Harmoney et al., 1997). Therefore, the challenge is to develop rapid methods that assess pasture properties, preferably via a single measurement taken at regular intervals. The approach taken to determine feedstuff and feed composition via spectroscopy suggested for indoor-managed animals may be applicable here. The question would be how and where from to obtain a representative sample to determine the relevant properties (e.g., at ground level or above ground). Additional challenges would arise from the fact that methods of assessment developed to predict biomass in pastures with pure or evenly distributed mixtures, may be inadequate in pastures without even species distribution. It is likely, therefore that these methods may require to be site- and sensor-specific (Wachendorf et al., 2018).

1.4 Environmental Monitoring

In this section, I consider environmental properties other than the nutritional environment. It has been long established that certain properties of the environment where an animal is kept have the potential to influence its performance and health. For example, high environmental temperature and humidity have the potential to affect adversely the output of animals, mainly through their adverse effects on feed intake (Wellock et al., 2003b). It is, therefore, unsurprising that there has been a long-standing interest in developing sensors to enable the monitoring of such environmental properties and subsequent corrective action. Such sensors include ambient temperature and humidity, concentration of noxious gases, such as ammonia (NH₃) and carbon dioxide (CO₂), and airflow and air quality monitoring. The use and accuracy of some of these sensors are very well established and are connected to barn operations, for example, when the environment is too hot or too cold, they trigger a change in the mechanical ventilation in pig and poultry houses. For some other sensors, such as those of NH₃ concentration monitoring, improvements in their accuracy are required, due to the frequent need for calibration due to drifting. However, given the increased interest in monitoring the excretion of such gases due to their link with the potential environmental impact of livestock systems, an effort to achieve this is currently being made.

1.4.1 Monitoring the Infectious Environment

One aspect of environmental monitoring that has been frequently overlooked is the quantification of the infectious environment. This is not due to the lack of recognition of the potential of the infectious environment to influence both livestock health

and performance (Sandberg et al., 2007), but mainly because it has been difficult to measure infectious agent distribution and concentration. In the past, the animal itself has been used as a 'sensor' for the monitoring of the infectious environment (Sandberg et al., 2006). Increase in pathogen burden in the animal itself or in its excretions has been used as a tool for management intervention, such as medication. One of the traditional ways of monitoring concentration of pathogens has been measurements of what is excreted in the environment, for example in the faeces, or accumulates in the manure or litter. This may be more relevant for pathogens transmitted via the faecal-oral route, but not always for pathogens that are transmitted through other routes, such as respiratory ones.

An additional bottleneck of using the animal itself as a 'sensor' for quantification of the infectious environment has been the delay between the sampling of the animal and the assessment of the sample obtained. However, significant effort is currently being made to overcome this delay and obtain an almost 'real time' assessment of pathogen burden. This is the principle of 'pen-side diagnostics'. In addition, alternative ways of infectious environment monitoring that do not involve the animal as the 'sensor' are currently being considered. These would be of greater value for 'true' and even 'real-time' assessment of the infectious environment. One of the promising approaches to achieve this is through the monitoring of Volatile Organic Compounds (VOC) in the barn environment. VOC are odours given off by all living organisms, including pathogens. In principle, as the condition of the living organism changes, the VOC concentration given off must also change. By monitoring the change in these 'smells' in the environment, one can envisage that one can assess the reason for the change, especially if it relates to the infectious burden. This is the approach currently being taken by a variety of specialist providers such as Roboscientific (<http://www.roboscientific.com/technology/>) who aim to sample automatically the air in a barn at regular intervals and then automatically analyse it to test for changes in the VOC. The challenge in this approach is to relate these VOC to the presence of specific pathogens and importantly to the risk of infection from them.

1.5 Granularity of Assessments

1.5.1 Frequency of Assessment

Obviously, the more frequent the measurement of the environment and animal dimensions are, the higher the accuracy of the assessment of the dimension would be and the more likely it would be to account for other sources of uncertainty, such as temporal variation. This would be particularly the case for the assessment of phenotypic traits that are associated with large errors, such as liveweight, or for traits that may be affected by random events within the farm, such as in the case of behavioural traits. The same would apply for the variation in feedstuff and ingredient composition, such as for example in the variation in the dry matter of silage due to

the conditions of its storage, or of coproducts that are affected by large plant-to-plant variation (Schroeder & Sedivec, 2018).

In the context of precision livestock management, part of which Smart Nutrition is, there are benefits if real-time quantification of a change in the environment or the animal is accompanied by immediate action to prevent any adverse effect on the animal and consequences on the system operation. This is the case, for example, when a sensor detects an increase in the ambient temperature, which is followed by changes in the mechanical ventilation within a farm building (e.g., an increase in fan speed). The same may apply when a pathogen detection in the farm environment triggers a preventative action, such as medication. In such a case the sooner the pathogen is detected, the higher the chances of success of the action.

However, animal digestion and metabolism do not operate like a ‘switch’, even for fast-growing animals like broilers, or high-yielding ones like dairy cows. For example, the process of digestion of a feed may take several days, especially for ruminant animals. In addition, animal metabolism is characterised by great plasticity and to a certain extent the existence of body reserves dampens any fluctuations in the nutritional environment. The mechanism of metabolic compensation, where an animal can compensate for a short-term reduction in nutrient intake, allows the animal to achieve this (Kyriazakis & Emmans, 1990). In addition, changes in behaviour may also enable the animal to cope with perturbations in its environment that have the potential to affect its nutrient intake. Non-dominant animals within a group have a more opportunistic feeding behaviour, such as frequent and shorter visits to a feeder in order to achieve their ‘desired’ feed intake. Cattle in the tropics graze more intensively at dawn when the environmental temperature is lower. Given this plasticity in physiology and metabolism, it is not surprising that feeding strategies that aim to regulate nutrient intake in the very short term have not yielded the desired outcomes (Molnar et al., 2018).

It is likely that technological advances will enable the assessment of phenotypes in several dimensions relevant to Smart Nutrition. They will enable the assessment of novel phenotypes, as is the case for behaviour traits, and may enable reassessment of traditional phenotypic traits, such as liveweight. There would be the challenge and indeed the temptation, to collect such data from a large number of animals instantaneously or almost real time. This will present several challenges, some of which are detailed in subsequent chapters of this book and are mainly associated with high dimensionality, data storage, and transmission, as well as date labelling and individual identification. It is possible that in the context of smart animal nutrition, such high dimensionality might not be necessary both in the context of the phenotypic traits and their temporal granularity.

1.5.2 Resolution of Assessment

Environment, Including Nutritional Environment There are now very clear recommendations about the number of samples required for the characterisation of the composition of forage, feed ingredients, and resultant feeds fed to animals

(Schroeder & Sedivec, 2018). The recommendations vary with the type of feedstuffs offered and account for the potential sources of variation that may arise in each of these feedstuff categories. For example, silage samples should be taken to represent several locations in the silo to ensure representation, and should be collected after fermentation is complete. Even for feeds stored in bags, which are assumed to have been mixed thoroughly, sampling is recommended because settling within a bag can be quite common.

Although the placement of environmental sensors in agricultural buildings has been a long-standing focus of farm building specialists, the increased availability of novel sensors has reignited the interest in their *quality*, *positioning*, and *numbers* required to assess a certain environmental property (Curi et al., 2017). The positioning of the sensors is crucial in providing the correct information to any system responding to it, such as is the case of the automated control in the number of exhaust fans that need to be switched on or off to return to desired environmental conditions. The number of sensors required to monitor a farm building is also important, given the creation of ‘microclimates’ within the building. This will clearly depend on what environmental property one aims to monitor. For example, Curi et al. (2017) modelled the required positioning of only 3 sensors for dry bulb temperature and relative humidity in poultry barns of various sizes, to support the ventilation system during critical periods of summer. For novel sensors, such as those aiming to monitor the infectious environment, very little information is known about their positioning and crucially their numbers.

Animal Knowledge about a particular animal phenotype at a particular point in time would help to provide the conditions needed to achieve desired outputs, e.g., through nutrition. This is the principle of *precision nutrition*, which is developed in some of the subsequent chapters. It relies on phenotype assessment being linked to the ability to identify correctly an individual, so that the animal receives the nutrition appropriate to its needs at a particular point in time. For some animal systems, this may be desirable or aspirational, e.g., dairy cattle and other livestock of breeding value, but it is unlikely to apply to less-value-per-animal systems such as pigs and poultry (Halachmi et al., 2019). For the latter systems, other resolutions of the animal phenotype may apply.

Resolution of an animal phenotype assessment will depend on what it is aimed to be achieved and how easy it is to measure it. For example, in extensive systems of production, it may be difficult to obtain measurements of every individual within a flock or a herd due to their spatial distribution. One method currently under development relies on the assessment of animal phenotype without individual identification. In some cases, the assessment of phenotype happens at specific points of the pen or the barn, and depending on its outcome, the animal is directed to another point of the pen where it receives a diet suited to the group of individuals with similar phenotypic characteristics (*targeted nutrition*). For example, in the Nedap pig feeding system (<https://www.nedap-livestockmanagement.com/finding-efficiency->

[automated-sorting-scales/](#)), pigs are weighed as they move towards the feeder and drinker and are separated in sub-groups according to their liveweight (e.g., light and heavy pigs) to receive a diet suitable to their sub-group body weight.

Variations of the above method may include assessment of the phenotype of ‘sentinel’ animals within a group, which are considered representative of the whole group. Feeding decisions may then depend on the assessment of their phenotype. Finally, a simple application of smart nutrition would be when the phenotype of a whole group of animals is monitored, without individually identifying them. In this case, the interest may be on the group average and variation within the group, so that feeding decisions according to these may take place. This is an improvement of the current *phase-feeding system*, which recognises the need to feed several diets to animals for a relatively short period of time to match closely animal requirements.

1.6 The Way Forward

Advances in sensor technologies in tandem with biological understanding are likely to give rise to an ever-increasing number of animal and environment dimensions of high granularity (high-dimensional data). The challenge, therefore, would be to define which dimensions are actually *useful* and *relevant* in terms of animal nutrition and management. For example, there is an increased awareness about both the positive and negative role plant secondary metabolites play in the consumption, digestion, and utilisation of feeds (Ku-Vera et al., 2020). It is likely that analytical methodologies would be able to generate information about the feed content of such secondary metabolites in the near future. The question is would such information be of value without a biological understanding of the modes of action of these metabolites on animal processes? A further question of relevance is how to reduce the number of dimensions captured to the actually relevant ones, especially when dimensionality is (artificially) high. There are now methods which enable this dimension reduction, especially when dealing with phenotype-related dimensions (Perez-Enciso & Steibel, 2021).

Ultimately the penetration and adoption of smart technologies in livestock systems will depend on the type of livestock we are dealing with and what it is aimed to be achieved by its system of production. For example, Perez-Enciso and Steibel (2021) argued that some livestock systems are more likely to adopt smart technologies precisely because of the difficulties associated with capturing and phenotyping their livestock, and because of the number of individuals involved. Aquaculture was used as a case in point, but one can imagine that the same arguments may apply to large-scale broiler production. On the other extreme are extensively kept ruminants, due to the challenges associated with tracking individuals distributed over large areas, the accurate description of the environment, and the transmissibility of the data captured. However, given the rapid evolution in the field of sensor technologies, it is likely that the sky will be the limit (Gonzales et al., 2018).

Like all technologies with the potential to be used by livestock systems, a defining factor for their adoption would be their cost and the return on investment they offer. Different economic and governance models that may enhance the adoption of smart technologies are currently being considered. Some of them deal with consequences that may not have an immediate tangible economic value, such as improvements in animal welfare or reductions in environmental impact (Pomar et al., 2011). Given the direction of evolution of livestock systems, such consequences may actually guide our need to adopt smart technologies.

Smart Nutrition was defined above as the method of feeding animals that involves the utilisation of smart devices. The focus of the chapter was on the information that needs to be captured by these devices to implement it. The component of Smart Nutrition that deals with the communication of smart technologies with other devices or networks, and the use of data analytics and artificial intelligence, to generate actions such as feed delivery or precise diet composition was considered outside the scope of this chapter, as it will be considered in detail by subsequent chapters. Addressing these issues is by no means a trivial exercise.

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Matching Feed Characteristics to Animal Requirements Through Plant Breeding

2

Leif Skøt, Christina Marley, David Lloyd, Alison Kingston-Smith, and Mike Humphreys

Abstract

There is an urgent need to reduce the environmental impact of livestock farming, and in this review, we focus on how forage, grain and protein crops through plant breeding can make a contribution to this. Systematic forage plant breeding is only 100 years old, and the genetic variation present in most forage crops is only just starting to be fully utilized. Perennial ryegrass is an example of how plant breeding has led to the development of varieties with increased digestibility and yield. However, new breeding targets will have to be identified, as we increase our understanding of the interactions between plants and the animals that consume them. Forage crops of the future must be able to utilize water and nutrients more efficiently to maximize production per given land area. Forage legumes fix their own nitrogen for the benefit of their own growth. As they are most often grown in mixtures with grasses, this also benefits the companion species. Indeed, multi-species swards can produce higher quantities of forage dry matter (DM) from lower N inputs and improve the productivity of grazing ruminants. Legumes also provide other ecosystem services, including improved soil structure and habitat for insect pollinators. Forage and grain legumes can also provide a source of homegrown protein for non-ruminant livestock animals. EU currently imports over 75% of its use of protein crops for its animal feeds. Increasing Europe's protein self-sufficiency requires an increase in the use of grain legumes, such as pea, soybean and faba beans. They, in turn, need to be better adapted to new climates, biotic stresses, as well as increased yield and protein content and composition. Basic breeding methods for outbreeding and inbreeding crops are

L. Skøt (✉) · C. Marley · D. Lloyd · A. Kingston-Smith · M. Humphreys
Institute of Biological, Environmental and Rural Sciences, Aberystwyth University, Gogerddan,
Aberystwyth, Ceredigion, UK
e-mail: lfs@aber.ac.uk

outlined, and current breeding targets are discussed in relation to animal nutrition and their contribution to reducing the environmental impact of livestock farming.

Keywords

Amino acids · Barley · Cereals · Clover · Faba bean · Forage crops · Legumes · Livestock farming · Livestock feed · Maize · Non-ruminant · Nutrition · Peas · Perennial ryegrass · Phosphorus · Plant breeding · Protein · Ruminant · Soya bean

2.1 Introduction

Livestock production is increasing rapidly and accounts for 40% gross value of agricultural production on a global level. A number of factors contribute to this. They include an increasing global population, rising living standards and consequent changes in dietary habits in many developing countries (World Agriculture – Towards 2015/2030 – An FAO Perspective; <http://www.fao.org/3/y4252e/y4252e00.htm#TopOfPage>). Twenty-six percent of the planet's ice-free land is used for livestock grazing and 33% of arable land is used for livestock feed production (<https://www.fao.org/3/ar591e/ar591e.pdf>). In 2019, there were 143 million pigs, 77 million bovine animals and 74 million sheep and goats in the EU-27. Just over half of the EU-27's meat production was from pigs (22.8 million tonnes) in 2019, and the EU-27 produced 13.3 million tonnes of poultry meat in 2019, a new high. In the UK there were 23 million sheep, 4.8 million pigs and 9.3 million bovine animals (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Agricultural_production_-_livestock_and_meat).

Livestock systems provide one-third of the protein consumed by humans, with two-thirds of these systems being forage-based and from global grasslands. The majority of ruminant livestock are still being fed forage crops, grown in areas that may be unsuitable for arable crops. This is usually grassland, which is in itself unusable for human consumption, but through livestock farming, is converted to high-value protein and other essential nutrients, that are more bioavailable than from plant sources. Grassland livestock systems will therefore continue to play a major role in farming and the provision of high-value nutrition. In more intensive ruminant livestock production, forage is replaced by or supplemented with starch-, oil- or protein-rich grain or pulse crops. In non-ruminant livestock production such as pigs and poultry systems, feed is sourced from soybean and other pulses, oilseed rape, sunflower, maize, wheat, barley and other grain crops.

Livestock agriculture is a significant contributor to greenhouse gas (GHG) emissions, being responsible for about 14.5% of the world's anthropogenic GHG emissions (Gerber et al., 2013). Most of this comes from methane (CH₄) emissions through enteric digestion by ruminant livestock, and from nitrous oxide (N₂O) via urine, excreta, manure, fertilizer application and management (Rojas-Downing et al. 2017).

One impact of extreme weather conditions due to climate change is the detrimental effects of soil moisture content of soil structure and biology and carbon influx. Grassland soils are more susceptible to compaction, due to grazing livestock or farm machinery when the soil moisture content is high and organic matter is low (Hamza & Anderson, 2005). However, grasses with extensive root systems may improve soil qualities through soil-root interactions (Kell, 2011; Humphreys et al., 2014; Marshall et al., 2016).

Discounting the extreme solution of eliminating livestock agriculture, which would generate major issues with food security, grassland use, soil fertility, increased use of pesticides and major humanitarian upheaval, more efficient use of resources could and should make significant contributions to reducing GHG emissions (Garnett, 2009; Peyraud, 2017). By better matching feed characteristics with the requirements of the animal, we can improve the sustainability of and reduce the environmental footprint of livestock farming. Grass and legume forage is the most sustainable feed for ruminant livestock animals, and there are many opportunities and an urgent need for research into how we best use grassland to convert it to nutritious and protein-rich food for humans, while reducing the environmental footprint. Similarly, we need to maximize production of animal feed crops sustainably in order to minimize the percentage of arable land it uses. In the following sections, we will focus on the most important aspects of nutrition of ruminant and non-ruminant livestock, current trends in crop breeding, and highlight ways in which our self-sufficiency in protein, particularly for non-ruminant animal feed can be increased through plant breeding.

2.2 Nutrition, Digestion and Utilization

2.2.1 Forage Composition and Digestibility

Ruminants are an important part of the food supply providing a means of converting fibrous feed grown on low-quality land to a high-quality product (milk and meat). This is because of the synergistic relationship with the rumen microbiota, which is a complex mixture of microbial organisms (Huws et al., 2018). Advances in sequencing technology have enabled us to understand the relationship between the ingested feed and the rumen microbiota in detail. Ingested feed is colonized by bacteria and fungi, which use the components of the forage as substrates for fermentation, driving microbial growth. It is the increase in microbiota that feeds the animal directly, because a proportion of the microbial biomass passes from the rumen to the acidic abomasum. This enables extensive hydrolysis of microbial cells and absorption of nutrients into the animal's bloodstream. There are successional phases of colonization, with particular communities of microbiota responding to and producing ecological niches (Edwards et al., 2008). In addition, the composition of the colonizing population is a result of the (bio)chemistry of the forage. For instance, the profiles of timing and number of phases in colonization of forage grasses and clovers could be differentiated by 16S sequencing (Wilkinson et al., 2018; Mayorga et al., 2016),

Therefore, understanding of early events in colonization, in addition to gross changes in steady state rumen fermentation will enable a better matching of delivery of feed nutrients to the rumen with enhanced incorporation and lower waste outputs. The two key wastes are methane and nitrogen, both due to inefficient use of feed in the rumen.

Ruminants are important components of global food security, but they use forage protein inefficiently (~30% incorporation) resulting in significant environmental problems and a need for supplementary protein feed to achieve productivity targets. Hence, dietary crude protein contents alone are not adequate measurements of the protein values of feedstuffs for ruminants, because of imbalances in ruminal protein use profiles. This is the result of the efficiency of microbial protein synthesis and rates of protein degradation in the rumen. Protein use efficiency is increased in the presence of soluble carbohydrate. The asynchrony hypothesis (Hoover & Stokes, 1991) is based on the imbalance between the provision of protein and carbohydrate in ruminant diets. The rumen microbiota requires soluble carbohydrates, and degradation of structural carbohydrates to drive microbial growth. In the absence of sufficient carbohydrates, the hyper-ammonia-producing bacteria can de-amine peptides to generate energy. This typically yields ruminal ammonia in excess of what is required for microbial protein synthesis thus contributing to inefficient use of dietary protein and environmental pollution from deposition of ammonia in urine and faeces. By increasing the immediate availability of soluble carbohydrate to the rumen microbiota the conversion efficiency of nitrogen can be improved significantly, resulting in higher protein in milk (Merry et al., 2006; Edwards et al., 2007; Miller et al., 2001).

One of the most important factors influencing the feed value of forages and therefore the performance of animals consuming that forage is forage digestibility. In a review of the effect of grass silage digestibility, a 10 g/kg increase in digestive organic matter in the dry matter (DOMD) was found to increase ewe liveweight post-lambing by an average of 1.3 kg and increase lamb birth weight by an average 52.3 g when offered to pregnant ewes. In beef cattle, the effect was an increase in liveweight gain by an average of 22.8 g d⁻¹. In finishing lambs, the same increase in silage digestibility was found to improve liveweight gain in finishing lambs by an average of 9.3 g d⁻¹. In dairy cows, the effect observed was an increased milk yield by an average of 0.33 kg d⁻¹ (Keady et al., 2013). Increased forage digestibility is often associated with a higher content of water-soluble carbohydrates (WSC), and this is discussed in Sect. 2.3.3.1.

2.2.2 Supply of Nutrition to the Animal

Barley is widely used as a feed for dairy and beef cattle because of its easily digestible starch, and relatively high protein content, including methionine, lysine, cysteine and tryptophan (Nikkhah, 2012). For ruminant nutrition, the issues are similar to those outlined above in forages, namely the balance and timing of carbohydrates and protein provision in their diets. On the other hand, lactic acidosis can result, if the starch is very easily digested by the rumen microbes. This disrupts

fibre digestion and reduces feed intake (Black et al., 2005). In terms of metabolizable energy available, there are significant differences between the performance of different barley varieties for cattle, but also for non-ruminants (Black et al., 2005). In pigs, the hindgut can contain a microbial population, so if the feed is unprocessed much of the starch is digested there, rather than in the intestine and stomach. This can lead to poor utilization of feed and reduced feed intake. Poultry is dependent upon their gizzard to disrupt the cell walls of the grain and expose the starch to digestive enzymes.

Energy in an animal's diet can also be supplied as lipid. Fat supplements are often in dairy cow nutrition to increase dietary energy density, increase metabolizable energy intake and maximize milk yield without the risks associated with feeding an excess of fermentable carbohydrates (Jenkins & McGuire, 2006). A potential approach to improving the nutrient supply of grass-fed animals is via enhanced total lipid content within grass feed. Increasing lipids in grasses will also significantly improve the supply of omega-3 PUFA (polyunsaturated fatty acids), which has beneficial effects in terms of animal health and fertility. Supplying high PUFA-containing oils may affect methane production in the rumen (Martin et al., 2011) and approaches to reduce this are an important component of climate change mitigation strategies (Scollan et al., 2010). There are significant concerns about the potentially negative effects of meat and milk fat consumption on human health (Garnett, 2009). However, forage-fed animals produce meat and milk with a lipid composition more favourable to human health than that derived from concentrate-fed animals (Daley et al., 2010). This is particularly associated with a more 'beneficial' ratio of PUFA to saturated fatty acids as fresh forages have a high PUFA content with total lipid comprising 50–75% 18:3 n –3 and 6–20% 18:2 n –6 (Dewhurst et al., 2003). Studies have shown a genetic correlation with FA composition suggesting the potential for genetic improvement leading to the development of high FA grasses (Dewhurst et al., 2003; Barrett et al., 2015). Perennial ryegrass varieties with a FA content that enhances still further the beneficial impact of forage feeding would be an important tool in the development of a sustainable livestock sector meeting the needs of the value chain and consumers.

2.2.3 Protein Supply

2.2.3.1 Forages

Legume forages are an important source of soil mineral nitrogen, known to increase the DM yields of subsequent cereal crops when sown in rotations (Marley et al., 2013) contributing up to 75 kg/ha of residual N available to following crops. This provides an opportunity to reduce reliance on purchased inorganic fertilizers (Lüscher et al., 2014; Peyraud et al., 2009). Legumes achieve this function through their ability to host N-fixing rhizobia (Garg & Renseigné, 2007). The diverse high-protein legume forages available in grassland systems include: white clover (*Trifolium repens*), red clover (*Trifolium pratense*) and lucerne (*Medicago sativa*). The attributes of white clover (crude protein (CP) 28%) are well-established within

grassland systems worldwide as a high-protein forage with superior digestibility across the grazing season vs other forages. Red clover is high yielding with high nutritive value (CP 19–22%), and highly palatable to ruminants. It is primarily conserved as silage, but can be grazed (Marley et al., 2007). Lucerne (alfalfa) has a high protein content (17–20%), and due to its deep rooting systems, has complementary responses to climatic conditions compared to red clover, with red clover and lucerne being high yielding in wet and dry conditions, respectively (Peterson et al., 1992; Humphries & Auricht, 2001). Overall, legumes supply essential nutrients from mid-summer to late summer, compensating for the decline in yield of grass swards. Feeding these forages individually to ruminants improves feed intake, doubling feed conversion and increasing productivity vs grass only (Marley et al., 2007), and they can be incorporated into livestock systems as traceable, low-cost sources of high-quality protein for ruminants.

In addition, red clover contains the enzyme polyphenol oxidase (PPO) at high activity (Lee, 2014). The enzyme catalyses the oxidation of diphenolic compounds to quinones, and they in turn form complexes with proteins when cells are damaged for example through ensilage (Sullivan & Hatfield, 2006; Lee et al., 2004; Theodorou et al., 2006; Lee et al., 2009c). This makes the proteins more resistant to rumen degradation, decreasing proteolysis and permitting more of the feed N to reach the abomasum (Sullivan & Hatfield, 2006; Jones et al., 1995; Winters et al., 2008; Lee, 2014). The potential for PPO to act in a fresh feed situation has also been demonstrated. A proteomics approach comparing red clover wild type and a mutant lacking PPO activity showed, even in the few minutes during which the animal produced the down bolus through mastication, cell damage allowed mixing of cellular compartments and complexing of PPO with proteins from cytoplasm and chloroplasts (Hart et al., 2016). The potential for exploitation of PPO to enhance protein protection is not limited to red clover and has been detected in meadow grasses such as cocksfoot (Lee et al., 2006).

The enzyme has also been associated with a reduction of lipolysis, and an increase in the content of polyunsaturated fatty acids in animals (Lee et al., 2009a, b). The mechanism by which this happens is not elucidated yet, but some of the suggestions include deactivation of plant and microbe lipases and binding of quinones to glycerol-based lipid-reducing lipolysis (Van Ranst et al., 2011).

Like many other forage legumes, the red clover genome contains a large family of PPO genes, which suggests a complex regulation of activity both temporally and spatially in the plant (De Vega et al., 2015; Winters et al., 2009; Webb et al., 2013; Sullivan et al., 2004). Nevertheless, a naturally occurring mutant with very low PPO activity was identified in red clover (Winters et al., 2008). This appears to be inherited as a single recessive mutation, which indicates simple Mendelian genetics. This germplasm represents a very useful resource for further study of the genetics, physiology and biochemistry of PPO in red clover.

2.2.3.2 Grain and Pulse Legumes

Agricultural use of soya for animal feed rather than human consumption represents another challenge. Europe and China both import a significant and increasing

amount of soybean protein for animal feed. According to the Food and Agriculture Organization of the United Nation (FAOSTATS), whilst China is one of the top ten producers of soya, it is also the largest consumer, responsible for 60% of global imports (USDA, 2018). The EU is only 5% self-sufficient in soya and imports 13 million tonnes of soya-based crude protein (FEFAC, 2017). Soya is the main protein component in concentrate diets for dairy, whilst for beef & sheep production concentrate diets use soya, oil seed rape and palm kernel cake and meal. It is also a significant proportion of the diet of non-ruminant animals (i.e. pigs and poultry).

The lack of sustainability of soybean production and supply as well as price fluctuations contribute to this as a major issue, highlighting a need for strategies to reduce reliance on soya bean meal. Nevertheless, soybean is the most important and preferred source of high-quality vegetable protein for animal feed manufacture. Soybean meal has a high crude protein content of 44–50% and a balanced amino acid composition, complementary to maize meal for feed formulation. A high level of inclusion (30–40%) is used in high-performance non-ruminant diets (<https://www.fao.org/3/y5019e/y5019e03.htm#TopOfPage>). There are alternative grain legumes in more temperate regions in the form of pea, beans, faba beans and lupin. Each has advantages and disadvantages in terms of management, amino acid profile and anti-nutritional factors. Field peas (dried peas) for example are harvested ripe. Dried peas are used whole or split and fed to livestock. “Protein peas” are field peas that have been developed in Europe in the 1980s as a high-protein, white-flowered, low-tannin, low-antitrypsin protein source for animal feeding. Field peas used for animal feeding (feed peas) can be fed raw or processed in order to improve their nutritional value. This demonstrates the potential for breeding of alternative protein crops for animal feed. Nevertheless, there is also potential for soybeans for continuing improvement and possibly wider adaptation to different growing conditions, particularly in a European context, in locations where grain soybeans cannot (presently) be economically produced. Development and exploitation of soybean genetics may be an appropriate strategy in some regions, together with developing other alternative plant protein sources. This is illustrated in a major European project to increase Europe’s protein self-sufficiency (<http://eucleg.eu/>), where soybean features together with pea, faba bean, alfalfa and red clover (Saleem et al., 2021).

2.2.4 Nutrition from Cereal Crops

Barley, maize and wheat, as well as other cereals, are extremely important sources of livestock diets. Nutrient content in different grain crops used for animal feed is shown in Table 2.1. Cereals are used as a source of energy and protein in animal feed. Barley has more CP than maize, and also a higher content of the amino acids Lysine, Methionine, Cysteine and Tryptophan. Hull-less barley varieties (that do not have a tightly attached hull, which is easier to remove) have more CP and starch than hulled varieties. Barley has lower starch content than corn, wheat and rye, but its relatively simple structure in barley makes it easily digestible in the rumen,

Table 2.1 Nutrient composition (g/kg) of barley and other cereals used in animal feeds

Nutrient	Barley	Hull-less barley	Maize	Wheat	Rye
Dry matter	880	880	880	880	880
Crude protein (CP)	115	132	88	135	121
Undegradable CP g/kg CP	280	350	500	250	200
Neutral detergent fibre	181	120	108	118	180
Acid detergent fibre	60	20	30	40	100
Starch	570	650	720	770	620
Fat	19	20	38	22	15
Ash	23	19	14	17	19
Lysine	4.3	5.0	2.1	3.5	4.0
Methionine + cysteine	4.2	5.6	3.0	5.1	3.6
Tryptophan	1.8	1.5	0.9	1.5	1.4
NE _L Mcal/kg	1.71	1.75	1.78	1.82	1.71

Data are from Nikkhah (2012)

NE_L is net energy for lactation

particularly if it has been pre-processed, as in dry-rolling. This allows for a more efficient utilization of protein (see Sect. 2.2.1). However, too much of easily accessible starch can cause acidosis and consequently poor feed conversion, and animal health issues. It is therefore important to mix the barley grain with a more fibrous diet.

2.2.5 Other Essential Nutrients

Although levels vary throughout the season, mineral (e.g. calcium, magnesium) and trace element concentrations (copper, zinc, boron) in legume forages are higher than grasses when grown on the same soil sites (Lindström et al., 2013; Fisher et al., 1996). Utilizing forage legumes will assist in developing more sustainable approaches to the management of essential nutrients within soil-plant-animal interactions, reducing the need for fertilizers or feed additives.

2.3 Plant Breeding

2.3.1 Breeding Methodology

2.3.1.1 Outbreeding Forage Crops

Forage crop breeding objectives are complex because they are defined with animal production in mind, and have to be translated into physiological and biochemical criteria which can be assessed at the population and individual plant level. Two important developments were reported. Fagan (1924) used chemical analysis to assess the nutritive value of the herbage. Secondly, Stapledon et al. (1924) first

presented the concept that agronomic work was moving away from a purely botanical outlook. Subsequently, results of analysis of palatability of pasture species were published (Davies, 1925). By 1932 the 'S' varieties (or strains) of ryegrass were being developed alongside studies on chemical composition and palatability. The breeding work had to be driven by clearly defined agronomic objectives as a prerequisite to breeding operations regardless of the crop type (Breese & Davies, 1969; Wilkins & Humphreys, 2003).

A new era of plant breeding was initiated in the late 1980s, focussing on increasing the efficiency of ruminant milk and meat production, with emphasis on digestibility and WSC. *Lolium* or ryegrass was then the key genus fulfilling a range of purposes.

In recent years the need to reduce the environmental impact of livestock production has been recognized. Traditional crop breeding has tended to focus on yield and the ability of crop varieties to resist or tolerate disease. Overall, there is an increasing interest in the role that quality traits can play in improving the efficiency of production. Improvements are needed to bring it towards zero carbon emissions. Significant progress has been made in reducing the use of industrially produced nitrogen fertilizers, synthesized from fossil fuels, by using mixed swards that incorporate nitrogen-fixing forage legumes. Current varieties used in seed mixtures are bred independently of each other. There is great potential to focus on improving the relationship between the grass and clover components of the sward by trialling breeding lines together and, for example, optimizing the transfer of fixed nitrogen from the clover to the grass. However, little work of this nature has been conducted to date largely for logistical reasons. The amount of phenotypic assessment required would be prohibitive without the use of automated evaluation.

Further environmental benefits can be made by optimizing the balance of quality traits in forage, namely WSC, crude protein, lipid content, neutral detergent fibre (NDF), and acid detergent fibre (ADF). Increasing WSC content in ryegrass is a trait that has been a breeding target (Wilkins & Humphreys, 2003). These sugars are rapidly released from the grass within the rumen, providing substrate for rumen microflora to ferment. This results in a reduction of cell wall breakdown in the rumen and reduces degradation of protein in the rumen, increasing the efficiency of protein uptake by the ruminant and with significantly less nitrogen being excreted as ammonia and nitrous oxide. This results in improved forage digestion, increased dry matter intakes, higher liveweight gains and higher carrying capacity in the field, and in the case of dairy production, increased milk yields (Lee et al., 2002; Moorby et al., 2006) (see also Sect. 2.2.1).

Increasing lipid content in forage modifies the microbial community structure in the rumen, decreasing the proportion of methanogenic protozoa and thus reducing methane emissions (Patra et al., 2017). Moreover, unsaturated fats compete with methanogens for hydrogen (Vargas et al., 2020). This, coupled with the health benefits of increasing polyunsaturated fats in milk and in meat means that breeding for increased lipid content in forage is currently a major focus. It is also likely that the crude protein content of forage legumes can be optimized for reduction of nitrogen losses. This will again depend largely on being able to accurately model the

interaction of companion species in a mixed sward (see Sect. 2.4.1.5). However, it should be recognized that for livestock fed exclusively by grazing, possibilities for complementing the diet are limited.

Most temperate forage crops, including grass and forage legumes are out-bred, often with a high degree of self-incompatibility (Vogel & Pedersen, 1993). Unlike inbreeding species in which pure-line cultivars are produced, forage crops are generally population cultivars, in which each individual plant in a population is genetically distinct, but bears sufficient similarity to other members of the population to satisfy statutory requirements for it to be accepted as a cultivar. Development of population-based varieties using recurrent selection schemes aims to increase the frequency of desirable alleles in the population, while still maintaining a high degree of heterozygosity to prevent inbreeding depression. The simplest form of this is *mass selection* or recurrent phenotypic selection (Burton, 1974). An initial spaced plant nursery is established from progeny of intermating parents (polycross). After 3 years of evaluation, the best plants are selected and intermated in a polycross. The progeny is used to establish a new spaced plant nursery, starting a new cycle of selection. This carries on until the genetic gain is sufficient to release a potential new variety. This is best suited for traits with high heritability, and not effective for quantitative traits. *Genotypic selection* relies on progeny testing. Seed from mother plants are used to establish progeny rows. The mother plants are maintained asexually. After 2–3 years of evaluation, the best mother plants are identified and used as parental material for further breeding and/or variety generation. *Among and within family selection*, the best plants within progeny rows (families) or swards are selected for further crossing to establish a new generation. Breeding schemes for cross-pollinating crops are described in more detail in textbooks and reviews e.g. (Vogel & Pedersen, 1993; Stoskopf et al., 1993; Casler & Brummer, 2008; Conaghan & Casler, 2011; Resende et al., 2013). Many forage breeding programmes use an iteration of this scheme: A founder population is planted in the field and selected on the basis of a number of traits, including heading date synchrony, presence/absence of disease, stature etc. Selected individuals are polycrossed in pollen-proof isolation houses, seed harvested as half-sib families and the mother plants retained (Wilkins & Humphreys, 2003; Grinberg et al., 2016; Skøt and Grinberg, 2017). Half-sib families are sown as small plots, and on the basis of performance in these trials, mother plants selected for variety production. Saved seeds of the best half-sib families from the initial polycross are then taken forward for the next generation of selection (Fig. 2.1).

The selection intensity required to successfully improve a population for a single trait depends on the heritability of that trait and the variability of the trait in the original population. Rates of selection of around 5–10% are typical. In out-breeding species, there is a further need to consider both the selection intensity and the need to select sufficient mother plants to avoid inbreeding depression. Where selection for multiple traits (for example, yield and quality traits) is required the size of the original population needed can rapidly become difficult to manage without a degree of mechanization. This is especially true for species like white or red clover, that are cultivated in mixed swards, which need to be assessed in the presence of a suitable companion grass and, in conventional trials, are botanically separated by hand to

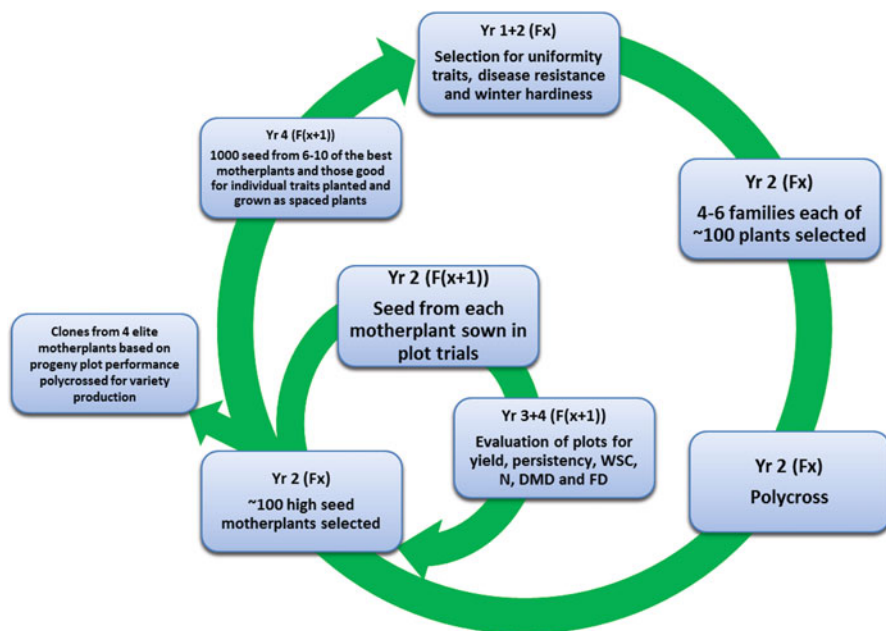


Fig. 2.1 Illustration of one cycle of the among and within family selection and breeding programme

calculate the content of each component. This inevitably leads to the need to grow and assess large numbers of field plots which, for space considerations and due to seed limitation at early generations, are generally small in size: for half-sib plots, this can be in the order of 1 m² per plot.

2.3.1.2 Cereals and Grain Legumes

The cereals and grain legume crops we are concerned with as animal feed sources, are inbred or can self-pollinate. This means that pure-line cultivars are made from crosses of two or more original parents. Three basic methods will be described here: *bulk*, *pedigree* and *bulk/pedigree methods* (Brown et al., 2014). All three begin with an initial cross between two parents. In the *bulk method*, the hybrid F₁ and subsequent generations perhaps up to F₅ are grown as bulk populations. As the crop is mostly inbreeding, seed will be produced predominantly by self-pollination. At the F₆ stage, single plants with the desirable traits are selected and seed from a head are grown in rows. Seed from the best head-rows is bulk-harvested and used in early yield trials. Seed from selected plots is used in subsequent advanced yield trials. Advantages of this method include its relatively low cost, and conscious selection is not imposed until the F₆ generation, by which time the populations are mostly homozygous, and not segregating. On the other hand, there is a long time between the initial crosses and yield trials.

In the *pedigree method*, the progeny from the F_1 hybrid are grown as single plants, and seed from the selected F_2 plants are grown in head rows. A number of plants from each of the best rows of the F_3 generation are selected, and seed are grown in head rows again. This is repeated until F_6 when near homozygosity is reached. The highest yielding rows are selected for early yield trials. This is a more costly and laborious scheme compared to the bulk method.

As the name suggests, the *bulk/pedigree method* combines the features of both schemes. As in the pedigree method individual F_2 plants are selected, and seed from those plants are grown in head rows. Selections are made among the rows of F_3 plants, and seed are bulk harvested to allow for preliminary yield trials at the F_4 stage. Selected plots are bulk harvested and plot trials are conducted on the F_5 generation. At the F_6 stage, single plant selections are made again, and the progeny is grown as plant rows. Seed from selected rows is harvested and used in a new round of yield trials in F_8 and beyond for advanced yield trials. This scheme makes it possible to discard inferior material at an early stage of the breeding process. The method requires more resources for evaluation in the early stages. Most breeding schemes aimed at developing pure lines are based on variations of this method. Techniques such as doubled haploidy and single seed descent have been developed in some species in order to accelerate the progress to homozygosity.

2.3.2 Genomic Selection

Conventional crop breeding strategies have limitations in terms of improving quantitative traits with low to moderate heritability. This includes traits such as yield, quality and persistence, particularly for perennial forage crops. Molecular marker technology has enabled the detection of genomic regions controlling trait variation, but it has had limited impact on crop breeding. This is partly due to the lack of relevant traits controlled by major loci. Genomic selection (GS) has the potential to overcome some of these limitations. The concept of GS was first described by Meuwissen et al. (2001). It uses a genome-wide set of DNA markers (usually single nucleotide polymorphisms – SNPs) anticipated to be in linkage disequilibrium (LD) with quantitative trait loci (QTL) of importance to the breeding programme. All the markers are analysed jointly in order to explain the total genetic variance by summation of all marker effects. These estimates are used to predict the breeding values of selection candidates. A training population that is intensively genotyped and phenotyped is used to develop a genomic prediction model based on the effect of each marker. This is then used to calculate the genomic estimated breeding values (GEBV) of candidates for selection, that are genotyped, but not phenotyped. The basic principle of GS is outlined in Fig. 2.2.

GS has revolutionized livestock breeding programmes worldwide, and is widely used in dairy cattle (Hayes et al., 2009; Hickey et al., 2017). GS also offers opportunities to increase the efficiency and effectiveness of plant breeding programmes and has been evaluated for large commercial breeding programmes for several crops including maize, barley, wheat, oats and sugar beet (Asoro et al.,

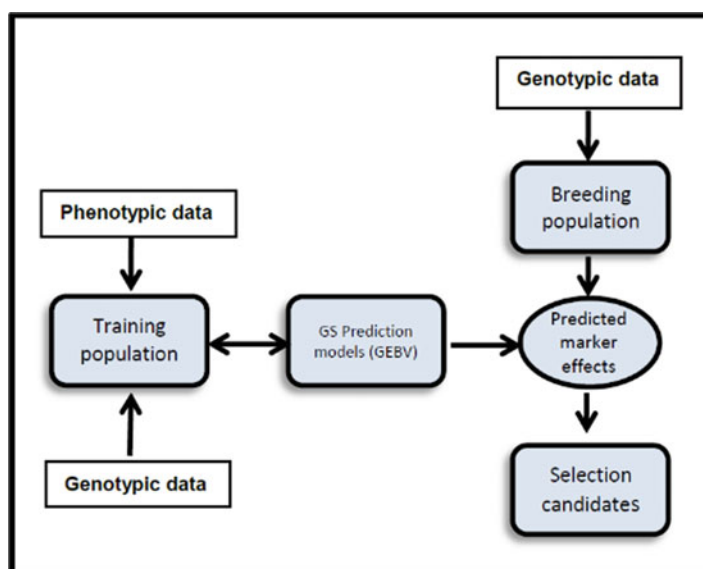


Fig. 2.2 Principle of genomic selection

2013; Wurschum et al., 2013; Zhao et al., 2012). GS could benefit plant breeding by: (i) reduce generation time, (ii) reduce or omit the need for lengthy half-sib progeny testing in outbreeding crops and (iii) increase selection pressure for difficult-to-phenotype traits (such as seed yield). Providing genetic gain in forage yield can be maintained through GS, omitting the HS progeny test in the population improvement cycle would halve the generation time and thus result in doubling the genetic gain (see Fig. 2.1).

The potential value of GS in perennial ryegrass is being assessed, and is at various stages of application (Hayes et al., 2013; Lin et al., 2016; Fè et al., 2015, 2016; Resende et al., 2014; Grinberg et al., 2016; Skøt & Grinberg, 2017; Faville et al., 2018; Arojju et al., 2020).

In inbreeding crop breeding schemes, it would be valuable to be able to predict the performance of inbred lines derived from two parents. This would potentially reduce the number of crosses that needed to be made, and thus save resources. The programme PopVar (Mohammadi et al., 2015; Sallam & Smith, 2016; Osthusenrich et al., 2017) is an example of genomic prediction that has the potential to predict the performance of inbred lines based on the performance of the original parents, and some assumptions regarding recombination frequencies.

2.3.3 Breeding for Forage Quality

Forage quality is most often associated with high digestibility and palatability (sensitivity to anti-nutritional factors and preferences for feed). A definition of forage

quality is its potential to produce a desired response in the animal (Ball et al., 2001). A number of variables that influence forage quality includes palatability. This depends upon things such as plant texture and leafiness, whether the material is infected with disease, how sweet it is or antinutritional factors. Another variable is intake. This again is associated with palatability. A third variable is digestibility – how much of the food will be digested and absorbed by the animal and utilized for further growth? The nutrient content of the intake is also important. The forage dry matter is composed of non-structural parts, sugars, proteins, lipids and starch, and structural parts include the cell walls (cellulose, hemi-cellulose and lignin). Some forage crops also contain antinutritional compounds, such as tannins (tannins can, however, also have beneficial effects on ruminant nutrition – see later), alkaloids, cyanoglycosides and phytoestrogens (again, the latter can also be beneficial for ruminant animals).

2.3.3.1 Water-soluble Carbohydrates and Digestibility

Humphreys (1989) showed that WSC content (mostly fructans) in perennial ryegrass is a polygenic or quantitative trait and that there was genetic variation among ryegrass varieties for digestibility, WSC and crude protein (N). He demonstrated a positive correlation between WSC and digestibility, and a slight negative correlation between WSC and N. An understanding of the microbial utilization of protein and carbohydrate in the rumen was developed, and this established the rationale for high WSC as a key breeding target (Kim et al., 2007; Lee et al., 2002; Moorby et al., 2006; Marley et al., 2007). It was hypothesized that increasing the water soluble carbohydrate (WSC) fraction of grasses would lead to improved ruminant utilization. Underpinning research on the biochemistry, metabolism, enzymology and genetics of WSC (fructan) metabolism in perennial ryegrass complemented this work (Wilkins & Humphreys, 2003; Turner et al., 2008).

There has been a continued emphasis on breeding for improved WSC and digestibility, but without compromising the other important traits, such as forage yield, disease resistance, seed yield and uniformity of flowering time (Wilkins, 1991; Wilkins & Humphreys, 2003). Balancing the selection for all important traits is one of the major challenges in forage crop breeding (Wilkins & Humphreys, 2003; Casler and Brummer, 2008; Conaghan & Casler, 2011).

Perennial ryegrass varieties with increased WSC content can increase milk production by up to 6% more milk per cow over the grazing season, increase dry matter intakes by up to 2 kg/head per day and a 3% improvement in diet digestibility (Moorby et al., 2006). Research on beef showed that high WSC varieties increased forage intake by around 25%, contributing to 18–35% higher daily liveweight gain enabling slaughter weights to be reached more quickly (Lee et al., 2002). In the lamb sector, high sugar grasses have led to a 10–15% higher daily liveweight gains with a 20% higher carrying capacity of swards containing the HSG varieties (Marley et al., 2007). Meta-analyses have concluded that an increase in the ratio of WSC:N correlates with an increase in N content in milk per unit of N ingested in the dry matter, and a reduction of N in the urine per unit N ingested (Edwards et al., 2007; Soteriades et al., 2018). The latter shows that a farm management system with high

sugar grasses leaves a lower environmental footprint, a small decrease in contribution to global warming potential and resource depletion, compared to one with standard varieties.

2.3.3.2 Fatty Acid Content

Lipids are normally stored in the seed, where they serve as a source of energy during germination. The energy content of lipids is roughly twice that of carbohydrates and proteins, so it would be of potential value to increase lipid content in forage rather than in the seed. The value of fatty acids in forage is twofold: The energy content increases the metabolizable energy (ME) per unit of dry matter ingested, and thus the potential for reducing methane emissions per unit of dry matter intake (Grainger et al., 2010). Lipids in grass forage are mainly found in the membranes of the stroma of chloroplasts, and they are rich in polyunsaturated fatty acids, particularly linolenic acid (C18:3) and linoleic acid (C18:2). Studies on various types of ryegrass material have shown that the total fatty acid content varies between 1% and 5% of dry matter content (Dewhurst et al., 2001; Palladino et al., 2009; Hegarty et al., 2013). The heritable part of this variation suggests that it is possible to breed for increased fatty acid content in ryegrass, and targets of 7–8% of dry matter have been suggested (Barrett et al., 2015). Milk fat depression in grazing cattle may happen at higher concentrations (Flowers et al., 2008). However, such high concentrations of fatty acids in ryegrass have not been achieved yet. It is also unknown what consequences it would have for other main constituents of the forage such as WSC and proteins.

A transgenic approach for increasing lipid content was described in *Arabidopsis thaliana* (Winichayakul et al., 2013). A lipid-encapsulation gene cysteine-oleosin was constitutively expressed together with diacylglycerol acyltransferase in order to increase energy content through the production of encapsulated lipids in the foliage. The concentration of lipids increases to 8% of dry matter. A similar approach was used in perennial ryegrass, and a 100% increase in lipid content was claimed for the GM plants compared to the controls (Barrett et al., 2015). While such goals may be possible to reach, the prospect of releasing GM varieties of wind-pollinated crops is not realistic at present.

2.3.3.3 Phosphorus

Phosphorus is the most important soil nutrient with regard to successful legume production due to the important role that phosphorus plays in facilitating the effectiveness of their symbiosis with rhizobia (Smith & Read, 2008). Legumes play a key role in the sustainability of agriculture, through their ability to host N-fixing rhizobia. Phosphorus requirements for optimal clover productivity for example are typically higher than non-legumes due to root nodules for N₂-fixation being P sinks (Sprent, 1999). Genetic variation for P acquisition and utilization has been demonstrated in a number of crops (Wissuwa & Ae, 2001; White et al., 2005), and associated QTLs identified (Ni et al., 1998). The viability of selecting for PUE in grasses is indicated by work on wheat demonstrating wide genetic variation in response to P supply (Osborne & Rengel, 2002).

The efficiency of use of this finite resource by livestock animals is of paramount importance. In animal feed, such as maize and soybean, P is usually present as phytic acid (*myo*-Inositol-hexakisphosphate) and salts thereof (phytate) (Kebreab et al., 2012). This is poorly utilized by non-ruminant animals (Nelson et al., 1968), resulting in environmental problems from excretion of P from pigs and poultry. Optimized feeding strategies can reduce excretion of P from the animal, and addition of microbial phytase enzymes improves P availability (Kebreab et al., 2012). The latter has been utilized in a transgenic strategy in which oilseed rape was engineered to produce more phytase enzyme in the seed by introducing a phytase gene from *Aspergillus ficuum* (Zhang et al., 2000).

Chemical mutagenesis methods have been used to generate mutants with lower phytate and a corresponding increase in inorganic P_i in the seeds of maize, soybean, barley and pea, for example (Raboy, 2001; Raboy et al., 2000; Wilcox et al., 2000; Warkentin et al., 2012; Rasmussen & Hatzack, 1998). All of them have reduced phytate in the seed with a concomitant increase in inorganic P_i . However, the further development of such promising germplasm has been hampered by deleterious pleiotropic effects such as reduced seed germination (Raboy, 2001; Meis, 2003), seed yield (Raboy et al., 2000) and vegetative growth (Pilu et al., 2005).

Several of the low phytic acid (LPA) lines are due to mutations in genes on the phytic acid biosynthesis pathway (Raboy, 2007). The *lpa1-1* mutant has, however, been shown to be in a locus encoding an ABC transporter gene, the role of which in phytate metabolism is not clear, and this knowledge was used to generate transgenic maize and soybean lines by silencing the gene in an embryo-specific manner (Shi et al., 2007). Transgenic maize and soybean lines were identified with low phytic acid and high P_i .

It should also be noted that phytic acid chelates with cations. The poor utilization of phytate in non-ruminant animals (and in humans) can lead to deficiencies in Fe^{3+} and Zn^{2+} (Raboy, 2007), and strategies to lower the phytate content in seeds would also help to prevent such deficiencies.

2.3.3.4 Grass Staggers or Hypomagnesaemia

Magnesium (Mg) is essential for living organisms as it is part of many basic processes. Low Mg status (hypomagnesaemia) causes a condition called tetany, or staggers in cattle and sheep. This occurs at significant frequencies (Kumssa et al., 2019). A more efficient alternative to using feed mixes, supplements or directly administering Mg is to ensure that the grass grazed by animals in the field, or eaten as hay or silage, contains sufficient Mg. Genetic variation in Mg content in ryegrass exists, and perennial ryegrass varieties, and hybrids of Italian and perennial ryegrass with high Mg have been identified (Kumssa et al., 2020). The genetics of Mg concentration in ryegrass is being investigated and phenotypic and genotypic data used to inform perennial ryegrass breeding programmes.

2.3.3.5 Phytoestrogens

Certain legumes, notably red clover can contain high levels of the phytoestrogens formononetin (7-hydroxy-4'-methoxyisoflavone) and biochanin A (5,7-dihydroxy-

4'-methoxyisoflavone). These compounds have been found to indirectly caused infertility in grazing ewes. Their mode of action is that these phyto-oestrogens are metabolized by the rumen microorganisms to daidzein (7-hydroxyisoflavone) and the isoflavan equol (7,4'- dihydroxyisoflavandiol) (Nilsson et al., 1967). Concentrations of equol in the blood can be determined to confirm the cause of infertility (Braden et al., 1971). It is the equol that has been found to have a direct effect on ewe fertility (Shutt & Braden, 1968; Cox & Braden, 1974) with equol concentrations in blood being the main method used to determine the levels of phyto-oestrogens in vivo (Braden et al., 1971). To overcome these effects, early plant breeding efforts to select for reduced phytoestrogen content in red clover began in the early 1980s (Gosden et al., 1984). This resulted in varieties, which are low in phytoestrogens, such as "Formica" (Boller, 1997). However, phytoestrogens in clovers can also have a beneficial effect on liveweight gain in sheep. In males, improved meat and carcass characteristics were found to be due to their anabolic effects (Moorby et al., 2004, Pace et al., 2006). Considerable progress has been made in the breeding of red clover with both enhanced and reduced levels of the main phytoestrogens, and this information has enabled the phytoestrogens from red clover to be also extracted and used for their health benefits in humans. Thus, there is an incentive to breed for bespoke varieties used for specific purposes rather than exclusively as forage for ruminant animals. Marley et al. (2011) concluded that to reduce the risks of infertility when offering forage legumes containing phytoestrogens to ruminant livestock, there was a need for a better understanding of factors that can alter the concentrations of oestrogens present in the plant and on the plant (as myco-oestrogens) when offered fresh and conserved as hay or silage.

2.3.3.6 Condensed Tannins

Certain forage legumes are known to contain condensed tannins (Mueller-Harvey et al., 2019). They have been of interest because they prevent bloat in ruminants (Jones et al., 1973) by binding to excess dietary protein, and reducing the protein degradation in the rumen as the tannin-protein complex is stable and insoluble in the pH of the rumen. As the tannin-protein complex then dissociates at $\text{pH} < 3.5$ and solubilization of protein occurs (Jones & Mangan, 1977), this in turn improves N utilization efficiency and increases the delivery and absorption of essential amino acids in the duodenum (Douglas et al., 1995). Condensed tannins are also known to have anthelmintic properties in the rumen, with research showing that lambs grazing birdsfoot trefoil had lower faecal egg counts and internal helminth parasites compared to lambs grazing ryegrass (Marley et al., 2003). Condensed tannins are present in significant amounts in birdsfoot trefoil and sainfoin, among forage legumes, but are not expressed significantly in the more commonly used legumes such as red and white clover and lucerne (Mueller-Harvey et al., 2019). Research has also shown that there can be considerable variation amongst different *Lotus* species and birdsfoot trefoil cultivars in condensed tannin concentrations (Marley et al., 2006). There has thus been significant interest in triggering expression of tannin biosynthesis genes in forage legumes through transgenic approaches (Hancock et al., 2012; Dixon et al., 2013). A thorough review of condensed tannins in forage crops

was published recently (Mueller-Harvey et al., 2019), and the reader is referred to that for more detailed information on the biochemistry and physiology of these compounds.

2.4 Building on Successes – What Plant Breeding Can Deliver for Livestock Nutrition

2.4.1 Forage Legumes

Forage legumes will play an increasingly important role as we move towards more sustainable agricultural systems. They perform a number of important ecosystem services, by fixing their own nitrogen from the atmosphere, improving soil structure and health, and providing a habitat for insect pollinators (McKenna et al., 2018; Lüscher et al., 2014). Many white and red clover breeding programmes target traits which are aimed to increase farmer uptake of these crops and thus increase their use. This includes improved persistency and grazing tolerance for red clover, abiotic stress tolerance and resource use efficiency in white clover.

2.4.1.1 White Clover

White clover, *Trifolium repens* L., is the most important forage legume of temperate regions (Frame et al., 1998; Duke, 1981; Abberton, 2007). It is typically cultivated for grazing purposes in a mixed sward with a companion grass, most commonly perennial ryegrass in the UK (Harris, 1987; Frame et al., 1998). It has a prostrate growth habit and spreads along the ground via stolons, rooting at nodes and producing trifoliate leaves at the nodal apices (Frame et al., 1998).

The benefits of inclusion of white clover in forage are well established. Its leaves and petioles have very high dry matter digestibility (DMD) of around 80%, while having a high crude protein content of around 25% DM (Søgaard, 1993; Allinson et al., 1985). Inclusion of white clover both in grazed swards and in silage increases voluntary intake by 10–15% (Lüscher et al., 2014). It increases milk yields in dairy cattle by 1–3 kg d⁻¹ compared with cattle fed solely on ryegrass (Ribeiro-Filho et al., 2003; Phillips & James, 1998; Wilkins et al., 2006). Liveweight gains of animals are also increased by inclusion of white clover in fodder (Yarrow and Penning, 2001).

Perhaps the most significant benefit that white clover imparts to grassland agriculture is its ability to fix atmospheric nitrogen N₂. The amount of nitrogen fixed in the field is difficult to estimate accurately and highly dependent on soil conditions but is in the order of 150–250 kg N ha⁻¹ year⁻¹ (Boller & Nösberger, 1987; Ledgard & Steele, 1992). While the majority of this fixed nitrogen is utilized by the legume host, a proportion passes into the rhizosphere, where it can be taken up directly by companion grasses. It is thought that around 75 kg N ha⁻¹ a⁻¹ is transferred directly to the companion grass in this way (Pirhofer-Walzl et al., 2012).

Nitrogen fixation enables livestock production with low inputs of synthetic N fertilizer. Outputs from sheep grazed continuously on mixed clover-ryegrass swards with no synthetic N input are around 80% of that of sheep grazed on ryegrass

monocultures receiving $420 \text{ kg N ha}^{-1} \text{ a}^{-1}$ (Orr et al., 1990). Loss of N to the environment through release of nitrogenous gasses and through leaching of nitrate is also substantially reduced when using mixed clover-ryegrass swards compared with ryegrass monocultures under high synthetic N fertilization (Parsons et al., 1991).

A key consideration in the breeding of white clover is the fact that it is used in grazed mixed swards. While yield and yield stability are important, more critical is the interaction between the clover and its companion grass and its response to grazing. A large range of morphological variability exists in ecotypes and cultivated varieties of white clover, with varieties on the Recommended List for England and Wales ranging from a leaflet area of 423 mm^2 to 1591 mm^2 (British Grassland Society, 2015). Leaf size reflects the overall morphology of the plant, with small-leaved varieties being lower-growing with smaller stolon internode length and, hence, denser stolon networks with larger numbers of rooting points. While larger-leaved varieties are higher yielding, small-leaved varieties are more resistant to grazing. Small-leaved varieties tend to be used for more intensive grazing purposes and large-leaved varieties for conservation use and for more lax rotational grazing (Frame et al., 1998).

White clover occurs naturally from the subtropics to the arctic and over a wide altitudinal range (Williams, 1987), but it has relatively modest tolerance for extremes of abiotic stress, for instance to winter damage (Collins & Rhodes, 1995) and water stress (Barbour et al., 1996; Brink & Pederson, 1998). It also has limited resistance to pests and diseases (Barnett & Gibson, 1975; Pederson & McLaughlin, 1989; Pederson & Windham, 1989).

Research initiated in the 1990s (Meredith et al., 1995) underpinned the breeding of novel white clover varieties derived from introgression of the rhizomatous trait from Caucasian clover (*T. ambiguum* M. Bieb) as a route to improving drought tolerance of white clover and persistence under grazing (Abberton & Marshall, 2005). A programme of hybridization and backcrossing to the white clover parent produced hybrids that are white clover-like in appearance, but which incorporate the rhizomatous growth habit (Abberton et al., 2003). The first variety ‘AberLasting’ from the programme was added to the UK National List in 2016, and is now in trials and commercial production.

Field experiments demonstrated that improved resilience to drought and frost compared to white clover was attained without compromising dry matter yield and forage quality, partly due to a greater root biomass at depth (Marshall et al., 2003). This genetic material is now included in the white clover breeding programme enabling the rhizomatous trait to be introduced into a range of recipient types to further improve grazing tolerance (Lloyd et al., 2017).

2.4.1.2 Red Clover

Red clover (*Trifolium pratense* L.) shares many of the properties of white clover, but cultivated varieties tend to have a more upright growth habit, with mature plants growing from a single crown with a strong, deep tap root. This limits its suitability for use in grazed swards as damage to the crown by the grazing action of ruminants or by trampling will kill individual plants with no facility for regeneration. However,

red clover's much higher yield in comparison to white clover makes it an attractive option for cutting managements, particularly for conservation in silage.

Red clover is known for its limited persistency, and it has typically been cultivated as a biennial. Substantial progress has been made in recent years to improve its persistency, with newer varieties like AberClaret maintaining good yields for as much as four harvest seasons (Marshall et al., 2017). Development of tetraploid varieties marked a considerable improvement in dry matter yield in the mid-twentieth century (Boller et al., 2010). However, there are challenges with seed production in tetraploid varieties that are difficult to resolve through breeding (Vleugels et al., 2016), and modern diploid varieties often match or outperform the best tetraploids.

A lack of persistency in red clover is likely in most cases to be due to susceptibility to pathogens. In the UK, the pathogens of most concern are the soil-borne ascomycete, crown rot (*Sclerotinia trifoliorum* Eriks.) (Vleugels et al., 2013) and stem nematode (*Ditylenchus dipsaci* Kühn) (Skipp & Christensen, 1990). The development of red clover varieties with reliable resistance to these pathogens is a central goal for introducing greater persistency and yield stability.

2.4.1.3 Birdsfoot Trefoil

The use of birdsfoot trefoil (*Lotus corniculatus*) in agriculture in the United Kingdom is negligible, even though it is native to the UK (Bonnemaison & Jones, 1986), and has been recognized as a forage legume there for almost 250 years, and that it is grown extensively in many countries (Seaney & Henson, 1970). One reason for this may be the fact that, of all the legumes, birdsfoot trefoil is one of the slowest to establish (Armstrong, 1974). Furthermore, experiments on the use of birdsfoot trefoil in grazed upland sites, showed that it was susceptible to poor over-wintering and low subsequent productivity and survival (Davies, 1969; Charlton, 1973). However, recent field trials at IBERS with birdsfoot trefoil varieties developed in South America have shown great promise in mixed swards in terms of ability to compete with the companion grass and persistence compared to white clover controls (David Lloyd, unpublished).

Moreover, birdsfoot trefoil has several attributes that give it potential advantages over the more widely grown forage legumes. It does not cause bloat (Jones et al., 1973; Ross & Jones, 1974) is more resilient on soils of low fertility than white clover (Duke, 1981) is extremely drought-tolerant (Duke, 1981), and highly palatable to stock in all seasons, up to flowering (Armstrong, 1974). It reduces internal parasites in sheep (Marley et al., 2003) and contains condensed tannins, which have been shown to improve rumen bypass of dietary protein (Mueller-Harvey et al., 2019). Condensed tannins can affect the proteomic profile of forage during degradation by rumen micro-organisms (Hart et al., 2016). These features may prove to be valuable under new climatic conditions and within farm systems reducing reliance on chemical fertilizer inputs.

2.4.1.4 Festulolium

Festulolium cultivars are species combinations involving either whole or part ryegrass (*Lolium*) and fescue (*Festuca*) genomes. They have been developed with the aim of expressing the forage yields and quality found in ryegrass combined with resilience to onsets of abiotic stresses typified by fescues (Humphreys & Thomas, 1993). Globally, due to drivers for sustainable responses to climate change, they have attracted increasing interest, and to date, a total of 78 such alternative cultivar species combinations (Humphreys & Zwierzykowski, 2020) have been developed. The majority incorporate perennial or Italian ryegrass with meadow or tall fescue, but recently alternative species have been used, e.g. Atlas fescue (*Festuca mairei*) from North Africa and *Festuca arundinacea* var *glaucescens* from Southern Europe. This is exemplified by AberRoot (perennial ryegrass × Atlas fescue) and the Aberystwyth and INRAe cultivars AberLink and Lueur (Italian ryegrass × *F. arundinacea* var *glaucescens*) (Humphreys & Zwierzykowski, 2020). They can assist in providing efficiencies in ruminant nutrition (Humphreys et al., 2014; Kamau et al., 2020), which are outlined below.

Due to ingestive mastication and perception of stress processes by plant cells nutrient composition of feed in the rumen is not stable. This has been proposed to affect microbial colonization thereby impacting on efficiency of feed utilization in the rumen. The timing of these events corresponds with periods of initial microbial attachment to the ingested forage (Huws et al., 2015), thus providing a plentiful supply of protein breakdown products, typically exceeding that which can be incorporated into microbial protein and giving rise to significant amounts of excreted nitrogen. Plant-mediated proteolysis (PMP) directly affects the efficiency of rumen transformations and generation of N₂O via soil processes (Kingston-Smith et al., 2003, 2005, 2012). Forage genotypes differ in their rates of PMP, providing potential to reduce protein waste through targeted plant selection and breeding. While we have repeatedly observed extremely rapid PMP in white clover, exceeding that in red clover or *Lolium* spp. (ryegrass), the mechanism and genetics underlying PMP are in the early stages of understanding. While there is no simple relationship between rate of proteolysis and total protease activity (Kingston-Smith et al., 2006), there is a link with initial protein content (Kingston-Smith et al., 2005), and control plant stress hormones (Kingston-Smith et al., 2012) or presence of secondary metabolites (Hart et al., 2016). PMP can be manipulated via its genetic control (Humphreys et al., 2014). Work with *Festulolium* hybrids has indicated that protein stability in rumen-simulated conditions differs between grass species and is related to gene dosage. Furthermore, protein stability of *F. arundinacea* var *glaucescens* is four times that of *Lolium* species, and when the *Festuca* genotype is combined with *Lolium* spp. the extent of protein retention can be maintained or even exceeded (Humphreys et al., 2014).

The potential of *Festulolium* in protein protection has been demonstrated in vitro (Humphreys et al., 2014). When *Festulolium* was used in a more realistic continuous flow system it was observed that certain hybrid varieties could support fermentation rates no different from those of a market-leading ryegrass, but with significantly lower ammonia release. This was achieved without compromising microbial protein

synthesis (Kamau et al., 2020). This indicates that *Festulolium* are capable of providing a high-quality ruminant feed, which can decrease the impact of livestock production.

2.4.1.5 Multi-species Swards

With climate change, farming practices need to adapt to develop resilience in food production and forage breeding is needed to meet this challenge. It is now recognized that grasslands are key providers of essential ecosystem services (Marshall et al., 2016), and that pastures of mixed forage species can be as productive as fertilized grass swards (Finn et al., 2013). Livestock research has also shown the potential for individual high-protein forage species to provide sustainable protein feed for livestock (Marley et al., 2007), with certain forages also having mechanisms that affect protein utilization due to reduced plant protein breakdown (Hart et al., 2016; Humphreys et al., 2014). This provides new opportunities to exploit species-rich pastures through the design of species mixtures based on the forage quality and complementarity of the individual species components.

Multi-species swards have been shown to have the potential to produce higher quantities of forage dry matter (DM) from lower N inputs (Finn et al., 2013) and to improve the productivity of grazing ruminants (Roca-Fernández et al., 2016). Compared to monocultures, the interspecific interactions of multi-species forage mixtures result in higher levels of dry matter productivity as a result of niche facilitation and complementarity in the forage species in the sward community (Finn et al., 2013). Increasing the diversity of forage mixtures is now widely acknowledged as a route to improve both biomass and protein yield per ha of land and to also promote the ecosystem functions delivered by grassland systems (Sturludóttir et al., 2014). Strategic selection of forage species for sward mixtures can facilitate complementary niche functions and deliver different beneficial ecosystem services. This includes above-ground niche spatial growth patterns and differing rooting biomass and architecture. This increases the opportunities for sward mixtures which can maximize resource use efficiency under differing and extreme climatic conditions (Wood et al., 2015). For example, the maintenance of an optimal botanical composition of high-protein forages over the lifetime of the system, through the use of multiple legume species that specifically vary in their rates of establishment and persistence can help deliver protein supply to grazing livestock (Sanderson et al., 2016).

2.4.2 Breeding Crops for Non-ruminants

In this section we will focus on cereal and grain legume breeding, but also include a subsection on efforts to use forage protein for non-ruminant animal feed. Cereal and grain legume breeding strategies are outlined in Sect. 2.3.1.2. Yield increase is an intrinsic part of these methods, so we will not specifically deal with this breeding target here. Likewise, breeding to increase P utilization in non-ruminant animals was dealt with in Sect. 2.3.3.5. Here we will concentrate on protein yield and quality.

2.4.2.1 Protein in Cereals

About 70–80% of the world's maize production is used for animal feed. Maize seed contains between eight and nine percent protein, but the quantity of two essential amino acids, lysine and tryptophan, is below the nutritional requirements for monogastric animals <https://www.fao.org/3/y5019e/y5019e0c.htm#TopOfPage>. Improving the protein quality in maize has therefore been of major importance. The timeline for the development of Quality Protein Maize (QPM) from the discovery of the *opaque-2* mutant with higher content of lysine and tryptophan through subsequent breeding to improve the endosperm quality and reduce undesirable pleiotropic effects has been described in detail (Prasanna et al., 2001, 2020) and (Maqbool et al., 2021). Nutritional evaluation of QPM has been performed with poultry (Panda et al., 2013). The benefits of deeding QPM grain to poultry include better weight gain, more efficient feed conversion and reduced need for supplemental nutrition. In pigs, some studies have also recorded better feed conversion ratio and reduced need for supplementary nutrition (Mpofu et al., 2012), and overall there is good evidence to indicate that QPM improves the feed value for both poultry and pigs (<https://www.fao.org/3/y5019e/y5019e0b.htm>).

Barley for animal feed has primarily been bred for high protein content. As with other cereals, the seed protein is also deficient in lysine, but high in non-essential amino acids such as proline and glutamate. These are not used by the animal, ending up in the manure causing nitrogen pollution issues. Doll and Koie (1975) reported the development of a mutant with a 40% increase in lysine. There were, however, problems with agronomic performance in terms of seed size and yield, hampering the development of new varieties. More recently antisense and RNAi technology were used to generate transgenic barley with reduced content of glutamine and proline, and increased levels of lysine, by changing the balance of seed storage proteins (Lange et al., 2007; Sikdar et al., 2016).

2.4.2.2 Protein in Grain Legumes

Feed rations for non-ruminant livestock are largely made up of cereals and protein feed. The EU is highly reliant on the import of soybean meal to fulfil this requirement. Most of this is from soya imported from South America. Approximately 20% of this is thought to be connected with illegal deforestation (Rajão et al., 2020). Replacing imported soybean meal with domestically produced protein is not straightforward. Soybean meal has the benefit of being inexpensive, readily available and, perhaps most importantly, far more familiar to feed compounders. A range of alternative plant-based protein sources has been proposed, most notably peas and faba beans. It is also feasible to breed soybean for more temperate regions, thus increasing the scope for more protein self-sufficiency in more temperate regions (Saleem et al., 2021). Soybean seed protein also has a well-balanced composition of amino acids except for low methionine. Soybean contains anti-nutritional factors, chiefly trypsin inhibitors and lectins (Liener, 1994), but they can be removed by heat treatment (Dei, 2011). Of lesser importance are oligosaccharides, goitrogens and oestrogens (Dei, 2011). Genetic variation among soybean germplasm in the content

of trypsin inhibitor and lectin has been demonstrated along with concomitant changes in feed value in rats (Gu et al., 2010).

Conventional breeding for improved content of methionine in seed protein has met with limited success. There is plenty of evidence indicating genetically controlled variation in methionine content (Panthee et al., 2006; Krishnan and Jez, 2018), but reliable methods to screen large numbers of plants for amino acid content have not yet been developed, and this represents a limitation (Krishnan & Jez, 2018). A transgenic approach whereby genes encoding zein have been introduced into soybean has resulted in very modest increases in the production of the heterologous protein in soybean seed (Dinkins et al., 2001). A promising avenue for improving the content of Sulphur containing amino acids appear to be the targeting of Sulphur metabolism in the plant (Krishnan & Jez, 2018). The success of this will depend on a good genetic and biochemical understanding of the relevant metabolic pathways.

Commercial varieties of dry peas (*Pisum sativum* L.), contain between 21 and 24% protein. Water-insoluble globulins form the main part of this, with vicilin being the largest fraction, followed by legumin and convicilin. Vicilins and convicilins are viewed as lower-value proteins due to their absence of Sulphur-containing amino acids in contrast to legumins, which have a sulphur amino acid complement or around 1–2%. The water-soluble albumins are also higher in sulphur amino acids than globulins, but have antinutritional properties, and reduce liveweight gain in livestock (Vaz Patto et al., 2015). Another anti-nutritional factor in pea seed is trypsin inhibitor (Clemente et al., 2015).

While natural variation can be used to alter legumin/vicilin ratios and albumin content, disruption of seed metabolism through induced mutation may have the potential to alter protein composition more radically, providing a resource that can be used by breeders to specifically tailor the nutritional value of peas for animal feed (Domoney et al., 2013). A thorough review of the genetic basis for pea seed protein, starch, anti-nutritional factors and micronutrients can be found in Robinson and Domoney (2021).

Faba bean (*Vicia faba* L.) has a higher protein content than pea at around 26–29% in commercial varieties, with the dominant fraction being legumin. A major barrier to greater adoption of faba bean as animal feed, particularly for poultry, has been the presence of the pyrimidine glycosides vicine and convicine (Crépon et al., 2010). Low vicine/convicine varieties of faba bean were first registered in 2019 and show promise for replacing animal feed, although it is likely that this will only impact soybean meal use in the premium food market in the short term.

Pathogens are a major source of yield decline in pulses. Of particular concern in pea are downy mildew (*Peronospora viciae*), pea wilt (*Fusarium oxysporum*), foot and root rots caused by various fungal species and powdery mildew (*Erysiphe pisi*) in late-maturing crops, and the main pests include pea and bean weevil (*Sitona lineatus*), pea aphid (*Acyrtosiphon pisum*) and pea moth (*Cydia nigricana*). In faba beans, leaf and pod spot (*Aschochyta fabae*), chocolate spot (*Botrytis fabae*) and, later in the season, rust (*Uromyces fabae*) are the major yield limiting diseases. This can be controlled by applications of fungicides, but improving resistance to these diseases is an important breeding target (Rubiales et al., 2015; Maalouf et al., 2019).

Table 2.2 Comparison of amino acid content between soybean seed and red clover foliage in percent weight terms

% weight	His	Thr	Cys	Lys	Tyr	Met	Val	Ile	Leu	Phe
Soybean meal	1.2	1.6	0.5	2.7	1.7	0.6	2.1	2.2	3.5	2.3
Red clover protein isolate	3.8	5.8	0.5	4.4	5.3	1.2	4.6	3.4	8.4	6.5

In faba bean pea and bean weevil, stem nematode (*Ditylenchus* spp.), bruchids (*Bruchus rufimanus*) and black bean aphid (*Aphis fabae*) are the most serious pests. Screening for resistance to stem nematode has yielded some promising results (Stoddard et al., 2010).

2.4.2.3 Protein for Non-ruminants from Forage

An alternative approach is to use protein extracted from sources not normally usable by non-ruminants. Of particular interest is the use of protein extracted from clover grown either with or without grass (Stødkilde et al., 2018). This has a number of potential advantages over pulse-derived protein. Grassland agriculture can be practiced on a wider range of land types than many arable crops, clovers are perennial and their cultivation relies far less on applied insecticides and fungicides. As Table 2.2 shows the content of the important Sulphur-containing amino acids in red clover foliage compares favourably with that in soybean seed.

Red clover varieties can be harvested for 3 years or more with no yield penalty (Marshall et al., 2017). Mature red clover roots penetrate far deeper than those of pulses, have better drought tolerance, and provide soil conditioning for successor crops (Lüscher et al., 2014). Red clover harvested for protein thus makes an ideal break in rotation on arable land, to interrupt the cycle of blackgrass and improve soil structure and organic matter content (<https://cereals.ahdb.org.uk/media/1388190/gs100-livestock-and-the-arable-rotation.pdf>). Furthermore, as the protein is extracted and removed, there is no requirement for investment in animal facilities in the producing farm. In an extracted form, red clover protein can provide a replacement for soybean protein that could be sold into existing markets and moreover, the extraction process would yield useful by-products including pinitol and isoflavones (currently used in an expanding health food supplement market) and residual fibre (value as ruminant feed, for AD or use in biocomposites).

2.5 Conclusions and Future Outlook

Ruminant animals are able to convert a fibre-rich forage diet into high-quality meat and milk products rich in protein for human consumption. This benefit is, however, offset by inefficiencies in rumen fermentation that contribute to emission of significant quantities of methane and nitrogenous waste. The challenge is to identify how nutritional requirements of ruminants can be satisfied by high-quality forages with a smaller environmental footprint. Systematic forage plant breeding has its beginnings

100 years ago, and early programmes resulted in important yield gains (4–5% per decade). Gradually, quality traits took on more importance (e.g. enhanced disease resistance and digestibility), resulting in varieties with high WSC content, and less fibre. The requirement for more sustainable production systems means that we are faced with the challenge of having to produce high-yielding, high-quality forages that enable efficient animal production with minimal environmental impact. In order to achieve this, we will have to identify opportunities for maximizing nutrient use efficiency in both forage crop and livestock animal components. Perennial ryegrass has been and is very successful due to its high yield, forage quality and persistency. New breeding targets will have to be identified as we increase our understanding of the interactions between plants and the animals that consume them.

Forage crops of the future must be able to utilize water and nutrients more efficiently to maximize production per given land area. We may have to consider alternative plant species to those currently in use, to increase the level of protein self-sufficiency or find alternative uses of existing forage crops, such as extraction of protein for non-ruminant livestock, high-value metabolites for industrial biotechnology or the health industry, and biorefining for energy production. This provides us with scope for significant improvements in key traits, such as forage quality and energy content, anti-nutritional factors and disease resistance. Genomic selection is among the new technologies that can help us to increase the speed of plant and animal breeding. It is already used successfully in dairy cattle and is gradually gaining importance in plant breeding. A prerequisite for all genetic improvement is continued research to reveal, which genes or parts of the genome are important for the traits we are seeking to improve.

In cereals and pulse legumes conventional breeding (including induced mutagenesis) for improved balance of essential amino acids in the seed protein is hampered somewhat by the lack of methods for screening large numbers of samples for amino acid concentration, but also by the occurrence of deleterious pleiotropic effects such as reduced seed size and yield and impaired vegetative growth. Overcoming these hurdles is not trivial, but essential. The development of QPM varieties demonstrates that it is possible to breed for improved protein composition in seed crops. Transgenic methods are also pursued in order to improve the protein composition in seed crops. The development of such germplasm into commercial varieties has not yet happened. Gene editing is a novel tool, which can target specific genes for changes in their coding sequence. A detailed description of this methodology is beyond the scope of this chapter, but it has enormous potential for the future.

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Circular Feed Production and Consumption in the Context of Smart Animal Nutrition

3

Luciano Pinotti

Abstract

Smart nutrition represents an innovation in farm animal nutrition and is one of the most promising ways to promote safe, high-quality animal products such as meat and milk, high animal welfare, and minimal impact on the environment. Smart livestock nutrition implies also the design of high nutritious diets for feeding animals in line with their needs and requirements. This goal can be achieved not only by selecting ingredients characterized by high nutrient density and digestibility, but also by looking for sustainable ingredients, including “circular” ingredients from waste and from nature. Using such alternative feed ingredients in the diet of farm animals is interesting for several reasons. Food leftovers are one way of converting losses from the food industry into ingredients for the animal feed industry, thereby keeping nutrients in the food chain. These materials can be extremely rich in carbohydrates, free sugars, and, depending on their origin, also in fats. Food leftovers, such as former food products (FFPs) and bakery by-products (BBPs) are subject to considerable processing including technological (milling, etc.) and heat treatments (cooking, extrusion, etc.). These impact not only the availability of nutrients and the kinetics of digestion but also on GIT/rumen health/functions and the animal response. FFPs and BBPs are safe from a microbiological point of view since; their microbiological loads are always below established tolerance levels. Using leftovers as feed also responds to the requirements of the circular economy. Understanding that food that is not suitable for human consumption is actually a resource rather than a waste product, our food industry can limit the amount of waste sent to landfill, thus saving costs and reducing the environmental impact of the food production chain. This approach can be considered a virtuous example of smart livestock

L. Pinotti (✉)

Department Veterinary Medicine and Animal Science, DIVAS, University of Milan, Milan, Italy

e-mail: luciano.pinotti@unimi.it

nutrition and feeding that can and will become an option in sustainable animal production optimization.

Keywords

Alternative feed ingredients · Animal response · Bakery by-products · Cooking · Digestibility · Digestion kinetics · Ex-food · Feeding stuffs · Former food · Former food products · Gut health · Leftovers · Logistics · Microbiological safety · Nutrients · Nutritional quality · Packaging · Processing · Rumen health · Swine · Waste

3.1 Introduction

Smart livestock nutrition is a breakthrough in animal feeding and represents a way to design and apply specific feeding approaches that meet animal needs in real time. The aim is to increase the nutrient utilization and the productive performance of animals and more in general to provide high welfare, safe and high-quality animal products with a low environmental footprint. However, to reach this goal, several issues have yet to be addressed.

Food and nutritional security depend on the livestock economy and the related constant supply of certain ingredients used as feed. The continuing population growth is likely to increase the food-feed competition between humans and animals in terms of crop consumption, land, and water use (WWF, 2014; FAO, 2018). According to FAO (2018), livestock consumes one-third of global cereal crops. Monogastrics (pigs and poultry) are the main competitors in terms of human-edible crop consumption, since their diets are based mainly on food grains that could be consumed directly by humans. On the contrary, almost all of the diet for ruminants is based on human-inedible crops. In terms of production, producing 1 kg of boneless meat requires an average of 3.2 kg of human-edible feed in monogastric systems and 2.8 kg in ruminant systems (FAO, 2018). Furthermore, ruminants add value to the food chain by converting natural resources that otherwise would not be usable by humans into food such as milk (FAO, 2018). Another example is soybean, which is the world's primary plant protein. Eighty-five percent of all soybeans are cultivated for feed purposes, primarily for pigs and poultry (WWF, 2014). These protein sources require large arable lands and a huge consumption of water for their growth.

Along with the food-feed competition, reducing greenhouse gas emissions (Patthanaissaranukool & Polprasert, 2016; Benavides et al., 2020) and water use (Flachowsky & Meyer, 2015; Dutta et al., 2020) are key issues for smart livestock nutrition and production. The concept of sustainability is therefore the pillar of this path of change.

There is a compelling need to reduce the use of crops in exchange for other feed sources with a similar nutritional profile, to improve their use and thereby decrease the ecological pressure from the feed production (Pinotti et al., 2019a). Both feed

producers and animal science researchers are thus investigating alternative protein/energy sources for animal nutrition such as insects, algae, and food losses.

FAO estimates an annual loss or waste of global food products between 30% and 50% before and after reaching the consumer (FAO, 2018). When landfilled, food leftover products lead to methane emissions and soil pollution. Use of proper processing technologies can offer more sustainable alternatives to the landfills. Examples are the aerobic composting (AC) and anaerobic digestion (AD) for managing food leftovers. Both the AC and AD help mitigate climate burdens by reducing landfill methane emissions as well as through life-cycle carbon (LCC) reductions via fertilizer and/or energy substitution (Shurson, 2020).

The re-entering of food leftovers from the food industry into the food chain could represent a more advantageous approach compared to AC and AD. Exploiting food leftovers to feed livestock, in fact, could be an effective way of improving this sector from a circular economy point of view, creating both economic and nutritional value (Fig. 3.1).

Typical food leftovers used in feed ingredients are biscuits, bread, breakfast cereals, chocolate bars, pasta, savory snacks and sweets, dairy, and other patisserie products (Guo et al., 2015; Giromini et al., 2017; Tretola et al., 2017a; Pinotti et al., 2019a). Since such products are not conventionally used as feed ingredients, in order to ensure optimal growth performance and health their nutrient value needs to be assessed before integrating them into animal diets. Because of the lack of a complete and detailed knowledge of the properties of these foods and their safe use in animal nutrition, the use of food leftovers as sustainable feed ingredients is still limited. To fill this gap, this chapter examines the state of the art of food leftovers and discusses their nutritional properties, technological implications, and possible safety issues when used as alternative feed ingredients. Their incorporation into livestock systems that incorporate smart animal nutrition principles, is also discussed briefly.

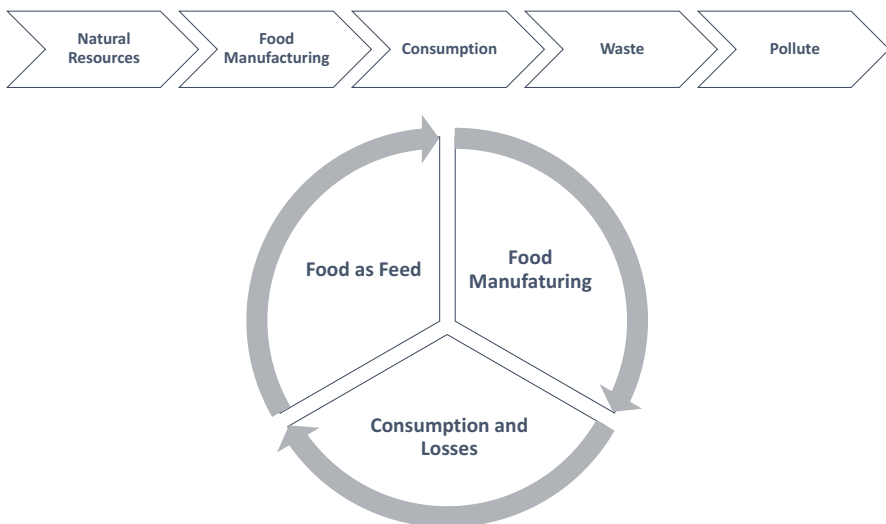


Fig. 3.1 Flow chart representation of the concept of moving from a linear to a circular economy based on food reuse in agri-food systems

3.2 General Characteristics of Food Leftovers Re-used in Animal Nutrition

“Food leftovers,” “ex-food,” and “former foodstuffs” all have the same meaning and refer to foodstuffs, other than catering reflux, that were manufactured for human consumption in full compliance with food laws, but which are no longer intended for human consumption for practical or logistical reasons or due to manufacturing problems, packaging or other defects and which do not present any health risks when used as feed (EU, 2013; Guo et al., 2015; EFFPA, 2016; Pinotti et al., 2019a). There are two main categories. Firstly, leftovers originating from the food industry, where bakery by-products (BBPs), such as bread and sometimes pasta, are the major source of nutrients. Secondly, confectionery products—former food products (FFPs)—are mainly composed of sugar-rich products such as biscuits, waffles, and chocolates. Snacks and other salty foods (chips and crackers) are usually part of the first category. There are thus two main types of food leftover on the market, namely salty materials (i.e. BBPs) and sweet materials (FFPs); however, sometimes they are mixed together.

An estimated 3–3.5 Mt of ex-food are currently processed annually in the EU (EFFPA, 2016). These foods are already recycled in animal nutrition; however, their use is still limited (3.3% of total amount potentially available in the EU) compared to the total EU food waste (EFFPA, 2016; Pinotti et al., 2019b; Luciano et al., 2020). For the same products (mainly BBPs used in animal nutrition), the annual production in the United States is estimated at over 500,000 tons (Liu et al., 2018). Figure 3.2 shows some examples of food leftovers that reach the former foodstuff processors before being converted into animal feed ingredients.

Both FFPs and BBPs are food leftovers that can be used as feed ingredients in monogastrics, such as pigs, and ruminants (EFFPA, 2016; Pinotti et al., 2021). Both categories of food leftovers stored by former foodstuff processors are reprocessed and, after being unpacked, sorted, dried, ground, and sieved, they can replace some of the existing raw materials used in various compound feeds. Some products such as sweets and dairy powders can be water dissolved and processed to obtain syrups. These syrups can replace molasses, which are used as a binding agent during the pelleting of feed (Pinotti et al., 2019a, b). Sweet materials can also be used directly. For example, Guo et al. (2015), proposed that chocolate candy feed, over 50% of which consists of simple sugars, could partially replace lactose in nursery pigs.

In fact, most of these products are often characterized by a high content of simple sugars (sucrose, lactose, fructose, and glucose) and sometimes fats. As a consequence, FFPs are generally highly caloric and can be used in monogastric omnivorous (poultry and pigs) diets as alternative energy sources in the place of cereals (Pinotti et al., 2019b). This is fundamental nowadays, especially for modern lean pig strains (average daily gain > 1 kg), which have high energy requirements and need nutritious and energy-dense ingredients (Luciano et al., 2020).

The re-use of food leftovers in the food/feed supply chain as feed ingredients aligns with the principles of smart livestock nutrition, thus increasing the efficiency as well as the sustainability of animal-based products. First, food leftovers could be



Fig. 3.2 Examples of former foodstuffs in the European former food processing industry. (Copyright Dr Luciano Pinotti, reproduced with permission)

used in the diet for animals in need of high amounts of one or more of energy, simple sugars, and fats. Furthermore, the carbohydrate content of food leftovers is highly digestible because of the thermal processing they undergo, thus working in favor of animals that need easy-digestible carbohydrate intake (Ottoboni et al., 2019).

Second, the reduction of the biomass of food leftovers sent to landfills and its recycling as feed ingredients decreases the environmental footprint of livestock nutrition. For this latter point, the synergy between the manufacturing plants of food leftovers and the livestock system is crucial to determine a constant and efficient supply of this feed ingredient.

The main issues regarding the use of food leftovers and dealing with smart livestock nutrition challenges focus on the evaluation of the quality of animal products, because few and incomplete data have been generated in this field so far.

3.3 Nutritional Quality of FFPs

Table 3.1 reports the main composition of both FFPs and BBPs and highlights that food leftovers are extremely rich in carbohydrates, and depending on their origin, also in fat (Liu et al., 2018; Pinotti et al., 2019b; Luciano et al., 2020). Of the carbohydrates, simple sugars (e.g. sucrose, lactose, glucose, fructose) represent a

Table 3.1 Comparison between the nutritional composition of different batches of food leftovers (former food products and bakery by-products (FFPs, BBPs)) and two conventional cereals (wheat, barley)

Item (% DM)	FFP	BBP	Barley	Wheat
Dry matter	88.0	88.0	88.0	88.0
Crude protein	10.9	11.4	11.0	12.4
Crude fat	9.8–10	6.50	2.80	2.10
Crude fibre	2.20–2.70	3.60	5.50	2.70
Starch	42.0–55.0	44.7	51.6	59.2
Sugars	14.0–20.0	14.2	2.20	2.40
Metabolizable energy (ME) growing swine (MJ/kg)	15.0–17.0	14.6	12.9	14.4

Data are expressed as percentage of dry matter (DM). Adapted from Giromini et al. (2017), Liu et al. (2018), and Luciano et al. (2020)

significant quota, especially when confectionary products are considered (Guo et al., 2015).

Giromini et al. (2017) assessed the composition, together with the *in vitro* digestibility, digestible and metabolizable energy of various types of food leftovers and showed that FFPs have a composition comparable to that of the cereals conventionally used in pig diets (Liu et al., 2018). Table 3.1 compares FFPs and BBPs with wheat and barley, two cereals commonly used in pig nutrition.

As shown in Table 3.1, from a nutritional point of view, food leftovers (FFPs and BBPs) cannot be considered a significant source of protein as they have a low nitrogen content, which implies a low protein content (about 10% on DM basis). Both FFPs and BBPs have a higher fat content than cereals: 10% in FFPs, while it is only around 2% in wheat. This high-fat content is also accompanied by a high starch content, which means that the different food leftovers make high energy-density feedstuffs.

Giromini et al. (2017) reported that food leftovers have a similar nutritional composition to wheat grain, although with a higher energy (metabolizable energy, ME) content. The energy value reported for FFPs was 16.95 MJ/kg for ME for growing pigs. Fats and starch are the main contributors to this energy content.

An additional nutritional property of food leftovers is high digestibility, which ranges from 79% to 93% DM, depending on the ex-food mixture used in their preparation. Although these results relate to only a few examples of different ex-foods on the feed market, food leftovers are energetic feed ingredients with a high value for feeding animals (Giromini et al., 2017; Liu et al., 2018; Luciano et al., 2020). Their composition, however, can vary and some compositional features (i.e. free sugar content) require further study in order to ensure an appropriate inclusion in animal diets.

A key difference with cereals is that food leftovers such as FFPs and BBPs are generally cooked. This thermal processing results in a more digestible starch compared to the unprocessed starch commonly used in feed (Giuberti et al., 2012; Rojas & Stein, 2017; Ottoboni et al., 2019; Chen et al., 2020; Lombardi et al., 2020; Torbica et al., 2021; Zhang et al., 2021). The digestibility of polymeric compounds

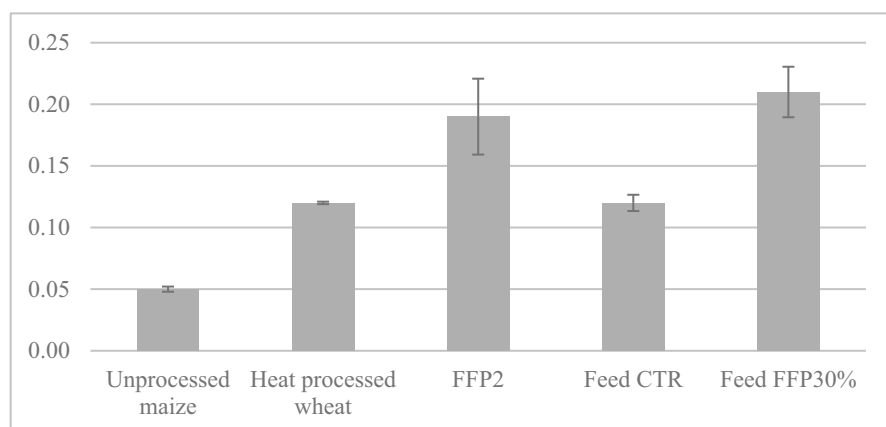


Fig. 3.3 Rate of carbohydrate digestion (/min), k , of cereal grains (unprocessed maize and heat-processed wheat), former food products (FFPs), and feed formulated without (Feed CTR) or with the inclusion of FFPs (Feed FFP30%) and relative standard deviation. (Adapted from Ottoboni et al., 2019)

such as starch is normally sensitive to the species and philological phase of the animals. However, high temperatures can modify the structures of the polymers resulting in a more highly digestible starch than the unprocessed cereals. This higher starch digestibility is an advantage not only for growing and/or finishing pigs but also for newly weaned piglets in which the gastrointestinal tract has not yet matured (Tretola et al., 2019a; Thomas & van der Poel, 2020). For example, Yin et al. (2010) observed that diets formulated with high-digestible starch increased the digestive and absorptive function of the small intestine and regulated amino acid metabolism, increasing their serum concentration and digestibility in weaned pigs.

Food and feed processing can modulate the kinetics of carbohydrate/starch digestion. The predicted glycemic index (pGI) is a parameter that can be used to classify the different sources of carbohydrates according to their digestibility, in order to choose the most valid option (Rojas & Stein, 2017; Ottoboni et al., 2019; Torbica et al., 2021). Ottoboni et al. (2019) recently evaluated the pGI, hydrolysis index, and carbohydrate digestion kinetics of different food leftovers, and of different diets containing and not containing FFPs as a cereal substitute. Figure 3.3 reports data on the hydrolysis (HI) and pGI of different feed ingredients and experimental diets. According to the classification proposed by Giuberti et al. (2012), in terms of the carbohydrate digestion rate, maize meal used as a control feed ingredient, was digested relatively slowly ($0.021 \leq k \leq 0.070/\text{min}$), while heat-processed wheat and all FFPs were digested rapidly ($k > 0.071/\text{min}$).

Data clearly indicate that including 30% FFPs as a substitute for conventional cereals (wheat, barley, corn) has a large impact on the carbohydrate digestion rate (k -Y axis), which indicates the rapid digestion of the carbohydrate fraction. In addition, the in-vitro digestibility, together with HI, pGI indexes, and DE and ME

values of FFPs were higher or comparable to the values found in cereal grains such as wheat. The main reason for this pattern is likely that all food leftovers are produced starting with cooked ingredients, in which the starch and other carbohydrates have been heat-treated (Rojas & Stein, 2017; Ottoboni et al., 2019; Chen et al., 2020; Thomas & van der Poel, 2020; Torbica et al., 2021; Zhang et al., 2021).

Regarding proteins, FFPs and BBPs are not a considerable source of CP, but their values are in line with the common cereals (Table 3.1). As seen above, high-temperature treatments can improve the digestibility of the starch content. Furthermore, high temperatures are also applied to promote the hydrolysis process by the solubilization of organic compounds to increase the bioenergy yield of food leftovers. However, high-temperature treatments promote also Maillard reactions and the formation of melanoidins, thus reducing the protein and sugar content and the VFA production. The optimization of the parameters of the hydrothermal process is a valid option to reduce the adverse effects of high temperature on food leftovers (Liu et al., 2021). In any case, this issue needs to be further addressed. Food industry leftovers should not, therefore, be considered as landfill waste and their use as an energetic resource in animal nutrition should be encouraged.

3.4 Food Leftovers in Pig Diets

The use of alternative feedstuffs, and especially food leftovers, is not new for the pig industry. Pigs are omnivorous; therefore, they can be fed with a mixture of nutrients as typically found in food leftovers (Pinotti et al., 2021).

Recent studies have investigated the effects of substituting 30% conventional cereals for 30% FFPs in the diet of post-weaning piglets on growth performance (Tretola et al., 2019a) and gut microbiota (Tretola et al., 2019b). Both *in vitro* and *in vivo* digestibility values were higher for FFPs diets compared to the control diet. Neither the average daily gain or feed intake were affected by dietary treatment. Conversely, piglets on the FFPs diets showed a lower feed conversion rate. This, therefore, suggests that integrating FFPs into post-weaning diets as cereal substitutes up to a level of 30% has no detrimental effects on pig growth performance (Tretola et al., 2019a). The same effects have been reported in later studies when the substituting rate of FFPs for cereal and other conventional ingredients in pig diets was up to 30% (Luciano et al., 2021a, b). Higher inclusion rates merit further investigations.

Gut health is crucial to ensure well-being and proper performance. The high digestible starch could therefore affect the gut microbiota in piglets. The inclusion of 30% FFPs in the diet of post-weaning piglets reduced the abundance and the biodiversity of gut bacterial population, compared to the control diet (Tretola et al., 2019b). However, subsequent studies observed any effect (Tretola et al., 2022). Therefore, the effect of FFPs on gut microbiota needs to be further addressed.

3.5 Food Leftovers in Ruminant Diets

The inclusion of FFPs and BBPs has been investigated mainly in monogastrics, such as pigs, and much less in ruminants. Both FFPs and BBPs are usually high in sugar, oil, and starch content, thus resulting in high energy content. This considerable amount of energy can affect rumen fermentation. Sugars ferment faster than starch or fibre in the rumen, although the rates of hydrolysis and fermentation vary greatly depending on the type of sugar and on the rumen environment.

Some of these aspects were addressed *in vitro* by Humer et al. (2018) using BBPs in a protocol that mimics the rumen physiology. Diets including high levels of BBPs (30–45% DM) have shown a better *in vitro* rumen degradation of starch, while the degradation of crude protein and fibre decreased. Specifically, the inclusion of BBPs by up to 30% of the DM had no detrimental effects on pH, fibre degradability and ruminal microbiota, and enhanced propionate production. In contrast, a higher inclusion level (45% DM) reduced rumen microbiota biodiversity, impaired ruminal fermentation, and fibre degradation, thus making these inclusion levels unsuitable, at least *in vitro* (Humer et al., 2018).

In 2020, Kaltenegger et al. (2020) evaluated the effects of integrating leftover BBPs in the diet of mid-lactating dairy cows on DM intake, milk production, and metabolic rumen profile. They gradually substituted 15% and 30% cereal grains with BBPs in dairy cow diets. Since the sugar and fat content in BBP-based diets was higher than in the control diet, there was a shift in nutrient profile from glucogenic to lipogenic. In particular, the DM intake was higher in cows fed with BBP-based diets. The increased nutrient and energy availability enhanced milk production and stabilized ruminal pH. The authors also found that feeding 15% BBP reduced the risk of sub-acute ruminal acidosis (SARA) in dairy cows, whereas 30% resulted in lower blood glucose and insulin levels, thus increasing the risk of SARA. This, therefore, suggests that in itself the rapid disappearance of sugar does not necessarily lead to health problems in dairy cows (Kaltenegger et al., 2020).

The inclusion of food leftovers in ruminant diet can be beneficial but needs to be further addressed with long-term studies and using different sources of food leftovers. In any case, the use of food leftovers for ruminants reduces both the waste biomass and the natural resources needed to crop the feed ingredients for ruminants. Furthermore, ruminants can upgrade co/by-products in high-quality animal products such as meat and milk.

3.6 Implications of the Use of Leftovers in Animal Feedstuffs

Food safety is one of the key aspects of smart livestock nutrition. Therefore, the inclusion of food leftovers into animal diets need to be addressed also considering the issues regarding food safety. The health of the animal ensures safer foods for human consumption, as well as preventing the use of therapeutic treatments (e.g. antibiotics). In this context, there are two fundamental aspects to consider: the microbiological load that can be affected by any contamination from moulds and

yeasts, the presence of packaging materials, and the issues regarding the logistics of the use of food leftovers in animal nutrition.

3.6.1 Safety Issues

Microbial Contamination

Recycling food leftovers entails grinding, mixing, drying, and possibly thermal treatments. All these processes affect not only the nutritional characteristics but also safety. One key aspect is the total number of microorganisms present in food leftovers. An interesting study by Tretola et al. (2017a) investigated the number of microorganisms in several FFPs in terms of total viable count (TVC). The TVC provides a quantitative estimation of the concentration of microorganisms such as bacteria, yeasts, or moulds spores in a sample. The count represents the number of colony-forming units (CFUs) per g (or per ml) of the sample. The various FFPs examined by Tretola et al. (2017a) showed how safe the samples were with a high level of hygiene. The mean TVC, which verifies the general hygienic conditions of food and feedstuff, was 4.92 ± 0.25 Log CFU/g. None of the samples exceeded the microbial load generally recognized in food and feed as the threshold limit above which spoilage can occur. Even considering the contamination of individual microorganisms, the result did not change: for all the organisms considered, the values were below the threshold.

In the same study, the counts of several microorganisms, such as *Staphylococci*, *Escherichia coli*, and *Bacillus cereus*, were found to be close to the detectable limit (Tretola et al., 2017a). The same was applied to *Clostridia*, with values well below the critical threshold, considering that 4 CFU/g logs is not considered risky. However, the major risk for the microbial contamination of animal feed is *Salmonella spp.* Of note, in all FFPs tested in the study (Tretola et al., 2017a), *Salmonella spp.* was never detected, thus matching the standard established by the main health authorities for the animal feed sector (Pinotti et al., 2019b; Luciano et al., 2020). These results, however, were expected, as the FFPs tested were dry and cooked at high temperatures during the production processes, which probably enhanced their microbiological stability. This is also very similar for yeasts and moulds, neither of which was detected in the materials tested (Tretola et al., 2017a).

Packaging Remnants

A further safety issue in food leftover applications in animal nutrition is related to the packaging materials. For example, the packaging of bakery products such as bread and biscuits must ensure their quality during transport and storage. In terms of types of materials, food packaging varies widely according to the food materials considered which are then used in the food leftovers formulation and preparation (van Raamsdonk et al., 2011; Tretola et al., 2017a, b, 2019c).

Processing methods to convert food leftovers into feed ingredients do not generally include the mechanical pre-removal of packaging materials (van Raamsdonk et al., 2011). The typical un-packaging process of food leftovers is as follows:

1. The packaging is broken down and reduced in size.
2. The now accessible products are processed into a ready product.
3. The remains of the packaging materials are finally removed.

More specifically, food leftovers are unpackaged automatically in order to process a large amount of product. Feed processors routinely mechanically remove packaging from packaged food in the feed plant; however, despite the removal of most of the packaging, small amounts of wrapping materials remain in the resulting feed. Consequently, a small amount of packaging remnants in the final product (feed) appears to be unavoidable (Tretola et al., 2017a, b, 2019c). Typical remnant residues in food leftovers include paper/paperboard, aluminium foil, and plastic (van Raamsdonk et al., 2011; Tretola et al., 2017b; Calvini et al., 2020; Luciano et al., 2022). The efficiency in the unpacking process can enormously vary between different FFPs processors, leading to final products with more or less packaging residues.

Tretola et al. (2019c) found that paperboard was the most detected contaminant followed by aluminium foil, and then plastic. Plastic is a synthetic material obtained by the polymerization of different monomers and therefore is also resistant at high temperatures. Microplastics are usually defined as plastic particles which are smaller than 5 mm (van Raamsdonk et al., 2020). Particles of 1–2 mm or larger can normally be detected visually, manually extracted, and quantified based on weight. This procedure has become a daily practice in the monitoring of former foodstuffs for their use in animal feeds (Tretola et al., 2017b; Calvini et al., 2020; van Raamsdonk et al., 2020). However, in spite of this variability in packaging materials, packaging remnants in FFPs are usually negligible (<0.10 g/100 g), which makes them safe (Tretola et al., 2017a, b, 2019c; van Raamsdonk et al., 2011).

Other Potential Contaminants

Other contaminants such as pesticides, toxins, and heavy metals have been detected mainly in crop, animal, and fish by-products. Since both FFPs and BBPs come from food primarily intended for human consumption, the level of these contaminants and more in general of the other hazardous contaminants seen above has been already assessed. After the processing to formulate them as feed ingredients, both FFPs and BBPs can be considered valid and safe.

Finally, some FFPs often contain chocolate and cocoa bean shells. Such ingredients are a source of theobromine, a substance that can be toxic and anti-nutritive at some levels and for some species (Rojo-Poveda et al., 2020). That is why, to ensure the safety of the feedstuffs, the European Food Safety Authority (EFSA) established the maximum permitted level of theobromine in the feed at the level of

300 mg/kg for complete feedstuffs, with the only exception of 700 mg/kg in a complete feedstuff with a moisture content of 12% for adult cattle (EFSA, 2008).

The inclusion of cocoa husks in pig diets did not affect growth performances and feed intake and improved the intestinal microbial balance (Magistrelli et al., 2016). Despite the potential risk of theobromine in feedstuffs, the balanced inclusion of theobromine in pig nutrition could exert beneficial effects on multiple levels. Negative effects on milk yield and fat content appear from 15 mg/kg theobromine in the diet of dairy cows (EFSA, 2008).

The characterization of the FFPs composition in polyphenols is also important, as hydrolysable tannin degradation products are possibly poisonous to ruminants (Hagerman et al., 1992). Therefore, attention must be given so that the advantages of feeding polyphenols are not offset by negative properties of tannins on feed intake, digestion, metabolism, and animal productivity.

3.6.2 Logistical Issues

The nature of food leftovers can sometimes represent logistical issues to incorporate them into modern smart nutrition systems, which rely on principles of precision. A major challenge is the seasonality of food leftovers, and its effect on nutrient composition. The chemical composition of the leftovers received by the FFPs processors can significantly vary during the entire year and become difficult to assure a final product with characteristics that are kept homogeneous independent of season. It is therefore essential for the FFPs processors to have a large portfolio of heterogeneous food leftovers that can be mixed together to obtain standard products that may differ in their ingredient formulation, but with a standardized chemical composition. Some of these principles are explored further in Chap. 4.

Another challenge is the handling of processed food leftovers from the manufacturing plant to the farm system and their incorporation into the ration. The manufacturing plant should be likely near the farming system or in any case where food leftovers are then used. The fact that manufacturing plants from abroad provide the processed food leftovers would reduce the beneficial impact of the use of food leftovers on environmental sustainability. The optimization of the logistics regarding processing (e.g. high-temperature treatments), transport, supply, and storage of food leftovers to the farm systems is crucial to ensure that the nutritional features of food leftovers are preserved.

3.7 Conclusions

Mitigating environmental impact is crucial for sustainable production in the live-stock sector. This can be achieved by reducing food waste through recycling, and especially by enhancing the management of food leftovers, with the added benefit of being alternative feed ingredients. Replacing traditional feed ingredients with food leftovers could also lead to reduced competition between humans and animals for

raw materials, such as common food cereals, and for land and water use. FFPs and BBPs are thus potential resources rather than waste products sent to landfill or otherwise disposed of in the natural environment.

From a nutritional point of view, food leftovers have a high content of sugars and starch, and depending on their origin, also fat. Accordingly, these products thus have a high value for animal feed because they often contain high amounts of energy. In addition, the food leftovers considered in this review are safe from a microbiological point of view since the microbiological loads reported in the literature were always below the tolerance levels established by various feed/food safety standard agencies (e.g. the Health Protection Agency and European Regulations). However, the use of food leftovers also involves safety issues related to packaging remnants being nearly always present in these products. However, their residual content can be negligible and therefore not an issue for the safe use of food leftovers in animal nutrition.

All these features make the reprocessing of food leftover biomass a highly attractive, sustainable, and abundant source of nutrients for the feed sector. This practice aligns with the principles of smart livestock nutrition for the provision of feeds of consistent nutrient composition. Therefore, the use of food leftovers can be considered a win-win opportunity for the environment and economy, without depleting natural resources, but reducing pollution in production processes, thus maintaining an ecological balance.

Some logistical concerns should be considered and further addressed for the food leftovers processing, collection, and transport.

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Assessment of the Nutritive Value of Individual Feeds and Diets by Novel Technologies

4

Knud Erik Bach Knudsen, Samantha Noel, and Henry Jørgensen

Abstract

Feed accounts for the largest cost item in livestock production. Optimising the feed to the animal needs is therefore pivotal to efficient animal production and to minimise environmental and climate impacts. Classically, feed has been optimised based on table values and with the possibility for adjustment due to differences in chemical composition of ingredients. The latter requires tedious and costly wet chemical methods and has further the limitation that it cannot be used for the measurement of the nutritive value in real time. Near-infrared reflectant spectroscopy (NIRS), which utilises the interaction between light and matter, holds the potential to be used as online tool for measurements not only of nutrient composition, but also on nutritional value, provided that sufficiently large reference databases are available. This chapter discusses the recent progress in the development of calibration equations for the measurements of the digestibility of nutrients and energy values based on NIR scans of feedstuffs and diets and faecal residues, and how NIRS can be used to control the quality of feeds from a feed mill in real time and optimise the provision of nutrients for animals during growth and production. The use of NIRS calibrations developed based on faecal residues as a tool to select pigs with improved nutrient digestibility and value is also described and discussed. Real-time quality control of feeds provided to the animal has a central role in the implementation of smart nutrition in livestock systems.

Keywords

Acid detergent fibre (ADF) · Amino acids · Apparent ileal digestibility · Calibration · Cross-validation · Digestible energy (DE) · Gross energy (GE) ·

K. E. B. Knudsen (✉) · S. Noel · H. Jørgensen
Department of Animal and Veterinary Sciences, Aarhus University, Tjele, Denmark
e-mail: knuderik.bachknudsen@anivet.au.dk

Crude protein · Faecal NIRS · Lysine · Metabolisable energy (ME) · Near-infrared reflectant spectroscopy (NIRS) · Net energy (NE) · Neutral detergent fibre (NDF) · Nitrogen free extract (NFE) · Nutritive value · Starch · Sugar + starch · Total tract digestibility · Validation

4.1 Introduction

Feed accounts for approximately two-thirds of the cost of livestock production. Accurate feed value information is therefore pivotal to optimal livestock production as it influences not only the feed efficiency but is also of great importance for minimising the environmental and climate change impacts from livestock systems. The nutritional value of a feed, however, varies widely between and within feeds due to factors like nutrient concentration and the digestibility of nutrient fractions that among other things are influenced by genetic, agronomic, harvest, storage, and processing. Cereal grains provide the majority of energy for monogastric species and have been found to vary considerably in terms of digestible energy (DE) (Bach Knudsen et al., 1987; Just et al., 1983a; van Barneveld, 1999; van Barneveld et al., 2018; Beams et al., 1996). For instance, in Australia where the impact of geography and climate is much larger than in most other regions, the difference in DE of 70 cultivars of wheat was up to 3.7 MJ/kg dry matter (DM), and for 125 cultivars of barley up to 4.3 MJ/kg DM (van Barneveld et al., 1999; van Barneveld, 1999). The Danish feedstuff database with cereals samples from much less diverse geographic regions also shows significant variations in nutrient concentration, DE, and metabolisable energy (ME); 187 barley samples differed by 2 MJ/kg DM, and 41 wheat samples by 1 MJ/kg DM of ME (Just et al., 1983b). It was also found that although the ME content of wheat in general is higher than that of barley, the barley samples with the highest ME were higher than the wheat samples with the lowest ME values. Factors of the feed that may influence the availability of not only energy content but also amino acids include protein source and type, starch characteristics, fat source and type, non-starch polysaccharides, and anti-nutritional factors (Cozannet et al., 2010; van Barneveld, 1999; Just et al., 1984b; Noblet & Perez, 1993; Bach Knudsen et al., 2013).

The most important factors for optimal nutrient utilisation are accurate estimations of the availability of energy and protein. Inaccurate estimation of these values of a feed may lead to a reduction in target animal performance, increased waste from animal production, and a higher environmental footprint of livestock production (Millet et al., 2018; Wang & Zijlstra, 2018). Optimisation of the feed is therefore pivotal to obtaining efficient animal production. This is commonly done by optimisation of feed mixtures based on table values (Patience, 2018) and, in some cases, by analysing the nutrient fractions (e.g. protein, fat, fibre) and using this information to adjust the energy value of the diet (Henry et al., 1988; Noblet & Perez, 1993; Just et al., 1984b). However, the digestibility of a nutrient fraction may vary considerably from feed to feed, which results in rather inaccurate estimates of

the nutritive value of actual batches (Just et al., 1983b), and since it is not possible to perform *in vivo* evaluations of the individual feed ingredients because of time and cost, there is a need to develop quick and reliable methods for the determination of the nutritive value of single feedstuffs for feed formulation and for control of complete feeds. So far, *in vitro* methods validated on a wide range of feedstuffs to measure the potential (maximal) digestibility have been the best option to account for variation in the nutritive value of a feed (Boisen & Fernández, 1997; Chen et al., 2014), but *in vitro* methods are not suited for measurements of the nutritive value in real time. For this purpose, near-infrared reflectant spectroscopy (NIRS) has a potential and has been widely used to evaluate the nutritional quality of agricultural products for several decades (Norris, 1996). NIRS has also the potential to be used as a technology to estimate the nutritive value in real time, but a limiting factor for the development of robust calibrations is the need for large reference databases (Wang & Zijlstra, 2018; van Barneveld et al., 2018). The main purpose of the current chapter is to give an overview of NIRS methods for predicting nutrient composition, digestibility of nutrients and energy, DE and ME of feedstuffs and diets, and optimise feed utilisation. The core of the chapter is based on the work performed in the European Union Horizon 2020 project Feed-a-Gene (Adapting the feed, the animal, and the feeding techniques to improve the efficiency and sustainability of monogastric livestock production systems) based on NIR scans of feedstuffs and diets from the Danish feedstuff evaluation system for pigs (Just, 1975, 1982; Just et al., 1983b). The outcome of that is used to speculate how NIRS can be used in smart-farming systems as a tool for online control of nutrient composition and quality in feed-processing plants and barns.

4.2 Principles in the Development of NIRS Calibrations

Spectroscopy is the scientific discipline that studies the interactions of light with matter. Light can be of different wavelengths, represented by the electromagnetic spectrum. The near-infrared (NIR) region of the electromagnetic spectrum ranges from 780 to 2500 nm (Fig. 4.1). In terms of wave numbers, the near-infrared region is 14,300–4000 cm^{-1} , the mid-infrared range is 4000–200 cm^{-1} , and the far infrared is 200–10 cm^{-1} . Absorption of light in the NIR region causes molecules to vibrate and rotate when subject matter is exposed to a particular NIR wavelength and if the vibration of the molecules is of the same frequency as the exposure wavelength. Under these conditions, an amplified signal is reflected and measured by a detector. In a simplified way, chemical bonds can be considered as weak springs holding together two or more atoms. These springs will vibrate naturally, and when energy from the light is added to the system they will vibrate more energetically. However, atoms in molecules are constrained by quantum mechanisms allowing only a few specific energy levels. When only two atoms are involved then the only vibration will be seen as a stretching, whereas when three or more atoms are involved the bonds can also bend, giving rise to a whole series of different vibrations. Stretch vibrations require more energy than bending vibrations, and different chemical

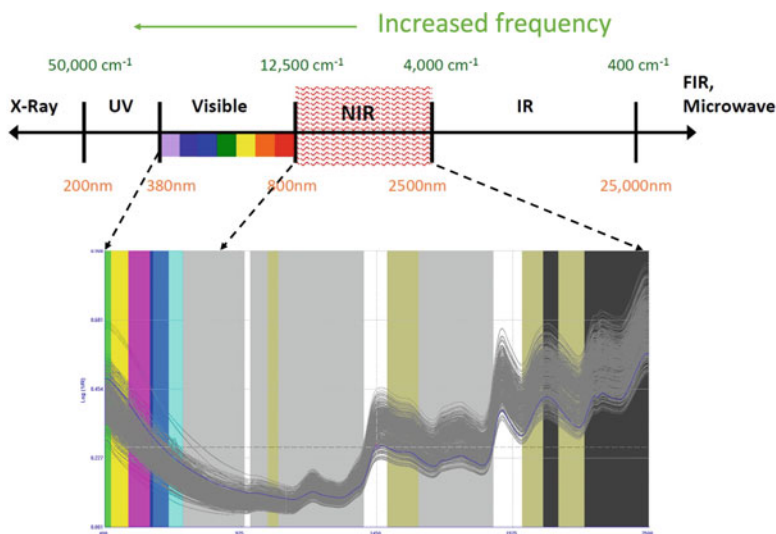


Fig. 4.1 Illustration of near-infrared spectroscopy of cereal samples. The abscissa is the wavelength in nanometre and the ordinate is the $\log(1/R)$ where R is the ratio of the intensity reflected from the sample and the intensity reflected from the standard

bonds (C-H, O-H, and N-H) vary in strength and hence the amount of energy required for the bond vibration to move from one level to the next. The absorptions in the NIR region, however, are generated from fundamental vibrations by two processes: overtones and combinations. Overtones will produce a series of absorptions approximately at multiples of the frequency. Combinations are rather more complex than overtones, as they share energy from fundamental absorptions. While the number of possible overtones from a group of fundamental absorptions in a molecule is limited to a few, a very large number of combinations will be observed as illustrated in the publication by Davies (2014) for NIR spectrums of chloroform (CHCl_3) containing only C-H bonds, methanol (CH_3OH) which contains combinations of C-H and O-H, and sucrose ($\text{C}_{12}\text{H}_{24}\text{O}_{12}$); the latter showing broad areas of absorption which are caused by multiple narrow, overlapping absorptions. Even more complicated absorption bands are found when analysing complex composed matrixes (Griffiths, 2002; García-Sánchez et al., 2017). The overtone of the functional groups and the combination of vibrations of the molecular bonds in close proximity to them provide information on the matrix of a sample. For instance, the total protein content can be determined chemically by measuring N concentration (including non-protein N), whereas N-H, peptide linkage, α -helix, and β -sheet information can be measured spectroscopically (Barth, 2007; Workman & Weyer, 2012). Fat can be measured chemically as the ether extract, whereas information about the carbon chains (CH_2), ether links (C-O), and double bonds ($\text{C}=\text{C}$) can be derived spectroscopically (Westad et al., 2008; Yoshida & Yoshida, 2003). Carbohydrates can be determined chemically as sugars, starch, non-starch

polysaccharides or by less specific analytical methods (crude fibre (CF), acid detergent fibre (ADF), neutral detergent fibre (NDF)), whereas functional groups of O-H, C-OH side groups, and C-O-C glycosidic bonds can be measured spectroscopically (Workman & Weyer, 2012; Zhbankov, 1992). Thus, the NIR spectra reflect structural information concerning the chemical component-specific nutrients induced by molecular vibrations of functional groups at a given wavelength (Shurvell, 2002; Weyer & Lo, 2002). These overtones and combination bands are called secondary vibrations and are weaker than the fundamental vibrations of the corresponding infrared bands, which makes NIR spectra complex with few significant peaks. The fact that NIR spectroscopy measures the same basic molecular vibrations (C-H, O-H, and N-H) as a variety of overtone and combination tones of virtually the entire near-infrared region gives rise to strongly overlapping, almost holographic NIR spectra that are exceptionally information-rich but at the same time are extremely difficult to interpret in the traditional manner (Blanco & Villarroya, 2002). NIR spectroscopic data, however, are characterised by being highly co-linear (i.e. two adjacent wavelengths are normally positively correlated with high correlation coefficients). A way of extracting information about these highly informative spectra is by applying chemometrics, a combination of mathematical and statistical methods, which is optimal for handling co-linearity (Agelet & Hurburgh, 2010).

Chemometrics have found widespread use for linking NIR spectra composing of broad overlapping chemical and physical information of all sample components in ill-defined absorption bands to known analytically measured variables as illustrated in Figs. 4.1 and 4.2. In short, it can involve the following steps:

1. Mathematical data pre-treatment of the spectra to normalise the data and maximise the signal
2. Reduction, in some cases, of variables (as spectra is multivariate), e.g. the removal of data points from parts of the spectra that add no information
3. Establishing calibration models with multivariate calibration methods based on the relation between the spectra and measured chemical or biological data set
4. Validation of calibration models by an independent data set

The most widely used pre-processing techniques in NIR spectroscopy can be divided into scatter-correction methods (multiplicative scatter correction (MSC), Inverse MSC, Extended MSC, Extended Inverse MSC, de-trending, standard normal variate and normalisation) and spectral derivatives (Rinnan et al., 2009). Mathematical pre-treatment of spectra is carried out to reduce noise or background information (smoothing techniques) and increases signal from the chemical information (differentiation). Different spectral pre-processing methods and model types can be used to minimise baseline offset and spectra distortions due to scattering such as standard-normal-variate or multiplicative scatter correction along with detrending and the use of second-order derivative for smoothing (Barnes et al., 1989; Agelet & Hurburgh, 2010; Rinnan et al., 2009).

The next step in the calibration development is to correlate either raw or pre-processed NIR spectra with one or more chemical-physical or biological

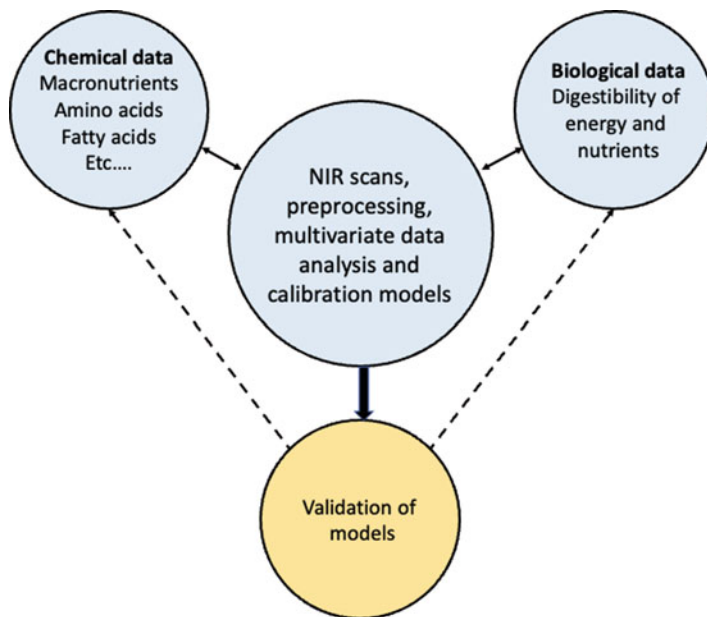


Fig. 4.2 Illustration of the relation of the NIR scans to chemical and biological data by multivariate data analysis for the development of prediction and validation models

property of a set of samples (Fig. 4.2). Before model building, it is common practice to assess for outliers by principal component analysis (PCA) and determination of standardised Mahalanobis distance; the latter is a measure of how many standard deviations a point is from the sample mean. The first assumption when carrying out a calibration is that there exists a linear correlation between analyte or property to be measured and its absorbance according to Beer's law. Several calibration methods work under these assumptions with multiple linear regression, principal component regression, and partial least squares as the best-known and used calibration methods (Agelet & Hurburgh, 2010). The calibration performance is usually evaluated using a combination of the following parameters: the regression coefficient (RSQ), standard error of cross-validation (SECV), coefficient of cross-validation (1-VR), standard error of prediction corrected for bias (SEP), relative SEP, ratio of performance deviation (RPD), and range error ratio (RER) (Sapienza et al., 2008). The RSQ describes the fit when the reference values are plotted against the predicted values where values closer to 1 are a better fit. The SECV shows how well the calibration model predicts the reference values when some samples are selectively removed. Lower SECV values indicate higher precision in model accuracy. 1-VR is the fraction of explained variance determined by cross-validation. The SEP evaluates the performance of the model on a set of independent samples indicating how the model will perform on new samples. The RPD is calculated by dividing the standard deviation (SD) by the SEP. The RPD gives an indication on whether the SEP values are low enough in comparison with the variation seen in the population used to make

the model. RDP values greater than 2 are preferred. The RER is the ratio of the range to the SD. Values greater than 10 are preferred. Relative SEP is calculated by dividing the SEP by the mean of the measured values and multiplying by 100.

The strongest and best-validated models are those where the calibration model can be tested on an independent data set which should be at least 20 samples according to the international standard (ISO-12099, 2017). While the number of samples is not a problem for most chemical components, it is far more difficult for biological parameters, such as digestibility of nutrients and energy, DE, or ME. In most but not all cases, the model accuracy cannot be better than the accuracy of the reference data. Since the chemical components are determined by higher accuracy than biological data, the accuracy of the prediction models for biological traits will usually be lower than that of chemical constituents.

4.3 Determination of Macronutrient, Digestibility, and Energy Value by NIRS

The energy value of a diet is determined by its chemical composition, the digestibility of the nutrients, and the utilisation of the nutrients (Just, 1975; Noblet & Henry, 1993). Usually, the energy value of a diet is expressed as DE, ME, or net energy (NE) (van Milgen et al., 2018; Just, 1975; Noblet & Henry, 1993). DE takes into account the energy of all the nutrients that apparently can be digested by the animals during passage of the entire gastrointestinal tract, ME accounts for the loss of energy that occurs in urine and gases, and the NE content corresponds for the difference between ME content and the so-called heat increment and the energy expenditure for “normal” physical activity (van Milgen et al., 2018). In popular terms, ME can be considered as a measure of the amount of energy a feed or diet provides for the animal, and NE is the response of the animal to the amount of energy provided. The usability of the different measures for energy of a feed has been debated for many years (Just, 1982; Noblet & Henry, 1993), and NE has usually been considered the most appropriate as it takes into account all the losses that occur when diet energy is transformed into animal products (Noblet, 2006). However, NE values for a feed depend on the characteristics of the feed, nutrients absorbed and the metabolic status of the animal with different NE values being derived for the same feed depending on genotypes, stage of growth, different physiological stages, and different climate conditions (Kil et al., 2013). Although NE from a theoretical standpoint is superior to DE and ME (Just, 1982; Noblet, 2006; Noblet & Henry, 1993), it cannot be used as a control measure in feed manufacture or as a tool for online monitoring of the composition and value of a feed as it partly relies on the animal response to the feed. As a practical approach, we therefore need to find methodologies that based on traits of the feed can be used as proxies for the feed values (van Barneveld et al., 2018). The *in vitro* method for organic matter digestibility is one such method (Boisen & Fernández, 1997), but since it relies on wet chemical methodologies for estimating the *in vitro* digestibility values it cannot be used for online control of the feed value (van Barneveld et al., 2018). NIRS has the potential to be used to predict the DE and

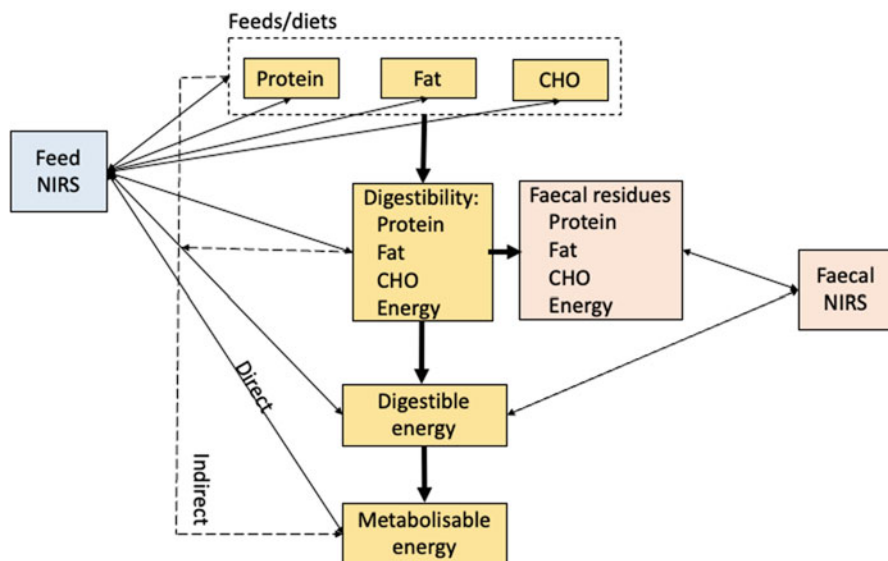


Fig. 4.3 Measurements of nutrient fractions, digestibility, digestible energy, metabolisable energy and net energy by near-infrared spectroscopy (NIRS) calibration to feed and dietary composition and composition of faeces. The calibrations in Feed NIRS are based on information on chemical composition of feeds and diets, digestibility of nutrients and energy, and digestible and metabolisable energy and used to predict the same parameters in independent data sets. The calibrations in Faecal NIRS are based on information on chemical composition of faeces and digestibility of nutrients and energy and used to predict the same parameters in independent data sets

ME values of the feed (Feed NIRS) along with the macronutrient composition, provided sufficient reference values are available (Fig. 4.3). In addition to establishing a direct link between the NIRS and the ME values, it is also possible based on NIRS estimates to calculate the ME using information from NIRS data on the composition of macronutrients (protein, fat, crude fibre, and NFE) combined with NIRS estimates of the digestibility of the same nutrients (Noel et al., 2022). A more recent approach has been to develop NIRS prediction models from the composition of faeces and to use these models to predict dietary nutrient composition, the digestibility of macronutrients, and energy and net energy of the feed (Paternostre et al., 2021; Bastianelli, 2013; Nirea et al., 2018; Schiborra et al., 2015).

4.3.1 Macronutrients

NIRS has long been used to predict the proximate composition of feeds and raw materials such as the content of crude protein (Williams & Cordeiro, 1979), amino acids (Chen et al., 2013), ADF, NDF, and starch (Barton, 1991; Campo et al., 2013), and recently also non-starch polysaccharides (ABVista, 2020). Some companies have built their own calibration databases by accumulation of data produced in their

own laboratories, whereas smaller companies can buy/rent calibration equations from the equipment manufacturer or from specialised companies as for instance (ABVista, 2020; CVAS, 2021; EVONIK, 2021) which propose calibration for almost all types of feeds and raw materials.

In a recent study, we scanned via NIR the individual feedstuffs and mixed diets that have been evaluated for energy content and protein quality for more than 40 years in the Danish feedstuff evaluation system (Just, 1975, 1982; Just et al., 1983b). In brief, a total of 858 feedstuffs and diets were divided into three groups: cereals, supplemental ingredients (co-products and protein-rich materials), and mixed diets as well as having all samples together in the total group (Noel et al., 2021, 2022). The samples were analysed for the chemical composition (ash, protein, fat, crude fibre, nitrogen-free extract (NFE), sugar + starch, starch, NDF, and ADF) and energy and the digestibility of protein (DAPro), fat (DFAT), crude fibre (DCF), NFE (DNFE), total fibre (DcTF), hemicellulose (DcHemi), and energy (DDE) (Table 4.1). Total fibre was calculated (cTF) as $cTF = 100 - (\text{ash} + \text{fat} + \text{protein} + \text{CF})$ and hemicellulose (cHemi) as $cHemi = \text{NFE} - (\text{sugar} + \text{starch})$. The samples in the total data set and the three groups (cereals, supplemental ingredients, feed mixtures) were randomly divided into a calibration and validation set with an 80:20 split. Before model building, the samples were assessed by PCA, and spectral outliers were determined by having a standardised Mahalanobis distance (GH) greater than 3. Groups of samples that were very different from the majority, including pure starches, pure sugar, roughage samples, and animal products, were removed from the data set. The remaining samples were re-assessed with PCA analysis to determine spectral outliers. Possibly mislabelled samples were also determined before model building by using modified partial least squares method and were removed as outliers. Cross-validation was used to determine the number of factors to include in the model and to validate the models (Noel et al., 2022). The number of factors to be included in the models was chosen to include as much information as possible without overfitting by assessing when the SECV reached its lowest value.

In spite of the diversity in types of feedstuffs and diets, the models developed on all sample types had high RSQ^{CAL} (0.92–0.98) in calibration for energy-contributing compounds and good fit in the validation with RSQ^{VAL} (0.9–0.98), almost as high as for the calibration set and with a slope close to 1 (Table 4.1). However, ash was poorly predicted, and gross energy was also only moderately well modelled (RSQ^{VAL} 0.84). Taken as a whole, our work on the chemical constituents showed good fit between the predicted and measured values even on this very diverse sample set. The NIRS calibrations can therefore be considered an alternative to conventional proximate analysis, with the advantage of being non-destructive, non-polluting, and almost immediate.

4.3.2 Digestibility and Energy Value

On the same data set of feedstuffs and diets from the Danish feedstuff database, we also performed NIRS calibrations on the total tract (TT) digestibility of energy, crude protein, fat, CF, NFE, total fibre (cTF), and hemicellulose (cHemi) (Table 4.1) (Noel

Table 4.1 Summary statistics comparing near-infrared spectroscopy (NIRS) calibration models and validation thereof for macronutrients, energy, digestibility and metabolisable energy of cereals, supplemental ingredients and complete feeds with the content of macronutrients in samples determined by wet chemical methods and with *in vivo* digestibility and energy utilisation in pigs

	N	Content of variables in the sample population					NIRS performance data					Validation				
		Cal/Val	Mean	SD	Min	Max	Calibration			Cross-validation		Intercept	Slope	RSQ	RPD	
							SEC	RSQ	SECV	1-VR						
Concentration, g/kg DM																
Ash		593/149	44.8	21.2	4.3	164.4	8.2	0.85	10.5	0.75		2.97	0.93	0.76	2.07	
Crude protein		607/150	180.8	86.2	27.7	708.2	12.8	0.98	15.7	0.97		4.46	0.97	0.95	5.11	
Fat		573/140	45.4	30.1	3.9	250.2	8.7	0.92	9.5	0.9		0.84	1	0.94	3.48	
Crude fibre		524/130	60.4	44.0	2.7	318.1	7.2	0.97	8.6	0.96		0.26	0.99	0.95	4.65	
NFE		525/129	672.4	129.7	182.8	897.2	16.6	0.98	19.2	0.98		16.49	0.98	0.98	6.19	
Sugar + starch		464/118	543.9	172.5	30.6	911.4	25.7	0.98	30.5	0.97		10.87	0.97	0.97	5.33	
Starch		489/125	481.3	183.3	2.8	916.3	40.2	0.95	44.7	0.94		12.04	0.97	0.93	3.78	
NDF		427/110	159.3	83.1	9.3	725.0	17.8	0.95	23.2	0.92		13.67	0.91	0.9	3.59	
ADF		430/112	76.7	55.2	1.8	377.3	9.7	0.97	11.9	0.95		-2.75	1.05	0.95	4.46	
Concentration, MJ/kg DM																
Gross energy		584/146	18.8	0.8	16.2	22.2	0.33	0.81	0.37	0.76		-0.49	1.03	0.84	2.27	
Digestibility, %																
DDE		549/135	80.4	9.2	23	98.2	2.2	0.94	2.7	0.92		11.54	0.86	0.86	2.84	
DAPro		520/130	77.4	9.1	21.9	95.9	3.5	0.85	4.6	0.74		29.9	0.61	0.58	1.60	
DFAT		472/122	29.9	17.1	0.3	100	7.4	0.73	9.0	0.61		-0.13	1.02	0.7	1.66	

DCF	419/122	88.9	8.2	30.3	99.4	9.4	0.7	11.3	0.56	-0.92	1.06	0.52	1.73
DNFE	441/100	43.8	16.6	6.5	100	1.5	0.97	2.2	0.93	-2.44	1.03	0.91	2.94
DcTF	395/115	49.8	16.8	7.1	100	10.1	0.63	11.2	0.54	-11.36	1.29	0.5	1.56
DcHemi	393/102	80.8	13.8	16.9	96.2	11.5	0.53	12.0	0.49	-7.31	1.17	0.33	1.34
Concentration, MJ/kg DM													
ME	528/130	14.6	1.7	4.6	19.9	0.5	0.91	0.59	0.87	1.76	0.88	0.84	2.45

Data from Noel et al. (2022)

Cal calibration, *Val* validation, *SEC* standard error of calibration, *RSQ* regression coefficient, *SECV* standard error of cross-validation, *I-VR* coefficient of cross-validation, *RPD* ratio of performance deviation, *NFE* nitrogen free extract, *NDF* neutral detergent fibre, *ADF* acid detergent fibre, *DDE* digestible dietary energy, *DAPro* digestible apparent protein, *DFAT* digestible fat, *DCF* digestible crude fibre, *DNFE* digestible nitrogen free extract, *DcTF* digestible calculated total fibre, *DcHemi* digestible calculated hemicellulose, *ME* metabolisable energy corrected to 50% protein deposition

et al., 2022). The calibration set used 393–549 samples and the validation set of 100–135 independent samples. The calibration models can be considered good for DDE and DNFE with RSQ^{CAL} of 0.94 and 0.97, adequate for DAPro and DFAT (RSQ^{CAL} 0.85 and 0.73), but generally poorer for the digestibility of the fibre fractions (DCF, DcTF, and DcHemi) with RSQ^{CAL} in the range 0.53–0.7. The variation in the RSQ^{VAL} set followed in general that of RSQ^{CAL} and was as expected at a lower level. It appears that the standard error of the prediction models was influenced by the concentration of the nutrients in the feed and the accuracy of the *in vivo* digestibility estimate. For instance, the SECV and SEP of DFAT were approximately double as high as DAPro, which again was double as high as of DNFE following, in inverse order, the mean concentration of the nutrients in the feeds (Table 4.1). A contributing factor for the higher SECV and SEP of fat and protein than of NFE is the larger *in vivo* variation in digestibility estimates (Fig. 4.4). The largest variation in the *in vivo* estimates of digestibility was seen for the fibrous components (CF, cTF, cHemi) (Fig. 4.4), which is caused by variation between animals in the retention time of fibrous components in the large intestine and

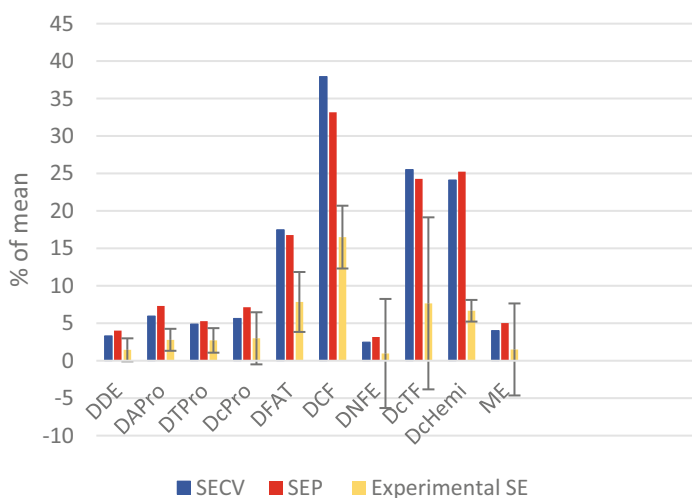


Fig. 4.4 Relative standard error, expressed as percentage of the mean, of NIR calibrations and measured digestibility values

SECV standard error of cross-validation of the NIR calibration as a percentage of the mean value, SEP standard error of prediction of the NIR calibration as a percentage of the mean value; Experimental SE, average standard error obtained when measuring the digestibility or metabolisable energy *in vivo* expressed as percentage of the mean value. Error bars represent \pm one SD. DDE digestible dietary energy, DAPro digestible apparent protein, DFAT digestible fat, DCF digestible crude fibre; DNFE, digestible nitrogen-free extract, DcTF digestible calculated total fibre^a, DcHemi digestible calculated hemicellulose^b, ME metabolisable energy

^aTotal fibre calculated by subtracting protein, ash, sugars+starch and fat from dry matter

^bHemicellulose calculated by subtracting sugars+starch from nitrogen-free extract

Modified data from Noel et al. (2022)

variation in microbial fermentation in the large intestine (Glitsø et al., 1998; Wilfart et al., 2007a, b).

A limiting factor for the development of strong NIR calibrations for digestibility and ME is the number of samples evaluated using a similar technique. In the study of Noel et al. (2022), it was also found that the model developed on the total database was better than those developed on groups (cereals, supplemental ingredients, and mixed diets) and better than those developed on cereals and reported in Table 4.2. In the study of van Barneveld et al. (1999), 157 samples of wheat, barley, sorghum, triticale, and maize obtained from *in vivo* studies performed in Australia, Canada, France, and New Zealand were used for calibration, and 27 for validation. The RSQ^{CAL} was 0.76 for whole grain and 0.72 for milled grain, which could be improved by 11% for whole grain and 14% for milled grain when proper adjustment was done for differences between sites for the *in vivo* studies. The adjustment due to site differences reduced the SECV for whole grain from 0.52 to 0.38 MJ/kg DM and for milled grain from 0.60 to 0.43 MJ/kg DM (van Barneveld et al., 1999). It appears likely that the results reported in the publications by Black and Spragg (2010) and van Barneveld et al. (2018) include some of the samples already reported by van Barneveld et al. (1999). In a study in Canada on 25 barley samples used for calibration and 12 samples used for validation, the RSQ^{CAL} and SEC were estimated to be 0.97 and 19.8 kcal kg⁻¹, respectively, which could account for 74% of the variation in barley DE content in the validation set which had SEP of 75.0 kcal kg⁻¹, more than three times higher than the SEC (Zijlstra et al., 2011). These data are essentially in line with data from an earlier study with barley that found an RSQ^{CAL} of 0.93 and a 1-VR of 0.69 and SEC (MJ/kg DM) of 0.128 and SECV of 0.279 (McCann et al., 2006) as well as the study of Pujol et al. (2007) where an RSQ^{VAL} of DOM of 0.87 was reported. Similarly, in a study by Li et al. (2016) using 86 maize samples for calibration and 29 for validation, the RSQ^{CAL} , 1-VR, and RSQ^{VAL} were 0.89, 0.87, and 0.86, respectively, when comparing the NIRS-estimated values with DE determined directly in experiment with pigs. RSQ^{CAL} and RSQ^{VAL} in the same order were reported with 24 sorghum samples used for calibration and 9 for validation (Hu et al., 2019). A good correlation was also found in the study of Zhou et al. (2012) with maize distillers grains with solubles (DDGS) where 69 samples were used for calibration and cross-validation and 23 samples for external validation. In this study, RSQ^{CAL} , 1-VR, and RSQ^{VAL} were 0.98, 0.93, and 0.91 and with SEC, SECV, and SEP(C) of 0.19, 0.33, and 0.31 MJ/kg DM, respectively. In our own subgroup of cereals, we found RSQ^{CAL} and RSQ^{VAL} for DE and ME of 0.85 and 0.79 and 0.76 and 0.73, respectively. Much poorer results for DE and DAPro compared to the chemical constituents were reported by Garnsworthy et al. (2000), probably because of limited variation in the samples and a small subset. Of the studies reported in Table 4.2, it is only the studies reported by Aufrere et al. (1996) and Paternostre et al. (2021) that are based on compound feeds.

ME of samples from the Danish feedstuff database could be modelled directly by NIR with RSQ^{CAL} , 1-VR, and RSQ^{VAL} in the order of 0.91, 0.87, and 0.84, respectively. For the RSQ 's, the values were only slightly lower than those of DE, and the SEC, SECV, and SEP(C) of 118.2, 141.7, and 162.8 kcal/kg DM,

Table 4.2 Summary statistics of near-infrared spectroscopy (NIRS) calibration models and validation thereof for the digestibility of energy, organic matter and nutrients, and metabolisable energy from different studies

Type	Calibration			Validation				Reference
	N	SEC	RSQ	SECV	1-VR	Slope	Bias	
Diet DE	83	0.37	0.87	0.43				Aufriere et al. (1996)
Diets ME	83	0.38	0.86	0.43				
Millet cereal grain	157/27		0.72	0.60 ^a				van Barneveld et al. (1999)
Millet cereal grain (IV)			0.86	0.43 ^a				2.13
Wheat DE	33	0.33	0.17	0.39	0.00			2.97
Wheat DAPro	31	0.02	0.22	0.02	0.00			1.00
Barley	39	0.128 ^a	0.93	0.277 ^a	0.69			1.00
Barley AIDPro	15/5							0.70
Barley DOM	15/5					1.01	0.080	0.289
Barley DDM	15/5					0.77	1.43	0.892
DDE of mixed grains	170					0.34	-0.21	1.22
Barley	25/12	0.083 ^a	0.97	0.27 ^a	0.86			0.485
Maize DDGS DE	69/23	0.19 ^a	0.98	0.158 ^a	0.89			2.6
Maize DDGS ME	69/23	0.20 ^a	0.98	0.33 ^a	0.94			0.74
Maize DE	87/29	0.196 ^a	0.89	0.34 ^a	0.93			0.91
Maize ME	86/29	0.206 ^a	0.87	0.266 ^a	0.87			0.88
Cereals DDE	288			0.273 ^a	0.85			0.275 ^a
				0.26 ^a	0.86			0.276 ^a
								2.65
								van Barneveld et al. (2018)

Mixed diets DOM	62	0.018 ^b	0.73	0.022 ^b	0.73						1.6	Paternostre et al. (2021)
Mixed diets NE	62	0.27 ^a	0.79	0.31	0.79						1.8	
Sorghum DE	24/9		0.94						0.16 ^a	0.90	3.15	Hu et al. (2019)
Sorghum ME	24/9		0.93						0.21 ^a	0.81	2.35	
Cereals DDE	201/54	0.016 ^b	0.85	0.017 ^b	0.81	1.23	-0.15	0.021 ^b	0.76	1.96		Noel et al. (2022)
Cereals ME	201/54	0.34 ^a	0.79	0.37 ^a	0.75	1.36	-5.17	0.47	0.73	1.56		

^aValues in MJ/kg; ^bValues in ratio; *DE* digestible energy, *ME* metabolisable energy, *NE* net energy, *DDE* digestible dietary energy, *DOM* digestible organic matter, *ADPro* apparent ileal digestible protein, *DAPro* digestible apparent protein, *DFAT* digestible fat, *DNDF* digestible neutral detergent fibre, *N* denote the number of samples that have been used for calibration (Cal) and validation (Val), *SEC* standard error of calibration, *RSQ* regression coefficient, *SECV* standard error of cross-validation, *I-VR* coefficient of cross-validation, *SEP(C)* standard error of prediction corrected for bias, *RPD* ratio of performance deviation

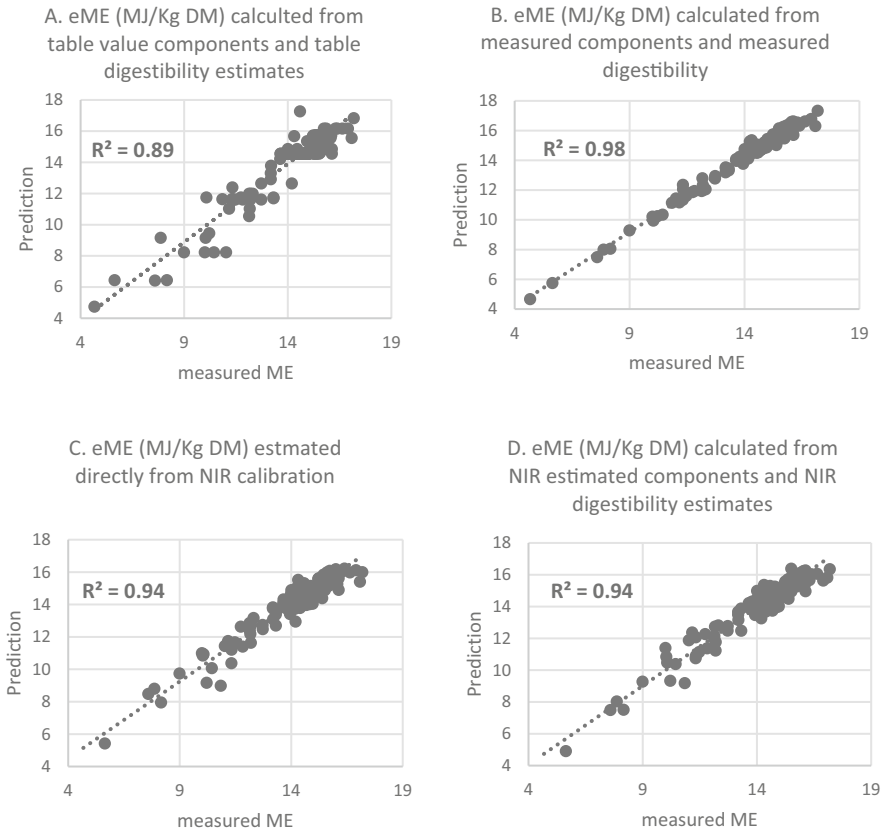


Fig. 4.5 Comparison of estimated metabolisable energy (eME) predicted by a NIRS equation for ME (part C) or with NIRS equation for macronutrients and digestibility of macronutrients (part D) with measured values of ME for 218 cereal and alternative ingredient samples. Panel A shows the eME using table values and panel B eME from experimentally determined values. The dotted line represents $Y = X$
Modified data from Noel et al. (2022)

respectively, can also be considered as acceptable. To further validate the use of NIRS to predict the energy value of individual feedstuffs, NIRS-estimated ME (eME) values were compared with ME values based on table values (Fig. 4.5a), experimentally determined values (Fig. 4.5b) or based on NIRS prediction of the nutrient composition and NIRS prediction of the digestibility of the individual nutrient fractions (Fig. 4.5c) or directly estimated from the NIR model for ME (Fig. 4.5d). The eME calculated in Fig. 4.5c was expressed by the following equation:

$$\text{eME (KJ)} = 10 + 20.5 \times X_1 + 36.7 \times X_2 + 14.7 \times X_3 + 17.3 \times X_4$$

where X_1 = digestible protein, X_2 = digestible fat, X_3 = digestible CF and X_4 = digestible NFE (Just et al., 1984a).

The RSQ of the cereals and individual ingredients could be improved from 0.89 obtained from using table values only to 0.94, when using NIRS-estimated nutrient fractions and NIRS-estimated digestibility or estimated directly from the NIRS calibration. The RSQ of the latter approaches was only slightly lower than obtained when estimating ME experimentally from measured nutrient fractions and measured digestibility. For mixed diets estimated by the calculated eME and the inclusion percentage of their individual components, however, the RSQ^{CAL} was lower, 0.84 compared to 0.89 for individual feedstuffs, and the improvements that could be obtained by estimating the ME directly from NIRS calibrations were only slightly higher ($RSQ^{CAL} = 0.85$) than by using table values only. When evaluating the outcome of the mixed diets the lower variability in data is important to take into account. Thus, the results of the study of Noel et al. (2022) show that NIR can be a useful and strong tool not only for estimating the chemical composition but also for the digestibility of nutrients and energy as well as ME. Thus, with the NIRS technology, we have a very promising tool to be further developed as online control of energy digestibility and metabolism in connection with the production of the feed in feed factories and in mixing of cereals and protein-rich ingredients for feeding systems in barns (Fig. 4.3).

4.3.3 Faecal Composition and Digestibility

Recent studies have also looked at the possibility of using NIRS directly on non-digested nutrient residues in faecal samples (FNIRS) to predict the total tract (TT) digestibility of nutrients (Bastianelli et al., 2015; Nirea et al., 2018; Schiborra et al., 2015; Paternostre et al., 2021) and to estimate the nutrient composition of diets (Schiborra et al., 2015) (Fig. 4.3). The rationale behind this is that the FNIRS contain information on diet characteristics and the TT of nutrients even though it has been transformed as it passes through the gastrointestinal tract of the animal. The results from two of the studies on the composition of faeces are shown in Table 4.3. The samples for the study of Schiborra et al. (2015) were obtained from five different digestibility experiments performed in Germany, Nigeria, and China involving 36 very different diets, the samples for the study of Bastianelli et al. (2015) from a digestibility experiment performed on one diet in France, but fed to animals of different genetic background, and the samples from the study of Nirea et al. (2018) from digestibility experiments performed in Norway and Denmark with four different diets. The RSQ^{CAL} and RSQ^{VAL} for the chemical composition of the faeces (Table 4.3) are generally lower than seen for the feed data (Table 4.1), presumably because the calibrations are based on fewer samples and because there may be more interfering compounds present in faeces than in the feed. The results obtained on FNIRS in terms of RSQ^{CAL} , 1-VR and RSQ^{VAL} and SEC, SECV, and SEP(C) for DE and DOM, however, are in general comparable to the results obtained with the calibrations developed directly on the feeds (Table 4.1). In a further development,

DDE	4 diets 158/40 faeces	0.023 ^a	0.88	0.026 ^a	0.85	0.79	0.20	0.025 ^a	0.87	Nirea et al. (2018)
DAPro		0.023 ^a	0.63	0.027 ^a	0.51	0.81	0.03	0.019 ^a	0.63	
DFAT		0.060 ^a	0.79	0.068 ^a	0.74	0.72	1.2	0.062 ^a	0.72	
DNDF		0.077 ^a	0.64	0.088 ^a	0.53					
Mixed diets										
DOM	62 feed 310 faeces	0.011 ^a	0.90	0.011 ^a	0.91				1.9	
DAPro		0.019 ^a	0.86	0.021 ^a	0.89				2.0	Paternostre et al. (2021)
DcTF		0.027 ^a	0.84	0.032 ^a	0.75				1.6	

^aValues in ratio; *NDF* neutral detergent fibre, *ADF* acid detergent fibre, *DDE* digestible dietary energy, *DOM* digestible organic matter, *DAPro* digestible apparent protein, *DcTF* digestible calculated total fibre, *N* denote the number of samples that have been used for calibration (Cal) and validation (Val), *SEC* standard error of calibration, *RSQ* regression coefficient, *SECV* standard error of cross-validation, *I-VR* coefficient of cross-validation, *SEP(C)* standard error of prediction corrected for bias, *RPD* ratio of performance deviation

(Paternostre et al., 2021) combined NIRS-spectra of feed and faeces, which gave rise to further improvements in the RSQ^{VAL} (Table 4.3). As was the case for the calibrations and prediction models for the TT digestibility of protein and fibrous components developed on the feed (Tables 4.1 and 4.2), the prediction models developed for these nutrient constituents on faeces are generally less precise than for energy and OM (Table 4.3). The potential with the FNIRS technology compared with the estimation of nutrient digestibility from the feed is that it can be used for large-scale phenotyping at farm level (Bastianelli et al., 2015; Nirea et al., 2018).

4.4 Determination of Amino Acids and Their Digestibility by NIRS

A correct supply of dietary protein and amino acids is important for optimal growth and protein accretion in pigs (Moughan et al., 2018b), as undersupply will have a strong negative impact on animal performance, and oversupply a negative impact on the environment in terms of nitrogen leaching to the aquatic environment, to drinking water, and nitrogen fallout from evaporation from animal housing and slurry storage facilities (Millet et al., 2018). Protein quality evaluation aims to determine the capacity of the feedstuffs and diets to meet the protein and essential amino-acid requirements, which is defined in terms of intakes required to meet metabolic needs for maintenance plus those associated with the protein needs for growth, egg production, pregnancy and lactation in females (Moughan et al., 2018b). The capacity of protein sources to meet the demand of animals is determined by the absolute and relative quantities of dietary indispensable amino acids in feed, the digestibility of the protein in the gastrointestinal tract, and the bioavailability of amino acids (Fig. 4.6) (Moughan et al., 2018a, b). This has classically been done by analysing the amino acid concentration and composition of the feed and estimating the ileal or TT digestibility of amino acids, but since amino acids in the large intestine are deaminated and converted into microbial protein and ammonia, it is generally agreed that the digestibility of amino acids should be estimated at the ileum (Moughan et al., 2018b; Stein et al., 2007). Originally, apparent ileal digestibility was used, but, today, standardised ileal digestibility of amino acids is used, which essentially is a factor conversion of apparent ileal digestibility data (Stein et al., 2007).

4.4.1 Amino Acids

NIRS is widely accepted as a methodology to predict amino acid composition in cereals and protein-rich feedstuffs, as an alternative to wet chemistry methods (Chen et al., 2013). Many models exist for different types of samples: sunflower meal (Fontaine et al., 2001), peas (Fontaine et al., 2001), cereal ingredients (Fontaine et al., 2002; Hoehler et al., 2005), millet (Chen et al., 2013), dried distillers grains with solubles (DDGS) (Zhou et al., 2012), processed animal proteins or meals (Dale

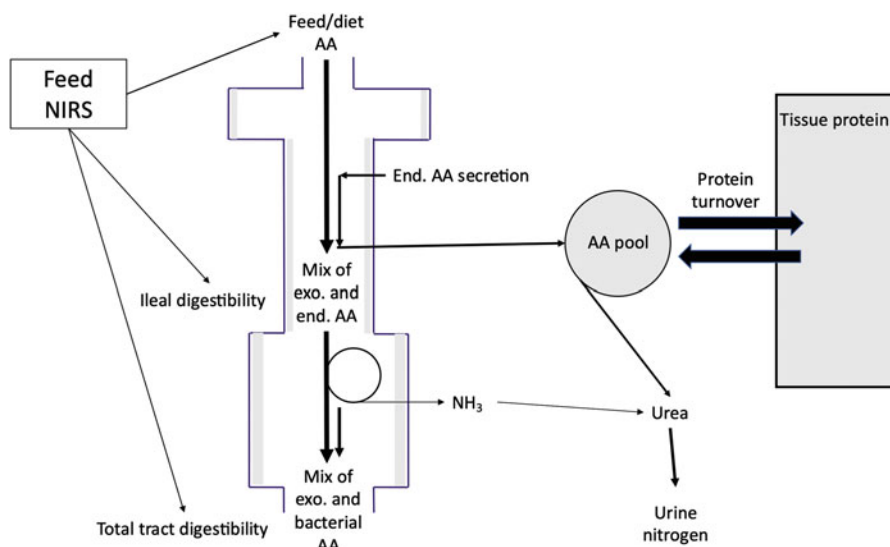


Fig. 4.6 Simplified model for protein digestion in the gastrointestinal tract and protein metabolism

et al., 2012; Fontaine et al., 2001; Hoehler et al., 2005), rice (Fontaine et al., 2002; Zhang et al., 2011; Wu et al., 2002), rapeseed (Chen et al., 2011; Fontaine et al., 2001), quinoa (Escuredo et al., 2014), peanuts (Wang et al., 2013) and soya bean (Fontaine et al., 2001; Pazdernik et al., 1997). The developed models were all developed on individual feedstuffs and showed that RSQ^{VAL} was dependent on the variability in the data set, but there were also differences in the models developed depending on the feed matrix. For instance, RSQ^{VAL} for lysine and methionine was 0.72 and 0.61 in maize, 0.86 and 0.89 in wheat, 0.93 and 0.84 in soya bean meal and full-fat soya, and 0.93 and 0.87 for meat meal products (Fontaine et al., 2001, 2002). NIRS has also shown promising results with reasonably high RSQ coefficients (0.814–0.963) for all amino acids but lysine (0.687) on compounds feeds (50 samples) with considerable variability in their composition and physical properties (Gonzalez-Martin et al., 2006). The statistical prediction descriptors – SEP, SEP(C) and bias – indicated that amino acid values in feed predicted with NIRS were comparable to those obtained with the chemical ion-exchange HPLC method (Gonzalez-Martin et al., 2006).

In our own work we found that the models based on samples from cereals, supplemental feed ingredients, and feed mixtures analysed together (Table 4.4) were less accurate (higher prediction error), but more robust (valid with a larger range of sample types and values) than models built on cereal, supplemental feed ingredients and feed mixtures separately (Noel et al., 2021). The calibration equations for crude protein and amino acids in the study of Noel et al. (2021) also showed high RSQ^{CAL} (0.91–0.99) and almost as good for validation (RSQ^{VAL} 0.87–0.97) as found elsewhere (Fearn, 2014). The SECV and SEP were low and in good agreement with each other, and the RSQ values for the total validation set

Table 4.4 Summary statistics comparing near-infrared spectroscopy calibration and validation models of crude protein and selected indispensable amino acid composition, and apparent ileal digestibility of cereals, supplemental ingredients and complete feeds with the concentration in samples determined by wet chemical methods and with *in vivo* ileal digestibility of protein and selected indispensable amino acids

	N	Content of variables in the sample population					NIRS performance data									
		Cal/Val					Calibration		Cross-validation							
		Mean	SD	Min	Max		SEC	RSQ	SECV	1-VR	Intercept	Slope	RSQ	RPD		
Concentration, g/kg DM																
Crude protein	607/150	180.8	86.2	27.7	708.2		12.84	0.98	15.73	0.97	4.46	0.97	0.95	5.11		
Lysine	395/94	7.9	6.7	0.9	44.4		0.84	0.98	1.3	0.96	0.35	0.97	0.96	6.39		
Methionine	395/94	2.8	1.6	0.3	9.7		0.29	0.97	0.41	0.93	-0.12	1.05	0.94	3.84		
Cysteine	395/94	3.3	1.6	0.3	11.1		0.37	0.95	0.44	0.92	-0.12	1.04	0.94	3.58		
Threonine	395/94	6.1	4.1	0.8	27.9		0.46	0.99	0.71	0.97	0.22	0.96	0.96	6.09		
Isoleucine	387/94	6.8	4.9	0.8	34.6		0.64	0.98	0.84	0.97	0.43	0.96	0.97	6.94		
Leucine	387/94	12.1	7.7	1.4	55.4		1.16	0.98	1.43	0.97	0.07	1.00	0.95	5.43		
Histidine	387/94	4	2.7	0.4	19.3		0.45	0.97	0.54	0.96	0.03	0.99	0.97	6.26		
Phenylalanine	387/94	8.1	4.8	0.6	36.6		0.86	0.97	0.95	0.96	-0.28	1.04	0.96	5.69		
Valine	387/95	8.5	5.2	1	36.2		0.72	0.98	0.84	0.97	0.16	0.98	0.94	4.59		
Arginine	387/94	10.5	8.8	1.2	52.7		0.99	0.99	1.89	0.95	0.51	0.94	0.97	5.62		
Tryptophan	163/37	2.2	1.6	0.2	9.1		0.46	0.93	0.45	0.92	0.07	0.93	0.87	3.62		
Apparent ileal digestibility, %																
Crude protein	150	73.4	7.2	34.9	93.7		3.12	0.81	4.03							
Lysine	102	84	7.9	62.4	97.7		2.6	0.89	3.67							
Methionine	102	85.4	6.2	55	97.6		2.31	0.86	4.17							
Cysteine	102	74.4	10.1	15	93.1		4.99	0.76	6.04							

Threonine	102	72.9	8.3	47.4	90.4	3.41	0.83	4.68				
Isoleucine	94	80.2	5.7	64.1	94.2	2.73	0.77	3.25				
Leucine	94	82.5	5.8	67	96.7	2.13	0.86	2.9				
Histidine	94	83.5	5.2	64.3	97.1	2.04	0.85	2.67				
Phenylalanine	94	83.1	6.6	54.2	96.1	2.68	0.83	3.22				
Valine	94	78.4	6.3	61.4	94.7	2.21	0.88	3.64				
Arginine	94	87.7	5.5	70.6	96.3	2.03	0.86	3.42				

N denote the number of samples that have been used for calibration (Cal) and validation (Val), *SEC* standard error of calibration, *RSQ* regression coefficient, *SECV* standard error of cross-validation, *I-VR* coefficient of cross-validation, *RPD* ratio of performance deviation
Modified data from Noel et al. (2021)

were much better than for the separate cereal and feed mixtures validation sets and similar to the supplemental ingredients (Noel et al., 2021). However, compared to calibrations derived from single sample types (i.e. wheat or maize (3–6.7%) (Fontaine et al., 2002), soya bean/soya bean meal (1.75–4.38%) (Fontaine et al., 2001), brown rice flour (3–15%) (Zhang et al., 2011), and soya bean (FOSS instrument, PLS model 2–16%) (Kovalenko et al., 2006)), the relative SEP values were higher but comparable to the ISO standards when the analysis was done in different laboratories (6.2–23.3 %) for determination of amino acids in chicken feed and maize (ISO-13903 2005). However, the overall SEP is higher than the reproducibility (~2–5%) of the reference method for amino acids reported by Fontaine et al. (2001).

4.4.2 Ileal and Total Tract Digestibility of Amino Acids

In a nutritional context, it is also important to know the digestibility of protein and the digestibility of protein and amino acids in the gastrointestinal tract (FAO, 2013; Stein et al., 2007). Estimates from NIRS calibrations have been used to predict the digestibility of poultry feed ingredients for some amino acids, allowing for more precise formulations on different batches (Hoehler et al., 2005; van Kempen et al., 1996; van Kempen & Simmins, 1997) than is possible by using crude protein as a proxy (van Kempen & Simmins, 1997). A preliminary study with 20 barley samples also demonstrated that NIRS could predict the digestibility of lysine, methionine, and cysteine in pigs (Pujol et al., 2007). However, our own study, reported in Table 4.4 based on 102 samples of cereals, supplemental feed ingredients, and mixed diets, is the largest hitherto (Noel et al., 2021). The RSQ values for predicting the digestibility of the amino acids were, as expected, lower than the RSQ for quantifying the amino acids, as variation in the digestibility of amino acids not only is caused by the feedstuff but also the presence of antinutritional factors as well as the influence of the endogenous secretion. Nevertheless, the RSQ for the digestibility of the most important indispensable amino acids (lysine, methionine, cysteine, threonine) is in general high with values above 0.76 and with low SECV values (<5%). From the study of Noel et al. (2021) it can also be noted that the RSQ values overall were better for the TT digestibility of amino acids than the apparent ileal digestibility parameters shown in Table 4.4. This is probably because the TT digestibility of amino acids is a closer reflection of the influence of the feed whereas for the apparent ileal digestibility the endogenous contribution would be larger (Noel et al., 2021). Moreover, sampling of ileal digesta is more variable compared to sampling of faeces. Taken as a whole, the developed models can be considered good enough to give usable estimates on the ileal and TT digestibility of amino acids although more samples undoubtedly would make the calibrations stronger.

4.5 Perspectives in Using NIRS for the Determination of the Nutritive Value and Incorporation into Smart Nutrition

As suggested above, NIR can be a useful and strong tool for estimating the chemical composition of individual feeds and feed mixtures, the digestibility of nutrients, amino acids, and energy, as well as DE and ME. The models can be used to adjust diet composition when using feed batches with variable composition, thereby helping the industry to deliver a uniform nutrient quality of feed mixtures. The models can further be ported to online equipment that can be installed in feed processing plants to enable more or less automatic adjustment of feed composition to ensure that the feed produced is holding a uniform nutritive value (Baeten et al., 2016; van Barneveld et al., 2018) (Fig. 4.7). Such an approach is illustrated in Fig. 4.8 where NIRS was used in a feed mill to adjust the diet composition depending on the content of protein and DE in wheat (van Barneveld et al., 2018). Over the course of 1 h of production, the crude protein concentration of the wheat varied by 4%, and the DE concentration by 1.2 MJ/kg. Further, the mean DE concentration was ~0.6 MJ/kg lower than the commonly used table value of wheat of 14.0 MJ/kg, which would usually be employed in the diet formulation. van Barneveld et al. (2018) stated that if diets were formulated as a starter feed, some piglets would receive a diet equating to 14.0 MJ DE/kg, while others would receive a diet equivalent to 14.7 MJ/kg, and the nutritionist would be expecting delivery of feed

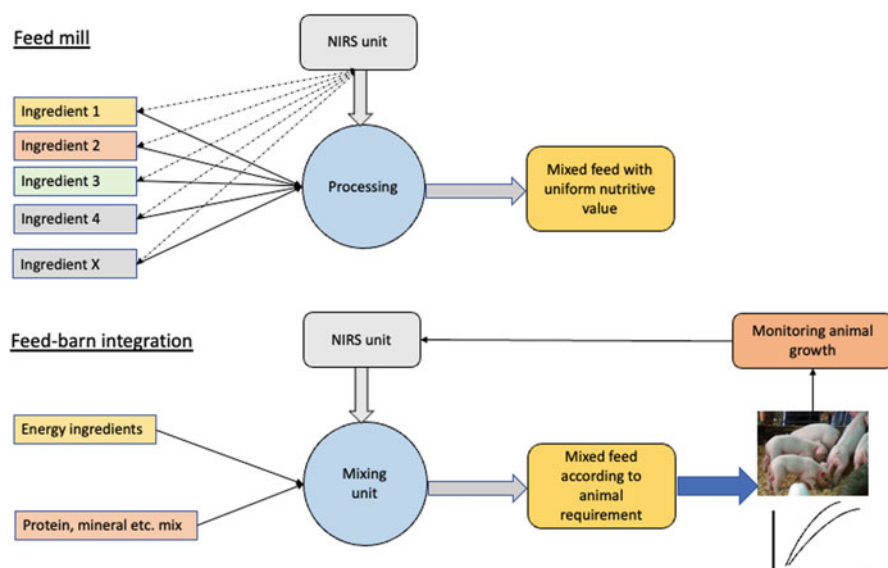


Fig. 4.7 Schematic representation of implementation of NIRS at a feed mill to adjust the feed composition with the purpose of producing mixed feed with a uniform composition and implementation in a barn to provide mixed feed according to the animal requirement

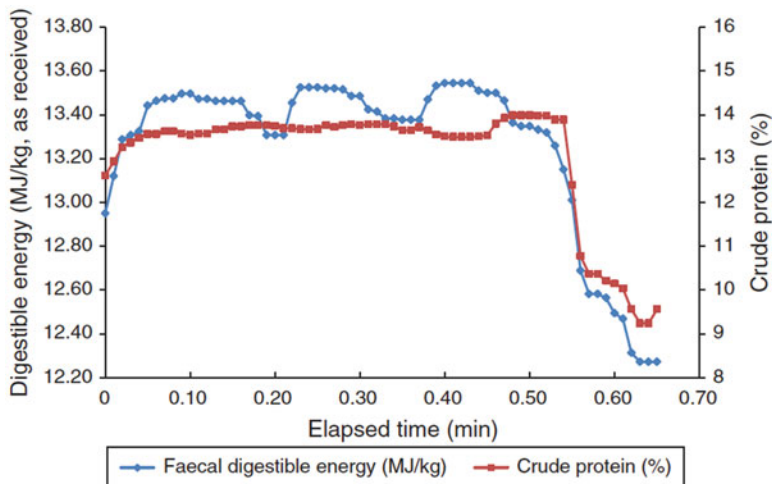


Fig. 4.8 Real-time near-infrared spectroscopy (NIRS) analysis of faecal digestible energy (MJ/kg as received) and crude protein (%) concentration of wheat included in pig diets over the course of 1 h of production. Elapsed time is the time since the start of the recording
Data from van Barneveld et al. (2018)

equating to 15.0 MJ DE/kg to these pigs and therefore provide a major source of variation in pig growth. The example provided in Fig. 4.8 will be similar and in some cases even more important in the production of feed mixtures for poultry, because of their very rapid body growth of poultry, which makes poultry very sensitive to variation in nutrient content and value. Moreover, assuming that the feed for farm animals in the future will have to be based on more co-products or alternative ingredients than used today, online adjustment of the feed composition will be even more important.

The NIRS technology also holds the potential for online adjustment of feed composition over the course of the growth period of both pigs and poultry (Fig. 4.7). The requirement of indispensable nutrients in proportion to energy decline as the animals grow and in cases where the feed for a barn is provided as a mix of cereals and protein concentrate, NIRS can be used to gradually adjust the mixing of the two ingredients according to the animal growth trajectory and thereby need. In theory, it would also be possible to adjust the feed composition on the basis of the need of the individual animal, but this will require feeding devices for the provision of feed on individual basis. For now, this prospect is most relevant for individually housed animals such as sows, but can potentially also be used for growing animals, provided that such feeders become available. Moreover, provided that sensors are available to monitor the animal capacity to grow, it would be possible to build NIRS into a system that can provide personalised nutrition according to such animal capacity for growth and nutrient utilisation.

The recent development of FNIRS to estimate the TT digestibility of energy and nutrients (Schiborra et al., 2015; Bastianelli et al., 2015; Nirea et al., 2018;

Paternostre et al., 2021) further holds the potential of being used in connection with pig-breeding programmes for selection of pigs with improved digestibility of energy and nutrients (Bastianelli et al., 2015; Nirea et al., 2018). Once a robust calibration equation is established, large-scale digestibility prediction using FNIRS can be used to get an estimated breeding value and genetic parameters to study the genetics of digestibility in pig-breeding programmes. Such an approach can be even more relevant in the future in connection with the use of farm animals to recycle biomass and nutrients into the food system that would otherwise be lost to food production (van Zanten et al., 2019).

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Large-Scale Phenotyping and Genotyping: State of the Art and Emerging Challenges

5

Donagh P. Berry

Abstract

The genome and phenome are both forms of big data in that they can be characterised by volume, variety, velocity, value, veracity and variability. A direct relationship exists between the phenotype and the genotype; the proportion of the variability in the phenotype due to differences in the genotype of a (sample) population is termed heritability. Phenomics in livestock generally relate to (a) animal identification, (b) measurements of performance (either output or inputs) and (c) measures of the prevailing environmental conditions. The use of genomics in livestock production includes: (1) genomic predictions, (2) parentage assignment, (3) animal/product traceability, (4) monitoring of major genes and congenital defects including karyotype disorders, (5) estimating coancestry or inbreeding, (6) quantifying breed composition and, importantly (7) facilitating more precise mating and management (e.g. nutrition) decisions. Facilitated by developments in agri-tech, such information will enable the development of tailored genotype-specific nutritional and management regimes. Such a strategy is not at all novel and is the basis for the diversity of production systems for generations; genotype in such situations was, however, synonymous only with breed. Genomics and phenomics will simply improve the granularity of differentiation from being among breeds to being within breeds. Challenges include (a) the return-on-investment, especially for phenomics, although from a breeding perspective, the cost of phenotyping is incurred by few but realised by many, (b) how to distil the masses of data to support decisions by diagnosing and prescribing management and nutritional strategies, and (c) data ownership and use. As more data accumulates on both the genotypes and phenotypes of

D. P. Berry (✉)

Teagasc, Animal & Grassland Research and Innovation Centre, Co. Cork, Ireland

e-mail: donagh.berry@teagasc.ie

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individuals, the ability to estimate the genetic potential of individual animals more accurately will improve.

Keywords

Agri-tech · Artificial Intelligence · Bespoke · Big data · Breeding · Breeding objective · Data ownership decision support · DNA · eXplainable · Farm · Feed intake · Genomics · Genomic selection · Genotype · Heritability · Inbreeding · Livestock · Major gene · Management · Methane · Parentage · Precision · Phenomics · Phenotype · Prioritisation matrix · Resilience · Return-on-investment · Sensors · Tailored · Variability · Variety · Value · Velocity · Veracity · Volume

5.1 Introduction

The concepts of phenotype and genotype were first muted at the start of the twentieth century (Johannsen, 1909). Nonetheless, the actual cited definitions of phenotype or genotype vary in the scientific literature (Mahner & Kary, 1997). The word phenotype originates from the Greek φαινο (i.e. “pheno”) and τύπος (i.e. “type”) and is used to describe a set of observable characteristics for an individual; “pheno” means “observe” as is the case for “phenomenon”. A phenotype, or trait, may be continuous (also called quantitative; e.g. milk yield and growth rate) or discrete (qualitative; e.g. did or did not succumb to disease); however, discrete traits are often treated as having an underlying liability function thereby justifying their analysis as quantitative traits.

The meaning of the word genotype is even more ambiguous. Genotype is generally used to refer to the genetic variants an individual possesses across all its nucleotides (i.e. DNA sequence); genotype may also simply refer to the alleles at a particular locus (i.e. location) on the DNA sequence. Moreover, animal breeders commonly use genotype to describe a particular strain of animal (e.g. animals of a given breed from a particular origin). In fact, Mahner and Kary (1997) argue that a genotype is actually a phenotype owing to the fact that this previously unobservable unit of heredity is now actually observable through genotyping.

The phenome was described by Soulé (1967) as the phenotype as a whole. The genome is defined as the complete set of information in an organism’s DNA (Alberts et al., 2002), including the mitochondrial DNA (and the chloroplast DNA in the case of plants). Phenomics as a discipline was originally defined as the systematic study of phenotypes on a genome-wide scale (Bilder, 2008). A more apt definition, however, is arguably the acquisition of high-dimensional phenotypic data on an organism-wide scale (Houle et al., 2010); this definition though assumes it is the acquisition which is the crux of phenomics and not other elements like the transfer, storage, editing and downstream analysis of the data, but it also considers that it must be organism-wide. Furthermore, Greenwood et al. (2016) extended the definition to specifically consider real-time data acquisition coupled with environment-level

features, the latter being important for downstream analysis. Biler et al. (2009) stated how phenomics must be transdiscipline, requiring expertise in genetics, molecular biology, cell biology, systems biology, mathematical modelling, statistics and information sciences all effectively communicating and collaborating on large-scale projects.

Genomics is cited to be the study of the structure, function and intragenomic interactions within the genome (Berry et al., 2011). Genomics may also be defined as the collective characterisation and quantification of all of an organism's genes, their interrelations and influence on the organism (WHO, 2002).

Phenomics and genomics are intrinsically linked. The expression of a phenotype is a function of the genotype of the individual. The study of genomic variants associated with performance often requires a phenotype for which to relate to; more recent strategies attempt to locate genomic variants affecting performance without actually using phenotypic data (VanRaden et al., 2011) albeit phenotypic data are still used to validate the discoveries. While the discipline of genomics has flourished from investment in recent decades (Houle et al., 2010), the field of phenomics, in livestock at least, has not been so fortunate. Nonetheless, adoption by agriculture of modified technological solutions applied in other domain areas, complemented with bespoke products for phenotyping, is addressing the phenomic gap. In fact, dissecting the influence of genomic features on a whole array of animal performance characteristics is now more limited by available phenotypes than by the availability of genotypes.

The objective of this chapter is to describe the fundamentals of genomics and phenomics, especially in how they relate to big data followed by commentary on the likely future developments in these data sources. Importantly, how both data sources can be combined to help deliver on smart nutrition and management is also demonstrated and discussed.

5.2 Big Data

The genome and phenome are both forms of big data. While many definitions of big data exist, the characteristics of big data can be represented by 6 (or more) V's:

- Volume
- Variety
- Velocity
- Value
- Veracity
- Variability

Volume Both the genome and phenome are classic examples of high dimensional data (i.e. volume), but while the genome is complex, its complexity pales in comparison to the dimensionality of the phenome. Although the potential number of genomic features for livestock is in billions, strong homogeneity in many regions

of the genome implies that the number of features that actually vary among individuals is, at best, in the (tens of) millions with only a few (usually 3 representing biallelic single nucleotide polymorphisms [SNPs]) values per feature (i.e. variant). Phenomics in livestock (as well as plants) is more and more being characterised by image measures both of which require considerable resources to store and transfer between locations. While consideration of data storage space is important, so is disk speed and network speed including bandwidth (Cole et al., 2011); for example, using solid-state disk drives for temporary storage where the available random-access memory is insufficient. In fact, whether the raw data should be stored ad infinitum should be explored on a case-by-case basis. In some instances, it may be cheaper to regenerate the data as could be the case for day-to-day herd management where data could be discarded once the animal exits the farm.

Variety The genome is finite and usually based on just one individual (unless host-pathogen interactions are modelled) while the phenome is often based on, or influenced by, multiple individuals each with complex interactions. While most genomic studies are based on SNPs, other structural variants like microsatellites, copy number variants, inversions, deletions and translocations do exist. Nonetheless, the variety of genomic data and also the format of the data provided by service providers (e.g. variant call format [VCF] files, SNP-chip output files) is relatively consistent across platforms, service providers and jurisdictions. The same is not true of phenotypic data which suffers from a whole variety of different ontologies of phenotypes, types of phenotypes and technologies to measure phenotypes (Hocquette et al., 2011); this contributes to a variety of resulting file formats and a whole range or variety of different features that can be measured on an individual.

Velocity The genome of an individual does not change over time; hence, one measure is sufficient per individual. The velocity at which phenomic data are generated, however, can be rapid with continuous measurements often the norm with some sensing systems (Greenwood et al., 2016). Being able to rapidly transfer and mine such data in a computationally efficient and effective manner is crucial for effective SMART nutrition or precision management; edge computing is one option to reduce the volume of data transfer whereby the analyses are executed nearer to source thereby contributing to lower latency and reduced requirements for data transmission.

Value The cost of genotyping was often a barrier to data generation; even sequencing costs are continuously reducing implying a relatively low value for genotype data per se. While some phenotypes are relatively inexpensive to generate, or in some instances may be viewed as free if paid for by others (e.g. liveweight, milk yield), deeper phenotypes like environmental metrics, feed efficiency, or granular measures of product quality or immune/metabolic status can be expensive to generate. Low-cost strategies, nonetheless, have some potential to predict some of these phenotypes; for example, video analysis to predict feed intake (Chizzotti et al., 2011). Because only one genotype exists per individual, and this does not change

over the lifetime of the individual, the value of the (entire) phenome is often multiples greater than that of the genome.

Veracity Genotyping or sequencing is more often than not undertaken by highly accredited laboratories using highly reproducible platforms like SNP chips (Berry et al., 2016). While DNA quality or handling can impact the veracity of the resulting data, strict quality control measures on the resulting genotype data (Berry et al., 2021b; Purfield et al., 2016) or sequence data (Bacci, 2015) are also often imposed to discard unreliable data. Nonetheless, genomic data are not always free of error; genotype-by-sequencing (Elshire et al., 2011) as an approach to genotyping can contain a large fraction of missing data which requires imputation. Imputation, in itself, introduces error (Berry & Kearney, 2011; Judge et al., 2016). Finally, calling of structural variants such as copy number variants is not consistent across calling algorithms (Rafter et al., 2018). Nevertheless, veracity of phenotypic data tends to be more of an issue given the heterogeneity of the tools used to measure the phenome, but also the contribution of the (past and present) environment to the eventual phenotype. These environmental influences are not always recorded for adjustment in the statistical model but, of course, also include human error in measurement or assessment. Many traits used in breeding programs are actually subjectively scored either by producers themselves (Pabiou et al., 2012) or by trained professionals (Berry et al., 2004; Ring et al., 2018). Similarly, many animal characteristics used in day-to-day animal management are subjectively scored (e.g. body condition score, locomotion score, lesion scores). This impacts the veracity of the phenotypic data.

Variability Genotype data tend to have a common format; even though there are two main vendors of SNP chips globally, the file output from both platforms can be identical (albeit with a difference in the metric depicting confidence in the called genotype). No matter what service provider generates the data, the outputs are the same. Moreover, service providers tend to have a regular workflow so the data often arrives at a constant rate and can be pre-planned. Phenotypic data, however, are highly variable for many traits both in when the data are generated and enters the database (e.g. seasonal calving systems for cattle, but also in the definition of traits like feed efficiency in different jurisdictions but also even within jurisdiction).

All-in-all, relative to genomic data, in the context of big data, phenomics tends to have a greater volume of a large variety of variable data generated at high velocity while also generally suffering from greater veracity.

5.3 Relationship Between Penotype and Genotype

Understanding the relationship between the variation in the phenotype and genotype is important for understanding the potential role of genomics in SMART nutrition and animal management. The relationship between the genotype and the phenotype can be described by the commonly used equation (Visscher et al., 2008):

$$\sigma_P^2 = \sigma_G^2 + \sigma_E^2 + \sigma_{G \times E}^2 + \sigma_{G,E}^2$$

where σ_P^2 is the phenotypic variance, σ_G^2 is the total genetic variance, σ_E^2 is the environmental variance, $\sigma_{G \times E}^2$ is the variance due to the genotype-by-environment interaction, and $\sigma_{G,E}^2$ is the variance attributable to the covariation between the total genetic effects and the environmental effects. The variance due to the covariation between the genetic and environmental effects is almost always ignored and while the existence of genotype-by-environment is acknowledged in livestock (Dillon et al., 2006; Roche et al., 2018), the extent of such interactions in most populations is often not viewed as worthy of consideration in most genetic evaluations, in ruminants at least. Nonetheless, genotype-by-environment interactions may be more important in the pig and poultry industry where a nucleus of genetically elite animals managed in a very controlled environment may be the source of germplasm to be used in commercial production systems, mainly consisting of crossbred animals (Wientjes & Calus, 2017). More importantly, however, acknowledging and exploiting genotype-by-environment is crucial for precision nutrition and management so that the germplasm on farm is aligned with the management and feeding system.

The heritability describes what proportion of the phenotypic variance is attributable to the additive genetic variance and is defined as

$$h^2 = \frac{\sigma_A^2}{\sigma_P^2}$$

where h^2 is the (narrow sense) heritability, σ_A^2 is the additive genetic variance (i.e. the variance due to additive genetic effects), and σ_P^2 is the total phenotypic variance. Hence, the heritability depicts the relationship between the phenotype and genotype describing how well differences in genotypes among individual accounts for the inter-individual differences in the observed phenotypes. A heritability value of 0.5 (considered “high”) means that, on average, half of the phenotypic differences among individuals are estimated to be due to (measurable) genetic differences. In fact, clearly demonstrating how the heritability represents the association between phenotype and genotype, a simple estimate of genetic merit for an individual can be calculated as:

$$\hat{A} = h^2(P - \mu)$$

where \hat{A} is the predicted genetic merit of the individual, h^2 is the (narrow sense) heritability, P is the phenotypic value for the trait of interest for the given individual, and μ is the population mean adjusted for nuisance factors such as age. Rearranging the equation provides an estimate of the phenotypic performance potential based on animal genetic merit which is obviously important for management and can therefore be used to calculate if genetic potential is being realised. This equation holds

irrespective of whether additive genetic merit is based on ancestry, own performance, or genomic data.

Heritability is important for determining the potential response to selection through breeding; by extension, the (realised) heritability can be deduced from the observed response to selection. Genetic gain per year can be described by the formula (Rendel & Robertson, 1950):

$$\Delta G = \frac{i \cdot r \cdot \sigma}{L}$$

where ΔG is annual genetic gain, i is the selection intensity, r is the accuracy of selection, σ is the genetic standard deviation and L is the generation interval. Heritability influences the accuracy of selection. All else being equal, the lower the heritability, the greater the number of records required to achieve a given accuracy of selection and thus genetic gain (Fig. 5.1). Nonetheless, the impact of low heritability on genetic gain can be overcome by having more information (i.e. phenotype or genotype) available, thus contributing to a higher accuracy of selection and thus genetic gain. Hence, despite historical commentary that low heritability equates to slow genetic gain, rapid genetic gain is indeed possible for low heritability traits (with exploitable genetic variation); in fact, genetic gain for low heritability traits can be faster than that for high heritability traits if all other parameters of the genetic gain equation are superior. Irrespective, the role of phenomics and genomics in achieving genetic gain is clear; more so, the relationship between phenotype and genotype implies a trade-off between accurate phenotypes in the pursuit of high heritability and thus a necessity for fewer records to achieve a high accuracy of selection, versus less accurate phenotypes contributing to a lower heritability and thus a requirement for more phenotypic records to achieve that elusive high accuracy of selection extending to rapid genetic gain. This is also important for management purposes as the accuracy with which the expected phenotypic performance is derived is a function of the accuracy of the estimate of genetic merit. While most animals will be well dead before they achieve a good accuracy of estimated genetic merit from relatives and own performance, genomics short-circuits this, enabling a high accuracy at birth (or whenever sampled).

The estimated heritability of a trait for a given population is also a crucial component for undertaking a statistical power calculation for genome-based association studies or indeed genomic predictions (Fig. 5.1). While many genome-based association studies state they are attempting to discover genomic variants associated with the phenotype, in reality, they cannot explain more variability in the phenotype than the (broad sense) heritability. Thus, the genomic association studies or genomic predictions are really attempting to explain the variability in the genetic merit of individuals. Low heritability implies a proportionally large environmental variance. Hence, like any experimental study (e.g. nutritional trial), the study size needs to be greater to negate any impact of greater environmental variability; the same holds for low heritability traits in genome-based association studies or genomic predictions.

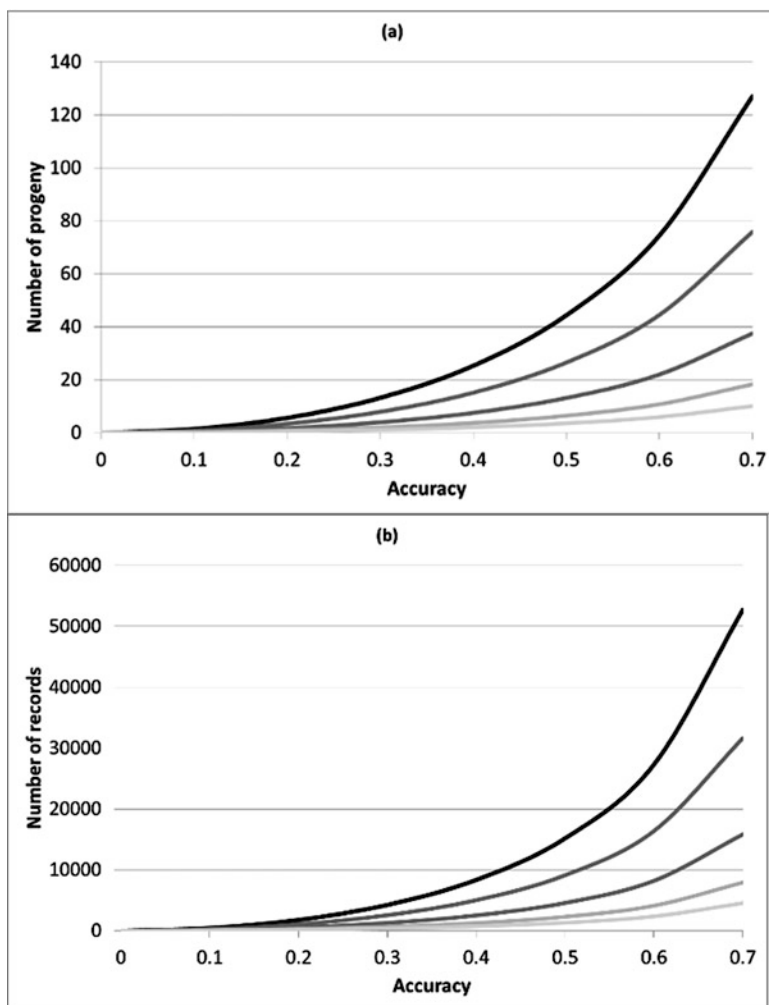


Fig. 5.1 For heritability values of 0.35, 0.20, 0.10, 0.05 and 0.03 (in order of increasing darkness of lines), (a) the number of progeny required to achieve a given accuracy of selection using traditional ancestry-based genetic evaluations and (b) the number of records of phenotyped and genotyped animals to achieve a given accuracy of genomic evaluations (based on 1000 effective chromosomal segments and 80% of the genetic variance accounted for by the genotyped markers)

The limitation to how much of the phenotypic variance can be explained by genomic variants is important for management purposes and fully appreciating the scope of genomic information in influencing management decisions. It is, nonetheless, likely that heritability estimates in most studies are under-estimates but also that fact that these heritability estimates do not account for the non-additive genetic component.

5.3.1 Increasing Heritability Through Better Phenotyping

Heritability, as defined previously, is the proportion of phenotypic variance attributable to (additive) genetic variation; phenotypic variance here is comprised of genetic variation and non-genetic variation which includes random noise:

$$h^2 = \frac{\sigma_A^2}{\sigma_P^2} = \frac{\sigma_A^2}{\sigma_A^2 + \sigma_E^2}$$

where h^2 is the (narrow sense) heritability, σ_A^2 is the additive genetic variance (i.e. the variance due to additive genetic effects), σ_P^2 is the total phenotypic variance, and σ_E^2 is the non-genetic variance often comprised of residual noise. Hence, assuming no change in genetic variance, reducing the extent of the residual variance will lead to an increase in heritability with all its associated benefits as already detailed. Phenomics has a huge role in reducing this residual noise:

- **Performance measures:** Obviously phenomics is crucial to generating phenotypic performance data on individuals. While sensors and technical equipment are synonymous with phenomics, research has also clearly demonstrated heritable genetic variation in traits subjectively scored by producers (Pabiou et al., 2012) or professionals (Berry et al., 2004; Ring et al., 2018); strong genetic correlations between the subjectively-scored traits and the eventual goal trait measured some-time later in life have been proven to be strong (Pabiou et al., 2012). Hence, subjectively-scored data still has uses in breeding programs and actually constitutes a large proportion of the emphasis of breeding goals of some farmed animals (Berry et al., 2021a). Nonetheless, technology is likely to be a major contributor to not only the generation of vastly more quantities of data on a wider variety of phenotypes, but also potentially the accuracy of such data. Moreover, electronic solutions such as Radio Frequency Identification (RFID) equipment can impact the precision to which a phenotype (e.g. liveweight, milk yield) can be assigned to an individual, minimising any source of human error in recording. The same is true for image and video analysis for quantifying behavioural traits or other traits like body condition score.
- **Repeated records:** The heritability of the mean of repeated records for an individual is greater than the heritability of a single measure (Judge et al., 2018). In fact, the heritability of the mean of n records is $\bar{h}^2 = \frac{nh^2}{1+(n-1)t}$ where \bar{h}^2 is the heritability of the mean of the observations, h^2 is the heritability of a single observation, n is the number of observations per individual and t is the correlation among the repeated observations (Berry et al., 2017a, b). Hence, phenotyping strategies to generate multiple records per animal are useful; in such situations for genetic evaluations, a repeatability statistical model is generally used (Mrode, 2014). Nonetheless, before embarking on generating multiple records per individual, the appropriate calculations (and logistical requirements) should be undertaken to evaluate whether a superior approach would be to phenotype more individuals

once, rather than phenotype the same individuals multiple times; this is the trade-off between heritability and number of observations which both impact the accuracy of selection but also the number of phenotyped animals can impact the selection intensity.

- **Deep phenotypes:** The observed phenotype of an animal is a function of not only the physical genome of the animal, but also how it is transcribed and translated into the eventual phenotype. Moreover, some phenotypes (e.g. methane production) are not only a function of the genome of the host, but also how that interacts with the genomes of other species (microbes) residing within the host. Being able to drill down to the different layers of expression (i.e. the transcriptome) may contribute to higher heritability estimates. Of course, such detailed phenotypes can also be extremely informative in day-to-day animal management. However, the collection of such granular data in a large population of animals taking cognizance of how it varies spatially across tissues and temporally across time may not be feasible, at least for a large number of transcripts. Moreover, should genetic variability exist in how the genome is transcribed or translated to proteins and the eventual phenotype, basing selection decisions on such deeper phenotypes may not be sensible if genetic variability either directly, or through an interaction with the environment, influences the expression pathway.
- **Statistical modelling:** Prior to the estimation of phenotypic variance, and subsequently its contributing variance components, the contribution of systematic environmental effects to the variance is removed. Such systematic environmental effects on livestock include animal gender, age, herd and feeding system, to name but a few. Hence, phenomics also has a role in firstly measuring or identifying such environmental influences, but also accurately allocating the correct level of each environmental factor to each individual observation and, in doing so, reduce the extent of residual variance. Advanced statistical modelling approaches (e.g. random regression models; Mrode, 2014) can also be used to more accurately model the data and error term while taking advantage of longitudinal data. As well as being useful in improving the accuracy of genetic evaluations, improved statistical modelling is crucial to disentangle nuisance effects from the underlying animal phenotypes for management purposes.
- **Parentage:** Genetic evaluations are founded on being able to correctly identify the parents of an individual from which the entire ancestry can be compiled. This is used to trace relationships among animals which are linked with performance metrics enabling the estimation of genetic merit for each animal in the family (including descendants with no performance records). Accurate parentage recording is therefore not only crucial to accurate genetic evaluations, but also to reducing the residual variance and thus increasing the heritability. By extension, correct parentage information is important for precision management, not only when designing mating plans to avoid inbreeding, but also when determining the genetic potential of animals. In the case of heterospermic inseminations in, for example, pigs, or mob mating in other species (e.g. sheep, cattle), genomics would be required to ascertain the sire (Berry et al., 2019a, b; McClure et al.,

2013) unless differences in distinctive heritable features (e.g. head colour) existed among the candidate sires.

5.4 Advances in Genomic Tools

Many different types of genetic markers exist and the history of such have been elegantly described by Schlötterer (2004) from allozymes to restriction fragment length polymorphisms and microsatellites, and eventually single nucleotide polymorphisms (SNPs) which are generally now the marker of choice. A SNP is a variation at a single nucleotide position of the DNA sequence which differs between individuals of the same species. Interest, however, also exists in structural variants like copy number variants (Rafter et al., 2018), and both insertions and deletions (Väli et al., 2008). Microsatellites are still used in parentage testing and forensics (and population genetic studies albeit being replaced by SNPs) in some species and in some jurisdictions. Microsatellites are highly polymorphic, have a high mutation rate and are both abundant and relatively well distributed across the genome; they are not easily amenable to multi-plexing and automation.

The shift towards the widespread use of SNPs was mainly to facilitate more readily automation and scoring of genotypes, thus contributing to a high throughput at a reasonable cost. This benefit is important to secure high adoption rate thus contributing to more accurate information to be used in SMART nutrition and other management decisions. Other advantages of SNPs (Schlötterer, 2004) include their low mutation rate, high abundance and the ease at which they can be considered in meta-analyses from multiple data sources given their high concordance across genotyping platforms and laboratories (Berry et al., 2016). Procedures exist to impute or predict microsatellite alleles from flanking SNP haplotypes (McClure et al., 2013). The high throughout potential of SNPs is enabled by the development of what is nowadays termed SNP-chip. Two main vendors of SNP-chips currently exist, both of which have considerable experience over many years: these are Illumina and ThermoScientific (formerly Affymetrix).

The genotyping process for SNP-chips using Illumina technology is based on hybridisation technology and described in detail by Zhao et al. (2018). For biallelic SNPs, two oligonucleotide probes are synthesised based on the flanking sequence for the nucleotide under investigation. The target sequence, which is fluorescently labelled, generates a signal following hybridisation with the two probes. The allele at the nucleotide position is subsequently called based on the emitted fluorescence intensity. Using a reference dataset of many samples, a proprietary clustering algorithm is applied to the fluorescent levels to distinguish between the three potential genotypes (i.e. homozygous wild, heterozygous, homozygous mutant).

There was an initial trend to reduce the density of SNPs on panels (Boichard et al., 2012; Judge et al., 2016) in the pursuit of reducing the overall cost. However, the cost of the actual SNP-chip hardware itself as a proportion of the actual entire service (i.e. collection of biological samples, DNA extraction, running the genotype platform, genomic evaluations) was becoming ever-smaller and thus cost savings from

reducing panel density were being diluted. The sweet-spot to enable accurate within-breed genomic evaluations for most species is circa. 50,000 DNA markers.

5.4.1 Use of Genomics in Livestock Production

The range of practical uses of genomic information in livestock production is summarised in Fig. 5.2 (Berry, 2019). These include (1) genomic evaluations, (2) parentage assignment, (3) animal/product traceability, (4) monitoring of major genes and congenital defects including karyotype disorders, (5) estimating coancestry or inbreeding, (6) quantifying breed composition and (7) facilitating more precise mating and management decisions. Of course, genomic information is also used in many different types of research programs.

5.4.1.1 Genomic Evaluations

By far, the overwhelming uses of genomic information in livestock is in the prediction of genetic merit of the individual and, by extension, the phenotype of the individual. The prediction of phenotypic performance from genomic information has been discussed at length elsewhere (Meuwissen et al., 2016). It must, nonetheless, be remembered that the heritability limits the predictive ability of the phenotype from the genotype but, if considering non-additive genetic effect, this upper limit is



Fig. 5.2 Selection of uses of genomics in livestock breeding and management

dictated by the broad sense heritability. Historically genomic predictions were based on single DNA mutations or a couple of mutations in a process termed marker-assisted selection (Dekkers, 2004). With some exceptions like mono- or oligogenetically inherited traits (e.g. mutations conferring congenital defects, double muscling and fecundity as well as lethal recessive mutations), the predictive ability of performance from a limited number of DNA markers was disappointing (Simianer, 2016), especially between families.

Three major developments contributed to what is now called genomic selection (Meuwissen et al., 2001) or polygenic risk scores in humans (Torkamani et al., 2018). The first development was the discovery of SNPs and other genomic markers through the sequencing and assembly of the genomes of different livestock species; the second advancement was the development of (relatively low cost) technology to generate genotype information on thousands of SNPs simultaneously in an automated process (i.e. SNP-chips); and the third development was the statistical know-how on using whole genome DNA markers (simultaneously) in predicting an outcome. All developments have advanced considerably in recent decades with new genomic markers identified (Bouwman et al., 2018) as well as a whole plethora of algorithms, including machine learning approaches that exploit the high dimensional genotype data in the prediction of performance (Gonzalez-Recio et al., 2014).

Accurate genomic evaluations are predicated on a reference or calibration population of animals that are both genotyped and phenotyped and ideally related to the population of selection candidates; the lower the heritability for a given trait, the greater the size of the reference population required to achieve a given accuracy (Fig. 5.1). Accurate genetic evaluations are important if such information is being used to tailor nutritional and management systems but must also be taken in the context of the heritability of the trait. Genomic evaluations based on SNP-chip data exploit what is termed linkage disequilibrium; this is the phenomenon whereby some DNA markers tend to be co-inherited. Hence, while the causal mutation may not be known, or the genotype of the causal mutation is not on the genotype panel, its effect can be selected via a correlation with a nearby (co-inherited) SNP marker that is genotyped. However, the link between the genotyped marker and the causal mutation can differ between families, strains, or breeds but can also break down during gameteogenesis. Hence, the reference population should ideally be updated with each advancing generation especially if new family lines are introduced. Having the genotype of the true causal mutation can help alleviate this; the genotype of the true causal mutation exists in deep sequence data that has undergone good quality control. Even if the true causal mutation does not pass quality control (e.g. low minor allele frequency), the chances of being in tighter linkage disequilibrium with a closer DNA marker (although technically this should also have a low minor frequency in this situation to be tightly linked) is increased.

Developments in genomics have contributed to a gradual increase in the number of animals that are whole genome sequenced, with the process of imputation (Sargolzaei et al., 2014) being used to impute (i.e. predict) the whole genome sequence of animals genotyped for only tens or hundreds of thousands of SNPs. This is possible because chunks of DNA are inherited across generations and once

the whole genome sequence of back-ancestors is available, then these chunks (called haplotypes) can be tagged by the genotyped SNPs and the chunk imputed. It is nowadays not uncommon for studies to use imputed whole genome sequence data on tens or hundreds of thousands of individuals (Purfield et al., 2019). Based on the current state of the art, the benefit of sequence data in genomic predictions of real-life data does not always match the investment (Meuwissen et al., 2016). This could be due to a multitude of reasons including: (1) an inability for the prediction model to actually locate the causal mutation(s) amongst the millions of other candidate causal mutations especially if the allele substitute effect is small, and (2) whole genome data, especially in the coverage often generated, contains errors which can be compounded by imputation and thus the errors contributed through the genotypes generated from (imputed) sequence data may actually negate any potential benefit in prediction accuracy accruing from the greater density genotypes.

Irrespective, access to (imputed) whole genome sequence data has enabled more powerful and complete studies that attempt to locate the causal mutations underpinning phenotypic performance; these studies are called genome-wide association studies (GWAS). The high-level objective of many of these studies is to locate the causal mutations which can then be genotyped on all animals and help in genomic evaluations across families, strains, breeds and generations. Nonetheless, in the majority of cases, only a small proportion of the genetic variance of quantitative traits, and by extension even less of the phenotypic variance, is likely to be explained by these mutations with some notable exceptions (DGAT1 in cattle – Georges et al., 1995; CDH1 in Atlantic salmon – Moen et al., 2015; growth differentiation factor in meat producing animals – McPherron & Lee, 1997). Hence, the marginal improvement in predictive ability per mutation is likely to be small. Nevertheless, other uses can be garnished from knowing the underlying causal mutations; Berry (2015) described other potential uses of known the causal mutations contributing to phenotypic differences including more personalised animal management (i.e. nutrition, medicine, reproduction) as described in Fig. 5.3. From a nutritional perspective, the term nutrigenomics is often synonymous with *feeding the genes*. While major genes do exist, it is more likely that nutrigenomics will relate more to the global genomic estimate of genetic merit for performance based on the cumulative effect of thousands of genetic variants as opposed to just a few. Such a concept is not at all novel. For example, the germplasm used in confinement dairy cow production systems differs to that used in grazing dairy cow production systems (Pryce et al., 2014); this divergence occurred without any direct knowledge of the animal genotype per se but represents nutrigenomics. Nonetheless, major genes do still exist and animals are often recommended to be managed or fed appropriately. For example, high fecundity sheep are often fed more energy and protein-rich diets in late lactation because of their likely greater little size compared to their lower fecundity counterparts. Similarly, cattle with the nt821 myostatin mutation (e.g. Belgian Blue cattle) should be fed a more energy-rich diet as growing animals to provide sufficient energy to deliver the required nutrients for rapid muscle growth.

Pharmacogenomics can also influence management decisions. Pharmacogenomics is the study of how an individual's genotype influences its response to medicinal

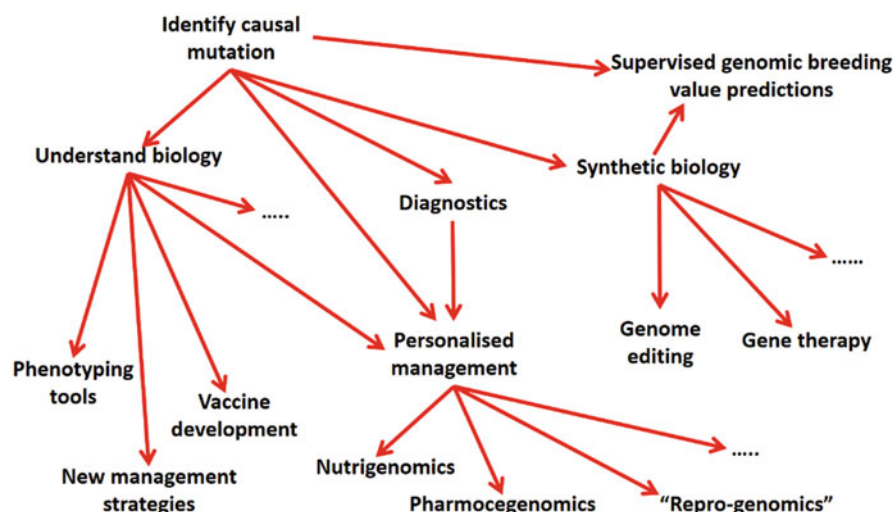


Fig. 5.3 Usefulness of identifying causal mutations to aid in livestock management

treatment. A good example of such is the use of codeine in human medicine; codeine is a class of opioid analgesics used to relieve pain, the efficacy of which is dictated by polymorphisms in the CYP2D6 gene. Pain relief may be inadequate in individuals who have two inactive copies of the CYP2D6 gene whose enzyme is needed to convert codeine to morphine (Pratt et al., 2012). Similar scenarios, not just limited to individual genes, could exist in livestock. Moreover, even understanding genetic predisposition to disease can help enact different management strategies. For example, enhanced screening or observations of at-risk animals could be performed. Similarly, prophylactic measures including administering vaccines could be targeted at more susceptible animals. Finally, nutritional or chemoprevention should be enacted for at-risk animals.

Genome-based management decisions do not, however, have to be limited to just within the farm gate. Genetic differences in meat-eating quality clearly exist among species (Berry et al., 2017a, b). Peri-mortem strategies can be adapted per animal based on its genetic prediction of meat quality thus maximising the likelihood of a consistent and pleasurable eating experience for the consumer.

5.4.1.2 Parentage Assignment and Traceability

Because each parent donates half its DNA to its offspring, genotypes (if taken from the correct animals) can be used to infer parent-offspring relationships. Parent-to-offspring errors vary from 7.6% to 10.0% in sheep (Berry et al., 2016), from 10.18% to 13.28% in cattle (Purfield et al., 2016) and from 8.4% to 14.6% in goats (Bolormaa et al., 2008). While mis-recording parentage errors affects genetic gain (Visscher et al., 2002), missing parentage information can also stifle genetic gain. Accurate parentage information is also important for precision breeding. The number of SNPs required for parentage verification and assignment, if optimally chosen, is up to 400 (Berry et al., 2019a, b). The number of SNPs for traceability is far less if

appropriately chosen (Weller et al., 2006). For example, the probability of two individuals carrying exactly the same genotype at 10 informative SNPs (i.e. a minor allele frequency of 0.5) is 5.5×10^{-5} (Weller et al., 2006). Farm-level samples are often taken routinely for some measure to track performance or animal health; one good example is bulk tank milk samples from dairy herds which are analysed daily or every 2 to 3 days. One such analysis undertaken is the count of somatic cells. High somatic cell count is indicative of clinical mastitis and is a costly disease with animal welfare repercussions. The count of alleles in the bulk tank somatic cells is proportional to the relative contribution of each cow's DNA to the bulk milk. By solving a set of linear equations comparing the genotype of the bulk milk to that of the cow, an estimate of cow somatic cell count can be derived (Blard et al., 2012).

5.4.1.3 Breed Composition

The breed composition of the progeny from at least one crossbred parent cannot be known with certainty without using genotype information. Breed assignment can help deliver on consumer expectation of traceable food products, as well as verify breed composition for herd- or flock-book registration. Furthermore, meat products originating from certain breeds sometimes command a higher price and thus there is an onus to verify breed composition. Accurate breed composition is also important for proper assignment of breed groups in genetic evaluation systems. While knowledge of breed is often deemed important when making nutritional and management decisions or for grouping animals, SMART nutrition or management in the future should be based on individual animal's estimates of genetic merit which, itself, incorporates breed differences. This is because as large variability in performance traits exists within breed as among breeds (Ring & Berry, 2020). In the future, animals of different breeds but of similar genetic merit will be penned or group managed as opposed to just based on breed. Using routinely available cattle genotypes from SNP chips, Judge et al. (2017) concluded that at least 300–400 SNPs (per breed) were required to accurately predict Angus and Hereford breed proportion.

5.4.1.4 Monitoring of Major Genes and Congenital Effects

Mutations in genes of known lethal effects as well as mutations leading to congenital defects (e.g. Duchesne et al., 2018) or in genes of known major effect (e.g. Grisart et al., 2002) are also now routinely included on most SNP-chips. Moreover, the flexibility afforded by SNP-chips, especially propriety SNP-chips, mean that mutations can be added as they are discovered for screening of the population and, where appropriate, purged from the population. Validation of the resulting genotypes from constructed probes on the SNP-chips is crucial. As previously discussed, knowledge of the variants an animal possesses for some major genes will affect how the animal should be fed and managed; a good example is the muscle hypertrophy associated with the myostatin where sustained rapid muscle growth will require an energy-rich diet.

5.4.1.5 Karyotyping

A karyotype is the term given to the number and appearance of chromosomes in a cell. Changes to the number or appearance of chromosomes is called a karyotype abnormality and the impact varies from no observable external difference, to reproductive failure, to embryo death. Cytogenetics was the approach traditionally used to karyotype individuals, but determining the number of copies of each chromosome from routinely available SNP-chip data has been demonstrated to be possible in cattle (Berry et al., 2017a, b) and sheep (Berry et al., 2018). Early knowledge of whether or not a nulliparous female can become pregnant will impact management decisions; infertile females will enter the feeding and management regime for slaughter as opposed to that for optimal growth for pregnancy. This is particularly important in species like cattle (and some sheep production systems) where age at first calving is later than the age at which the female would be ready for slaughter.

5.4.1.6 Inbreeding and Mating Advice

Incorrect or missing pedigree information biases co-ancestry estimates among potential parents. For example, the estimated relationship between two full sibs with no parentage recorded (or incorrect parentage) is assumed zero, but genotype information can help resolve such discrepancies. Moreover, in the absence of genotype information, the assumed co-ancestry between two individuals is simply the expectation. For example, full sibs, on average, share half their DNA, but considerable variation exists around this average. By knowing the genotype of each full-sib, the expected inbreeding of the progeny from the mating could be predicted; it can never be known a priori due to mendelian sampling during gametogenesis. Moreover, many lethal recessive mutations (i.e. DNA mutations that result in the death of the embryo or foetus) have been purged out of most populations by restrictions imposed that parents cannot be carriers of known lethal mutations. In the future, when (almost) all animals, male and female, are genotyped, it will be possible to develop more accurate mating advice schemes to avoid the matings of carrier animals and minimise the accumulation of inbreeding. Moreover, strategies such as the estimation of gametic variance of an individual (Santos et al., 2019) could be informative in predicting the expected heterogeneity of offspring from a given individual or mating. Knowledge of the inbreeding of an animal can also be used to modify the genetic merit of an individual aiding better approximation of the expected phenotypic performance of an animal; the reduction in performance due to inbreeding is termed inbreeding depression and has been demonstrated to exist in many species (Leroy, 2014).

5.4.1.7 Precision Management

Prediction of (genetic) predisposition to disease is a rapidly growing discipline in human medicine (Vogenberg et al., 2010), as is personalised nutrition (Ordovas et al., 2018). More accurate predictions of genetic merit through the exploitation of genotypes enable tailored management strategies like feeding animals differently depending on their genetic merit for performance. As well as potentially improving performance, bespoke management systems can also contribute to less wastage

within the industry. Genomics can also be used to better understand host-pathogen interactions and, from this, enact action(s) (e.g. boosting the innate immune system) given the genotype of the pathogen. The concept of precision management in light of information gleaned from genomic information is discussed later.

5.5 Phenomic Tools

Phenomics in livestock generally relate to (a) animal identification, (b) measurements of performance (either output or inputs) and (c) measurements of the prevailing environmental conditions. The relatively recent convergence of technologies and approaches has certainly made phenotyping more possible. Such technologies include those associated with high-throughput phenotyping coupled with bioinformatics and computational capabilities to mine the generated data including hierarchical models that link the different layers underlying the eventually expressed phenotype. While phenomics can broaden the armoury of animal or environmental features available by measuring new traits or potential environmental contributors to the phenotypic variability, phenomics can also measure traditional traits better and more frequently on more animals. An example is RFID with automated liveweight measures removing the necessity for the operator to not only manually record the liveweight of the animal as it moves within the weigh crate, but also correctly assign that record to the animal; the electronic transfer of the data to a central repository also ensures rapid data transfer with minimal error. The same is also true of automated feed intake measures or using feeding behaviour data to identify animals off feed. This is important to enact proactive management regimes rapidly and appropriately. Furthermore, traditional traits which may have required the animal to be sacrificed can now be assessed on live animals (e.g. CATSCAN used to predict carcass composition but also additional phenotypes like rumen size and fat deposition on the pedal bone of the hoof). Of course, advances in data analytics such as visualisation techniques and outlier detection have huge potential as part of the quality control pipeline of future phenomic endeavours. Importantly here though for management purposes is to be able to disentangle measurement/statistical outliers from biological outliers; the latter is obviously extremely interesting from a management perspective.

Opportunities for improved phenotyping is immense given the ongoing developments especially in sensing systems, Internet-of-Things and data analytics. While being able to measure traditional traits more accurately is certainly a benefit, arguably of greater benefit will be the opportunity to measure what are called difficult-to-measure traits on a large population of animals and, in fact transform them to easy-to-measure traits. These measures can be used not only for both breeding programs, but also for day-to-day animal management (e.g. oestrus detection, early detection of off-form animals, feeding schedule). Sensing systems deployed on the animal itself to measure a whole plethora of different attributes include technologies such as accelerometers, magnetometers, gyroscopes, visual,

sensors, audio sensors and location sensors as well as equipment to measure temperature, gastrointestinal function, heart rate and respiratory rate (Greenwood et al., 2016; Halachmi et al., 2019). Devices such as thermal imaging or actual cameras to measure in multiple dimensions are now becoming affordable; these have been complemented by developments in algorithms with advanced cognitive capability which can match or even exceed human capability in undertaking specific tasks. Detailed reviews of the plethora of technologies available are discussed extensively elsewhere (Greenwood et al., 2016; Halachmi et al., 2019). Halachmi et al. (2019) concluded that wearable technologies dominate the market for sensing in livestock but in less-value-per-animal systems (e.g. sheep, goat, pig, poultry) one sensor, like a camera or robot per farm, rather than one sensor per animal, will become common. Halachmi et al. (2019) also stated that the development of methods to turn the data into actionable solutions is critical.

While a whole range of sensing mechanisms and commercial products exist which predict many such features, arguably the greatest benefit will be from combining such information sources, complemented with available information on ancillary animal and environmental features like animal age, prevailing weather and genetic merit. More importantly, however, is rather than simply monitoring and predicting performance will be the ability to diagnose positive and negative breeding and management decisions. In other words, while early predictors of soon-to-be-sick animals are important, being able to diagnose early why animals are getting sick is arguably more important. This feedback mechanism is crucial for precision management and nutritional advice but must also be sufficiently flexible and knowledgeable to be able to account for changes in the genetic merit of the animals over time.

5.5.1 The Emerging Phenotypes

The phenotype observed by producers (e.g. growth rate, milk yield) is often that of greatest interest to the producer. However, such phenotypes are complex by their very nature implying that they could be decomposed into their component traits, which are also called the intermediate phenotypes. For example, growth rate could be decomposed into the weight due to bone, fat and lean growth (each of which actually has its own economic value) and even these could be sub-divided into smaller components or even their distribution around the body. Similarly, milk yield is a function of protein, fat and lactose (as well as other minerals, vitamins and bioactive compounds). However, protein is comprised of caseins and whey which in themselves are constructed from more granular components, as is milk fat. In fact, many layers exist between the genome of an individual and its eventual phenome including the transcriptome, the metabolome and the proteome. Also of growing interest is the epigenome (Goddard & Whitelaw, 2014). A good example of the importance of gene expression in the development of a phenotype is the butterfly which morphs from the caterpillar without obviously any change in the genome.

Sophisticated technologies now exist to quantify each of these layers on a large scale although their expression differs temporally and spatially across the individual. Being able to delve deeper into such layers can facilitate a greater understanding of the underlying biological construct and help develop, not only more efficient breeding programs, but also revised management strategies to optimise performance.

The same is true for measuring and understanding the microbiome of livestock. While much commentary is on the rumen microbiome, the microbiome at other locations like the mouth (Alipour et al., 2018), reproductive tract (Clemmons et al., 2017) and mammary system (Li et al., 2018) may also be informative. Using a sample population of Holstein cattle, Jami et al. (2014) demonstrated how the ratio of bacterial phyla Firmicutes to Bacteroidetes was related to milk fat yield, via its indicator of the metabolism of the animal. Jami et al. (2014) also reported how a reduction in Bacteroidetes in the gastrointestinal tract was associated with poorer feed efficiency. Hungate (1966) was one of the first to develop the technique to cultivate anaerobic microorganisms but these have now been replaced by modern sequencing methods coupled with sophisticated downstream bioinformatics analyses. While targeted amplicon sequencing was the traditional (and is still very common) method for taxonomic profiling of a sample, this is now being replaced by next-generation sequencing platforms; the former does not enable species detection and also lack functional information (Escobar-Zepeda et al., 2015). Shotgun sequencing enables more functional insight as well as aiding the *de novo* assembly of microbial genomes. Such functional information can be extremely useful for management purposes evaluating, at a very granular level, the impact of changing environment (e.g. nutrition) on the function of the digestive tract but also informing, based on past evidence, what changes need to be made to rectify any unfavourable observations. It may not be necessary to actually undertake analyses on an individual animal basis but instead possibly a pooled sample of contemporaries could be used as the experimental unit for management purposes. Host genetic influences on the microbiome have also been reported to exist with heritability estimates of between 0.02 and 0.30 for relative abundances at the genus level (Camarinha-Silvia et al., 2017; Beaumont et al., 2016). Hence, the microbiome in itself could become a phenotype of use not just for management purposes but also for use in breeding programs, and importantly linking the two and, in doing, (a) identifying individuals that deviate from expectation and (b) manage the individual(s) accordingly based on their expected microbiome. Genomic and bioinformatics developments in metagenomics like longer read sequencing but also quantifying the microbiome RNA to provide accurate measures of the activity of the functional metabolic pathways will also provide temporally informative data to help inform management and SMART nutritional strategies.

Also important is the host-pathogen genome interaction for understanding animal disease especially how the host can exert some control over the life cycle of the pathogen; this can be beneficial not only to the host itself, but also potentially reducing or halting transmission to the wider population.

5.6 Case Studies of the Marriage of Genotype and Phenotype

5.6.1 Breeding Objectives of the Future

The breeding objective of a breeding programme is comprised of a list of traits each appropriately weighted based on (perceived) importance. Conditions for inclusion of a trait in a breeding objective are as follows:

1. It must be important.
2. It must exhibit exploitable genetic variation.
3. It must be measurable in a large population of animals related to the selected candidates; if not, it must be genetically correlated with a trait which is measurable in large numbers.

Examples of the relative emphasis on different traits within breeding objectives of ruminants are given by Berry et al. (2021a), with the emphasis on traits in international dairy breeding objectives summarised by Cole and VanRaden (2018). Current breeding objectives tend to be holistic in nature including both performance traits (e.g. growth rate, milk production) and functional traits (e.g. reproductive performance, birthing difficulty, health, temperament). The presence of all traits in a breeding objective provides the framework for simultaneous selection for improvements in all traits despite often antagonistic genetic correlations existing among some traits.

Economic modelling is used to decide the weights on individual traits within several breeding objectives although, in some jurisdictions and species, economic modelling is only used as a guide with the final weights on individual traits often decided by a committee; for some, desired gains (Cameron, 1997) exclusively is used to decide on the weighting factors where, as the name suggests, the objective is to achieve a desired rate of gain for some traits. Breeding objectives are routinely updated based on new information and knowledge both on the traits of likely importance in the future, but also their associated (future) costs and value. Because generation intervals of some livestock species (e.g. cattle) tend to be particularly long (6.03 to 6.71 years in cattle; McParland et al., 2007), such breeding objectives especially, must be very futuristic.

Suites of traits poorly represented in many breeding objectives of different species include (granular) product quality, feed (including digestive) efficiency, environmental efficiency, as well as animal health and well-being. Spectroscopy methods are coming to the fore as potential predictors of all such suites of traits. De Marchi et al. (2014) reviewed the literature on the applicability of mid-infrared spectroscopy of milk to predict granular milk quality traits while the use of near-infrared spectroscopy for predicting the quality of meat in multiple species has also been reported (Bresolin & Dórea, 2020). McParland et al. (2011, 2012) and Wallen et al. (2018) both demonstrated how mid-infrared data of dairy cow milk could be used to predict feed intake and efficiency with McParland et al. (2011, 2012) also further demonstrating its predictive ability for energy balance of dairy cows, a trait

associated with animal well-being and resilience (Friggens et al., 2017). Dehareng et al. (2012) reported on the ability of milk mid-infrared spectroscopy to predict methane emissions in dairy cows; milk urea nitrogen of milk, also predicted from mid-infrared spectroscopy of the milk (Grelet et al., 2020), is used as a proxy for nitrogen use efficiency in dairy cows (Guliński et al., 2016). The advantage of infrared spectroscopy as a phenotyping tool is that it is fast, non-invasive, non-destructive and amenable to in-line measurements. Mid-infrared spectroscopy of milk in dairy production systems is particularly advantageous in that the samples are already being collected on individual cows for routine milk testing with all samples subjected to infrared analysis with the purpose of reporting back to producers the fat, protein and lactose concentration of the milk; the producers themselves already pay the full cost of the service so, therefore, these new phenotypes are close to free of charge once the prediction equations are developed. Partial least square regression is the method of choice for relating the spectral data to the gold standard phenotype; other approaches (Wallen et al., 2018), including a suite of machine learning approaches (Frizzarin et al., 2021), fail to consistently improve on the status quo and any improvements in predictability tend to be small (Frizzarin et al., 2021).

Environmental traits like methane emissions and both nitrogen and phosphorus use efficiency are growing in importance (Stiles et al., 2018). The gold standard for measuring methane emissions is calorimeters where the animal resides within a relatively small enclosed area for a short period of time during which all gaseous emissions are measured. While the measurements taken are highly precise, for grazing ruminants at least, the animal is removed from its natural environment with the potential consequence of not only stressing the animal and thus biasing the emissions, but also removing potential (genetically controlled) contributing factors to emissions like herbage selection and activity. The same can be true of nitrogen use efficiency where the gold standard is to accurately measure all inputs and outputs in enclosed metabolic chambers thus again removing the animal from its natural environment. Hence, phenomic strategies must be able to balance the precision of measurement and the applicability of the outcome to commercial reality; such a proposition is particularly relevant for the pig and poultry industries (but of late also the cattle industries) where selection may be exercised on deeply phenotyped individuals managed in a highly controlled environment which may not be representative of commercial reality. Strategies, nonetheless, do exist to obtain relatively accurate measures of gaseous emissions from ruminants without resorting to unrealistic calorimeter chambers. The GREENFEED system is now commonly used in ruminant research to measure methane emissions. However, firstly, many of these machines are being deployed on animals fed indoors, generally young growing animals, while in reality the vast amount of methane produced is by the mature herd who, for beef cattle at least, spend most of their time grazing. The relevance of genetic evaluations for methane emission measured indoors on growing animals against (grazing) mature animals is untested. The same is true for feed intake measures, in beef cattle at least, where the measures are generally taken on the young growing animal yet the main culprits are the mature herd. Significant genetic variability in feed intake among dairy cows does exist and this is correlated with

feed intake in growing heifers (Berry et al., 2014), although the genetic correlations between feed intake in lactating dairy cows fed indoors and those grazing pastures are weak (Berry et al., 2014). It is therefore crucial that phenotyping strategies are not undertaken solely because they can, or that the strategy of least demand is pursued, but instead the strategy chosen is most relevant while also cognisant of practicality.

A suite of traits which is growing in importance for pigs and poultry, but potentially also for dairy cows as herd size expands, is the area of social interactions (Pérez-Enciso & Steibel, 2021). This is particularly important with the transitioning from single-unit housing to open houses in livestock, especially within the EU. Several technologies, however, do exist to measure social interactions (Fernandes et al., 2020), and exploitable genetic variability in social interactions has been demonstrated (Nielsen et al., 2018). A further phenotype of potential interest to both breeding and management systems is resilience to the impact of climate change be it either the stress of prevailing weather conditions (i.e. temperature and rain), the reduced availability of feed for grazing animals (or transitioning from one feed to another as the weather changes), as well as the potential exposure to exotic diseases previously not encountered. While phenotypes for many of such traits exist (Nguyen et al., 2016), as does genetic variability (Nguyen et al., 2016), arguably most of the research here will be on the appropriate modelling solutions to depict resilience.

Water use efficiency is also likely to become a very pressing issue in many jurisdictions with a conflict already growing between water availability for human use versus for animals. Steinfeld et al. (2006) argued that 64% of the world's population is expected to live in water-stressed basins by the year 2025. The recent availability of mechanisms to measure water intake has facilitated the generation of phenotypes for exploration of the underlying genetic mechanisms. Rusakovic et al. (2017) reported heritability estimates of 0.35 to 0.50 for traits like daily number and duration of visits for water, water intake and rate, and drinking time in turkeys coupled with weak genetic correlations with the performance traits investigated. This implies the presence of genetic variability and while selection for performance is unlikely to have affected these water-related measures, it also implies that selection for improved water use efficiency is unlikely to massively affect genetic gain for performance (other than through a reduction in selection intensity for the latter). Genetic variability in feeding behaviour traits has also been demonstrated to exist (Howie et al., 2011; Kelly et al., 2020). Of course, while such behavioural phenotypes are useful phenotypes for potential inclusion in breeding programs, their routine monitoring can also be hugely beneficial for SMART animal management (Borderas et al., 2009; Schirmann et al., 2016). Borderas et al. (2009), for example, reported that sick dairy calves visited feeders less often with greater duration per feed. Nonetheless, many such studies are explanatory analyses describing the associations between animal (health) status and behaviour while fewer have actually progressed these explanatory models to be predictive models where the feeding behaviour data are used to predict health outcomes sufficiently early to be

able to invoke remedial action; it is the latter which is really important and will be the main benefit from such technologies in animal management.

5.6.2 Precision or Personalised Management

Personalised management is where the management of an individual is optimised to its genotype; this is a form of genotype-by-environment interaction. Personalised management or personalised nutrition is not a new concept in livestock production; different feeding management in late gestation sheep has long been recommended depending on the number of lambs in utero, as has alterations to dry period feeding levels in sows or cows differing in body condition score. Similarly, energy-rich diets are recommended for animals with a high genetic potential for muscle growth. So-called polygenic risk scores (Torkamani et al., 2018) that combine genetic predisposition (from genotype information ideally also considering non-additive genetic effects) with (historical and prevailing) phenotypic data can greatly aid in the day-to-day but also strategic management decisions. It is here where real opportunities for technologies like digital twins (Haag & Anderl, 2018) have potential.

A digital twin, as the name suggests, is a digitalised representation of an actual physical system and can be used to evaluate the impact of different management strategies. Digital twins have gained prominence enabled by the Internet of Things that facilitate high dimensional and granular monitoring in real time often using a combination of miniature sensing devices and remote sensing systems. Therefore, digital twins rely on excellent phenomic (and genomic) data. The twin can essentially model different “what if” scenarios which have obvious benefits (if accurate) in evaluating alternative management and nutritional strategies or modifications thus aiding in final decision-making. However, digital twins are more amenable to representing human-made systems which can be synchronised with virtual systems but complex natural systems like livestock may not be so amenable to good and accurate digital representations. Importantly, a digital twin must demonstrate a return on investment and such does not exist currently for livestock.

Genetic merit (with the possible exception of breed) is not always explicitly considered in prediction models for developing personalised nutritional and management strategies. Nonetheless, for heritable traits, genetic differences contribute to phenotypic differences amongst animals and should therefore be considered when trying to synchronise management to genetic potential. For example, the genetic standard deviation for 305-day milk yield in Irish dairy cows is 919 kg (www.interbull.org). Therefore, using normal distribution theory, the difference in yield between the top versus the bottom 10% of cows is expected to be 3225 kg. Similarly, assuming a genetic standard deviation in growth rate of growing cattle of 0.13 kg/day (Crowley et al., 2010), this equates to a difference of 0.46 kg/day between the top and bottom 10% of individuals. Clearly, therefore, genetic merit should form part of any prediction model or associated digital twin.

While genetic variability indeed contributes to phenotypic variability, other non-genetic effects specific to individuals also contribute to the observed phenotypic variability. Such effects are commonly termed permanent environmental effects; the name stems from the fact that they are environmental effects (i.e. non-genetic and thus not transmitted to descendants) but are permanent to the animal. The variance contributed by this permanent environmental effect is the difference between the heritability and the repeatability. For milk production in dairy cows, for example, the heritability may be 0.30 while the repeatability may be 0.52 (Suzuki & Van Vleck, 1994) suggesting that 22% of the phenotypic variance can be due to the permanent environmental variance. Routinely measured phenotypes as input variables to the statistical model can be used to estimate the individual permanent environmental effects which can then be included in the prediction model improving its accuracy.

Estimates of the genetic merit of an animal for a given trait may also be used for modifying the decision rules within decision-support tools. For example, a cow with a genetic predisposition to uterine infection or ovarian cysts may be enrolled into a routine reproductive tract ultrasonography examination. Similarly, a somatic cell count in primiparous dairy cows of $>200,000$ cells/ml may cause an alert for subclinical mastitis, but this threshold may be lower if the cow in question is known to have genetic predisposition to mastitis. An analogy in human medicine is when patients are asked about any family history for certain diseases by doctors trying to more accurately diagnose ailments. Such personalised management could, of course, also be at the level of the herd exploiting herd best linear unbiased estimates (BLUES) to tailor not only the breeding goal of the herd, but also the expected response to selection for each trait given the herd BLUE for that trait (Dunne et al., 2019; Kenny et al., 2021). However, of utmost importance is that while models are transitioning from being descriptive to being predictive, they must now start to aid in the diagnosis of the underlying issues along with prescription of what to do. This requires input from subject-matter experts (i.e. SME) in relation to animal husbandry and thus pan-disciplinary actions to achieve the end goal of improved, more-informed decision-making are crucial.

5.7 Challenges

Developments in agri-tech and the growing accessibility of sensing systems for measuring a whole plethora of metrics open up opportunities as well as create challenges for future livestock breeding programmes and management. The opportunities include the generation of vast quantities of objective measures not only on the animal itself, but also reflections of the prevailing environmental conditions (for use in the statistical model). Practical challenges relate to the return on investment from the whole range of technological solutions being proposed, how to relay summary statistics from the vast quantities of data in a usable and understandable format to the end user (for management purposes), and finally issues associated with data ownership. Other challenges not discussed further (but

discussed at length elsewhere) relate to trait ontology and standardisation of measurement (Hocquette et al., 2012), computational resources (Cole et al., 2011), including interoperability, as well as data mining techniques (Gonzalez-Recio et al., 2014). More recently, the concern of data hacking and malware has come to the fore and the potential impact this could have on day-to-day business operations (Ritenour, 2020).

5.7.1 Return-on-Investment

Tight profit margins and volatility in product price (and costs of production) which are particular features of primary agriculture are major influencers as to whether producers could (or should) invest in genomic or phenomic technology. Hence, a clear return-on-investment needs to be demonstrable. An approach for producers to calculate a return-on-investment from genotyping (along with an accompanying excel file) was provided by Newton and Berry (2020). The approach pursued was sufficiently generic to be applicable to all species once the parameters required were known for the population. These parameters included the number of female replacements retained, the replacement rate, the average lifespan of females, the reliability of genomic and traditional evaluations, parentage error rate, the heritability and standard deviation of the breeding goal, and the genotyping cost.

The cost of phenotyping depends on the phenotype of interest. Some phenotypes may be viewed as free since they are already collected and paid for through other sources (e.g. recording of animal births and parentage as part of national traceability systems) while other phenotypes may be very expensive to measure. Often when embarking on using a new technology for phenotyping on farm, only the initial capital cost is considered; however, there is obviously a depreciation and maintenance cost of such sensor systems also as well as possible license fees. Sensor drift can be a big issue in that accuracy can deplete with time; for example, simple things like putting a new object into a shed (e.g. a tractor or mixed wagon) can influence the acoustics of the shed thus potentially impacting any such sensors but the ramifications of such may not be immediately recognised. Rather than a large initial investment, warranty-based approaches could also be adopted; these approaches are based on a commitment by the vendor that a given level of performance should be achieved and only if that performance is achieved, will the purchaser pay the annual fee. Nevertheless, the costs of phenotyping is often incurred by few but the benefits reaped by many. Hence, considerations should be given to a levy on animals or products to subsidise or pay for a phenotyping (and associated systems) strategy. This could be viewed as a type of royalty or license for the generated intellectual property. Such an approach will incentivise continuous innovation. For example, assuming the output from the Irish dairy, beef and sheep sector is 8 billion kg milk, 550,000 tonnes of beef meat and 55,000 tonnes of sheep meat, then the charge per kg output per one million euro cost of phenotyping animals for a breeding programme would be just 0.013 cents, 0.18 cents and 1.8 cents, respectively.

5.7.2 Useful and Meaningful Decision-Support Tools

Making sense of vast quantities of high-velocity data can become unwieldy and even counter-productive. While artificial intelligence or machine learning systems are being heralded as the saviour to precision agriculture, these algorithms, like most before them, simply take data as inputs, process the data and generate an output which is hopefully useful to someone. Being able to decipher such data streams into value-creating decision-support tools that are compatible and complementary to other such tools will be a major challenge; greater interaction with end-user focus groups will be of utmost importance to ensure the developed tool is fit for purpose. One such technique to help achieve this is user-centred design. User-centred design is an iterative design process in which developers of the technology concentrate on the users and their needs throughout the entire design and development process. The outcome is a highly usable and accessible product. Technologies designed without understanding context-specific needs and value-driven concerns can lead to low adoption at farm level and societal rejection at market level. Decisions that are made in collaboration with the end-user are better informed, more democratic and have more legitimacy, resulting in increased trust and acceptance.

Developing areas like explainable artificial intelligence (XAI) systems will have a major role in demonstrating how the solutions have been arrived at, and thus can be readily understood (and therefore more accepted) by the end user; counterfactual analysis or other recommender systems will provide direction on what decisions are likely to best deliver gains within the confines of the respective features. Decision capture techniques could be useful to understand why some recommendations were not acted upon by individual farmers leading to an improvement in such recommendations over time.

As already discussed, analytical intelligence must progress from describing what has happened to what is likely to happen in the future (i.e. predictive modelling). Crucially, however, the actual diagnosis of the problem must be identified and corrective actions prescribed (Fig. 5.4; Smith, 2020) – *“There comes a point where we need to stop just pulling people out of the river. We need to go upstream*

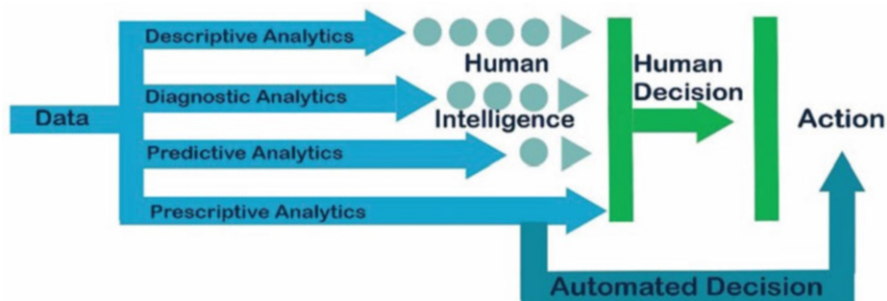


Fig. 5.4 The interaction between human intervention and analytical intelligence in arriving at a decision (adapted from Smith, 2020)

and find out why they're falling in" – Desmond Tutu. Accurate diagnoses and prescription of management and SMART nutritional recommendation will have to be underpinned by comprehensive phenotyping strategies (and genomic information) distilled down to informative evidence of what is occurring. Correspondingly, as the reliance on human input erodes, the trust on the underlining analytics will have to intensify.

Several successful value-create decision-support tools exist across species, not least the aforementioned breeding objectives which collapse vast quantities of information on a whole range of traits into a single index value per animal. Other management tools based on the principles of selection index theory are also in use (Dunne et al., 2020, 2021; Kelleher et al., 2015). In the example of the calf transaction index proposed by Dunne et al. (2021), the value of a young calf is predicted based on its genetic merit, some other animal-level features (e.g. gender) but also some features of its dam (e.g. parity). More importantly, however, is its compatibility in that it shares traits and economic values with the breeding indexes used to select and mate the parents used to generate this calf. Hence, dairy producers who use bulls that are supposed to generate high-value calves (Berry et al., 2019a, b) will, on average, have calves born that are predicted to be more valuable.

While many decision-support tools, especially those based on mating advice, tend to predict the expected mean performance, the variability in predictions will also become important. One such approach is to calculate the expected variance in progeny genotypes (Santos et al., 2019) which can then be used to generate the distribution in expected (total or additive) genetic merit for all evaluated traits (and overall breeding objective). Such a tool could be particularly useful in establishing the risk of calving dystocia for a given mating, especially for beef-on-dairy matings (Berry, 2021). In such circumstances, dairy producers may opt for bulls with a slightly greater mean genetic predisposition to calving difficulty but with a greater likelihood of producing genetically more homogenous calves and thus fewer very large calves which may require veterinary intervention during calving.

5.7.3 Data Ownership

Data ownership is becoming a contentious issue which has not been unequivocally addressed in livestock production at least. This is particularly important with commentary on the potential monetisation of data. Of real concern for some national genetic evaluation bodies for cattle and sheep, in particular, is the development of proprietary genetic evaluations or even genetic evaluations within herds or groups of herds, something which is the norm in the pig and poultry industries.

Importantly, owning a database may not necessarily automatically imply ownership of the data within as the rights of the database owner only relate to the database and not the individual elements. In some instances, the data collected on animals is stored locally and data ownership and privacy issues are not an issue here since the data are stored and often interrogated locally. More recently, however, the data, as well as being stored locally, are also transferred to a central server (e.g. cloud) where

it is aggregated with other data. In such situations, the producer has potentially surrendered the sole custody of the data. Many potential uses by others of the information generated from producer data could include:

1. Price discrimination for farm outputs – purchasers of farm outputs could downgrade the price willing to pay for a product based on the knowledge that, for example, the livestock to be sold will soon no longer meet the desired specification so the producer is compelled to sell to avoid penalties.
2. Price discrimination for farm inputs – knowledge of the (urgent) requirement for inputs can affect the price charged by the providers of such inputs. Economists term this first-degree price discrimination, and in such situations, it is the service providers that capture the benefits accruing from efficiencies at the farm level.
3. Others creating additional value from the output of the farm – purchasers of the farm outputs could obtain a competitive advantage over competitors by marketing superior products from their identified clients.
4. Lesser competition – larger procurement agencies could have a distinct competitive advantage over smaller agencies if the former has greater access to farmer data.
5. Enforcement of regulations – access to farm data by governments, retailers, or other actors provides evidence for violation of, or compliance with regulations such as standards for animal welfare and environmental stewardship.
6. Improved contemporary farmer performance through access to successful management “recipes” developed by others via peer-to-peer learning.

Ownership relates to property and there are three main types of property: real property, personal property and intellectual property; agricultural data is relatively unique in that it is a mixture of all three types. Therefore, the producer must provide evidence that (s)he fulfils the criteria for all three property types, namely the farmer owns the land from which the data were generated, owns the equipment (and possibly even developed the equipment) that created the data and generates the intellectual property from the resulting data; once others are involved in either of the three steps, then ownership is more ambiguous. Copyright law does not necessarily cover data ownership generated from technological devices as it is lacking a human creativity component (Gartner & Brimsted, 2017) and does not fall under the definition of an “author” (Farkas, 2017). Gartner and Brimsted (2017) in their commentary of data ownership, stated that data could constitute a trade secret in that it fulfils the criteria of (a) being secret and (b) being attributable to a company.

5.8 Conclusions

Developments in genomics and other omic technologies have increased rapidly in most recent decades as has the application in accelerating genetic gain. The cost of genotyping/sequencing is also reducing. The opportunity for advancements in phenomics is potentially far greater especially in real-time phenotypes where the

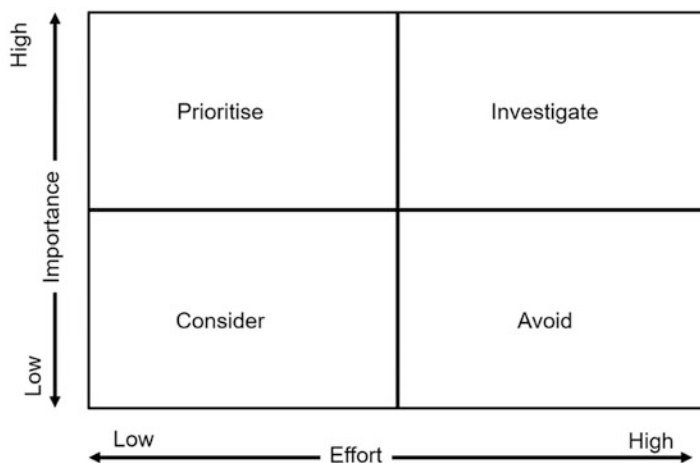


Fig. 5.5 Prioritisation matrix for phenotyping strategies in relation to their importance for breeding or management against the effort required to generate the data

ensuing information can be rapidly relayed to the producer to undertake remedial action, where necessary. A whole myriad of different technologies exists for assessing a whole plethora of different phenotypes. A prioritisation matrix (Fig. 5.5) should be used to help in making a decision on which trait(s) to pursue. Such traits should ideally be high impact but preferably, the solutions should be low cost. From lessons in the past, it is clear that both breeding and management programs must coevolve to fully reap the benefits of advancements in both.

The translation of outputs to outcomes will require the collation of data and information from multiple sources into a series of value-creating SMART nutrition and management tools. It is, however, important that biologists and animal husbandry experts reengage with the outputs from any prediction models translating predictions into diagnoses and prescriptions for the end user and, in doing so, reap the full benefit of the developments in phenomics and genomics. Given the heritability of many performance traits, it is crucial that accurate genomic predictions of performance on an individual animal level are fully integrated into these tools. The marriage of both genomic and phenomic tools will enable more precise, efficient and effective production systems with management guidelines suggested at a farm level while at the time recognising the heterogeneity of the animals within.

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Mathematical and Statistical Approaches to the Challenge of Forecasting Animal Performance for the Purposes of Precision Livestock Feeding

Maciej M. Misiura, Joao A. N. Filipe, and Ilias Kyriazakis

Abstract

Provision of feeding strategies tailored to the dynamic, preferably individual-level nutrient requirements is expected to greatly reduce the mismatch between nutrient supply and demand of most animals and could lead to minimisation of excess nutrient excretion observed in many pig production systems. Approaches to account for the individual variation in growth and consequent nutrient requirements are typically recommended to be largely data-driven to minimise the potential effects of different a priori assumptions on quantification of variation in populations. Evidently, the ability to develop such methods is largely dependent upon the availability of the relevant data, which should consist of regular measurements of the chosen traits of interest. Historically, the acquisition of such data has been challenging, but it is becoming increasingly more common due to technological advancements, which automate animal identification and collection of the necessary information. Without constraints associated with data collection, the next key element needed for a successful implementation of precision feeding strategies concerns testing and evaluation of mathematical, statistical and machine learning models to predict individual pig performance and body composition from data. The development of these models is still in the early stages and warrants further research. In this chapter, we review recent methodological aspects of forecasting pig performance and suggest possible future research

M. M. Misiura (✉)

School of Natural and Environmental Sciences, Newcastle University, Newcastle upon Tyne, UK

J. A. N. Filipe

Biomathematics & Statistics Scotland, Rowett Institute of Nutrition and Health, University of Aberdeen, Aberdeen, UK

I. Kyriazakis

Institute for Global Food Security, School of Biological Sciences, Queen's University Belfast, Belfast, UK

directions. Specifically, we focus on the following main aspects of forecasting pig performance: (1) exploration of the available data; (2) determination of which variables to forecast; (3) choice of suitable models; (4) estimation model parameter estimation; and (5) model evaluation. We conclude that the development of a more rigorous framework for forecasting and estimation of traits across individual animals is likely to benefit from: (i) selection of parameter estimation methods (needed to yield or improve values of the unknown model parameters during data fitting) that give sufficient information on uncertainty and correlations to provide increased robustness of estimates and forecasts; (ii) a more standardised assessment of outcomes across studies to allow for a better evidence synthesis; and (iii) reconsideration of certain modelling assumptions whose validity may hold only for a specific range of conditions.

Keywords

Allometry · Bayesian inference · Body weight · Data-driven modelling · Exponential smoothing models · Feed intake · Finisher pigs · Forecasting · Forecasting metrics · Forecasting pig performance · Growing pigs · Growth · Markov Chain Monte Carlo · Maximum likelihood estimation · Mechanistic modelling · Neural networks · Parametric models · Precision livestock feeding · Precision livestock management · Smart farming · Uncertainty quantification

6.1 Introduction

Precision feeding and management strategies for growing livestock require data-driven solutions to the problem of how to account for variation in growth and consequent nutrient requirements among individuals in populations (Gaillard et al., 2020; Pomar et al., 2009, 2019). A crucial aspect in solving this problem concerns forecasting of animal performance from past data (Pomar & Remus, 2019), which typically consists of serial measurements of body weight and feed consumption from electronic feeding stations and weighing platforms (Gaillard et al., 2020; Pomar et al., 2019). Forecasts utilising these data would facilitate provision of suitably adjusted individual-level or pen-level feeding strategies. Therefore, the inability to generate accurate forecasts of animal performance is likely to have a considerable impact on the overall quality of formulated feeds, potentially leading to either a waste of valuable nutrients from over-supplementation or production losses and welfare concerns from under-supplementation.

While precision feeding and management is an emerging research area, a diverse array of mathematical and statistical approaches, ranging from regression to moving average models has been utilised to forecast animal performance. This methodological diversity is a product of factors including: (1) differences in assumptions of how the underlying biological processes could be described using mathematical relationships; (2) relevance and availability of data; and (3) time frame to be forecasted, known as the forecast horizon (Bergmeir & Benítez, 2012). For example,

the amount of data could greatly influence model selection, with a general tendency to favour simpler models when there are limited data and vice versa (Hindman, 2015; Schumacher & Dreger, 2004). Similarly, different forecast horizons, which could be conditional upon the preferred frequency of feed adjustments may warrant the development of different models (Hyndman & Athanasopoulos, 2018), as the short-term growth may be reasonably approximated via simpler, linear mathematical relationships, which do not hold over the long-term (Filipe et al., 2018).

As the number of different approaches to predict animal performance for precision feeding and management purposes is growing (González et al., 2018), it could be worthwhile to take a step back and examine these approaches in more detail to gain a better understanding of their strengths and weaknesses, and thus, inform the direction of the future research in this field. In this chapter, we use growing and finishing pigs as an example to address this objective, but the ideas developed should apply to the challenge in other livestock species. Consequently, the aims of this chapter were to examine recent methodological developments concerning forecasting growth or intake responses for precision feeding and management of pigs. The chapter is structured to reflect the typical workflow of a modeller, which begins with data description and visualisation, and culminates in fitting models to data.

6.2 Data Description

For the purposes of precision feeding and management, regular pen-level or individual-level measurements of feed consumption and body weight are typically collected. In the current state-of-the-art farming operations, these data are recorded as soon as animals are engaged with the appropriate devices, such as electronic feeding and weighing stations (Nedap, 2020; Schauer Agrotроник GmbH, 2020).

Consequently, animals could potentially generate multiple data entries during e.g. a twenty-four-hour period, as most livestock species engage in eating activities more than once a day (Alameer et al., 2020). At an individual level, there is likely to be considerable heterogeneity in the number of feeding bouts and amounts consumed during each bout (Allcroft et al., 2004). To allow for a clearer and simpler comparison of performance among individuals, and to aid the overall interpretability, we consider the artificial scenario in which these data are pre-processed and expressed at regular (e.g. daily) intervals.

Here, the starting point is the definition of the following main quantities: (1) daily feed intake, DFI_t (kg/d) at age, or time t (d), which is the sum of all feeding events consumed during each d; (2) body weight, BW_t (kg) at time t (d), which could be e.g. an average of all bodyweight measurements taken throughout each d, or the last bodyweight measurement recorded for each d (this information could also be verified using alternative technologies, such as ones based on the image analysis (Amraei et al., 2017; Fernandes et al., 2020)). Using DFI_t and BW_t , it is also possible to readily define the following additional variables:

(i) daily bodyweight gain,

$$DG_t = BW_{\tau(i)} - BW_{\tau(i-1)} \text{ (kg)} \quad (6.1)$$

(ii) period cumulative feed intake, provided that there are either no missing DFI_t data, or that missing DFI_t data are suitably imputed:

$$CFI_t = \sum_{i=1}^{n(t)} DFI_{\tau(i)} \text{ (kg)} \quad (6.2)$$

(iii) period cumulative body weight gain,

$$CG_t = \sum_{i=1}^{n(t)} (BW_{\tau(i)} - BW_{\tau(i-1)}) = BW_t - BW_{t_0} \text{ (kg)} \quad (6.3)$$

where $n(t)$ is the number of observations at time t , and $\tau(i)$, ($i = 0, 1, \dots, n(t)$) are the time points when observations took place for a given animal. Combinations of some of these variables or traits are typically utilised to develop models to forecast future performance from data on past performance.

6.3 Determining What to Forecast

Forecasting could be defined as the prediction of values of a variable (output, Y) based on known past values of that variable, and/or on covariate variables (inputs, X). Forecasting could also be viewed as a two-step procedure consisting of extraction of the underlying trends from the observed data, and consequent extrapolation of these trends into the future (Hyndman & Athanasopoulos, 2018). The starting point is usually the identification of appropriate relationships between inputs and outputs. To gain a quantitative insight into these relationships, mathematical models relating inputs to outputs which aim to capture the key aspects of the observed data are typically developed; these models usually involve one or more parameters that are unknown in advance and must be estimated from the observed data.

If the aim is to forecast growth responses, then a reasonable output could be BW_{t+H} , DG_{t+H} or CG_{t+H} , where H is the forecast horizon and a suitable input could be: DFI_t , CFI_t , time itself, or even past values of some of these variables. Similarly, to forecast intake responses, these relationships could be reversed, so that DFI_{t+H} or CFI_{t+H} are the desired outputs. Evidently, there are many different combinations of these variables that could be utilised for model development and selection of the most appropriate set of variables is essential to ensure optimal

forecast accuracy. However, this selection is not always immediately obvious, particularly if the underlying biological meaning is overlooked. In the precision feeding and management literature, growth responses are usually forecasted with models that directly output either $BW_t + H$ (Brossard et al., 2017; Hauschild et al., 2012; Peña Fernández et al., 2019; Quiniou et al., 2017) or $DG_t + H$ (Aerts et al., 2003; Hauschild et al., 2020), whereas feed consumption is typically forecasted with models that directly output $DFI_t + H$ (Hauschild et al., 2012, 2020) or $CFI_t + H$ (Brossard et al., 2017). In most cases, these traits are directly related to time. However, focusing on the the traits' relationships to time is not considered to be advantageous, as it does not have a firm biological basis (Wellock et al., 2004).

Figure 6.1 shows scatterplots of BW_t , CG_t and DG_t against time, CFI_t or DFI_t , of an individual pig kept in typical commercial conditions growing from approximately

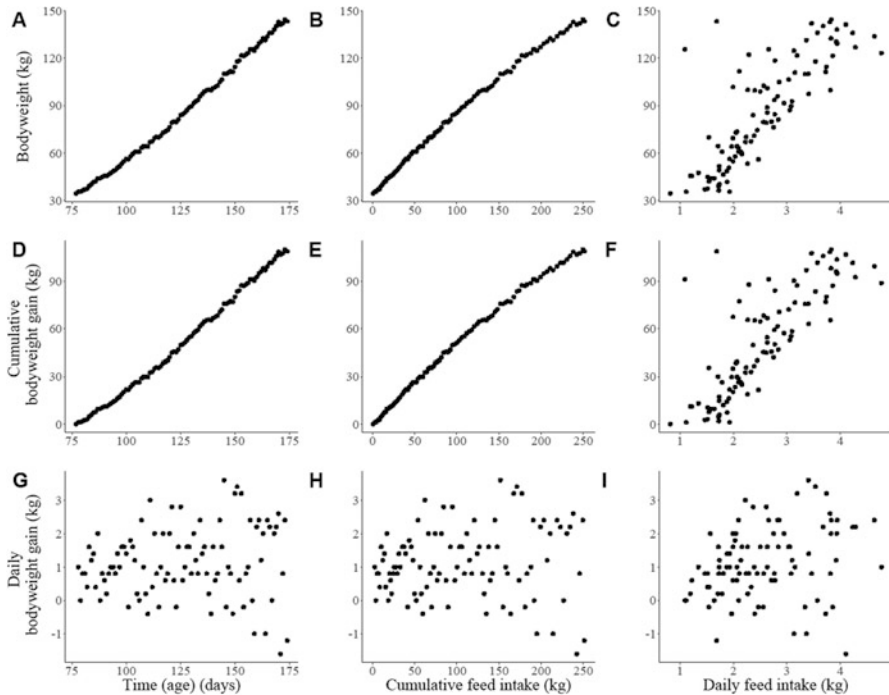


Fig. 6.1 Scatterplots of: (a) BW_t (kg) versus time (d); (b) BW_t (kg) versus CFI_t (kg); (c) BW_t (kg) versus DFI_t (kg); (d) CG_t (kg) versus time (d); (e) CG_t (kg) versus CFI_t (kg); (f) CG_t (kg) versus DFI_t (kg); (g) DG_t versus time (d); (h) DG_t (kg) versus CFI_t (kg); and (i) DG_t (kg) versus DFI_t (kg) of an individual growing pig from the beginning of the data collection period. Data was collected during a typical, commercial growing-finishing phase from post-weaning (approximately 35 kg) until slaughter weight (approximately 120 kg). In this scenario, the data collection period did not include the period associated with weaning and thus, an explicit distinction is made between body weight and cumulative bodyweight gain as these two variables have different starting points. *Abbreviations:* BW_t , bodyweight at time t (d); CG_t , period cumulative bodyweight gain up to time t (d); DG_t , daily bodyweight gain at time t (d); CFI_t , cumulative feed intake up to time t (d); DFI_t , daily feed intake at time t (d)

35.0 kg until 120 kg. Upon visual inspection, there are notable differences in the strength of an association between these pairs of variables. Consequently, this could impact the ability to extract the underlying trends. For example, there are more day-to-day fluctuations and less evident trends in the plots of DG_t against time and feed consumption (CFI_t or DFI_t) compared to the plots of BW_t or CG_t against time and feed consumption (CFI_t or DFI_t). This is not unexpected from a biological standpoint, as other unobserved mass flows (i.e. excretion of solids and fluids, water consumption, etc.) are likely to cause short-term fluctuations, whose magnitudes are much larger with respect to DG_t than with respect to BW_t or CG_t . These fluctuations could present considerable challenges in separating noise from the actual trend and are likely to be particularly problematic when growth responses are expressed based on DG_t . To reduce the effects of these longitudinal random variations on the trend extraction and forecasting, it could be prudent to consider either BW_t or CG_t instead of DG_t as the main output. In this case, the key remaining decisions concern the choice of a suitable input, likely either time or feed consumption, and the identification of an appropriate mathematical input-output relationship. These decisions could benefit from considering the underlying biology. For example, it is commonly accepted that animals grow by converting food into biomass and time by itself is not a consistent driver of growth (Black, 2009; Whittemore & Green, 2001). Thus, a biologically consistent growth response model could relate feed consumption over a period of time to changes in body weight over the same period (Filipe et al., 2019); the relationship between these two variables is likely to be nonlinear (Demmers et al., 2018; Kuhi et al., 2004; Schulin-Zeuthen et al., 2008; Van Buggenhout et al., 2004).

6.4 Fitting Models to Data: Parameter Estimation Methods

Most models described in this chapter are considered to be parametric, that is, they assume data relationships containing a limited number of parameters. Typically, some of these parameters are unknown in advance and they have to be estimated (learned) from data during the fitting process to yield or improve the knowledge of their plausible values (Robert, 2007). To do this, a parameter estimation procedure is required and typically involves minimising a predefined loss function, which measures model misfit to data (Bergmeir & Benítez, 2012). In this section, the two key methods for parameter estimation, namely Maximum likelihood and Bayesian estimations, are outlined; their relative advantages and disadvantages in the context of precision feeding and management are also discussed.

6.4.1 Maximum Likelihood Estimation

Maximum likelihood estimation is one of the most frequently utilised statistical frameworks for parameter estimation (Stigler, 2007). In the context of precision feeding and management, maximum likelihood estimation is also the usual

procedure for fitting models to data. It focuses on the likelihood function (Babtie & Stumpf, 2017):

$$L(\theta|Y) = \Pr(Y|\theta) = \prod_{t=1}^n \Pr(Y_t|\theta), \quad (6.4)$$

where Y are the data across different time points, $\Pr(Y|\theta)$ is the probability of observing Y given a mathematical model with parameter values θ . Consequently, maximum likelihood estimation seeks to find the values of θ , $\hat{\theta}$, that maximise the probability of observing the given data (Robert, 2007):

$$\hat{\theta} = \arg \max_{\theta} L(\theta) \quad (6.5)$$

While maximum likelihood estimation has many useful statistical properties, such as consistency and efficiency (Clayton, 2013), and is readily available in most software packages, it also suffers from several drawbacks, which could limit its applicability for precision feeding and management purposes. Specifically, this methodology generates only point estimates and gives insufficient information about the uncertainty and correlations in the estimated parameters and variables (Babtie & Stumpf, 2017). Thus, maximum likelihood estimation does not provide sufficient safeguards against misprediction, which in the context of precision feeding and management, could eventually translate into a suboptimal allocation of resources. Moreover, these concerns are further amplified by the reports suggesting that maximising complex likelihood functions spanning over multiple parameters is challenging and often results in unstable solutions (Robert, 2007). Other parameter estimation methods could not only yield better-quality point estimates, but also yield a more extensive insight into uncertainty (Beerli, 2005; Bewley & Griffiths, 2001), which is a crucial, but often an overlooked aspect of forecasting.

6.4.2 Bayesian Estimation

One of the main alternative approaches to maximum likelihood estimation is Bayesian estimation, built on the theorem of Bayes, which can be expressed by the following equation (Robert, 2007):

$$\pi(\theta|Y) \propto L(\theta|Y) \times \pi(\theta), \quad (6.6)$$

where $\pi(\theta|Y)$ denotes posterior distribution of the unknown parameters θ , and is proportional to the likelihood function, $L(\theta|Y)$, multiplied by a prior distribution of the unknown parameters, $\pi(\theta)$. The likelihood function is the same as in eq. (6.4) and contains a model of how the variation in the data was generated (Bijak & Bryant, 2016). The prior distribution is specified before fitting to data and intends to capture

any information or beliefs about parameters that could be available before fitting to data (Robert, 2007).

An immediate advantage of Bayesian estimation compared to maximum likelihood estimation is its probabilistic nature. The outcome of the analysis is an entire distribution of the data-based values, which accounts for uncertainty and correlations in the estimates (Babtie & Stumpf, 2017) and thus, provides better safeguards in case of misprediction. Figure 6.2 provides a comparison between parameter estimates obtained using either maximum likelihood estimation or Bayesian estimation for a model of body composition (in terms of the growth of protein and the growth of lipid) fitted to the two datasets on growing pigs. Bayesian estimation seems more informative as it allows for a more comprehensive exploration of the obtained solution. A further advantage of this methodology is its ability to readily handle data that are sparse or incomplete (Dunson, 2001). For precision feeding and management, this could be particularly relevant in scenarios where there is minor malfunctioning of the data collection devices, or where there are issues obtaining regular measurements from some individual animals.

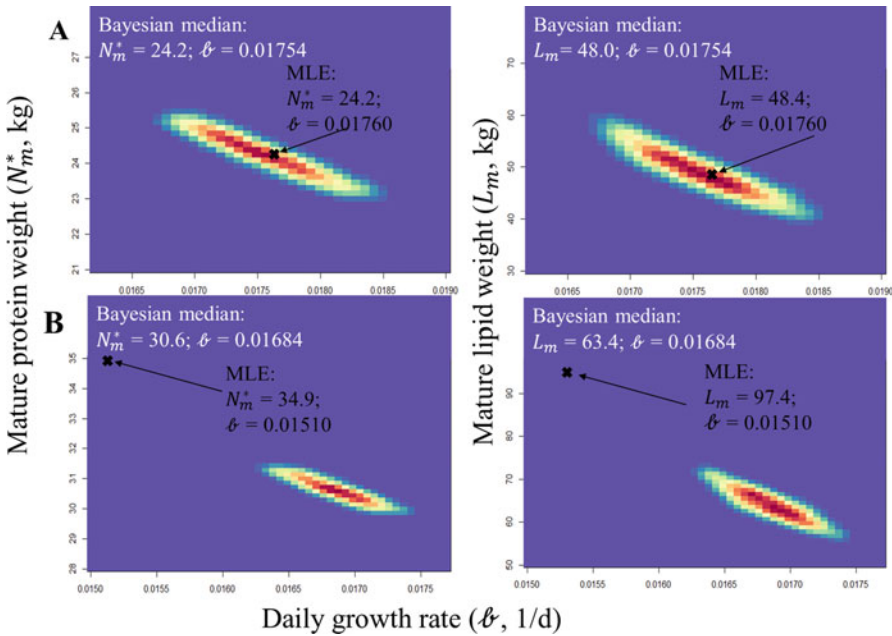


Fig. 6.2 A comparison of maximum likelihood estimation (MLE) and Bayesian estimation for learning unknown parameters of a model of body composition. Fitting was carried out separately for two individual pigs from two distinct pig populations: (a) the two parameter estimation methods converged to the approximately same solution; (b) the two parameter estimation methods converged to two different solutions. Results of Bayesian parameter estimation are given as two dimensional marginalised posterior distributions of sampled parameters. Results of maximum likelihood estimation are given as single-point estimates. *Abbreviations:* N_m^* mature protein weight (kg), L_m mature lipid weight, δ daily growth rate controlling how fast the size at maturity is reached

The main criticism of Bayesian estimation concerns specification of prior distributions, as this step could have a notable impact on parameter estimation. For example, misspecification of prior distributions could result in biased inferences (Robert, 2007). However, this concern could be readily remedied by specifying prior distributions that do not narrowly constrain the parameter space (Gelman et al., 2017; Gelman & Hill, 2006; Lemoine, 2019). In these cases, parameter estimation requires no expert knowledge and is predominately data-driven, although the lack of constraints could carry additional computational costs. It is also important to note that a further potential vulnerability of Bayesian and maximum likelihood estimations may occur when the distribution of data, expressed through the likelihood, is unknown or inaccurate (Filipe & Kyriazakis, 2019).

6.4.2.1 Markov Chain Monte Carlo

For most models, the posterior distribution $\pi(\theta|Y)$ is not usually available in its closed form and needs to be sampled from instead. This is commonly done by utilising the Markov Chain Monte Carlo (MCMC) methods, although other methods such as Variational Inference or Approximate Bayesian Computation are also becoming more prevalent (Gamerman & Lopes, 2006).

In brief, the MCMC methods aim to sample parameter values iteratively so that their distribution after a given amount of sampling follows the underlying posterior distribution (Robert, 2007). There is a large body of literature (Brooks et al., 2011) concerning the development of the most efficient sampling algorithms, but the two main common algorithms are: (1) the Metropolis-Hastings and its extensions (Hastings, 1970; Roberts & Rosenthal, 2001) and (2) the Hamiltonian Markov Chain and its variants, particularly the No-U-Turn Sampler (Girolami & Calderhead, 2011; Hoffman & Gelman, 2014). An illustration of how the Metropolis-Hastings algorithms perform parameter searches is given in Fig. 6.3, adopted from Speagle (2019). The basic idea of the Metropolis-Hastings algorithm is to start with a random initial starting point and then sample a new candidate point around a previous one. If this candidate point is more likely than the previous one (according to the distribution we want to sample from), then it is accepted. If it is less likely, then it is accepted with a certain probability or rejected otherwise. Consequently, the Metropolis-Hastings algorithm can be defined as (Gamerman & Lopes, 2006):

1. Initialise the iteration counter to $j = 1$ and set an arbitrary initial value for θ_0 to θ .
2. Propose a new value for θ , θ'_{j+1} by generating a random sample from a proposal distribution $q(\theta'_{j+1}|\theta_j)$.
3. Compute the acceptance probability of the proposed move:

$$T(\theta'_{j+1}|\theta_j) = \min\left(1, \frac{\pi(\theta'_{j+1})q(\theta_j|\theta'_{j+1})}{(\theta_j)q(\theta'_{j+1}|\theta_j)}\right).$$

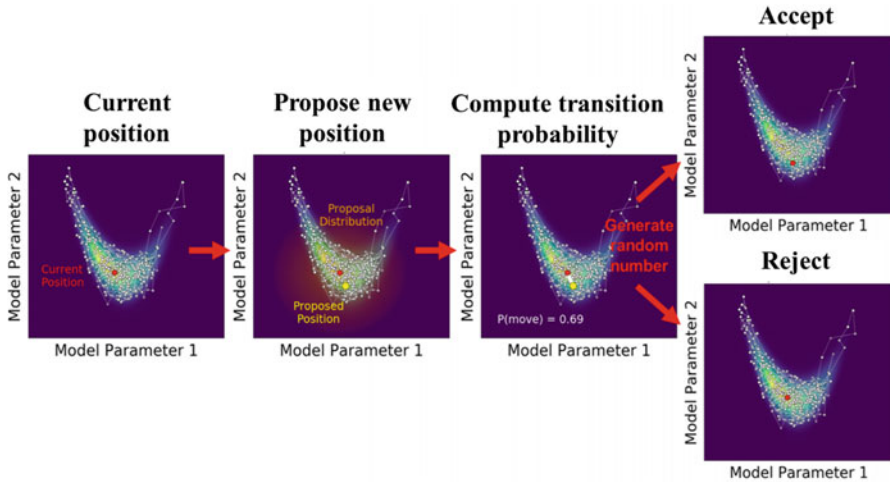


Fig. 6.3 Graphical illustration of the Metropolis-Hastings algorithm (adapted from Speagle (2019)) to approximate the posterior distribution in Bayesian parameter estimation

4. Generate a random number: u_{j+1} from $[0, 1]$.
5. If $u_{j+1} \leq T(\theta'_{j+1} | \theta_j)$, accept the proposed move and set $\theta_{j+1} = \theta'_{j+1}$. Otherwise reject the move and set $\theta_{j+1} = \theta_j$.
6. Change the iteration counter from j to $j+1$, return to 2 and repeat until convergence.

The Metropolis-Hastings algorithm has been ranked among the ten most influential algorithms for science and engineering developed in the twentieth century (Beichl & Sullivan, 2000). However, it is worth pointing out that the Metropolis-Hastings algorithm can be slow to converge (especially for complex, multimodal posterior distributions) and thus, may not be the most efficient algorithm in the context of ‘real-time’ estimation.

6.5 Model Evaluation

One of the primary objectives of forecasting in the context of precision feeding and management is to generate real-time predictions of animal performance (Pomar et al., 2019). However, before this can be achieved in practice, it is typically necessary to evaluate several candidate models to decide which one is the most appropriate. In this section, we describe how this evaluation procedure could be tackled. Note that there are inconsistencies concerning the use of forecasting terms across different research fields and studies. To avoid any ambiguity, the reader is referred to a comprehensive glossary of forecasting terms by Armstrong (2001).

In most cases, the process of forecasting begins with fitting a suitable model to data via a procedure to estimate the unknown parameters of the model (Sect. 6.4).

Once the best set of parameters is obtained, the goodness of fit of a model is further evaluated using statistical measures, such as the Akaike Information Criteria (AIC) (Akaike, 1974), or the coefficient of determination (R^2) (Nagelkerke, 1991), which quantify how well the observed data are replicated by the model and, in the case of the AIC, penalise for model complexity. The subsequent step involves assessment of errors from forecasts of the future yet unseen output values, which generates an insight into the overall generalisability and extrapolative ability of a model. In practice, this is usually carried out by evaluating the accuracy of forecasts generated using data that was withheld from fitting (validation data).

Different forecast evaluation criteria exist and they are comprehensively reviewed by De Gooijer and Hyndman (2006). In general, the commonly used criteria (Table 6.1) could be grouped into the following three main categories: (1) scale-

Table 6.1 Summary of the common forecast evaluation criteria categorised as: (1) scale-dependent criteria, obtained from the estimated error between the observed data and forecasts ($e_t = Y_t - \hat{Y}_t$); (2) scale-independent criteria based on the percentage error, obtained from the ratio of the estimated error to the observed data ($p_t = 100 \times \frac{Y_t - \hat{Y}_t}{Y_t}$); (3) scale-independent criteria based the relative error, obtained from the ratio of the estimated error to the error obtained from a naïve, standard approach, such as a simple moving average ($r_t = \frac{Y_t - \hat{Y}_t}{Y_t - Y_{naive}}$)

Criterion	Common abbreviation	Calculation
1. Scale-dependent		
Mean squared error	MSE	$\text{mean}(e_t^2)$
Root mean squared error	RMSE	$\sqrt{\text{mean}(e_t^2)}$
Mean absolute error	MAE	$\text{mean}(e_t)$
Median absolute error	MdAE	$\text{median}(e_t)$
2. Scale-independent based on the percentage error		
Mean absolute percentage error	MAPE	$\text{mean}(p_t)$
Median absolute percentage error	MdAPE	$\text{median}(p_t)$
Symmetric mean absolute percentage error	sMAPE	$\text{mean}\left(2 \times \frac{ e_t }{(Y_t + \hat{Y}_t)}\right)$
Symmetric median absolute percentage error	sMdAPE	$\text{median}\left(2 \times \frac{ e_t }{(Y_t + \hat{Y}_t)}\right)$
3. Scale-independent based on the relative error		
Mean relative absolute error	MRAE	$\text{mean}(r_t)$
Median relative absolute error	MdRAE	$\text{median}(r_t)$
Geometric mean relative absolute error	GMRAE	$\text{geo_mean}(r_t)$
Relative mean absolute error	RelMAE	$\frac{\text{mean}(e_t)}{\text{mean}(Y_t - Y_{naive})}$
Relative root mean squared error	RelRMSE	$\frac{\sqrt{\text{mean}(e_t)}}{\sqrt{\text{mean}(Y_t - Y_{naive})}}$
Log mean squared error ratio	LMR	$\log\left(\frac{\text{mean}(e_t)}{\text{mean}(Y_t - Y_{naive})}\right)$

Abbreviations: Y_t the data at time t , \hat{Y}_t the forecasted data from a model under consideration at time t , \hat{Y}_{naive} the forecasted data from a naïve approach standard approach at time t

dependent criteria (obtained from the estimated error between the observed data and forecast); (2) scale-independent criteria based on the percentage error (obtained from the ratio of the estimated error to the observed data); and (3) scale-independent criteria based on the relative error (obtained from the ratio of the estimated error to the error obtained from a naïve, standard approach, such as a simple moving average).

As highlighted by De Gooijer and Hyndman (2006), care should be taken when choosing the appropriate forecast evaluation criteria. For example, while scale-dependent measures could be useful when comparing different models in the context of the same dataset, these measures are not recommended when comparing different models across various datasets, especially when these datasets have different scales (Hyndman & Koehler, 2006). This could be relevant if comparisons are made across datasets, which consider different stages of growth or originate from animals of different breeds or species. In precision feeding and management of pigs, there is no standardised procedure on how forecast evaluation should be conducted, but a more uniform approach could improve interpretation of findings across different datasets (McNamara et al., 2016). For simplicity, it could be prudent if future studies utilise scale-independent criteria based on the percentage error as the basis for all forecast evaluations.

6.6 Current Forecasting Approaches

6.6.1 Double Exponential Smoothing

Double exponential smoothing (DES) (Brown, 1959), or the Holt's linear method (Holt, 1957) is a type of weighted moving average of past observations. While different representations of this model are available, one of the most common representations is in terms of variables representing latent (unobserved) states and the observed variables. In this state-space form (Hyndman et al., 2008), DES is an iterative process:

$$Y_t = l_{t-1} + b_{t-1} + \epsilon_t \quad (6.7)$$

$$l_t = l_{t-1} + b_{t-1} + \phi_1 \epsilon_t \quad (6.8)$$

$$b_t = b_{t-1} + \phi_2 \epsilon_t, \quad (6.9)$$

where l_t and b_t are the level (i.e. the moving average values) and change (i.e. either increasing or decreasing value) of the trend (Hyndman & Athanasopoulos, 2018) at time t and are typically initialised as $l_0 = Y_{t_0}$, $b_0 = Y_{t_1} - Y_{t_0}$ (Wheelwright et al., 1998). Parameters ϕ_1 , ϕ_2 ($\phi_1, \phi_2 \in (0, 1)$) are known as the smoothing parameters, which control the weight given to each observation and should be estimated from data. The recent observations are given more weight than the older observations and these weights decrease in an exponential manner with time lag (Young, 2012). The

error term, ϵ_t is the one-step within sample forecast error at t and is usually assumed to be normally distributed, i.e.

$$\epsilon_t = Y_t - \hat{Y}_{t|t-1} \sim N(0, \sigma^2) \quad (6.10)$$

with zero mean and constant variance, σ^2 , with σ^2 estimated from data.

For precision feeding in pigs, Hauschild et al. (2012) utilised the DES model to generate one or seven d ahead forecasts of the individual BW_t and DFI_t of 40 growing gilts fed ad-libitum (Pomar et al., 2007). Forecasts of BW_t were reported to be more accurate (population-level average percentage error of 1.85) than forecasts of DFI_t (population-level average percentage error of 12.5). In another study, Quiniou et al. (2017) evaluated performance of one day ahead individual-level BW_t forecasts generated using the DES model in the context of data from 94 restrictively-fed growing barrows and gilts from post-weaning until slaughter weight, but a different metric was used. The chosen metric was the root mean square error (RMSE), which does not enable a straightforward comparison with the outcomes reported by Hauschild et al. (2012). However, Brossard et al. (2017) utilised the DES model to generate one or seven days ahead forecasts of individual BW_t and CFI_t of 119 nucleus pig fed ad-libitum from post-weaning until slaughter weight, and evaluated these forecasts in terms of the RMSE. Overall, the RMSE reported by both Quiniou et al. (2017) and Brossard et al. (2017) were similar, with the lowest RMSE values reported to be around 1.20 kg.

6.6.2 The Local Linear Trend Model

In the local linear trend model, both the level and the change of the trend follow random walks. This model has the form (Durbin & Koopman, 2012):

$$Y_t = \theta_{1,t} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma^2) \quad (6.11)$$

$$\theta_{1,t} = \theta_{1,t-1} + \theta_{2,t-1} + w_{1,t}, \quad w_{1,t} \sim N(0, \sigma_{w_1}^2) \quad (6.12)$$

$$\theta_{2,t} = \theta_{2,t-1} + w_{2,t}, \quad w_{2,t} \sim N(0, \sigma_{w_2}^2) \quad (6.13)$$

where the initial states θ_{1,t_0} and θ_{2,t_0} are typically estimated from the following bivariate Normal (N_2) distribution:

$$\begin{pmatrix} \theta_{1,t_0} \\ \theta_{2,t_0} \end{pmatrix} \sim N_2 \left(\begin{pmatrix} m_{0,1} \\ m_{0,2} \end{pmatrix}, \begin{pmatrix} \sigma_{\epsilon_1}^2 & 0 \\ 0 & \sigma_{\epsilon_2}^2 \end{pmatrix} \right) \quad (6.14)$$

Here, there are two mutually independent sources of random errors: ϵ_t and $w_{i,t}$, and as such, the local linear trend model could be classed as the Multiple Source of Error (MSOE) state-space model (Leeds, 2000). Note that while the DES model

represented by equations in Sect. 6.6.1. contains only one source of error, it is possible to express it in the MSOE form to further illustrate its close relationship with the local linear trend model (Leeds, 2000).

For precision feeding purposes, the local linear trend model was developed by Hauschild et al. (2020) to forecast the individual-level DFI_t and DG_t of 130 growing and finishing pigs, which were exposed to considerable stressors including changes in the environmental conditions and health challenges. These authors evaluated performance of one d ahead forecasts generated from this model using normalised errors. Overall, these normalised errors ranged from approximately 1% to 10% and increased with the length of the forecast horizon. It was also recommended that the local linear trend model should be used instead of the DES model for data originating from animals that exhibit considerable deviations from their typical growth and feeding patterns, although the two models were not explicitly compared.

6.6.3 Dynamic Linear Regression and Recursive (Rolling) Window Linear Regression

Just like in the classical regression, univariate dynamic linear regression (DLR) attempts to model the causal relationship between an output and at least one input. However, the parameters are no longer static and vary over time by typically assuming that they follow random walks. The simplest DLR model, describing the relationship between two variables Y and X has the form (Petrís et al., 2009):

$$Y_t = \theta_{1,t} + \theta_{2,t}X_t + \epsilon_t, \quad \epsilon_t \sim (0, \sigma^2) \quad (6.15)$$

where the time-varying parameters $\theta_{1,t}$ and $\theta_{2,t}$ typically follow independent Normal (N_2) distributions:

$$\begin{pmatrix} \theta_{1,t} \\ \theta_{2,t} \end{pmatrix} \sim N_2 \left(\begin{pmatrix} \theta_{1,t-1} \\ \theta_{2,t-1} \end{pmatrix}, \begin{pmatrix} \sigma_{w1}^2 & 0 \\ 0 & \sigma_{w2}^2 \end{pmatrix} \right). \quad (6.16)$$

When $\sigma_{w1}^2 = \sigma_{w2}^2 = 0$ for any t , the DLR turns into the classic, static regression:

$$Y_t = \theta_1 + \theta_2 X_t + \epsilon_t, \quad \epsilon \sim N(0, \sigma^2) \quad (6.17)$$

Note that an alternative formulation of the DLR, without an explicit specification of random walks for parameter dynamics is also possible. Such models are also better known as the recursive linear regression or rolling window regression models and involve fitting to data in an iterative manner. These data are weighted using either the rectangular or exponential window to shape the “memory” of the estimator and these two weighting procedures are visualised in Fig. 6.4, adapted from Young, 2012. The rectangular weighting window is also the implicit basis on which these

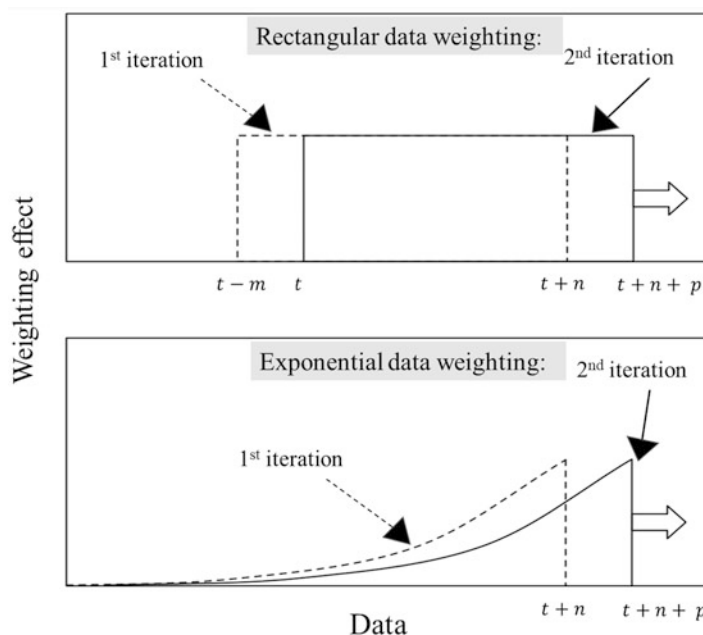


Fig. 6.4 Rectangular data weighting and exponential data weighting (adapted from Young (2012)) that form an implicit basis of the recursive (rolling) window linear regression models; $\{t-m, t, t+n, t+n+p\}$ denote different time points, which could correspond to e.g. daily feed intake or body weight measurements

linear regression models have been applied in the context of precision feeding and management.

Aerts et al. (2003) first developed recursive linear regression models with a rectangular window size, ranging from 3 to 7 datapoints, for forecasting BW_t of 2400 group-housed broiler chickens (fed either restrictively or ad-libitum) with daily forecast horizons ranging from one to seven d. These authors compared forecast accuracy of this model to the three static deterministic models (i.e. no time-varying parameters), which included the classical linear regression relating CFI_t to BW_t , and two nonlinear models: (i) the Gompertz model relating time t to BW_t and (ii) the diminishing returns model relating CFI_t to BW_t (Parks, 1982). Similar accuracy, in terms of the mean relative prediction error, was reported for the one d ahead forecasts from all models under consideration. However, the two nonlinear models outperformed the recursive linear model for longer forecast horizons. This recursive linear model was also recently evaluated by Peña Fernández et al. (2019) in the context of forecasting individual-level BW_t for 240 growing-finishing boars and gilts fed restrictively. Forecast accuracy, in terms of the mean relative prediction error of this model, was reported to range from 1.00% to 3.30% in forecast horizons from one to seven d.

6.6.4 Possible Limitations of the Current Forecasting Approaches

The mathematical properties of the models described in Sects. 6.6.1, 6.6.2, and 6.6.3 could have important consequences on their overall generalisability for precision feeding and management purposes.

A first possible limitation relates to the assumption of linearity, as the three aforementioned models are all linear with respect to the explanatory variables (Hyndman & Athanasopoulos, 2018). While most responses can be approximated by a linear relationship within a short-term window, the confidence in linear forecasts are likely to decrease, as the forecast horizon increases from e.g. one d to three, or seven d and so on. This is illustrated in Figure in the context of the artificial data generated by a nonlinear process. Here, the DES model was first fitted to a training dataset to parameterise the model, followed by forecasts of future values that were compared to the values in a validation dataset. Clearly, the forecast error increased systematically with increasing forecast horizon. A further concern, particularly relevant for the recursive linear regression with a rectangular window, relates to the choice of the length of this window, as this tuning parameter is often unknown in advance, but is required to run the model. Testing different window lengths could be computationally expensive, particularly if this procedure needs to be repeated for every new dataset obtained within and across breeds and species (Fig. 6.5).

The second limitation relates to the biological interpretability of the model parameters, which is particularly challenging in the context of the DES model (Sect. 6.6.1) and the local linear trend model (Sect. 6.6.2). The key parameters governing these models correspond to either weighting factors of the previous observations or to different components of stochastic processes assumed to underpin data and thus, lack biological interpretation. As highlighted by Wellock et al. (2004), models that contain biologically meaningful parameters are usually preferred, since they could offer additional insights regarding (e.g. feed utilisation or degree of maturity). Consequently, this additional information could be utilised for other purposes, such as breeding (Knol et al., 2016).

The third limitation concerns how these aforementioned models respond to shocks, or perturbations, which in the context of precision feeding and management could be caused by temporary physiological and/or environmental disturbances (Kyriazakis, 1997; Kyriazakis & Tolkamp, 2011). It is expected that models that use weighted averages of past observations or errors (Sect. 6.6.1) and models with time-varying parameters that follow random walks (Sects. 6.6.2 and 6.6.3) will cope with short-lived perturbations differently than deterministic, static models. For example, consider the DLR model (Eq. (6.15)) and its static counterpart (Eq. (6.17)). The former describes a stochastic trend, while the latter describes a deterministic trend (Hyndman & Athanasopoulos, 2018). By model construction, in the first case, short-lived disturbances are likely to cause a more lasting change to the

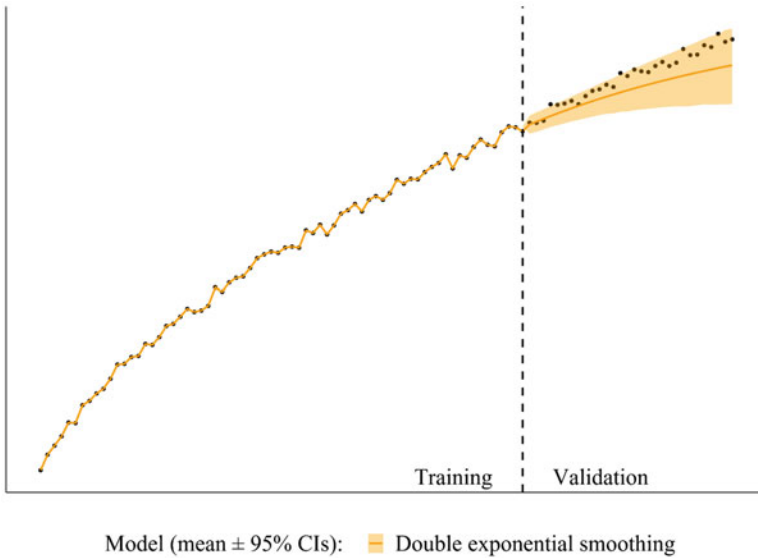


Fig. 6.5 Fitting the double exponential smoothing model to an early (training) data to estimate the unknown model parameters, followed by forecasting of a future (validation) data. Data were generated from an artificial nonlinear process. The vertical black line precedes the start of forecast horizon and is the last measurement in the training data, from which forecasts of future data are generated. Please note that the model predicts values which are below the validation data, but are within the 95% CIs (denoted by the shaded region). *Abbreviations:* 95% CIs 95% confidence intervals

forecasted trajectory than in the second case, as illustrated in Fig. 6.6 in the context of artificial data generated by a linear process. Consequently, it is important to consider carefully whether a stochastic or a deterministic description of a trend is likely to be more useful. This decision could be informed by the actual data; for example, deterministic trends are likely to generate more robust forecasts in the context of data from animals, whose performance is subject to infrequent and/or comparatively minor perturbations.

6.7 Alternative Approaches

Given the limitations described in Sect. 6.6.4, we present three potential alternative approaches that could at least partly address some of the aforementioned concerns. Development and evaluation of these alternative approaches could be an area for the future research.

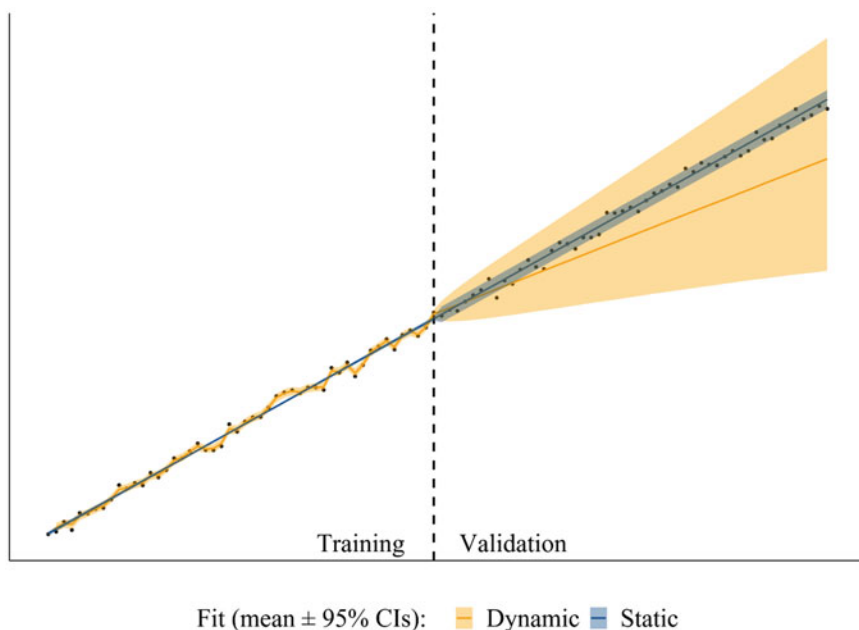


Fig. 6.6 Fitting the dynamic linear regression (orange line) and the static linear regression (blue line) to an early (training) data to estimate the unknown model parameters, followed by forecasting of a future (validation) data. Data were generated from an artificial linear process. The vertical black line precedes the start of forecast horizon and is the last measurement in the training data, from which forecasts of future data are generated; shaded regions denote the 95% CIs. *Abbreviations:* 95% CIs, 95% confidence intervals

6.7.1 Other Exponential Smoothing Models

The DES model is one of the several models from the innovations state space (Hyndman et al., 2002) that could be grouped together to form the monotonic exponential smoothing family of models. These monotonic exponential smoothing models consist of an equation that describes the observed data, Y_t and equations that describe how latent states (the level, l_t and the change, b_t) evolve over time. These models could be readily compared using their forecast function, $\hat{Y}_{t+H|t}$, where H denotes the forecast horizon. Models that are directly related to the DES model are summarised in Table 6.2. While most of these models are linear (Hyndman & Athanasopoulos, 2018), there are several nonlinear extensions that could potentially be better suited to the task of forecasting performance in the context of precision feeding and management. Yet, the lack of biological interpretability of the parameters in these models and the way these models would respond to e.g. short-term perturbations are still likely to limit their overall applicability and generalisability for some of the pig production systems under consideration.

Table 6.2 Summary of the main models from the monotonic exponential smoothing family presented in terms of their state-space representation (that is, in terms of variables representing latent (unobserved) states and the observed variables) and the consequent forecast equation

Model name	Trend	Forecast equation	Level and change equations	
			Additive error	Multiplicative error
Simple exponential smoothing	Linear (horizontal)	$\hat{Y}_{t+H t} = l_t$	$l_t = l_{t-1} + \phi_1 \epsilon_t$ $b_t = 0$	$l_t = l_{t-1}(1 + \phi_1 \epsilon_t)$ $b_t = 0$
Double exponential smoothing/the Holt's linear method	Linear	$\hat{Y}_{t+H t} = l_t + H b_t$	$l_t = l_{t-1} + b_{t-1} + \phi_1 \epsilon_t$ $b_t = b_{t-1} + \phi_2 \epsilon_t$	$l_t = (l_{t-1} + b_{t-1})(1 + \phi_1 \epsilon_t)$ $b_t = b_{t-1} + \phi_2(l_{t-1} + b_{t-1})\epsilon_t$
Damped Holt's linear trend method	Linear	$\hat{Y}_{t+H t} = l_t + \phi_H b_t$	$l_t = l_{t-1} + \phi_3 b_{t-1} - 1 + \phi_1 \epsilon_t$ $b_t = \phi_3 b_{t-1} + \phi_2 \epsilon_t$	$l_t = (l_{t-1} + \phi_3 b_{t-1})(1 + \phi_1 \epsilon_t)$ $b_t = \phi_3 b_{t-1} + \phi_2(l_{t-1} + \phi_3 b_{t-1})\epsilon_t$
Multiplicative trend	Nonlinear	$\hat{Y}_{t+H t} = l_t b_t^H$	$l_t = l_{t-1} b_{t-1} + \phi_1 \epsilon_t$ $b_t = b_{t-1} + \phi_2 \epsilon_t / l_{t-1}$	$l_t = l_{t-1} b_{t-1}(1 + \phi_1 \epsilon_t)$ $b_t = b_{t-1}(1 + \phi_2 \epsilon_t)$
Damped multiplicative trend	Nonlinear	$\hat{Y}_{t+H t} = l_t b_t^{\phi_H}$	$l_t = l_{t-1} b_{t-1}^{\phi_3} + \phi_1 \epsilon_t$ $b_t = b_{t-1}^{\phi_3} + \phi_2 \epsilon_t / l_{t-1}$	$l_t = l_{t-1} b_{t-1}^{\phi_3}(1 + \phi_1 \epsilon_t)$ $b_t = b_{t-1}^{\phi_3}(1 + \phi_2 \epsilon_t)$

Abbreviations: $\hat{Y}_{t+H|t}$ forecasts from a given forecast horizon H from the last time point t , l_t level of the trend at time t , b_t change of the trend at time t , ϵ_t one-step within sample forecast error at time t , $\epsilon_t = Y_t - \hat{Y}_{t|t-1} \sim N(0, \sigma^2)$; ϕ_1, \dots, ϕ_n are the number (n) of smoothing parameters

6.7.2 Machine Learning: Neural Networks

In most real-life scenarios, the exact knowledge of the data generating process could be questioned (Clark, 2004). Instead, it could be possible to rely on a purely data-driven approach to identify suitable relationships between variables, but this largely neglects previous empirical evidence obtained in the context of quantifying these relationships. An example of a purely data-driven approach are the neural networks models. First conceived as a simple mathematical representation of the human brain (Fukushima, 1975; Ivakhnenko & Lapa, 1967), neural networks have generated plenty of research attention in the wider forecasting literature (Huber & Stuckenschmidt, 2020; Kourentzes et al., 2014). They have also been applied in animal production science in the context of: (1) growth control of group-housed broiler chickens and pigs (Ahmadi et al., 2007; Demmers et al., 2018; Johansen et al., 2019; Roush et al., 2006); (2) prediction of feeding behaviour in pigs (Alameer et al., 2020; Cross et al., 2018); and (3) prediction of body composition of pigs (Fernandes et al., 2020).

In broad terms, all neural networks with the exception of the single-layer perceptron (Auer et al., 2008) are structures, where known data inputs are introduced at the input nodes and passed through at least one hidden layer storing some intermediary values of the data, which are then eventually translated into outputs (Zhang et al., 1998). A simple example of the neural network model is given in Fig. 6.7, where values of the three input variables X_1 , X_2 , X_3 pass through the sequence of hidden layers, where weighted sums are computed and then used as inputs in the activation function, which introduces nonlinearity in the model. In this setting, for each node in a

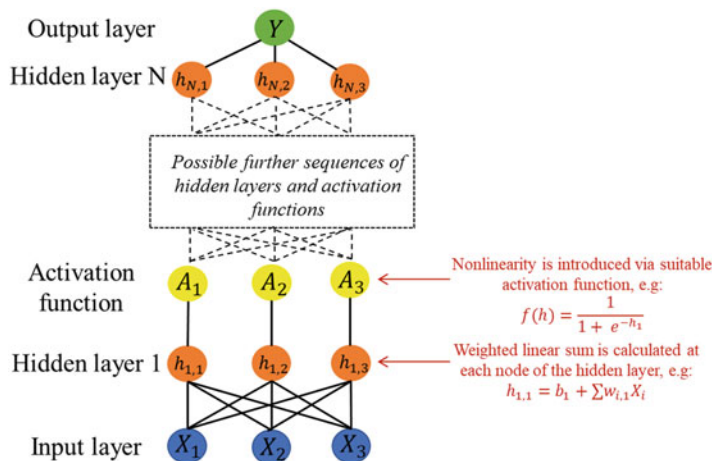


Fig. 6.7 Graphical illustration of a multi-layer, feed-forward neural network with three inputs (X_1, X_2, X_3) that are converted to a single output (Y) through a combination of weighted linear sums at each node of the hidden layer (h) fed to a sigmoidal activation function (A) that introduce nonlinearity in the model

Table 6.3 Most frequently utilised activation functions ($f(h)$) that introduce non-linearity in each of the hidden layer (h) of a neural network model

Name	Equation
Logistic	$f(h) = \frac{1}{1+e^{-h}}$
Hyperbolic	$f(h) = \frac{e^h - e^{-h}}{e^h + e^{-h}}$
Rectified linear function	$f(h) = \max(0, h)$
Exponential linear activator	$f(h) = \begin{cases} h, & h \geq 0 \\ e^h - 1, & h < 0 \end{cases}$
Linear	$f(h) = h$
Softmax	$f(h) = \frac{e^{h_1}}{\sum_c e^{h_c}} \cdots \frac{e^{h_c}}{\sum_c e^{h_c}}$

hidden layer, there are several parameters, known as weights and biases (Zhang et al., 1998), that need to be estimated from the data. An activation function is typically either a sigmoidal or a hyperbolic function, but other functions are also increasingly used (Huber & Stuckenschmidt, 2020) and are listed in Table 6.3. For forecasting, the two most common types of neural networks include: (i) feed-forward neural networks, where connections from inputs to outputs via all layers are only in one direction; examples of these types of neural networks are the multi-layer perceptrons (Gardner & Dorling, 1998) and radial basis functions (Mulgrew, 1996); and (ii) recurrent neural networks, where directed cyclic graphs could be found; examples of these types of neural networks are the long-short term memory (Hochreiter & Schmidhuber, 1997), or gated recurrent unit (Dey & Salem, 2017) models.

While neural networks could offer a flexible way of modelling nonlinear data, these methods have also been reported to have several notable drawbacks, which could make them impractical for precision feeding and management purposes, namely: (a) they are structurally complex (Makridakis et al., 2018) and thus, have limited biological interpretation and explanatory power; (b) they typically require substantially larger amounts of training data for parameterisation than other available methods (Forman & Cohen, 2004) and (c) they give little insight into uncertainty (Dunson, 2018).

6.7.3 Deterministic Trend Models

For growing animals kept in relatively stable conditions that do not pose any considerable long-term growth challenges, deterministic trend models allow a flexible way to describe a variety of different relationships between inputs and outputs. Furthermore, several deterministic models could provide a more mechanistic description of the underlying biological processes and thus, further increase parameter interpretability. A summary of the main common families of deterministic models utilised in biological and ecological modelling is given in Table 6.4. While these some of these models, such as the monomolecular model relating body weight gain to feed consumption (Kuhi et al., 2004; Schulin-Zeuthen et al., 2008) are commonly utilised in the context of animal growth modelling, these models have not yet been fully evaluated in the context of forecasting individual-level

Table 6.4 Summary of the main families of deterministic models utilised in biological and ecological modelling

Name	General form	Specific examples	Advantages	Disadvantages
Polynomials	$\sum_{i=0}^n \theta_i X_t^i$, where i is an integer	Linear: $\theta_1 + \theta_2 X_t$ Quadratic: $\theta_1 + \theta_2 X_t + \theta_3 X_t^2$	Easy to understand	Hard to justify biologically Higher order polynomials are likely to overfit Unable to capture processes with clear bounds
Piecewise polynomials	$\sum_{i=0}^n \theta_i X_t^i, X_t < s_1$ $\sum_{j=0}^o \theta_j X_t^j, s_1 < X_t < s_2$ \vdots $\sum_{k=0}^p \theta_k X_t^k, s_{i-1} < X_t < s_i$ $\dots \exp(\dots X_t^{\dots})$	Hockey stick: $\begin{cases} \theta_1 X_t, X_t < s_1 \\ \theta_1 s_1, X_t > s_1 \end{cases}$	Additional flexibility over polynomials since they can approximate bounded processes	Identification of switch points can be difficult, complicating parameter estimation Often inconsistent with the notion that many biological processes should be continuous
Exponential based		Monomolecular: $\theta_1 (1 - e^{-\theta_2 X_t})$ Gompertz: $\theta_1 \exp(-\theta_2 \exp(-\theta_3 X_t))$	Very flexible – Able to approximate a variety of different data patterns Large body of literature covering applications to animal growth modelling	Estimation of upper bounds could be challenging
Power law based	$\frac{(\dots)^{\theta_1}}{(\dots)^{\theta_2}}$, where θ_1, θ_2 are non-integer	Allometry: $\theta_1 X_t^{\theta_2}$ Hassell: $\theta_1 X_t / (\theta_2 + X_t)^{\theta_3}$	Very flexible – Able to approximate a variety of different data patterns Phenomenologically common in the context of many biological processes	Estimation of exponents could be challenging and not numerically stable
Rational	$\frac{\sum_{i=0}^n \theta_i X_t^i}{\sum_{j=0}^m \theta_j X_t^j}$	Michaelis-Menten: $\theta_1 X_t / \theta_2 + X_t$ Holling type III: $\theta_1 X_t^2 / \theta_2^2 + X_t^2$	Very flexible – Able to approximate a variety of different data patterns	Estimation of upper bounds could be challenging Complex structure of derivatives

Specific examples include functions that are commonly utilised in the context of modelling biological and ecological data. For more examples, see Bolker (2008)

Abbreviations: X_t , inputs at time t ; s_n , switch points at time t ; $\theta_1, \dots, \theta_n$, are the number (n) of parameters in a given model

performance of growing pigs. An initial evaluation of different deterministic models utilised to forecast individual growth responses in pigs have been recently carried out by (Misiura et al., 2020): the allometric model (power-law based) has been reported to generate the most reliable forecasts across individual pigs, especially when forecasts have been made over ‘longer -term’ forecast horizons exceeding 1–2 days ahead.

6.8 Concluding Remarks

In this chapter, recent methodological developments concerning forecasting growth or intake responses in the context of precision feeding and management of pigs were reviewed. Overall, the development of a more rigorous framework for forecasting and estimation of traits across individual animals is likely to benefit from: (1) selection of parameter estimation methods (needed to yield or improve values of the unknown model parameters during data fitting) that give sufficient information on uncertainty and correlations to provide increased robustness of estimates and forecasts; (2) a more standardised assessment of outcomes across studies to allow for a better evidence synthesis; and (3) reconsideration of certain modelling assumptions whose validity may hold only for a specific range of conditions.

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Smart Pig Nutrition in the Digital Era

7

Ludovic Brossard, Jaap van Milgen, Jean-Yves Dourmad,
and Charlotte Gaillard

Abstract

Pig farming systems face an increasingly diversified challenge to consider simultaneously the economic, environmental, and social pillars of sustainability. For animal nutrition, this requires the development of smart feeding strategies able to integrate these different dimensions in a dynamic way and to be adapted as much as possible to each individual animal. These developments can be supported by digital technologies including data collection and processing, decision making and automation of applications. Classical traits such as feed intake and growth benefit from new technologies that can be measured more frequently. New sensors can be indicative for other traits related to body composition, physiological status, activity, feed efficiency, or rearing environment. A challenge for data collection is to obtain information on a large number of animals and with sufficient frequency, quality, and precision and use it cost-effectively. Another challenge is to analyse the ever-increasing volume of data and use it in decision-making. Nutritional models for pigs and sows, classically mechanistic, have to evolve to integrate real-time data. With the development of data-driven modelling methods (e.g., machine-learning or deep-learning), a synergy between mechanistic models and data-driven approaches is required in smart pig nutrition. Moreover, the practical application of smart pig nutrition must consider the evolution in pig farming systems towards increased diversity in terms of size, space allowance, and outdoor access, and return on investment. Finally, the transition of pig nutrition in the digital era must consider the social acceptance of an increasing role of digital technologies in animal production systems.

L. Brossard (✉) · J. van Milgen · J.-Y. Dourmad · C. Gaillard
PEGASE, INRAE, Institut Agro, Saint-Gilles, France
e-mail: ludovic.brossard@inrae.fr

Keywords

Activity · Artificial intelligence · Automaton · Concept-driven modelling · Data collection · Data-driven modelling · Data processing · Decision support system · Fattening pigs · Feed efficiency · Feed intake · Gestating sow · Health status · Lactating sow · Mineral · Nutrition · Nutritional requirements · Performance · Physiological status · Pig farming system · Precision feeding · Rearing environment · Sensors

7.1 Introduction

In pig farming systems, feeding represents around two-thirds of the total production cost, with a main contribution during the fattening period. Improving feed efficiency is thus of prime importance for the economic sustainability of pig farms (Gaillard et al., 2020a). Over the past decades, this has involved the selection of fast-growing animals with a lower feed conversion ratio and higher lean content of carcass at slaughter, and feeding strategies have mainly been adapted to allow the maximization of performance (Knap & Rauw, 2008). At the same time, reproductive performance of sows has been drastically improved, both in terms of prolificacy and number of piglets weaned per year (Dourmad, 2019). This implies to carefully consider the short- and long-term effects of sow nutrition on birth weight, survival, and growth of piglets on milk production and on fertility and longevity of sows (Dourmad, 2019). Besides the maximization of performance, new objectives arose more recently with an increasing societal concern for the environment, animal welfare, and reduced use of medication, making the optimization of feed formulation and feeding strategy a much more complex challenge.

The potential environmental impact has been a major issue for pig production since the nineties. To reduce nitrogen, phosphorus, and trace elements in pig manure, and in gaseous and odour emissions, intensive research towards a better agreement between nutrient supply and requirement has been undertaken mainly on growing pigs (Dourmad & Jondreville, 2007) and more recently on gestating and lactating sows. In practical feed formulation, this resulted in the inclusion of maximal constraints on total P and crude protein content of diets, and the increased inclusion of crystalline amino acids and phytase in diets. At the same time, feeding programmes have evolved to account better for the changes in the nutritional needs of pigs according to growing stage or reproductive status. Nutrition is thus a major lever to mitigate the environmental impacts of pig production, through the reduction of energy use and emissions associated with the production of feed ingredients (Garcia-Launay et al., 2018). In this perspective, life cycle assessment is also developing for multi-objective feed formulation to reduce the environmental impacts arising from livestock feeding (Mackenzie et al., 2008; Garcia-Launay et al., 2018).

In many countries, animal welfare is nowadays becoming one of the main concerns of citizens and consumers concerning animal farming (Boogaard et al.,

2011), which has consequences for pig nutrition. Indeed, feeding strategy and feed composition are levers affecting animal welfare, but feeding also needs to be adapted to the changes induced by the different welfare regulations or commercial specifications, especially in terms of housing (e.g., group-housing of gestating sows), farming practices (e.g., cessation of castration of male pigs), or feeding practices (e.g., providing a fibre-rich diet to gestating sows). For instance, in a field study, Cariolet et al. (1997) showed that appropriate management of the body condition of sows through adequate individual feeding is very important not only for performance, but also for welfare. However, the body condition and body fatness may be different when maximizing sow welfare compared to maximizing reproductive performance. Restricted feeding of gestating sows and fattening pigs, which may induce competition and aggressiveness among pigs, has also been questioned and it was shown that high-fibre diets are of major interest to induce satiety without excessive energy intake (Meunier-Salaün & Bolhuis, 2015).

Another important evolution in recent years is the increasing demand of society and consumers for the reduction of medication in livestock production (Lusk et al., 2006). This has been mainly driven by the development of microbial resistance to antibiotics, which is a major human and animal health issue. This is a main issue for piglets at weaning, which are at high risk of digestive disorders and frequently receive medication. In sows, the risk of health problems is highest around farrowing through lactation, with possible adverse effects on the sow herself and on the litter. The nutrition of sows, especially at the end of pregnancy, around parturition and during lactation, and of piglets during lactation and at weaning, appears a major tool to maintain health while reducing medication through individualized supplies. This may involve the feeding of sick individuals (i.e., detected with symptoms) during short periods (e.g., the period of farrowing or weaning) with a specific diet (e.g., supplemented with an additive or natural compound) or using “targeted” medication.

Pig production systems, as well as other animal production systems, are also questioned by society at a more global level in terms of sustainability. For instance, the question of competition between feed for animals and food for humans is increasingly raised, with practical implications in terms of feed ingredients. Some production chains or countries put specific constraints on the origin of feed ingredients, such as being non-Genetically Modified Organisms (GMO), locally produced, without additives or medication, and without deforestation. Housing conditions are also questioned by consumers and citizens with demands for more space, more diversified environment, and outdoor access. All these aspects may affect, directly or indirectly, nutrient requirements, feed formulation and feeding equipment. The development of organic farming with specific constraints on housing, feed ingredients and additives, and the very high cost of protein sources also raises specific questions for feed formulation. More generally, a compromise has to be found between animal productivity and welfare.

Pig farming systems thus have to face an increasingly variety of challenges to consider simultaneously the economic, environmental, and social pillars of sustainability. For animal nutrition, this requires to develop smart feeding strategies able to integrate these different dimensions in a dynamic way and consider as closely as

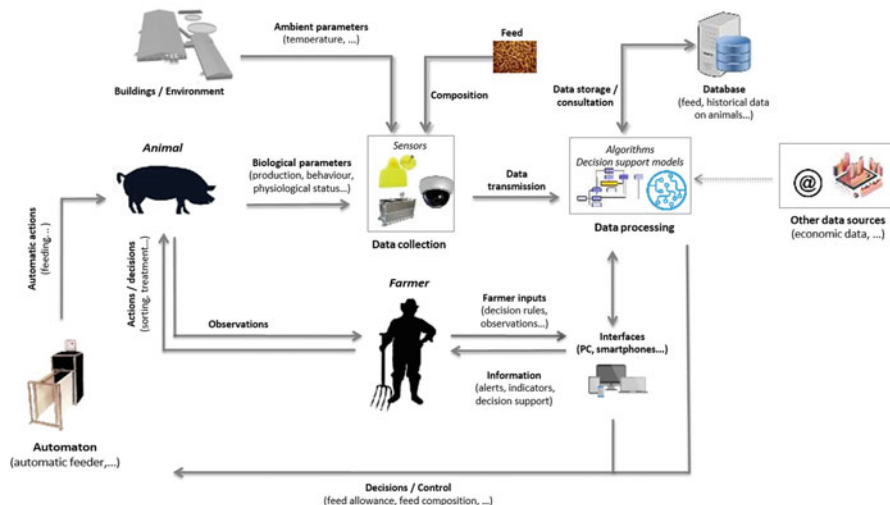


Fig. 7.1 General principles of the precision farming approach with focus on precision nutrition in pigs: description of the steps from data collection to automatic action, including data processing and decision making. (Adapted from Allain et al., 2014 and Gaillard et al., 2020a)

possible the specific requirements of each individual animal. In this perspective, precision livestock farming, defined by Wathes et al. (2008) as “the management of livestock production using the principles and technology of process engineering”, offers renewed opportunities with application in nutrition and feeding. A general description of the precision farming approach is illustrated in Fig. 7.1. The overarching approach involves data collection and operational functions running “online” in real-time, often using models and algorithms that have been adjusted “offline” using historical data. The digital era with the development of big data, artificial intelligence (AI) and mathematical modelling offers a new paradigm for livestock production (Piñeiro et al., 2019). Much more information is available on individual animals and their environment, and at a much higher frequency. Smart pig nutrition can benefit from the high throughput availability of data to address the challenges pig production is facing. The number of pigs in a farm has increased drastically over the past decades, but using sensors and robots allows considering pigs as individuals (again). In the following sections, first we will remind briefly the principles of precision farming approaches adapted to pig nutrition; then we will review the information available on (i) sensors and data collection on animals, environment, and feed (ii) the different types of models available for decision support in precision feeding with some examples of results of these approaches.

7.2 Principles of Precision Farming Adapted to Pig Nutrition

In this section, we briefly present the principles of precision farming adapted to pig nutrition, following the indications given in Fig. 7.1.

7.2.1 Data Collection

The data may be collected by humans (e.g., sow prolificacy, insemination, farrowing, measurement of backfat thickness) or by sensors or robots (e.g., occurrence of oestrus, feed intake, live weight, physical activity, room temperature, humidity). These data provide information about the status of a biological trait (e.g., body weight measured on a scale) or of its proxy (e.g., a surface measurement from an image as a proxy for body weight, backfat thickness as a proxy for total body lipid).

7.2.2 Data Processing

The data collection provides a large volume of data on a daily basis. In most cases, these data have to be processed before being used and/or stored in a database. This includes cleaning, validation, and management of missing values and outliers and abnormal values, which requires defining thresholds. Sometimes specific algorithms (i.e., succession of data processing and analysis steps) that have been previously developed offline have to be applied on the collected raw data to estimate criteria with a biological significance, for example, to convert measurements of a proxy into an estimate of the trait of interest (e.g., use of data collected from an accelerometer, or a camera to estimate the energy requirement for physical activity). This can be done by averaging or smoothing the data (Friggens & Robert, 2016), which will then serve as inputs to models to predict animal nutrient requirements.

7.2.3 Algorithm Development

In the case of precision feeding, the decisions relative to nutrition or to other management purposes are generally based on mathematical nutrition models designed to operate in real-time (Hauschild et al., 2012 for growing pigs; Gauthier et al., 2019 for lactating sows; Gaillard et al., 2019 for gestating sows). The AI with the application of machine learning from historical data in combination with real-time data can also be used for the prediction of a risk (e.g., risk of occurrence of health problem), an event (e.g., the ovulation), or performance (e.g., upcoming feed intake and milk production of a lactating sow) that can be used for the determination of nutrient supplies.

7.2.4 Implementation Through Automation

The data available in the database are used to help the farmer to take decisions (e.g., providing medication to a pen of pigs when a suspicion of health problem has been detected) or to provide a robot (e.g., a smart feeder) with the required information for the distribution of a tailored ration to a given pen or pig. In the case of precision

feeding, the implementation of the decision about the ration to be fed may be performed by the feed distribution system (i.e., the ration to be fed is first prepared in a centralized location and then sent to a feeder, as proposed by some commercial systems) or by the feeder itself (i.e., the ration is prepared locally at the feeder, just before being distributed, for instance as with Automatic and Intelligent Precision Feeder developed by Pomar et al. (2011) for growing pigs, or some commercial automatic feeders for sows). The preparation of the ration is often done by mixing two diets, one with high content of nutrient and the other with low content, ensuring that their mix will cover the range of requirements. The first approach is generally applied for pen feeding and the second one for individual precision feeding. In both cases, the feeding system (i.e., the system that identifies the animal, operates feed distribution, and records the feed intake and/or feed disappearance) is used to collect information about the feeding behaviour and feeding performance.

7.3 Data Collection on Animals, Their Environment, and Their Feed Use: The (R)evolution of Sensors

As seen in the previous section, the first step in the application of precision feeding and nutrition is based on knowledge about animals (e.g., status, performance) and their environment to provide data to nutritional models estimating the nutrient requirements of pigs and to adjust the nutrient supply accordingly. Due to size of pig farms, this implies the collection of data more or less automatically using sensors. In the last decade, much progress has been made in the development of sensor technologies and sensors have become affordable for application in many domains, including in animal feeding. Concerning smart nutrition in pigs, relevant traits to be measured relate to performance (e.g., growth, feed and water intake, reproduction), body composition, digestive efficiency, metabolic status, health and sanitary status (e.g., inflammation, temperature), behaviour (e.g., social ranking, physical activity, feeding, drinking), environment (e.g., humidity-temperature-index, light intensity, noise), and, of course, the nutritional quality of the feeds. This implies that different types of sensors are required to record the trait or proxy with different frequencies. Knight (2020) indicated that sensors in livestock production can be divided into three categories: (i) sensors attached to or inserted in the animal, (ii) sensors near the animal that can also record environmental conditions, and (iii) “sensors” collected on the animals (e.g., hair, urine, faeces) and analysed. Due to some particularities of pig production (e.g., number of animals per farm, duration of productive life, size of animals, difficulty to put wearable objects on pigs or to obtain other biological samples), most of past literature focused on data collection from sensors near the animals. In the following section, recent developments and challenges for the use of sensors in smart pig nutrition will be presented, with Table 7.1 summarizing the measured trait and the associated sensor(s).

7.3.1 Measuring Performance

Knowledge of growth and feed intake is essential to adapt nutrition as they determine to a large extent the nutritional requirements of the pigs. Consequently, measuring performance has always been a key point in pig production. Although measuring body weight is not new per se (i.e., it can be done “manually”), the development in sensors allows to simplify and automatize the measurement. For example, body weight is an inherently variable trait, due to eating, urinating, and defaecating patterns. The use of sensors allows to measure body weight very frequently, thereby allowing to assess the “value of the data”. Measuring individual feed intake in group-housed pigs is virtually impossible, but is nowadays feasible using feeding stations and individual animal identification (Cornou & Kristensen, 2013; Brown-Brandl et al., 2019).

7.3.1.1 Individual Identification

Automatic identification of an animal is the first step in monitoring production efficiency. Pigs can be identified automatically and in a reliable way by radiofrequency identification (RFID; Cornou & Kristensen, 2013). Combining RFID with farm equipment allows to obtain real-time data that can be sent to the farmer or to an automated decision support system for further action. In pigs, ear-tags with an RFID chip are used and the pig can be detected when it enters a system equipped with a reception antenna (e.g., at the feeder). Brown-Brandl et al. (2019) reviewed different RFID systems for livestock. Although the technique is simple, it presents some drawbacks such as the cost of the chip, sensitivity to interference (e.g., from the pig itself, other pigs, and the environment), loss of tags, stress during tagging (for both the pig and the farmer), and the removal before slaughter to recycle the RFID ear tag (Benjamin & Yik, 2019). The development of machine-vision, based on cameras and data treatment using AI methods, allows to track animals and, in some cases, identify animals without marking them (Benjamin & Yik, 2019; Wurtz et al., 2019; Alameer et al., 2020). These systems are based on a top-view camera for shape recognition with an accuracy (given as the number of correctly identified images as percentage of the whole dataset) up to 92% or, more recently, with a front-view camera for facial recognition (e.g., Hansen et al., 2018; Marsot et al., 2020) with an accuracy up to 96%. Commercial systems using facial recognition are tested in farms in China to manage individual pig performance and health.

7.3.1.2 Body Weight

Body weight is used as input in nutritional models to predict growth and the resulting nutrient requirements. Manual measurement of body weight is stressful for animals and time consuming for farmers. Few farmers actually weigh their animals, but they may have a good eye to estimate body weight visually. Different technologies exist that automatically record body weight based on foreleg weighing (Ramaekers et al., 1995), image analysis (Tscharke & Banhazi, 2013), walk-through systems with machine-vision (Wang et al., 2008) or weighing scales, and photogrammetry to determine the pig three-dimensional shape (Wu et al., 2004). Recent developments

relate mainly to machine-vision and “real” 3D images (e.g., Fernandes et al., 2019). Available commercial systems are based mainly on weighing scales, sometimes associated to other (feeding) systems or machine-vision, with or without individual identification. However, these systems are mainly found in research environments and selection farms of breeding companies. Their use in production farms is limited due to cost or maintenance and, more importantly, the interest of measuring body weight alone.

7.3.1.3 Electronic Feeding Stations

As for body weight, information on feed intake is essential for precision feeding. Feeding stations can be used to provide information on daily feed intake and feeding behaviour, but they can also be used to distribute an individualized and daily adjusted ration to a growing pig or a sow. These systems have been used for a long time in genetic selection farms for individual growing pigs. In commercial farms, these devices are mainly used for group-housed sows during gestation with the main objective to control individual feed allowance and composition. Devices for lactating sows are also being used more and more to favour high feed intake while avoiding feed spillage. Investment costs probably explain why electronic feeding stations are not widespread yet for growing pigs. However, developments in precision feeding devices could help to increase their use, in combination with systems to estimate body weight (Fig. 7.2).



Fig. 7.2 Example of electronic feeding station used for growing pigs (a), gestating sows (b), and lactating sows (c) at the UE3P unit (Pig Physiology and Phenotyping Experimental Facility, <https://doi.org/10.15454/1.5573932732039927E12>, INRAE Saint-Gilles, France)

7.3.1.4 Water Consumption

Water consumption can be used as an indicator of the health status of animals and can serve as a tool to prevent or detect diseases (Cornou and Kristensen, 2013). It is usually measured for the whole room in the barn. Connected water flow meters equipped with individual animal recognition systems have been developed to record individual water consumption, and the time and quantities of each visit. These devices are now also available as commercial versions. Machine-vision systems to estimate water consumption have been used in experimental settings (Kashiha et al., 2013). Water can be used to deliver antibiotics at the individual or group level, increasing the interest of connected water dispensers to check and measure distribution of these substances.

7.3.1.5 Estimation of Body Composition

Body composition and changes in body composition during different production stages are of great interest to individualize the diet, especially in gestating sows. Body composition intends to inform on the partition of protein (lean), lipid (fat), and mineral (bone) within the animal and the changes that occur during the different phases of production (i.e., growth, gestation, lactation).

Backfat thickness is a simple indicator of body lipid mass, which is often measured with ultrasound. However, the technique is performed manually and should also be carried out as much as possible by the same technician. It is time consuming, and the equipment and skilled technicians are costly (Halachmi et al., 2019). This technique is therefore not suitable for automatic and frequent measurements. Automatic digital recording of body composition could save labour and deliver unbiased quantification (Spoliansky et al., 2016). Swantek et al. (1999) reported that bioelectrical impedance may be used to accurately assess changes in body composition of finishing pigs weighing 50 to 130 kg, but not outside this range. They used live body weight, length, and reactance and resistance measurements in regression equations and estimated the fat-free lean mass with high accuracy. Some commercial devices based on this technique have been proposed but their use remains limited. Imaging techniques that have been used to study body composition with great precision include dual-energy X-ray absorptiometry, computed tomography, and magnetic resonance imaging (Scholz et al., 2015). Animals need to be anaesthetized and, because of the cost of the equipment and operation, and the low frequency of use in terms of measured animals per day, the use of these techniques is limited to experimental farms or for selection purposes and they are not suitable for high throughput measurements in commercial farms. The use of camera imaging to evaluate body condition score/conformation has been demonstrated in cows (e.g., with 3D camera, Le Cozler et al., 2019) and could have potential for growing pigs and sows as well (Doeschl-Wilson et al. 2004, 2005). Automatic and frequent measurement of body composition remains a technical challenge despite its relevance for smart pig nutrition.

7.3.2 Activity

Physical activity affects the energy expenditure of pigs. The cost of standing is much higher in pigs than in other livestock species (Noblet et al., 1993) and standing and walking activity in pigs is several times more energy-consuming than lying (van Milgen et al., 2008). Activity can be recorded automatically using photo-cells, force sensors for sows housed in crates (Oliviero et al., 2008), accelerometers for sows in loose-housing or crates (Cornou & Lundbye-Christensen, 2012), and through machine-vision. The application of activity measurements includes precision feeding (e.g., to cover difference in energy requirements, Marcon et al., 2017) and farrowing detection.

Quantification of behaviour and activity using accelerometer is realized mainly using AI. Video analysis using machine-vision is currently receiving considerable attention because it is non-invasive, it does not require manipulating the animal (e.g., to install the equipment), and it does not affect the behaviour of the animal or its pen mates (e.g., nuisance or novelty behaviour towards the equipment). The majority of studies attempting to use machine-vision technology to automatically detect behaviour in pigs has been conducted on groups of growing pigs, with a few studies targeting single-housed sows or suckling piglets (see Wurtz et al., 2019 for a review on this topic). Conventional 2D cameras are the most commonly used cameras (Alameer et al., 2020), even if recent studies use more and more 3D cameras (Matthews et al., 2016). Images obtained through these cameras are analysed using machine-vision, which relies on AI algorithms. These techniques allow to obtain information on segmentation of individuals within the group (with possibility to count animals), to track activity (e.g., to calculate an activity index of individuals or of the group activity), estimate feed or water use, to detect postures or score gaits, up to more advanced detection of specific types of behaviours (e.g., tail biting, postures linked to thermal comfort; Wurtz et al., 2019).

7.3.3 Pig Physiological/Health Status

Smart pig nutrition can also be used in relation to the physiological and health status of pigs. However, this requires to assess this “status” of the animal which is, by definition, multi-dimensional. These different dimensions call for different smart management actions, including nutrition such as the modification of feed allowance and/or composition (e.g., amino acids, minerals, micronutrients, fibre, additives). It goes without saying that there is no single sensor that can assess the health status of a pig and the combined information from different sensors will be required to automatically detect and characterize deviations of what could be considered as “normal”. Changes in some of the previously described measures (e.g., activity, body weight, feeding and drinking behaviour in conjunction with the quantity eaten or drunk) are probably the best indicators of disease (Cornou & Kristensen, 2013). Also, biological samples can be very “revealing” about the physiological status of the animal. However, blood sampling and taking biopsies are invasive procedures.

They are being used for research purposes but they may not be the “smartest solutions” for smart pig nutrition in a production setting. Biological samples can also be obtained using less- or non-invasive techniques through the sampling of faeces, urine, saliva, hair, and breath. If the origin of the sample needs individual identification, containment of the animal may be required.

7.3.3.1 Pig Body Temperature

The occurrence of fever or heat stress can be detected by measuring the temperature of pigs. Body temperature can be recorded automatically using ear-based sensors (Benjamin & Yik, 2019), whereas skin temperature can be measured using infrared imaging (Sellier et al., 2014). However, especially the latter is related to ambient temperature so it should be taken always in the same area of the pig, at the same distance, and preferentially combined to another way of measuring temperature (i.e. rectal measurement). Image analysis using the pig’s thermoregulatory behaviour has also been used for automatic environmental temperature control (Wouters et al., 1990).

7.3.3.2 Sound Analysers

Sound can be recorded via microphones and the electrical signals can be processed and categorized in real-time by computer algorithms (Benjamin & Yik, 2019). Coughing sounds have been used for early detection of respiratory diseases. Soundtalks R (Leuven, Belgium), a commercially available sound detection package, recognizes sounds in a localized area, enabling treatment for respiratory disease and ventilation changes at the pen (Silva et al., 2008). Different types of sounds (e.g., frequencies) can also be used to quantify pain and stress (Halachmi et al., 2019).

7.3.3.3 Metabolic Biosensors

Biomarkers or detection of specific metabolites may be relevant as their variation could help to understand animal responses and, consequently, to adjust their ration. Neethirajan (2017) reviewed existing biosensors and associated technologies used to detect the level of antibodies in the body as they should stay within a certain range in absence of health disorders. This author also reviewed the microfluids used to detect analytes of interest, or the different screening methods to detect the antibiotics in food. These new technologies are generally quick, accurate, and reliable if they are done in a controlled environment. Indeed, biosensors are still affected by environmental factors which limit their use.

7.3.3.4 Detection of Infectious Agents

Several methods are being developed to detect pathogens. Neethirajan (2017) reported technologies as Imaging Ellipsometry to detect viruses linked to reproductive or respiratory diseases, a label-free bio-sensing method (SERS) to detect bacteria, and polymerase chain reaction (PCR), a highly specific and sensitive molecular technique, to detect microbes from an animal sample (serum, lung tissue) or drinking water. On-site detection can be done using PCR thanks to portable and

affordable devices. Developments are still needed to increase rapidity of diagnosis and use of less invasive samples.

7.3.3.5 Saliva

Saliva is a fluid, which can easily be sampled via a mouth guard with an integrated device analysing uric acid and hydrogen peroxide and interpreting these measurements to monitor health (Kim et al., 2015). These biomarkers are highly selective and indicate the level of oxidative stress of the animals (Bandodkar & Wang, 2014; Rubio et al., 2019). Identifying animals with high levels of these biomarkers could be used to identify the origin of stress and, if relevant, adapt their ration, for example, by adding antioxidants in the diet. Monitoring lactate variation in saliva via carbon nanotubes and graphene is another practice, which is being used for the detection of health conditions in animals (Mannoor et al., 2012; Matzeu et al., 2015).

7.3.3.6 Urine

A wide range of metabolites are excreted via the urine that can potentially serve as biomarkers for the physiological status of the animal. Using non-targeted metabolomics, van der Peet-Schwering et al. (2020) observed that the dietary protein content was associated with differences in a large number of metabolites in the urine, some of which were metabolites of amino acids. Although the time and cost required to collect and analyse the samples are currently prohibitive for use in real-time smart pig nutrition, it may prove to be a useful tool to rank animals in terms of efficiency of protein use at an early stage and feed them accordingly.

7.3.4 Digestibility and Feed Efficiency Assessment Through Faecal Analysis

Although sensors can be used to detect deviations from the “normal situation” (for a given pig or for a group of pigs), they can also be used to detect differences among animals “in a normal situation”. Digestibility measurements typically require that animals are housed individually in digestibility cages for several days to measure feed intake and totally collect faeces (Labussière et al., 2019). New methods such as near-infrared reflectance spectroscopy (NIRS) have been developed to estimate digestibility rapidly and on a large number of animals and possibly individually (if faeces can be collected on an individual basis). The NIRS methodology is especially suited to account for differences in digestibility among animals (Bastianelli et al., 2015). In contrast to the total collection methods, estimating digestibility using NIRS only requires a representative faecal sample of the animal (Nirea et al., 2018; Labussière et al., 2019). Nirea et al. (2018) reported that NIRS predicted adequately the chemical composition of faeces and the digestibility of nutrients for organic matter, crude protein, and growth energy. Labussière et al. (2019) reported that the NIRS method provided good estimates of digestibility when pigs were heavier than 60 kg and when fed a diet with a high fibre content.

Therefore, the NIRS method can be considered as accurate and cost-effective to assess differences in digestibility among pigs. This information could be used to refine prediction of nutrient utilization and requirements for individuals using nutritional models, especially for sows where samples could be easier to collect.

Several studies observed a relationship between the faecal microbiome and feed efficiency (Tan et al., 2017; McCormack et al., 2019a). Methods to phenotype the microbiota have been developed to use this information on farms. For example, the transplantation of faecal microbiota from highly feed-efficient pigs to pregnant sows resulted in an improvement of the feed efficiency of the offspring (McCormack et al., 2019b). However, the transplantation of faecal microbiota had a negative effect on growth on the offspring, which limits the application in commercial farms. Niu et al. (2015) reported that some bacteria were correlated with apparent digestibility of crude fibre and that the abundance and diversity of the gut microbiota varied with the age of the pig. Therefore, targeted manipulation of bacterial populations (e.g., by changing the fibre composition in the diet) could be used to improve digestibility and feed efficiency (Le Sciellour et al., 2018).

7.3.5 Characterizing the Environment of Pigs

In the previous sections, we described how to characterize the animal using information obtained through different types of sensors. Beyond these individual characteristics, environmental factors (e.g., feed quality, temperature, humidity, and air quality) can influence animal health, nutrient requirements, and productivity. Environmental sensors can easily be installed in the barns to continuously monitor characteristics that are described in this section.

7.3.5.1 Sensors to Measure/Evaluate Feed Quality (NIRS)

Feed ingredients are inherently variable in nutrient composition. Although this variation is reduced considerably in the manufacturing of complete diets, variation in nutritional composition remains (e.g., related to the frequency and quality of analyses at the feed mill, the mixing of ingredients). It goes without saying that successful application of smart nutrition relies on knowledge of what the pig actually eats, and NIRS appears to be a fast and accurate method to estimate the nutritional value of the diet and use this information in real time (Noel, et al. 2020; Bach Knudsen et al., 2023).

7.3.5.2 Temperature and Humidity Sensors

A continuous control of the environment, especially the temperature and humidity, is needed to reduce the negative effects of thermal stress when temperature is above or below the thermo-neutral zone of the animal (which varies with age, sex, and physiological stage). Thermal stress is not an issue limited to tropical regions because it can also occur in temperate regions during warm Summer months (Renaudeau et al. 2012). Thermal stress induces changes in metabolic heat production to maintain the animal body temperature in a physiologically safe range. Consequently, it

affects energy intake and/or maintenance requirements (Renaudeau et al. 2011). Whether an animal experiences thermal stress does not only depend on ambient temperature but is also linked to the relative humidity. Indeed, animals may tolerate high temperatures under dry conditions, but this may induce heat stress under humid conditions. This has resulted in the development of climatic indexes like the temperature-humidity index (THI, Thom, 1959) to define the level of heat stress in farm animals (Berman et al., 2016), including sows (Wegner et al., 2014, 2016). In practice, temperature and humidity can be easily measured continuously and automatically in barns through simple and affordable sensors, informing the farmers about the conditions that may result in thermal stress. It gives the opportunity to adapt the feeding strategy (e.g., energy or amino acid content, hours of distribution) to compensate the potential decrease of intake due to thermal stress and maintain animal productivity (Mayorga et al., 2019).

7.3.5.3 Air Analysers

Air quality can be measured via an electronic nose, a device able to discriminate between different odours. This can be used in barns to identify and quantify the volatile organic compounds produced by pathogens, host–pathogen interactions, and biochemical pathways (Guffanti et al., 2018). This non-invasive automated technology matches with the concept of precision farming supporting farmers with early warning systems for the identification of production, health, and welfare problems on farms (Halachmi et al., 2019). The concentration level of noxious gases such as ammonia (NH_3) and carbon dioxide (CO_2) can affect animal health and productivity in several ways (Choi et al., 2011). For example, Massabie et al. (1997) reported that high levels of NH_3 and CO_2 could decrease appetite and weight gain in growing-finishing pigs. Therefore, air quality should be controlled continuously to optimize the operation of the ventilation system and assure the health and productivity of the pigs.

7.3.6 Challenges in Data Collection for Smart Pig Nutrition

The main criteria for using a technique to measure the status of a pig are: a) the accuracy of estimation, b) the financial costs, and c) the possibilities for exploitation in field conditions. The minimal information for smart pig nutrition includes frequent information on growth and feed intake and, if possible, at the individual level. The rapid evolution of techniques (e.g., machine-vision, feeders) suggests that these data could become available and affordable for pig farms in the near future (Piñeiro et al., 2019). They are already available for “high-value animals” such as sows or nucleus stock. For growing pigs and piglets, their large number and short lifespan put constraints on the devices and the management of data: how to obtain information on a large number of animals and with sufficient frequency, quality, and precision and use it in a cost-effective way? The “classical” information on growth and feed intake (and thus feed efficiency) are without doubt the most promising traits to be considered in smart pig nutrition because of the cost of feed comprises the largest

part of the production cost. Information on body composition and traits related to the health status are also important, but they need further development to scale up in commercial farms.

Sensors are increasingly used jointly with AI methods. This parallel evolution allows to collect and analyse a large volume of data. The application of AI methods is important to rapidly and automatically analyse information that would otherwise require a “trained eye” (e.g., machine-vision). However, even with a trained eye, it is not possible to keep track of everything that happens in a barn 24 h a day, seven days a week. It is indeed impossible for anyone to analyse all the data originating from sensors, implying that some data processing and analysis will be required before the resulting information could be potentially useful to a human being. It is therefore important that consideration is given as to who should make a decision based on the information originating from the sensors (i.e., the computer, the farmer, or even the pig?). Developments in this area need to consider that there will be differences in expectations and skills between farmers with respect to smart pig nutrition. Consequently, there is no “one-size-fits-all” as certain farmers may want to have more information and decide themselves what action to take, whereas others will rely more on the system to act. Systems for data collection must be adapted regarding the “farming style”, also ensuring that the minimal information is available to allow application of smart nutrition.

7.4 Evolution of Nutritional Models

As described in Sect. 7.2 and Fig. 7.1, after data on pigs or sows and their environment have been collected, models are applied using these data to determine nutrient requirements and then adapt feed to these requirements. This is an essential step to help decision and smart nutrition application. Models used in smart pig nutrition have been mainly mechanistic (i.e., they describe biological mechanisms and their dynamics using mathematical equations). They have been used for decision support tools (e.g., InraPorc, van Milgen et al., 2008). These models help to define quantitatively the functioning of a biological system based on causal relationships and they can be used to generate predictions and recommendations in practice (Ellis et al., 2020). However, they have limitations such as obtaining sufficient inputs on-farm. Methods coming from AI are more and more used in precision farming. These are data-driven methods as they predict desired outputs of a system using available data without accounting for the biological relationships between inputs and outputs. These methods include machine-learning that learn automatically from data. Deep-learning methods use several layers of data treatment and transformation, for instance through artificial neural networks, to learn from data. With the development of these data-driven modelling methods, a synergy between mechanistic models and data-driven approaches could be beneficial for the development of smart pig nutrition (Ellis et al., 2020), using data streams to apply mechanistic models in real-time and hybridization of both approaches to parametrize mechanistic models by data-driven systems.

7.4.1 Fattening Pigs

There has been a longstanding history of the development and use of nutritional models describing growth in pigs. The first (semi-) mechanistic models (i.e., based on mechanisms description but also empirical and statistical relationships) were developed by Whittemore and Fawcett in the mid-seventies (1974) and they have evolved into more mechanistic models (e.g., Halas et al., 2004) and software tools such as InraPorc (van Milgen et al., 2008). These models rely on historical information of (populations of) pigs to characterize the dynamics of nutrient intake, use, and partitioning. This information is then used to estimate the requirements for different nutrients. Although the concepts of these models can be used as decision support tools in smart pig nutrition, the use of data is very different. Rather than using data to characterize the animal, decision support systems in smart pig nutrition need to predict traits such as the expected feed intake and growth in real-time so that a feed can be given according to the expected nutrient requirement (Fig. 7.3).

Hauschild et al. (2012) developed a model to estimate the amino acid requirements of individual growing-finishing pigs in real-time. The empirical part of the model uses information such as feed intake and body weight recorded during the previous days to estimate the expected feed intake and weight gain for the current day using a double exponential smoothing forecasting time-series method. To do so, the model requires at least seven consecutive feed intake measurements and two body weight measurements to predict the expected daily feed intake and body weight. Based on these predictions, the mechanistic part of the model uses factorial equations to predict the amino acid requirements (expressed on a standardized ileal digestible (SID) basis per kg of feed). They showed that daily feed intake and body weight trajectories of an animal could be predicted, respectively, 1 day or 7 days in advance, with an average mean absolute error of 12.5% and 1.9%, respectively. The authors indicated that the forecasting of feed intake did not perform as well as for body weight because it was calibrated to estimate a smoothed consumption

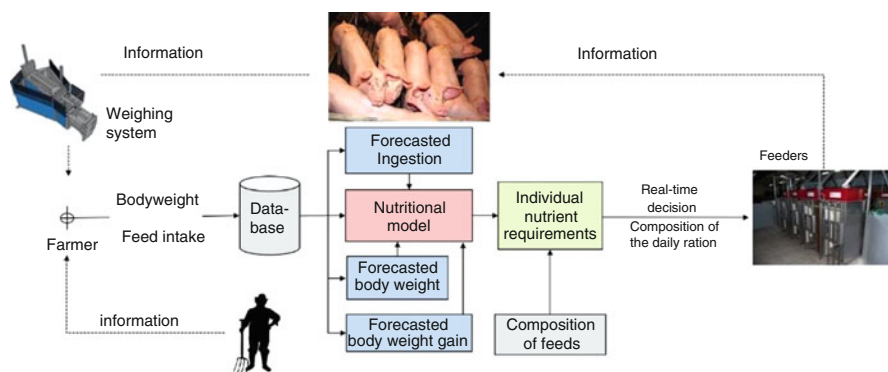


Fig. 7.3 Schematic representation of a decision support system, including a nutritional model, for the precision feeding of fattening pigs

trajectory without accounting for daily variations. Brossard et al. (2017b) used the same method to predict daily cumulative feed intake 1 day in advance using the real data from 8 to 20 previous consecutive days with residual mean square error of prediction of 0.5 kg/d. They applied the multivariate adaptive regression splines (MARS) method to predict daily or weekly body weight with at least 7 and up to 20 consecutive measurements with a residual mean square error of prediction of 1.1 kg/d. Other approaches are also being developed. Peña Fernández et al. (2019) used dynamic linear regression models, with feed supply daily as input, for the real-time prediction of weight and feed efficiency of individual fattening pigs. They predicted the individual pig weight 1 day ahead or 7 days ahead with average mean relative prediction errors of $1.0 \pm 0.4\%$ and $3.3 \pm 1.3\%$, respectively. The difference in criteria used to estimate the fitting capacity makes the comparison of methods rather difficult. However, it shows the variety of methods available. The mechanistic component of the Hauschild model was used in two animal trials (Zhang et al., 2012, Cloutier et al., 2015). In Zhang et al. (2012), the model accurately predicted the SID Lys requirement of pigs of 25–55 kg body weight but underestimated the requirements of heavier animals. Cloutier et al. (2015) updated the method but observed a slight underestimation of requirements for pigs of 25–55 kg body weight and an adequate estimation for heavier pigs. This was explained by differences in quality of estimation of maintenance requirements, efficiency of Lys retention and the proportion of protein in weight gain. Three trials evaluated the overall approach of estimating the effect of a conventional feeding system versus a precision feeding system in growing-finishing pig operations on performance, nutrient utilization, body composition, and environmental costs (Andretta et al., 2014; Pomar et al., 2014; Andretta et al., 2016). Pomar et al. (2014) found that a daily phase-feeding strategy (mixing two feeds) reduced nitrogen (N) intake by 7.3%, phosphorus (P) intake by 4.4%, N excretion by 12.6%, P excretion by 6.6%, and feed cost by 1% compared to those of a 3-phase feeding strategy. Andretta et al. (2014) found that a multiphase individual feeding strategy reduced the SID amino acid intake by 27%, P excretion by 27%, and N excretion by 20% compared to those of a 3-phase feeding strategy. Andretta et al. (2016) found that an individual feeding strategy reduced SID Lys intake by 26%, N excretion by 30%, and feeding cost by 10% compared to those of a group-feeding strategy. These three trials show that using precision feeding techniques to feed growing-finishing pig diets that are tailored daily is an effective approach to reduce nutrient excretion without compromising performance. These results also confirm that combining precision feeding with real-time modelling of requirements can improve feed efficiency (i.e., decrease feed cost and environmental load). The evolution of predictive models to include real-time data and help in decision making for smart feeding pig nutrition is at its beginning. Models can still be improved to better estimate amino acid requirements, by better representing the individual proportion of protein in body weight gain and the factors controlling the efficiency of Lys utilisation in individual pigs (Remus et al., 2020a, c), or estimate in real-time body protein mass and daily protein content of the gain (Remus et al., 2020b). Sensors could help to characterize animals beyond growth and feed intake, with criteria related to feed efficiency, health status, and answer to

environmental conditions like heat stress. However, there is still a long way to go to integrate all these aspects in models and use this in nutritional strategies. For example, after detecting an health or environmental issue, which nutritional strategy should be applied?. This is a challenge due to the lack of understanding (and of nutritional models) for these stages where interactions between nutrition, management, environment, growth, and feed intake are very complex. Current technology can feed pig groups based on their weight. Some private companies have been started to experimentally test automatic feeders with a decision support tool allowing precision feeding application. However this type of feeders is not yet commercially available.

7.4.2 Sows in Gestation and Lactation

Mechanistic models such as InraPorc (Dourmad et al., 2008) have been developed to simulate the daily energy and nutrient partitioning in reproductive sows. These models represent the sow as the sum of different compartments: body protein, body lipids, body minerals, and the uterus. Equations describing the nutrient utilization are used to predict daily energy, amino acid, and mineral flows from feed to storage in body reserves or in foetuses, output in milk, loss as heat, and excretion in faeces and urine. They allow to predict, on a daily basis, the energy, amino acids, calcium, and phosphorus requirements according to production objectives, or to simulate the changes in body condition of sows according to their performance and nutrient intake.

These models have been recently renewed to be used for precision feeding for lactating (Gauthier et al., 2019) and gestating sows (Gaillard et al., 2019). These nutritional models, which aggregate the equations required for the calculation of nutrient requirements, are connected dynamically to the flow of information provided by different sensors or by the farmer and to feeding “robots” that handle and implement the decisions taken to optimize the nutrient supplies to each individual sow, each day (Fig. 7.4).

This approach allows to account for the large variability of nutrient requirements between sows in commercial farms, resulting from the variability in performance, appetite, and body condition, and the changes occurring over time due to the reproductive function (i.e., development of foetuses or production of milk) (Gauthier et al. 2019; Gaillard et al. 2020a). For gestating sows, energy and nutrient requirements are calculated according to the age, body weight (maintenance requirement), body condition at mating (requirement for body reserves), and expected litter size (requirement for conceptus) of the sow. For lactating sows, the energy and nutrient requirements are calculated according to body weight (maintenance), litter size and growth (used to predict milk production), and appetite of the sow. Figure 7.5 illustrates the requirement for SID lysine in lactating and gestating sows from commercial farms equipped with smart feeders. During lactation, the SID lysine requirement is highly variable mainly due to differences in litter growth rate (as an indicator of milk production) and sow appetite (Fig. 7.5, left panel, Gauthier et al.,

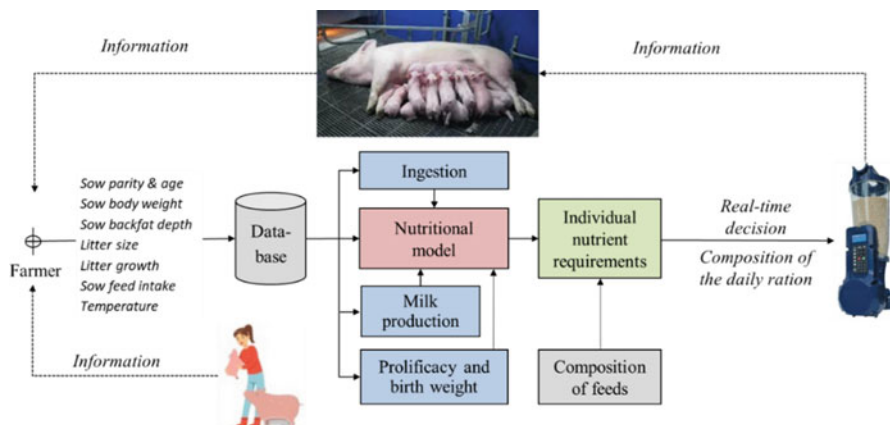


Fig. 7.4 Schematic representation of a decision support system, including a nutritional model, for the precision feeding of sows. (Adapted from Gauthier et al., 2019 and Gaillard et al., 2019)

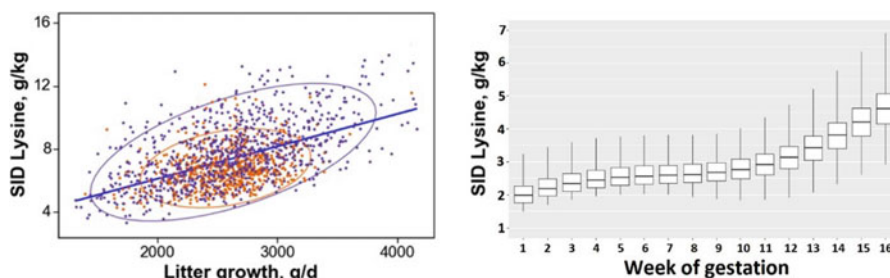


Fig. 7.5 Variability of standardized ileal digestible (SID) lysine requirement per kg feed, according to litter growth rate during lactation (left panel, from Gauthier et al., 2019) and according to stage of gestation (right panel, from Gaillard et al., 2019) of sows

2019). During gestation, the SID lysine requirement is also highly variable and varies with gestation stage, sow parity, and prolificacy (Fig. 7.5, right panel, Gaillard et al., 2019).

The challenge in this approach is to get the information required for the calculations of requirements. Body weight, physical activity of sows, and ambient temperature are required to calculate the maintenance requirement. Body weight can be measured at different times, for instance when moving the sows from the gestation to the farrowing pen. Backfat thickness, which is used in combination with body weight to determine the status of body reserves, can be measured at the same time. The use of automatic weighing scales in the feeding stall allows to obtain much more frequent data, and accelerometers can also be used to evaluate the physical activity of sows (Ringgenberg et al., 2010). However, this type of “mechanical” equipment may be difficult to maintain in the long term, and video and image analyses may be a more promising, robust alternative for the real-time evaluation of

body weight (Cang et al., 2019), activity (Ahrendt et al., 2011; Labrecque et al., 2020), and perhaps body condition.

To operate in real time, precision feeding systems for lactating sows require to accurately predict expected feed intake and milk production on a daily and individual basis to determine the optimal nutrient content of the ration. For feed intake, the prediction can be performed from intake data measured during the previous days, and in combination with prototypes of trajectory curves determined offline using deep-learning approaches on the bases of historical data, as proposed by Gauthier et al. (2021). In the same way, milk production, which cannot be measured, can be estimated from historical data (from the same farm or from similar farms) of litter growth rate and the number of suckling piglets using classical statistical approaches (Ngo et al., 2012) or deep-learning methods. In addition to the information relative to the body weight and activity of the sow, which affect the maintenance requirement, precision feeding systems for gestating sows require to estimate the total litter weight at birth, which is used to calculate the requirement for reproduction.

The interest of precision-feeding strategies for gestating sows was evaluated by Gaillard et al. (2020b). In that study, a conventional 1-phase feeding strategy (CF) was compared to a precision feeding (PF) strategy, which consisted of mixing two diets with either a low (L) or a high (H) nutrient content. The SID lysine content was assumed to be 4.8, 3.0, and 6.0 g/kg feed and the protein content to be 14, 9, and 16% in diets CF, L, and H, respectively. On average, diet L represented 89% of the feed to be delivered by the PF strategy. Compared to the CF, the average dietary SID Lys content was 29.5% lower with PF, while average calculated dietary P content was 14.5% lower. The simulated proportions of sows that were given an excess or deficient supply of SID Lys were reduced with PF. Compared to CF, the PF strategy allowed for a 3.6% reduction in feed cost per sow during gestation, and reduced N and P intake (by 11.0 and 13.8%, respectively) and excretion (by 16.7 and 15.4%, respectively).

Likewise, Gauthier et al. (unpublished) evaluated the potential of precision feeding for lactating sows. A conventional one-phase (C) feeding strategy was compared to a precision feeding strategy which consisted of mixing two diets with a low (L) or high (H) nutrient content. The SID lysine contents were 8.5, 4.8, and 10.5 g/kg of feed, and the protein contents were 16.0, 12.7, and 18.0% in the C, L and H diets, respectively. On average, the rate of incorporation of diet L was 53%. Compared to the one-phase strategy, precision feeding resulted in a 5.1% decrease in total protein intake, an 8.5% reduction in N excretion, and a decrease of 1.5% in feed cost. However, these results were obtained by simulation and remain to be evaluated experimentally, including the possible effects on performance.

7.4.3 Modelling Mineral Requirements

Minerals are a major component of pig nutrition. P and calcium (Ca) are necessary for bone development and they are involved in numerous biological functions. Dietary P from plant origin are not well digested by pigs, and addition of mineral

P and/or phytase increases feed cost. Moreover, the oversupply and the low digestibility of P also results in high P excretion, which affects the environment. Therefore, models that precisely predict mineral requirements are needed to optimize supplies and minimize excretion (Brossard et al., 2017a). Pigs have important mineral body reserves that can be mobilized to support the metabolic requirements so that a deficient mineral supply does not affect growth, at least on a short-term basis, conversely to an amino acid deficiency. An insufficient P supply in the growing period can be compensated for during the finishing period by increased absorption and accretion (Gonzalo et al., 2018), without affecting performance or bone strength at slaughter. In sows, mineral mobilization during lactation can be compensated during the next pregnancy (Jondreville & Dourmad, 2005). This offers more flexibility for mineral nutrition and more opportunities for precision feeding.

Different models are available to calculate mineral requirements of growing pigs and sows (Jondreville & Dourmad, 2005; NRC, 2012; Symeou et al., 2014; Bikker & Blok, 2017). These models allow dietary P and Ca supplies to be adjusted to pig performance and physiological status, but they do not consider the effect of body mineral reserves on the efficiency of P and Ca absorption and retention. In recent years, for growing pigs, more dynamic and mechanistic models have been developed that represent P and Ca ingestion, absorption, and retention, using the body mineral reserves as a driver for absorption and retention (Létourneau-Montminy et al., 2015; Misiura et al., 2020). These dynamic mechanistic models could be used to improve the decision support tools for mineral precision feeding. However, most of these models are research models and have to be adapted to be integrated in decision support tools for precision feeding.

When precision feeding is applied with the mixing of two diets, as is usually the case, it may be difficult to simultaneously adapt the supplies of amino acids and minerals due to different dynamics in the evolution of requirements to these nutrients over time. This was the case in the study on gestating sows from Gaillard et al. (2020b), who evaluated the effect of a precision feeding strategy based on digestible lysine requirement. They showed that this strategy was not as efficient for P because of the different dynamics of P and lysine requirements. They concluded that three diets would have been required for an optimal joint fitting of mineral and amino acid supplies.

7.4.4 Inclusion of Models in a Whole System for Practical Application

As detailed in previous sections on models, models are being developed to include the real-time integration of data and could be integrated in whole systems (Fig. 7.1). In practice, data from sensors providing information on body weight, feed intake, body composition, activity and health status (through body temperature), and ambient temperature, can and will be more and more collected in real time and on individual pigs. Models included in decision support systems can use these data and determine the best individual ration for the next day. After an eventual checking by the farmer, this information would be sent to precision feeders allowing direct

application of precision nutrition in the farm. In a case of heating wave, the decision support models could provide a warning and propose an adaptation of energy content of feed to mitigate effect of heat stress. In the same way, if sensors detected pathogens on some animals, decision support models could provide an alarm and activate either a distribution of antibiotics through water for these animals or an adaptation of diet to compensate deviation in requirements in some nutrients due to the specific health issue. Such a whole integrated system requires an interoperability of sensors, decision support tools and automates. This implies also to rethink feed formulation and to have an adapted system (feed lines, silos) for feed management and distribution to the feeders; indeed, precise feeding is based in many cases on the mixing of two diets, that must be adapted to the different stages (sows, growing pigs) in the farm. It requires also data management systems (locally in the farm and/or in an external computer server (cloud) to give access to various information), and adapted interfaces to allow farmer to interpret information released and help him to activate or not some actions.

7.5 Conclusion

Sensors and data collection in pig production evolve with the development of precision farming. Data can be obtained more and more precisely on individual pigs and their environment and be used for smart pig nutrition. However, there are still challenges to measure relevant, and individual criteria indicative for the physiological status of animals and their response to changes in nutrition or the environment. This information is essential to refine management of production, health, and welfare of pigs through nutrition. This requires to go beyond current nutritional models and to consider more criteria than only feed intake and growth. Precision feeding in fattening pigs and sows as presented in this chapter is a good example on how data-driven and concept-driven approaches can be combined. This requires improvement to use the full potential of both approaches and their application as decision support. Although performance (i.e., through feed intake and growth) is relatively straightforward from a modelling perspective, addressing issues related to animal health and welfare is much more complex. However, the interpretation of the dynamics of feed and water intake and growth may prove to be useful traits to “quantify” health-related mechanism such as resistance and resilience to external or internal stress factors (e.g., heat, disease) (Nguyen-Ba, 2020).

Technologies evolve and so do pig farming systems. Gestating sows have been reared in groups for several years and loose-housing systems are now developing for lactating sows. Alternative systems are also being developed with changes in terms of bedding, size of groups, space, and outdoor access. The competition between feed for animals and food for humans implies the use of new or more diverse feed ingredients. Consequently, data collection and models for smart pig nutrition have to be adapted to this diversity of situation. This will also partly determine practical application of smart pig nutrition. Will it be applicable only in very controlled rearing conditions or also in alternative systems (e.g., organic, with outdoor access)?

Will it be applicable up to individual levels everywhere or at different scales (individual, pen, room) depending on farm structure, type of feeding (liquid vs dry feeding)? The practical application of smart pig nutrition will also depend on the capacity to prove its economic relevance: will the gain offered by smart pig nutrition (feed efficiency, health, welfare) be sufficient to ensure an acceptable return on investment? Moreover, it is without doubt that automation has brought and will bring changes in the life of farmers. Hard and repetitive tasks can mostly be done automatically nowadays, but a farm cannot be run without a farmer. There are different “farming styles” with different needs and expectations concerning smart pig nutrition and in which the information and the corresponding action can be taken by the computer, the farmer, or the pig. However, for a successful implementation of smart pig nutrition, it should be the farmer who decides who should be in control.

Finally, the use of Big Data has become increasingly important in society. Smart phones and the Internet of Things rely on it and, here too, the question can be asked of “who is in control?”, in addition to the question “whose data is it?”. Although the attitude towards the use of these technologies varies from person to person, their implementation in agriculture will probably be perceived with much more scepticism by society, especially for use in animal production (e.g., Wathes et al., 2008; Boogaard et al., 2011; Werkheiser, 2018). How will automation and Big Data be seen in relation to current animal production systems, and will there be a place for this in alternative production systems, such as organic pig production? Will automation be perceived as an opportunity to see animals as individuals and provide individualized management (e.g., feeding, medication) or will it be perceived as a further industrialization of pig production systems? An open discourse on these issues and questions with society will be crucial to ensure that progress is made based on reason than emotion.

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Martin J. Zuidhof, Mohammad Afrouziyeh, Sasha A. S. van der Klein, and Jihao You

Abstract

The growing world population will dramatically increase demand for poultry meat and eggs, which are efficient, affordable, and high-quality protein sources. Substantial innovation will be required for poultry producers to meet this demand in a socially responsible way. Despite their high potential value, the real power of sensor technologies, data acquisition, data processing, and automation is only beginning to be harnessed by the agriculture sector. The poultry industry is likely to undergo a fundamental transformation to precision livestock farming and smart poultry nutrition, which will use big data to optimize real-time management and feeding decisions. Although smart poultry nutrition can be applied at a flock level, even greater improvements can be achieved by focusing on individuals. This requires a shift from the current flock-level focus. Smart poultry nutrition systems collect real-time information on the individual animal and its environment, and implement a feeding decision to provide the right amount of the right feed to the right bird at the right time. This allows smart poultry nutrition systems to immediately and automatically deal with the nutritional needs of birds that vary in body weight, growth rate, or health status. From a nutritional perspective, the primary objective is to match nutrient supply to nutrient requirements. Nutrient requirements can be inferred from each animal's unique age, composition, and stage of production. Optimal feeding decisions should take into account the current status of each animal, market conditions, environmental impact, and animal welfare considerations. These factors can be linked in models that integrate nutrient intake to animal response predictions to optimize feeding decisions, which can then be implemented by precision feeding systems. Although it would be advantageous to maneuver the individual bird (smallest manageable unit)

M. J. Zuidhof (✉) · M. Afrouziyeh · S. A. S. van der Klein · J. You
University of Alberta, Edmonton, AB, Canada
e-mail: mzuidhof@ualberta.ca

toward a desired outcome, further research quantifying individual nutrient responses and variation thereof is needed. Poultry supply chains will need to collaborate with scientists in various fields, including agricultural and environmental sciences, statistics, economics, computing science, and engineering to tackle the new questions and hypotheses revealed by a new smart poultry nutrition paradigm.

Keywords

Broilers · Broiler breeders · Egg production · Feed Conversion Ratio (FCR) · Feed intake · Flock requirements · Growth · Individual requirements · Layers · Layer pullets · Machine learning · Nutrient requirements · Nutrient responses · Poultry · Precision Feeding · Precision Livestock Farming · Real-time · Sensors · Simulation Modelling · Smart Agriculture

8.1 Introduction

Precision livestock farming (often abbreviated PLF) is an enterprise-level management system based on continuous automatic real-time monitoring, either at a group level or ideally, at the level of an individual animal. Sensor information is used first to inform production decisions and then to automatically implement actions to improve efficiency, animal health and welfare, and optimize the environmental impact of livestock production (Berckmans, 2014; Astill et al., 2020). Precision feeding (often abbreviated PF) is providing the right animal the right amount of the right feed at the right time. Smart poultry nutrition (SPN) is a system that makes use of data from sensors to determine what an animal needs in real-time, and being coupled to a feed delivery apparatus makes the right quantity of feed of the desired composition available to a domesticated bird or group of birds. Smart poultry nutrition and precision feeding are therefore subsets of precision livestock farming. Arable land and water resources are diminishing while demand is growing for transparency in food production processes. Sustainable intensification, including precision livestock farming innovations, must be adopted (Elferink & Schierhorn, 2016) and will be instrumental in feeding the growing world population in a socially responsible way.

Smart poultry nutrition uses state-of-the-art sensor, data acquisition, data sharing, and data processing technologies to automate poultry feeding. It makes use of data collected in real-time to implement optimal poultry feeding strategies. With few exceptions, smart poultry nutrition technologies are at a pre-commercial stage. However, the poultry industry stands to benefit greatly from precision livestock farming and smart poultry nutrition; a fundamental industry transformation seems inevitable. The poultry industry and the research community is currently focused on feeding and managing large flocks. Feeding and managing individuals, which Halachmi and Guarino (2016) termed “the per animal approach”, will yield further optimization. Collecting information on the individual allows us to tailor feeding

decisions to appropriately address variation in body weight (BW), rates of growth and development, and health. Sensing the current status and calculating the trajectory and production level of an animal or group of animals informs models that, when coupled with an appropriate automated system, can implement tailored feeding and management decisions that maneuver each animal more efficiently toward the desired economic, environmental, and social outcomes.

A primary goal of smart poultry nutrition is to match nutrient intake with nutrient requirements. Nutrient requirements are dynamic, changing with age, stage and level of production, reproductive status, health status, and environmental conditions. Meeting nutrient requirements in real-time will minimize nutrient intake, which will reduce the cost of feeding, and minimize excretion of excess P and N (Andretta et al., 2016; Pomar et al., 2011), and production and emission of greenhouse gases, largely from manure (EPA, 2022). Minimizing nutrient wastage would reduce the inputs required to feed poultry and, in turn, the arable land base required to produce poultry feedstuffs, and reduce energy and water required for crop production. Precision livestock farming also aims to identify the health and welfare needs of each individual animal. Precision livestock farming and smart nutrition systems allow managers to tend to these needs in real-time, while reducing labor costs and improving the welfare of animals. Assuming that the cost of required technologies will become low enough to justify use, smart poultry nutrition as a part of a precision poultry farming system has the potential to significantly increase the sustainability of poultry production.

8.2 Current State of Smart Poultry Nutrition

Precision feeding depends on a desired objective. This dictates the composition and/or quantity of feed required to advance an individual from its current state to a final desired outcome. Smart poultry nutrition systems employ sensors that measure factors like the identity of an individual bird, body weight, body or environmental temperature, or light intensity. These data inform the system of a bird's current state, and an algorithm uses that information to estimate the nutrients required to reach the next desired state. In real-time, a feed delivery apparatus automatically implements the most appropriate feeding decision.

The fields of precision feeding and smart poultry nutrition are in their infancy. Until recently, monitoring of individual feed intake has been limited to manual data collection from individually caged birds, and only in research settings. Development of systems to automate the monitoring of feed and water intake has progressed slowly over the last 2 decades. Puma et al. (2001) presented one of the first systems for automated monitoring BW, and feed and water intake of individually caged birds. This system generated continuous high-resolution data that allowed the authors to quantify individual variation in feed and water intake. Bley and Bessei (2008) developed the first system for monitoring individual feed intake and feeding behavior of poultry (ducks) housed in groups. These authors identified individual ducks using radio frequency identification (RFID) transponders attached to the wing.

Hybrid Turkeys, a commercial poultry breeding company, developed a similar system for real-time monitoring of individual feed intake and BW of group housed turkeys (Tu et al., 2011). Its primary intended use was to measure feed conversion ratio (FCR), for use in genetic selection programs. Most primary breeders have similar systems for monitoring individual feed intake, but have kept their technology proprietary. Thus, a lot of public research and development is still needed to realize the environmental and financial benefits of smart poultry nutrition on a global commercial scale.

Aerts et al. (2003) reported a system to grow broilers on a pre-determined growth trajectory by daily monitoring of BW, and model-based feed allocation decisions. This flock-level system used automated BW scales that were used to implement feed allocations intended to limit growth according to a pre-defined growth trajectory. Also at a group level, Aydin et al. (2015) developed a system for real-time monitoring of broiler chicken feed intake using sound analysis of birds pecking at a feeder. An advantage of this system was the ability to monitor feed intake in a non-invasive way, but the system was not able to collect feed intake data at an individual bird level.

More recently, Zuidhof et al. (2017) developed a system for controlling feed intake and monitoring BW and feed intake of individual chickens in a free-run setting (Fig. 8.1). The system was designed for broiler breeders, but has also been used successfully for research with broilers (van der Klein et al., 2020c), layers (van der Klein et al., 2020b), and heritage chicken lines (Afrouziyeh et al., 2021). Whereas other systems to this point could monitor feed intake or BW or both, this precision feeding system was unique in its ability to control feed intake, which is crucial for implementing feeding decisions in a smart poultry nutrition system. Using this precision feeding system, the research team has demonstrated consistently the ability to grow group-housed broiler breeder pullets and cockerels with a BW



Fig. 8.1 Precision feeding system capable of controlling feed intake, and monitoring BW and feed intake of individual group-housed birds

coefficient of variation of under 2% by the time of photostimulation (van der Klein et al., 2018a, b; Zuidhof, 2018). This was accomplished by measuring the BW of each broiler breeder in real-time, and allowing access to feed only when the birds weighed less than the predefined target BW. Mika et al. (2021) recently disclosed another pre-commercial system for control and monitoring of feed intake for individual loose-housed poultry. Zuidhof et al. (2019) have further developed their precision feeding system to provide up to four different diets, based on the unique attributes of each bird that enters a feeding station. The first studies are currently underway with the objective of investigating the impact of dietary metabolizable energy levels and BW trajectories on body composition of hens, and subsequent sexual maturation rates and egg production. Importantly, the same group has developed a sensor-equipped nest box to record egg production at the level of each individual hen.

8.3 Matching Nutrient Supply to the Nutrient Requirements of Poultry

Classically, the concept of a nutrient requirement refers to the minimum level of a nutrient that produces the maximum response in a specific response variable. In this chapter, however, we will use a more practical definition of requirement, that is, the expected quantity of a nutrient required to achieve a specific outcome. For example, in this chapter the metabolizable energy (ME) requirement of a broiler breeder refers to the amount of energy that we expect a bird of a defined BW to consume to maintain itself, to grow at a defined rate, and to produce a defined daily egg mass. Similarly, in this chapter the lysine requirement of a broiler refers to the amount of lysine that must be consumed by the bird to maintain itself and grow at a defined rate.

The ultimate goal of feed formulation is to perfectly match the nutrients supplied in real-time with the nutrient requirements of each individual bird, thus minimizing nutrient waste. Phase feeding is a pragmatic but imperfect attempt to realize this goal commercially. Phase feeding is the feeding of several diets, each for a short period of time to roughly meet age-specific nutrient requirements. It accommodates logistical constraints around feed manufacture, delivery, and storage, but in terms of nutrient efficiency, it leaves a lot of room for improvement. Optimal dietary amino acid (AA) levels decrease with age in growing meat-type poultry. In order not to limit growth potential, dietary nutrients such as lysine are provided at approximately the average level required during each phase. However, nutrients are almost always either under- or overfed using this approach.

If the duration of each phase were to be reduced, overfeeding of nutrients could be reduced substantially. Figure 8.2 illustrates theoretically how a reduction in phase duration from 14 days to 1 day would reduce the overfeeding of nutrients while simultaneously allowing the animals to express their genetic growth potential. Sensors can identify an individual and measure its BW in real-time. From this data, a precision feeding system could calculate growth rate and adjust the ratios of nutrients provided to each individual bird to meet its real-time nutrient needs for

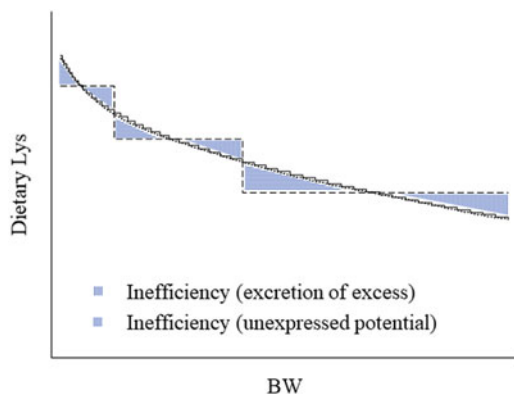


Fig. 8.2 Phase feeding associated inefficiencies due to excess provision of nutrients or unexpressed potential. The dotted line represents the nutrient requirement of broilers over a 6-week period. The dashed line indicates the lysine provided in a 3-phase feeding program. The solid black line indicates lysine provided using a daily adjustment in formulation. The area contained between the dotted line and the other lines represents inefficiencies due to excess provision of nutrients or unexpressed potential productivity

maintenance and growth. One practical way of adjusting feed formulation over the growing period would be to use a precision feeding system to blend two or more diets varying in energy:nutrient ratios, so as to provide the correct nutrient balance in real-time.

8.3.1 Smart Diet Formulation

Feed formulation is a complex process in which not only nutritional but also economic, environmental, and social factors must be taken into consideration. Rather than focusing on nutrient requirements in the classic sense (the minimum nutrient level required to maximize a response), good information about growth and yield responses to increasing nutrient levels is paramount for optimization. The NRC committee (NRC, 1994) identified the value of using mathematical models to identify optimal concentrations of dietary nutrients and energy to achieve poultry production goals. Practically, it is important to deal with variability in market conditions and feed ingredient composition. Because of nutrient variability in feedstuffs, commercial nutritionists often over supply nutrients (Symeou et al., 2016). This ensures that they meet their legal obligation to provide at least the minimum level of nutrients indicated for specific diets, and typically means that animals meet expected levels of productivity, but at an environmental and economic cost due to excretion of excess nutrients.

Fluctuating market conditions affect feed ingredient cost and product value. These, in turn, impact optimal dietary nutrient concentrations and ratios. Thus, it is essential to define the product (e.g., a broiler of a certain weight), and the anticipated

economic value of the product, including each sub-component. Optimization is only possible when both nutrient requirements and nutrient availability from feedstuffs is known. Thus, smart poultry nutrition requires both mathematical characterization of nutrient responses and a precise knowledge of available nutrients in feedstuffs. Sensor technology such as near infrared spectroscopy (NIRS), which is used to predict proximate nutrient analysis of feed ingredients, is an important element of a smart poultry nutrition system.

8.3.2 Variability in Nutrient Composition of Feedstuffs

Nutrient composition of feed ingredients can vary due to plant genetics and environmental conditions during crop production. If such variability is not considered, nutrients can easily be under- or over-supplied in livestock diets (Symeou et al., 2016). Unbalanced diets increase feeding costs by reducing animal performance and efficiency and increase emission or excretion of unused nutrients that contribute to environmental pollution. Therefore, variability in feed ingredient nutrient composition and availability must be considered when formulating diets. There are several approaches to deal with nutrient variability in feed formulation.

8.3.3 Margin of Safety and Stochastic Programming

Commercial diets are usually formulated by linear programming software based on expected nutrient levels of each ingredient. These are often unique for each formulator, and based on ingredient composition tables, experience, and batch analysis. Assuming a normal distribution in the nutrient levels of feedstuffs, formulating diets based on the assumption of a fixed (expected, or mean) nutrient concentration would result in under-supply of nutrients half of the time. Therefore, feed formulators use safety margins to prevent underfeeding nutrients. This reduces the risk of underperformance but increases the risk of excessive nutrient excretion.

A margin of safety approach was suggested by Nott and Combs (1967) as a simple way to adjust nutrient matrices to compensate for nutrient variability. They suggested subtracting one-half of a standard deviation (SD) from mean nutrient values. This approach increases the probability of achieving the desired nutrient level from 50% to approximately 69%, but also increases the likelihood of oversupplying nutrients and cost. This strategy can be adapted. Stochastic programming is a programming method that incorporates variability and uses this inherent uncertainty to predict the likelihood of specific outcomes (Pesti & Seila, 1999). Roush et al. (2007) demonstrated that in a normal situation where nutrient variability exists, stochastic programming enabled a formulator to precisely match a desired probability of meeting the specified nutrient level. Hence, stochastic programming can be used to minimize over-formulation while managing the risk of underperformance of the animals being fed.

8.3.4 Grain Handling

Separation of carloads of a feed ingredient delivered to a feed mill based on the average nutrient content into above- or below-average batches is often used to reduce nutrient variability. An approximate nutrient analysis can be easily done using real-time NIRS technology. Alhotan et al. (2014) indicated that crude protein variability of feedstuffs can be reduced at least 50% by separating each of the ingredient batches based on the average nutrient into 2 bins; the reduction in crude protein variability with the 2-bin method was a result of reduced variability of its components, AA, and non-protein-containing compounds. As this approach can reduce the SD of crude protein in each batch, the benefit can be surpassed using a stochastic programming method that takes the SD of nutrients into account in feed formulation practice. Therefore, it is recommended to separate batches based on their average nutrient content, and use these batches as separately defined ingredients. This would reduce performance variation and increase the probability of achieving the desired nutrient level whether or not a stochastic feed formulation method is used.

8.3.5 'Nutrient Response' Thinking Is Critical to Deal with Marketplace Variability

Nutrient requirement specifications published in primary breeder management guides, the National Research Council (NRC, 1994), and in many other books are fixed dietary nutrient levels that maximize a performance variable but do not necessarily yield maximum profits. Maximum performance is ambiguous for several reasons. First, there are many potential response criteria related to the dietary concentration of nutrients (e.g., growth rate, yield, egg production, or health and welfare). Second, nutrient requirements are usually defined based on group (flock) responses. In reality, individual birds have different nutrient requirements because of their unique genotype, body composition, and stage of life (Andretta et al., 2016; Archer et al., 1999), and the environments they are exposed to. A closer match of nutrient supply to unique nutrient requirements could be achieved in some cases by creating small groups of animals with similar nutrient requirement (e.g., grading broiler breeders based on their BW in a flock). This could reduce nutrient excretion and increase profit. A shift in thinking from flock-level to individual animal nutrient responses is necessary to realize the benefits of smart poultry nutrition (Zuidhof, 2020b).

Roland et al. (1998) suggested that nutrient requirements are not fixed, but they vary when the objective is to maximize profit. Maximizing performance and maximizing profit are different objectives. Practical feed formulators aim to define a least-cost combination of ingredients that satisfies a set of nutrient specifications that are designed to meet the nutrient needs of the average animal over a given period of time. This is done by including constraints, usually a minimum level of a nutrient that must be incorporated into the diet. In the absence of nutrient response data, the

art of feed formulation often depends on the formulator's experience about how much lower specific nutrient levels can be set without seriously compromising performance. For nutrients that are not limiting or are inexpensive, no constraints are needed. When feed is formulated in this way, some nutrients may be included above the required level, with excess nutrient excretion to the environment, while simultaneously missing the economic optimum (Castrodeza et al., 2005). Thus, optimization must depend on a carefully constructed objective function that simultaneously includes profit, environmental sustainability, and social responsibility. A shift in thinking has already begun from the concept of "nutrient requirement" to "nutrient response" (Morris, 1983), however this has been slow to gain traction in the poultry realm.

Considering that there are acceptable (below maximum) levels of performance over a range of energy and nutrient requirements, it is reasonable to let product value and ingredient prices dictate appropriate nutrient levels when formulating the most economical diet. Wu et al. (2005) pointed out that a wide range of dietary ME levels (2684–2992 kcal/kg) are used by the egg industry. Using a wide range of dietary ME levels (2535–3035 kcal/kg) for laying hens, Afrouziyeh et al. (2011) developed a nonlinear optimization model for dietary energy. They clearly showed that egg prices and feed ingredient costs affected the dietary ME level that maximized profit. Similarly, total sulfur AA levels required for maximum profit varied from 562 to 859 mg/d for DeKalb Delta hens (Ahmad & Roland, 2003), depending upon feed ingredient cost and egg prices. The relative cost of energy rich vs. protein rich ingredients in particular can substantially affect the optimal formulation.

8.4 Mathematical Models to Aid Smart Poultry Nutrition

Models help us understand systems by linking inputs and outputs. Much research is often required to deduce relevant mathematical functions, which describe the nature of relationships between parts of a system, and coefficients, which describe the relative contribution of specific characteristics of the relationship. Mathematical models are an integral part of smart poultry nutrition. Mathematical modeling is a tool to represent and understand parts of a system by simplification, integration, and linkage of parts. The simulated unit can be small (e.g., an individual chicken) or large (a flock, a farm, or feed mill). The mathematical models representing the functionality of the system can be used to generate and test scientific hypotheses. Mathematical models have also been used to develop tools for predictive and decision-making purposes (Haag & Kaupenjohann, 2001). With the increasing availability of big data within the poultry industry, there is an opportunity to integrate information from various sources and develop practical tools. The start of this integration of information lies in understanding the concept of nutrient conversion into final products, where mathematical models can help understand nutrient requirements and nutrient intake.

There are two main types of mathematical models: (1) empirical or statistical models and (2) mechanistic models. Empirical models are mathematical equations

validated using data (Bonate, 2011) and are often used to understand how discrete factors (treatments) impact performance results in poultry production (Zoons et al., 1991). Empirical models are most useful when the parts of the mathematical equation can be intrinsic to the reality it describes; parameters represent a real component of the system (Thakur, 1991). This means that the parameters in these models are biologically relevant and directly applicable in practice. This also facilitates the development of mechanistic models from empirical work (Thakur, 1991). In the field of nutrition, mechanistic models simulate underlying biological mechanisms or processes. When parameter values in these models change over time, the models are referred to as dynamic. Such models allow for the evaluation of changes and dynamics in the system of interest (e.g., Kebreab et al., 2009). In the search for sustainable poultry nutrition practices, both types of models are needed to understand the link between performance, nutrient requirements, and nutrient intake.

8.4.1 Growth and Egg Production

Nutrient requirements of poultry depend on many factors such as genotype, growth potential, body size, environment, health status, age, and physiological state (Leeson & Summers, 2001). In general, the goal for meat production is to optimize growth of lean tissue, often with emphasis on breast muscle tissue. Although egg production is a paramount consideration for determining nutrient requirements of laying hens, body weight maintenance and the rate of gain also contribute significantly to nutrient requirements.

To this end, growth models are used to study BW relative to age, and (allometric) maturation rate of various body parts relative to BW (Hurwitz et al., 1991; Zuidhof et al., 2014; van der Klein et al., 2017). Well-fitting growth models for meat-type poultry can aid the prediction of nutrient requirements and thus feed intake (Emmans, 1981), or of optimal slaughter age, and accommodate differences in growth responses due to changes in environmental conditions (EFG Software, 2019). The Gompertz growth function (Gompertz, 1825) or modifications thereof (Tjørve & Tjørve, 2017; Emmans, 1981) have also been used to describe the weight–age relationship for body parts, but these have not always fitted well, depending on the body part (Hurwitz et al., 1991). Huxley’s equation (Huxley & Teissier, 1936) has been more commonly used to describe the body part weight – BW relationship (Zuidhof, 2005). With improvement of computational tools in the past years, multiphasic models and multiphasic random regression models have been proposed to estimate individual variation in parameter estimates (Kwakkel et al., 1993; Wang & Zuidhof, 2004; van der Klein et al., 2020b; Zuidhof, 2020a). Random regression models are gaining in popularity because variation around certain parameters can be attributed to an individual. As such, not only treatment effects but variation in model coefficients due to unique individual differences can also be estimated. A better understanding of the growth and development of individuals allows better prediction of the nutrients required to support that growth.

The goal for growth in poultry reared for egg production is to optimize physical characteristics such as body composition to support egg production. For that purpose, multiphasic models could be used, which include both the rearing and adult phase (Kwakkel et al., 1993; Zuidhof, 2020a). However, the exact relationship between growth curve shape (model parameter estimates) and egg production remains to be elucidated. In broiler breeders, there is a similar challenge to achieve an optimal body composition, but the challenge to identify an optimal growing strategy is more complicated. Broiler breeder feed restriction programs need to be redefined after decades of almost no change in body weight recommendations in spite of continuous genetic increases in body weight, lean yield, and efficiency. Zukiwsky et al. (2021b) and Afrouziyeh et al. (2020) designed experiments in which they used multiphasic Gompertz equations to design strategic new growth profiles that were precisely implemented with a precision feeding system. Using biologically meaningful parameters, they altered the amount and timing of pre-pubertal and pubertal phase BW gains. A major advancement in their work was the use of continuous model parameters to develop novel growth profiles, and this was the first true attempt at optimization of growth trajectories.

Compared to growth models, fewer egg production models have been published. Narinc et al. (2014) reviewed mathematical models of egg production curves and concluded that development of models with biologically meaningful parameters is needed. In addition, they stressed that up to now, most models have used flock level data, instead of individual egg production results for model development and fit. If biologically meaningful variation around curve fit can be determined, breeding efforts could focus not on egg production itself but also on egg production curve shape. More recently, Bendezu et al. (2019) and Sakomura et al. (2019) took more mechanistic approaches by modeling sexual maturation, egg components, and ovulatory cycles to predict egg weight, rate of lay, and nutrient requirements in egg-laying poultry.

8.4.2 Energy and Nutrient Requirements

Because it is useful to employ the concept that animals eat for the purpose of meeting their energy (Emmans, 1981) and other nutrient requirements (Gous, 2016), energy and nutrient partitioning models are useful tools to predict feed intake. In such models, nutrient requirements are inferred by nonlinear functions whose parameters best fit (minimize variation) the relationship between ME intake and its ultimate fates, such as maintenance, storage (BW gain), and egg production. The aim is to maximize the energy available for productive purposes such as growth or egg production. This might be achieved by reducing energy requirements for maintenance through nutritional strategies such as targeted restricted feeding, or through breeding practices. These models have their origin in Byerly et al. (1980) and Schulman et al. (1994). Romero et al. (2009b) further developed these into nonlinear mixed models, which allowed for estimation of maintenance requirements for individual birds. This is a critical advancement for smart poultry nutrition, because

of its “per animal approach.” This approach also provided a novel model-based efficiency measure, Residual Maintenance Requirement (RME_m), which refers to the degree to which the ME requirement for maintenance (ME_m) of an individual differs from what would be expected for the average animal in a population. Random variables (variables that account for variation of individual members of a group) have been added to energy balance models to account for the effects of age (van der Klein et al., 2020a), environmental temperature (Romero et al., 2009a; Pishnamazi et al., 2015), photoperiod (van der Klein et al., 2020a), and nutritional strategies such as varied energy intake levels (Hadinia et al., 2018) on maintenance requirements.

Sakomura et al. (2015) used a similar factorial approach to estimate AA requirements of broilers, based on body protein, feather loss, feather protein, rate of deposition of feather-free body protein, and rate of deposition of feathers. The Reading Model (Fisher et al., 1973) has been widely used to predict AA requirements of laying hens. Further factorial refinement to account for requirements for body maintenance (Sakomura et al., 2015), yolk, albumen, and shell on laying and non-laying days would enhance prediction of AA requirements for laying hens, but requires further research. Reis et al. (2018) evaluated adjustment of the factorial models of Sakomura et al. (2015) to account for a distinct efficiency of utilization for AA used for feather-free body and feathers. Sakomura et al. (2019) integrated several linear models from the literature, including those predicting AA and energy requirements, into a mechanistic model simulating egg production and energy requirements in laying hens and broiler breeders. They suggested that these simulation models, integrating information on requirements and production levels, could aid in predicting economic efficiency, and maximizing profitability for each producer rather than applying least cost formulation at the feed mill level. The application of these AA requirement models would help in optimizing feed composition for highest productive performance combined with lowest environmental output. For example, smart poultry nutrition systems could be used to predict real-time AA requirements for individual birds, similar to an approach used in grow-finish pigs (Hauschild et al., 2020). However, as Bonato et al. (2016) indicated, studies investigating mathematical models estimating protein and AA deposition and requirements are scarce.

Calcium (Ca) and phosphorus (P) requirements are also important with respect to bone and eggshell metabolism. Kebreab et al. (2009) and de Vries et al. (2010) reported on the development and evaluation of a mechanistic model of Ca and P dynamics in layers. The aim of this model was to be a tool to evaluate feeding strategies for reducing P excretion to the environment. The model predicted an increase in P retention in bone and egg from 8.4% to 25.4% of digestible P intake at the lowest and highest concentration of dietary Ca inclusion, respectively. Subsequent experimental results showed a similar increase from 11.5% to 24.1%, respectively. Novel precision feeding strategies could also be evaluated using the aforementioned model. For example, hens could be fed low Ca diets after oviposition, and higher Ca levels during the afternoon and night when eggs are expected to be in the shell gland. This approach has been referred to as split feeding (van Emous & Mens, 2021; Keshavarz, 1998). This approach would minimize mobilization of

Ca from the bone, which would increase hen welfare and reduce P excretion to the environment. Such a scheme based on actual oviposition times from an integrated RFID-equipped nest box would allow tailoring of feeding programs for individual hens.

Previously, Pomar et al. (2011) concluded that precision-fed grower-finisher pigs reduced P excretion by 38%. There is a paucity of research on Ca and P dynamics in broilers. Although improvements are anticipated as a result of a better match between nutrients supplied and real-time nutrient requirements (see Fig. 8.2), there is insufficient research characterizing individual bird nutrient requirements to know how much a smart poultry nutrition approach might reduce environmental P output in poultry.

8.4.3 Long-Term Effects of Nutrition

Finding an optimal nutritional strategy appears to be a growing problem in commercial egg-type breeds. Layer pullets often reach sexual maturity early, which compromises their ability to support long-term egg production (Baxter & Bédécarrats, 2019). Producers are trying to ensure animals have a high enough energy intake during the short period of pubertal development, while managing lighting schedules to delay sexual maturation, in an attempt to prevent a negative energy balance after the onset of lay. A second nutritional challenge is the calcium and phosphorus balance related to bone and egg-shell metabolism and persistency in egg-shell quality (Riczu et al., 2004; Molnár et al., 2016). Hence, there is a considerable difference between nutrient requirements to develop the body for start of lay (fat deposition, bone development, and reproductive organ development) and during lay (sustaining egg production and egg quality, reduced body growth; Kwakkel et al., 1991). Physiological triggers might not initiate the development of the reproductive tract and egg production in broiler breeders if growth has not occurred in a balanced manner during the rearing phase (Zuidhof, 2018). These multifactorial long-term challenges also require assessment of underlying physiological aspects of reproduction (Hanlon et al., 2020), where mathematical models can also aid in understanding dynamics of reproductive signaling molecules (van der Klein et al., 2020d). Simulation studies that employ mathematical models to estimate body growth, egg production, and AA requirements (e.g. Sakomura et al., 2019) will help the smart poultry nutrition community to develop testable hypotheses that will undoubtedly contribute to optimizing poultry feeding strategies.

Nutrition can have intergenerational effects in poultry (van Emous et al., 2015; Dixon et al., 2016). The extent of the reported effects of maternal nutrition on offspring performance varied (Dixon et al., 2016), but it is clear that small changes can have significant economic effects in large-scale integrated production systems. For example, increasing maternal BW on the order of 20% increased male offspring 42-day BW by over 8% (Bowling et al., 2018; Humphreys, 2020; ad libitum fed offspring). Thus, an integrative system approach to nutritional modeling is needed. The more complex and multifactorial our systems become, the less likely trends or

relationships will be easily discovered and evaluated. Therefore, further steps may require adopting machine-learning techniques (see next section).

Poultry breeding companies have invested in tools to collect big data for individual phenotyping characteristics important for matching nutrient intake to requirements, including individual feed intake recording systems and scales that passively record BW measurements repeatedly. Within the field of animal breeding, precision nutrition and the related mathematical models are also playing a significant role. Statistical models, including the sire and animal models, have aided the estimation of breeding values and selection of the most superior individuals for many years. Additional computing power and improved models for breeding value estimation including genetic information has also improved prediction accuracy for feed efficiency traits such as residual feed intake and FCR (Abdalla et al., 2019). Berghof et al. (2018, 2019) provide a recent development in adapting animal models to include factors to estimate breeding values for variation in traits. This aims at improving the resilience of birds, which would mean, for example, less deviation from a growth curve after environmental disruption. In addition, the use of crossbred offspring phenotypes in breeding programs also improves accuracy of breeding value estimation (Christensen et al., 2015). Most commercial products in the poultry industry are crosses of pure lines, therefore, selection for crossbred performance, including feed efficiency, will help move towards more accurate selection pressure in pure lines.

8.4.4 Further Developments

Most of the studies described above use data collected under controlled circumstances to develop models to make predictions that support practical decisions. Many flock-based performance and environmental parameters are already passively collected using sensor technology. We are on the cusp of having many new technologies available to aid precision livestock farming and smart poultry nutrition systems. Some are already affordable, while some sensor technologies are likely much farther from being commercially feasible. Load cells are already commonly used to measure BW, and feed and egg weights. In combination with RFID chips and strategically placed RFID readers, growth trajectories of individuals, individual feed intakes, and egg weights can be measured. This information informs progress toward production goals such as flock uniformity, efficiency, egg production, and egg size management. Effective management of rooster BW can increase mating success, and increase fertility and chick production (Zuidhof, 2018). Early identification of injuries or disease can be discovered with these sensors, which can contribute to welfare improvements. Our research group has developed an RFID-equipped nesting box that can connect time of lay and egg weights for hens in real-time. This information can inform within- and between-day nutrient requirements for egg production in individual hens, increase the effectiveness of split feeding programs, or increase egg size uniformity. When integrated in a smart poultry nutrition or

precision livestock farming system, it could help to identify and correct egg production problems in individual hens.

Sensors can be passive, wearable, or even active if they are able to move throughout a production facility on rails or autonomous mobile robots. Thermistors and infrared cameras can provide feedback about environmental temperature, or even peripheral or core body temperature. Activity can be measured by serial image analysis or accelerometers. Light intensity and spectral analysis can be measured, and cameras can be used to evaluate feather condition, bird size, and bird movement. Microphones and audio analysis can be used to detect stress, thermal discomfort, and the presence of respiratory diseases. These data can be used to refine nutrient requirement predictions. Sensors can measure airspeed or important environmental gases such as CO₂, O₂, NH₃, and H₂O. Other sensors, though farther from commercial implementation, are being developed to detect skin conductivity or total body electrical conductivity, which could predict body composition that could be used to further refine nutrient requirement estimates for individual animals. Even more remarkable are sensors to detect glucose, bio-nanosensors to detect metabolites, and sensors to detect pathogens (Neethirajan, 2017). As additional sensors are added in smart poultry nutrition and precision livestock farming systems, environmental controls and feeding regimes can be adjusted optimally.

Application of scientifically developed models on field data might already provide insight in discovering relationships between performance, nutrient requirements, and nutrient intake. It could also provide decision-making tools based on real-time data and environmental circumstances. It is clear that the models supporting a sustainable poultry production chain will span across the different disciplines. It will be necessary to integrate information coming from nutrient supplier (controlling nutrient balances), poultry producer (controlling environment affecting nutrient requirements), and breeding companies (providing the genetic background to adapt to nutritional circumstances).

8.5 Big Data

Big data refers to the huge volumes of data that are generated automatically every day by sensors and computers. The Internet of things (IoT), which consists of devices with embedded sensors connected to a global network, is a huge infrastructure that makes these big data accessible. Big data is often under- or un-utilized, yet it has the potential to transform business decisions. Big data also refers to a field of processing and analyzing these vast amounts of data. It can be defined in three dimensions: “volume,” “variety,” and “velocity,” which relate to quantity, form (e.g., text, audio, and images), and the speed at which data is generated (Berman, 2013). Big data relies on high-performance hardware and software to capture, form, manage, store, share, and visualize the data. Big data analysis can extract important information that can reveal hidden patterns and correlations. To deal with big data, analytical techniques such as machine learning and data mining are used.

In the poultry industry, the field of genetics and breeding has been the only field where big data has been extensively leveraged (Astill et al., 2020). Development has been slowed by lack of digitalization, low or unclear value propositions, or low perceived return-on-investment (Ellis et al., 2020). Collecting data in a conventional way (e.g., recording BW and feed intake manually every 2 weeks in one trial) does not meet the definition of big data. However, data can be accumulated from a large number of trials for different flocks at different locations over a long period of time to generate huge datasets that might be used for big data analysis. Deployment of precision livestock farming systems that continuously monitor health, welfare, production, and environmental impact of individual animals opens the door of opportunity for big data analysis. Van Hertem et al. (2017) provided one of the first examples of precision livestock farming application in the poultry industry. In their study, five broiler farms were equipped with cameras, microphones, and climate and feed control, and a number of variables pertaining to the environment, behavior, and productivity were measured. They noted that although farmers were able to visualize the data, further development and use of the data for generating production indices or smart warning systems would be desirable. Another example is a precision feeding system for broiler breeders that aims to increase flock uniformity while precisely implementing desired growth trajectories (Zuidhof et al., 2019). The system uses RFID to monitor real-time BW and feed intake data while allocating feed to individuals only when needed. The precision feeding system generates data from individuals at a high speed compared to traditional techniques. Zuidhof (2018) reported the birds visited a precision feeding station on average 61 times per day, which is a relatively high rate of data flow. Feeding and feed seeking activity of individual birds was captured, which has been used to extract many different additional features of individuals, including hunger, deduced from motivation to seek feed (Zukiwsky et al., 2021b); early disease detection, deduced from changes in feed seeking and feeding patterns; estimates of nutrient requirements and feed efficiency that provide insights into individual bird variation (Zukiwsky et al., 2021a; van der Klein et al., 2020a) over a variety of time frames (Afrouziyeh et al., 2022); or even detection of oviposition events in individual hens (You et al., 2020). In combination with RFID-equipped nest boxes, it is straightforward to envision a split feeding approach (Keshavarz, 1998) to feeding hens based on their unique oviposition patterns.

Visualization of each bird's data yields unique insights not only into performance, but also about the preferences and temperaments of individual birds. For example, individual broiler breeders have distinct learning rates during the precision feeding system training period. They also have preferred times of day (or night) for feeding, unique feeding frequency and feed seeking patterns. We have also been able to identify pathogen exposure and locomotion issues by observing changes in feeding patterns and body weight trajectories.

Currently, nutrient requirements are flock- rather than individual-based (Liebe & White, 2019). Since individuals within a flock have different growth potential and reproductive rates, response-based models that link nutrient intake of individuals with their productive outputs would be more useful for minimizing waste. Precision

livestock farming systems are still in a very early stage, but a foundation is being laid for big data analytics in poultry production.

8.6 Machine Learning

Machine learning is a subfield of artificial intelligence, which is a branch of computing science. Machine learning can be broadly defined as computational methods to improve performance and make accurate predictions based on experience (Mohri et al., 2018). It also refers to educating computers to perform certain tasks without explicitly programming them for those tasks. Machine learning is different from statistical models because machine learning is data-driven, and it is less influenced by assumptions about data distribution and the homogeneity of variances. With respect to computational cost, machine learning is better suited for exploring and revealing relationships in big data. Advantages of machine learning include its ability to handle a large number of variables resulting from big data variety, and better results can be expected with increased data volume and velocity. Generally, the machine-learning process includes data collection, data preprocessing, feature extraction, model selection, model training, model evaluation, tuning parameters and hyper-parameters, and, finally, prediction.

Many different machine-learning algorithms can be selected, including supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, transduction, and learning to learn (Information Resources Management Association, 2020). Among them, supervised learning, unsupervised learning, and reinforcement learning are most commonly used. The objective of *supervised learning* is to build a relationship between input and corresponding output. Supervised learning can use regression for continuous data, and classification for discrete data types. It separates data into groups with similar characteristics. In contrast, *unsupervised learning* aims to investigate the underlying pattern in input data without any information from output data. It often uses clustering and principal component analysis techniques. Unsupervised learning primarily reduces dimensionality. *Reinforcement learning* uses algorithms that learn to interact with the environment with the goal of maximizing reward.

To investigate the relationship between inputs and outputs, supervised learning models can be built using algorithms such as support vector machines and artificial neural networks. Outputs can then be predicted by the model from different input datasets. Regression, which predicts quantitatively, can be used in many scenarios in the poultry industry. Felipe et al. (2015) predicted total egg production of meat quail using phenotypes such as BW, BW gain, egg production, and egg quality measurements as input variables. In their study, an artificial neural network performed better than other models. Artificial neural networks can capture complex relationships between covariates and the variable of interest. For broilers, a dynamic neural network could predict BW from environmental variables such as light, ventilation, humidity, and temperature (Johansen et al., 2019). The weight and behavior of broilers can be predicted by supervised learning algorithms using images

as input data (Mortensen et al., 2016; Li et al., 2019; Johansen et al., 2019). Supervised learning has many potential applications in the poultry industry, including egg grading, poultry catching, and environment control (Jaiswal et al., 2005; Omid et al., 2013; Soltani & Omid, 2015; Debauche et al., 2019). Binary and multiclass classification can predict discrete categorical output variables such as egg grades (Thipakorn et al., 2017), or identification of binary (yes or no) egg-laying events based on real-time BW and feeding data recorded by a precision feeding system (You et al., 2020). Morales et al. (2016) and Ramírez-Morales et al. (2017) used supervised machine learning to detect egg production problems early by analyzing egg production curves. In these studies, problematic days were manually labelled by experts to train supervised machine-learning algorithms.

Although machine-learning applications for poultry management and reproduction have been studied, few applications in poultry nutrition have been reported. Despite this, machine learning has a lot of potential in smart poultry nutrition. Nutrition is particularly complex because of the vast number of nutrients whose dietary levels have many potential interactions. Study designs cannot handle this complexity using a systematic factorial approach because a factorial design increases in an exponential manner with each additional nutrient and each additional nutrient level that researchers wish to study. Classical statistical models have been limited to investigating a limited number of variables simultaneously. In contrast, machine learning is good at dealing with a large number of variables in the presence of complicated nonlinear interactions and would be a valuable tool for researchers in poultry nutrition. Unfortunately, the livestock nutrition community as a whole lacks the training and experience to pursue this approach to discovery.

8.7 The Future of Smart Poultry Nutrition

The ultimate goal of smart poultry nutrition is to provide the exact nutrients required by each individual animal at the precise time that they are required. This field is in its early days. Its focus is currently on using data more effectively, and it is fueled by sensor data collected by precision livestock farming and precision feeding systems. Fortunately, capture of such data is increasing rapidly in quantity and diversity in research and commercial settings. In the poultry industry, there is increasing application of sensor technologies, primarily in the environmental control space. To date, there are no commercial precision feeding systems that could actually implement smart poultry nutrition decisions at the level of the individual bird. A lot of research and development is still needed to realize the potential of the growing amount of big data available. Per animal level research will need to quantify nutrient responses not only to individual nutrients, but predict complex animal responses to many nutrient-level interactions. Integrative research is needed to better understand the effects of nutrient intake on the metabolism of individuals in different stages of growth, development, and production, and then link that information to feed formulation strategies that will optimize economic, animal welfare, and environmental objectives given dynamic market conditions. It is imperative that nutrient sensing systems such

as NIRS be integrated in real-time to minimize the guesswork around available nutrient levels in feedstuffs, to ensure accuracy in diet formulation. Feeds will most likely need to be formulated for blending so as to provide a continuum of potential rations to meet the nutritional needs of each individual bird, and of course cost-effective precision feeding systems that implement feeding decisions in real-time will need to be developed and deployed.

This research will require investment not only by the poultry industry, but also by national and regional governments because of its importance for food security and the need for the new knowledge to exist in the public domain. There is an imminent need to produce more food for the world's growing population, and we must find a way to do this on an existing arable land base, with minimal negative environmental impact. The amount of data from a growing number of sensors and sensor types will grow exponentially in the near future. These big data, from both research and industrial sources, can and should be integrated to refine and improve smart poultry nutrition systems in real-time. The challenge ahead is complex, and nutritionists will need new skillsets that will come from formal training in mathematical biology and computing science in addition to the more traditional fields of nutrition, biochemistry, physiology, management, and health. To realize the benefits of smart poultry nutrition, machine learning and other forms of artificial intelligence will undoubtedly play an increasing role.

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Advanced Technology in Aquaculture – Smart Feeding in Marine Fish Farms

9

Martin Føre, Morten Omholt Alver, Kevin Frank,
and Jo Arve Alfredsen

Abstract

In this chapter, we discuss how digital tools can be used to achieve more intelligent feeding and nutrition in commercial cage-based farming. Using farmed salmon as a model species, we first outline industrial practices in cage-based farming, and then present the state-of-the-art in how digital technologies are being utilized in aquaculture research and industry. We then discuss how the intelligent feeding methods of the future could be devised based on the current state-of-the-art, and further how these could potentially be important for ongoing industrial developments toward new production concepts for fish farming.

Our findings show that many of the digital components required to realize intelligent feeding systems in commercial fish farms are already in place, or under development. It is thus already possible to start combining existing systems into new technological solutions that improve our ability to monitor, adjust, and optimize the feeding process in aquaculture fish production. This is the focus of several ongoing research efforts that aspire to apply the principles of precision fish farming. A similar trend is also present in the industrial sector, manifested through the rapid growth in the portfolio of commercially available products for feeding optimization in aquaculture.

Keywords

Fish farming · Smart fish nutrition · Feeding technology · Precision fish farming · Atlantic salmon · Aquaculture · Intelligent fish feeding · Sustainable fish farming ·

M. Føre (✉) · M. O. Alver · J. A. Alfredsen

Department of Engineering Cybernetics, NTNU (Norwegian University of Science and Technology), Trondheim, Norway

e-mail: martin.fore@ntnu.no

K. Frank

SINTEF Ocean AS, Trondheim, Norway

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Biosensors · Telemetry · Optical sensors · Hydroacoustic sensors · Mathematical fish modelling · Sensor fusion · Underwater robotics · Intensive fish farming · Marine fish farms · Feedback control · State estimation · Future methods for fish farming

9.1 Introduction

This chapter focuses on digital applications within fish farming in the context of smart fish nutrition. Our definition of digital technology here includes any type of instrument, sensor system, apparatus, or vehicle designed to aid humans in conducting monitoring and actions otherwise done manually. Moreover, we also consider computer systems, mathematical models, and other theoretical constructs intended to replace or support human analyses of a particular situation. As the term implies, the common denominator in the tools, systems, and methods we will cover is that they are rooted in technological and highly digitized areas of science such as computer science, embedded systems, control engineering, and artificial intelligence. We do this in the firm belief that such tools will be essential to achieve the dual goal of enabling growth in the fish farming industry while ensuring that production is efficient, ethical, and sustainable.

The combined effects of an increasing world population, a dwindling access to unexploited arable land suitable for farming, and the capture fisheries industry approaching the upper limits for sustainable capture rates have led to an imbalance in that while the need for human foodstuffs increases, the potential for increased production through the conventional food-producing sectors decreases. Aquaculture needs to have a role in closing this gap and is often highlighted as a main component in finding a solution enabling a steady food supply for a growing human population.

Modern aquaculture has become a cosmopolitan industry that extends from extensive rearing where most of the production is determined by the ambient environment to intensive production where nutrition supply and other key elements in the production environment and conditions are under human control. Production currently includes more than 100 different species of animals and plants, reared in production units ranging from indoor tanks through semi-natural ponds to marine sea-cages, in either freshwater, brackish water, or sea-water environments.

The 2017 global production of aquatic plants, various types of finfish, shellfish, crustaceans, and other aquatic animals amounted to 112.000 kilotons in total (Fig. 9.1). Of this, freshwater fish (predominantly carps, barbels, tilapia) constituted almost 40%, followed by plants (e.g., brown, red, and green seaweeds 28%), mollusks (e.g., clams, oysters, mussels 15%), crustaceans (e.g., shrimps, crayfish, crabs 7.5%), diadromous fish (e.g., salmonids, eels, sturgeon 5%), marine fish (e.g., sea bream, sea bass 2.5%), and miscellaneous animals and animal products (<1%).

Although this is an order of magnitude lower than total terrestrial agricultural production volumes (more than 5.200.000 kilotons in total cereals, fruit, vegetables,

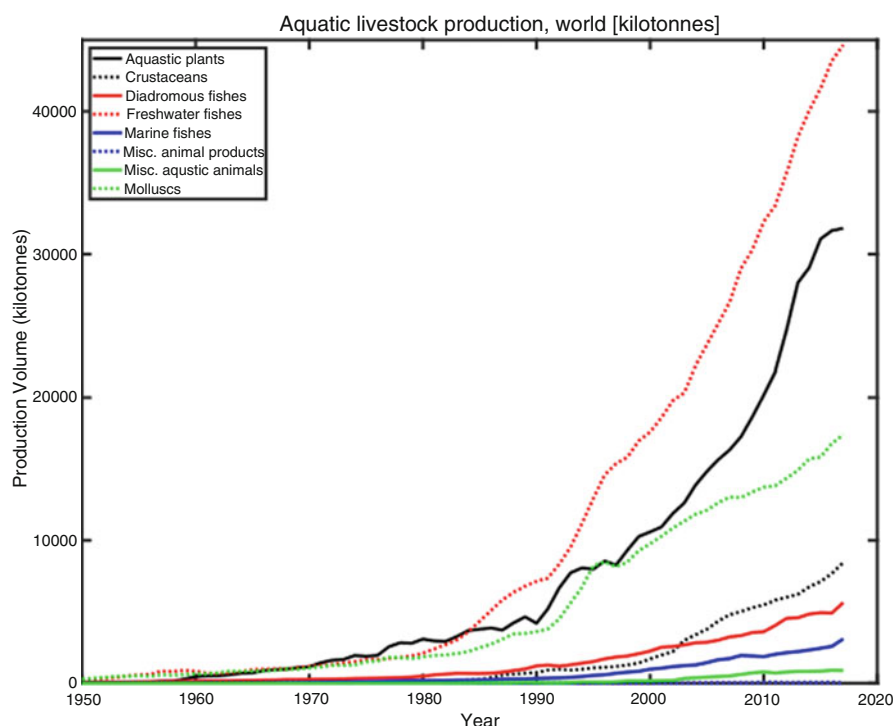


Fig. 9.1 Annual global aquaculture production of aquatic organisms divided into species categories for 1950–2017. All numbers are retrieved from the FAO Fisheries and aquaculture statistics website (FAO, 2020a)

and livestock), comparable numbers are found when the focus is limited to animal-based production (Fig. 9.2).

Trends in production volume seen over the last decades clearly show that fish production is increasing faster than other livestock production (with a possible exception of chicken). Moreover, breaking down terrestrial livestock production into the “big four” (i.e., cattle, pig, chicken, and sheep) reveals that aquaculture production of fish is closing in on cattle production in terms of volume, while shellfish and crustacean production surpassed sheep production in the mid-nineties. All these factors imply that aquaculture is already cementing its position as a cornerstone in providing animal protein for human consumption.

9.1.1 Scope and Structure

We set out to explore how advanced technology can be applied to feeding in aquaculture to ensure efficient, sustainable, and welfare and health promoting fish production. To limit the study to a manageable scope for a book chapter, we have

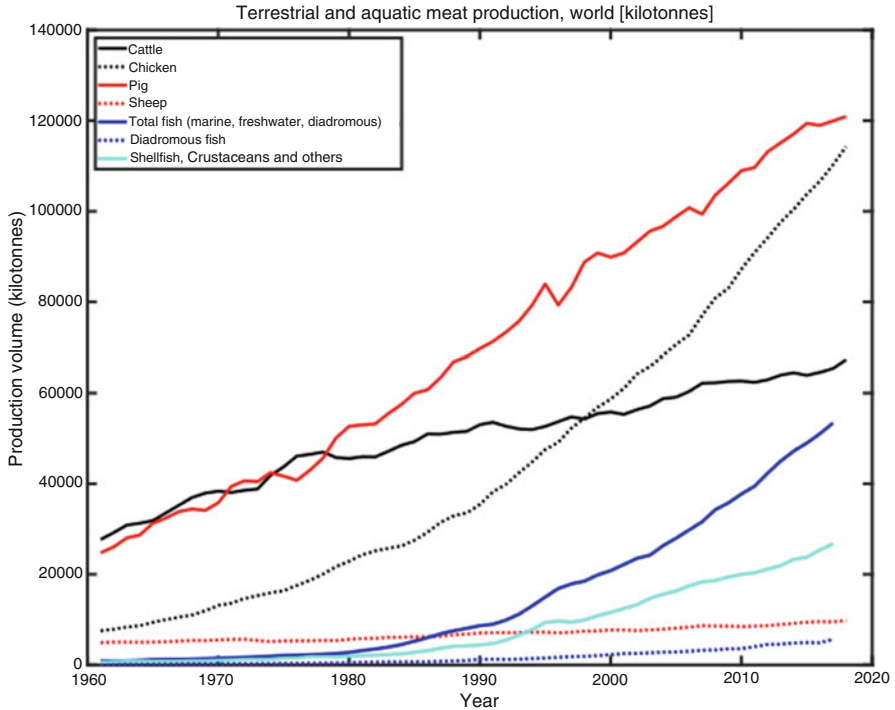


Fig. 9.2 Comparison of different meat production sectors in both terrestrial and aquatic environments for the world in total. All numbers are retrieved from the FAO statistics websites for fisheries and aquaculture (FAO, 2020a) and agricultural production (FAO, 2020b)

focused on Atlantic salmon as a model species, and on the on-growing phase where proper feeding and nutrition have the largest impact on both farming economy and sustainability.

While Sect. 9.1 provides a generic view on aquaculture production in the world, Section 9.2 contains an overview of the salmon industry and current farming practices, with a particular focus on feeding. Section 9.3 is focused on how digital technology can be used to augment and improve current feeding practices, while Sect. 9.4 finalizes the study by exploring the role digital technologies will play in the future introduction of new methods for feeding fish in aquaculture.

9.1.2 Choosing a Model Species: Sea-Based Atlantic Salmon Farming

Statistics show that the greatest aquaculture production is freshwater based, particularly through herbivorous species such as carp and tilapia. It could hence be considered natural to choose a species in either of these groups as a model when

talking about aquaculture production of fish. However, the production of such species generally occurs in extensive or semi-intensive production systems, rarely requiring the use of high-technology solutions. For instance, much of the global carp production is conducted in ponds where they feed on aquatic plants, and thus do not need humans to actively supply them with nutrition. This is a setting where technologically advanced feeding systems or protocols would be unnecessary, a notion that is also underlined by the fact that the most common species farmed in freshwater often attain low prices at markets, rendering the economic potential for investments into new technologies lower.

Although intensive farming of predatory fish is arguably less sustainable than more extensive farming of herbivorous fish, the meat attains much higher price in international markets. The higher price is linked with a higher production cost, and one of the key challenges in intensive fish farming is to provide the fish with proper amounts of feed, at proper times of day, and with the right type of nutrient composition to ensure good growth and healthy animals.

Atlantic salmon (*Salmo salar*) is one of the most successful species in intensive fish farming, with around 2.4 mill. tons produced globally in 2017 (FAO, 2020a) and the entire value chain now being industrialized. The ongrowing phase of salmon production is most commonly conducted in marine fish farms, predominantly located at higher latitudes that offer the environmental conditions salmon are naturally adapted to. Several of the major salmon-producing countries (e.g., Norway, UK, Canada) are considered high-cost countries where labor costs tend to dominate the production costs in most industrial segments. To still be profitable in these countries, the salmon industry has therefore developed toward larger production units (i.e., larger cages with more fish in each) and an increased usage of technological solutions to control and automate segments of the production process. This has been a successful recipe, as is evident when comparing the production numbers for diadromous fish (mainly salmon) with other livestock production volumes in Norway (Fig. 9.3).

In this setting, Atlantic salmon serves as a good model species from aquaculture in being the most technologically advanced form for aquatic livestock production, and also representing one of its industrial success stories. In conclusion, one may summarize the reasons for salmon as one of the most suitable model species as followed:

1. Salmon is a high-value species with high profitability.
2. The salmon industry has a large global production volume.
3. Salmon is produced in large production units and with a relatively high level of automation.
4. The industry has a high technological development rate (e.g., many new production concepts being tested in Norway).
5. Production optimizations have potentially large positive impact on sustainability.

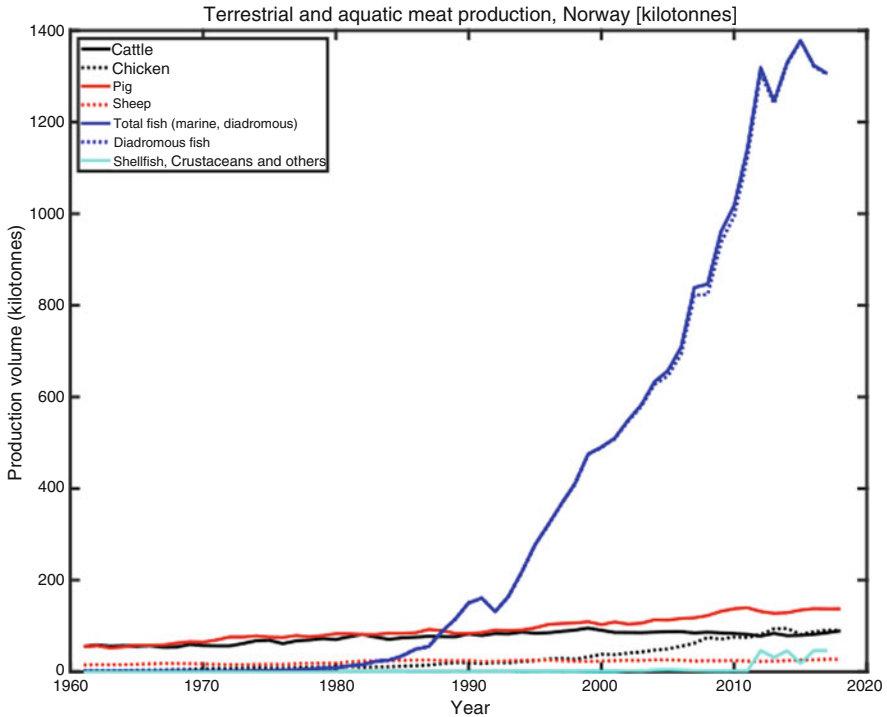


Fig. 9.3 Comparison of different meat production sectors in both terrestrial and aquatic environments for Norway divided into species categories for 1950–2017. All numbers are retrieved from the FAO statistics websites for fisheries and aquaculture (FAO, 2020a) and agricultural production (FAO, 2020b)

9.2 Intensive Cage-Based Aquaculture of Atlantic Salmon

9.2.1 The Natural Life Cycle of Atlantic Salmon

The life cycle of the anadromous *Salmon salar* (further called only salmon) begins with fertilized eggs being hatched in the gravel beds of rivers and streams, whereupon they live as yolk sac larvae for 3–8 weeks (Aas et al., 2010). After the yolk sac has been consumed, the fry needs to learn how to forage to achieve the nutritional input required for them to grow and develop. Soon after starting to feed, the fry will develop into the parr stage, thereby adapting a more camouflaging coloration allowing them to blend better together with their surroundings, rendering them less susceptible to predation and more efficient as hunters. They spend up to 1–8 years as parr in their native stream, before going through a process called smoltification, where their endocrine system and physiology is altered from being adapted to living in freshwater to tolerating saltwater. Once this change is complete,

the fish change from being negatively rheotactic (i.e., swimming against the current to maintain their position in a stream) to exhibiting positive rheotaxis (i.e., moving with the current toward the sea). Meanwhile their skin changes into a silvery hue and finish better accustomed to a pelagic life at sea.

After arrival into the sea, the salmon migrate from their native coastline and into the open ocean where they spend their ongrowing period that may last several years. Although less is known about the lives of Atlantic salmon during this phase, it is apparent that they use this time to forage and grow in preparation for their final life stage wherein the fish return to their native stream to reproduce (Aas et al., 2010).

9.2.2 Current Practices in Aquaculture: From Egg to Market

9.2.2.1 The Salmon Production Cycle

The aquaculture production cycle for salmon starts with the harvesting of eggs from broodstock fish. These fish are typically large individuals with a specific genetic makeup that has been developed through targeted breeding selecting for desirable qualities such as rapid growth, disease resistance, and low aggression. The eggs are then fertilized and incubated in vats at hatcheries, which are facilities specifically aimed at hatching salmon fry, which are then reared in tanks to allow them to swim freely. When the yolk sac is consumed, the salmon fry are immediately weaned onto a diet of formulated dry feeds, and are then reared as parr in freshwater until smoltification. Growth and time to smoltification are accelerated through active light and/or temperature manipulation. The fish are then transferred to the sea, where the majority of the ongrowth is achieved through intensive feeding. Although this phase is most commonly conducted in marine sea-cages, there is an increasing tendency toward keeping the fish longer in the land-based facilities, mainly to reduce the extent of time where the salmon are exposed to lice infestations or to better control the production environment during earlier ongrowth stages. After a period typically lasting around 18 months, the fish have reached a marketable weight of around 5 kg, and are then slaughtered, processed, and shipped to markets for sale, either as pure fish meat or as derived products.

Through all phases between weaning and slaughter, the farmer's ability to provide the fish with the right type of nutrition, at the right times and in the right amounts, is a key success factor.

9.2.2.2 Main Industrial Challenges

Intensive salmon aquaculture first arose during the 1970s in Norway as small-scale production conducted in wooden cages. Since then, the industry has grown rapidly, driven by both a generally increasing demand for seafood in a growing middle-class population and increasing demands for fresh fish in international markets. As the industry has grown in volume, so have the challenges within areas such as animal health and welfare, environmental impacts, sustainability, health safety and environment (HSE), and economy. Together with ectoparasites (e.g., sea-lice), pathogens, and escapes, inefficient nutrition is one of the most important single challenges

facing the industry today, much due to its impacts across several areas. For instance, overfeeding leads to direct economical waste and eutrophication of the near environment, but may also attract wild fish that can act as vectors for diseases/parasites to wild fish populations. Conversely, underfeeding will reduce fish growth and hence economic gain, but may also impair fish welfare and health. Using new digital methods to achieve intelligent nutrition and feeding in aquaculture can thus contribute to making the industry more economically and ethically sustainable through several different pathways.

9.2.3 Fish Growth: The Core Process in Intensive Fish Farming

While the hatchery-based phases conducted in freshwater mainly aim to provide the fish with an early life history that through proper nutrition promotes good fish health and proper development through the rest of the production cycle, the main aim of the sea-based ongrowing phase is to make the fish grow as quickly and efficiently as possible, essentially by converting feed into high-quality fish.

The main factor behind fish growth in intensive aquaculture is the ability of the farmer to ensure that the fish receive the feed in proper quantities and are able to ingest and assimilate it. Moreover, it is of key importance in this phase (as in all preceding phases) to ensure that the nutritional composition of that feed matches the requirements of the fish (Ytrestøyl et al., 2015; Glencross, 2020). Providing the fish with sufficient feed at the proper time intervals also helps avoid impaired welfare effects and keep growth rates sufficiently high.

Growth rates of salmon in sea-cages also depend on the prevailing environmental conditions at the site. While factors such as temperature and oxygen affect growth rates by modulating metabolic processes, other factors such as water current and waves may induce physical effects that induce responses in the fish that may lead to increased energy expenditure at the cost of somatic growth. Unwanted events such as diseases and parasite outbreaks are also known to impact growth negatively both in the short and possibly long term. Farming operations may also affect fish growth, either directly through, for example, starvation periods prior to delousing operations or transfer of fish between cages, or indirectly due to reduced appetite caused by increased post-operation stress levels.

The fish growth process has several effects on both the local and the global environment. Such impacts may be direct, as is the case with feed loss and excretion of feces to the local environment. Both these nutrient pathways may have a nitrifying and eutrophication effect on local primary production, as well as impacts higher in the trophic system in that feed spills tend to lead to aggregations of wild fish near or beneath fish farms (Dempster et al., 2009; Sanchez-Jerez et al., 2011). Such aggregations of wild fish contribute to dispersing the nutrient flow between fish growth and the environment more widely among the trophic layers. However, they may also represent an added risk factor for the dispersal of diseases among wild and farmed fish.

In salmon farming, and most other forms of intensive aquaculture, feed represents the largest single cost. Specifically, the feed consumed in the on-growing phase represents up to 50% of the total production costs of a salmon fillet (Fiskeridirktoratet, 2020). Suboptimal feeding thus has obvious economic consequences for the farmer in either reducing growth resulting in longer production cycles (underfeeding) or increased spills (overfeeding). However, overfeeding in fish farming also has global impacts as many of the resources used in fish feed, fish meal, and fish oil in particular are global commodities that are becoming increasingly scarce due to overexploitation and competing claims from other industrial segments. Ultimately, this influences sustainability, also in areas far from the actual farming operation since many such resources are harvested in other parts of the world. For instance, much of the fish meal and fish oil used in feed for European aquaculture may be produced from fish captured off the coast of South America, meaning that the impacts of the production process extend well beyond local conditions. Because of these challenges, the fraction of marine ingredients in Norwegian salmon feed decreased from 90% in 1990 to around 30% in 2013 as marine ingredients have been replaced with plant resources such as soybeans, sunflower and wheat for protein, and rapeseed for lipids (Ytrestøyl et al., 2015).

9.2.4 The Feeding Process: From Factory to Fish Gut

The feeding process in commercial salmon farming is built up as a chain of steps from the assembly of the feed components until the pellets are ingested and assimilated by the fish (Fig. 9.4). Each of these steps entail certain elements that are relevant to consider when discussing digitization of fish feeding. In the following, we will give a brief account of these elements.

9.2.4.1 From Raw Materials to Feeding Barges

Fish feed production is done in large factories typically placed in proximity of other marine industries (e.g., fish processing plants), or logistical hotspots (typically harbors), to ensure good access to raw materials. The first step in producing formulated feeds for salmon farming is to select exactly which raw materials are needed and at which proportions these should be mixed. Water is then added to the mixture to create a “dough” that is usually extruded into cylindrical pellets and dried. These processes need to be well balanced to ensure that the pellets are hard enough to be transported without excessive breakage and heavy enough to sink once delivered to the cage, while also being possible for the fish to digest efficiently.

Once the pellets are produced and ready to ship, they are packed for transport, either by loading into 1000 kg sacks for further transport via trucks and boats or by direct loading into silos in feed transport ships. While trucks are still used to deliver feed to smaller sites located close to shore, most modern commercial sites are served by feed delivery ships. These ships may hold up to about 3000 m. t. of feed and may serve several locations while they travel along the coast. Feed is then pumped directly from the silos onboard the ship to the silos at the feeding barge at the site.

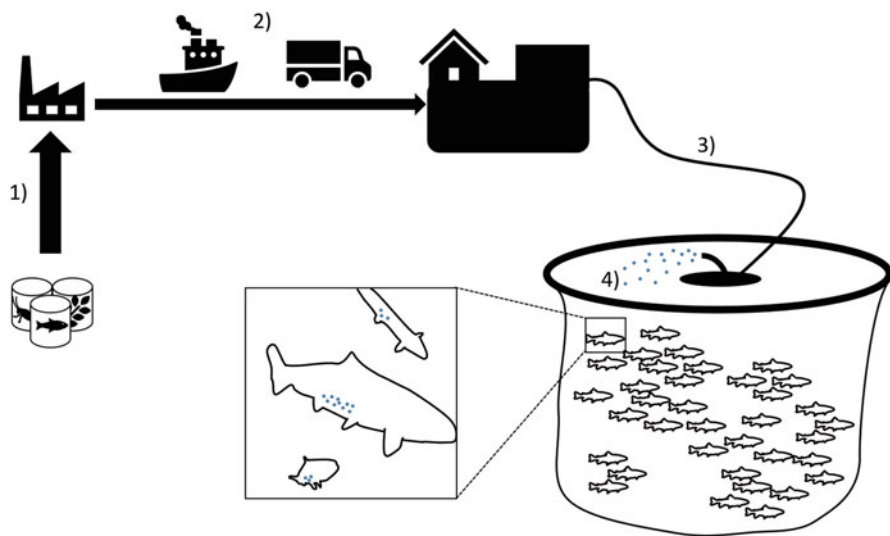


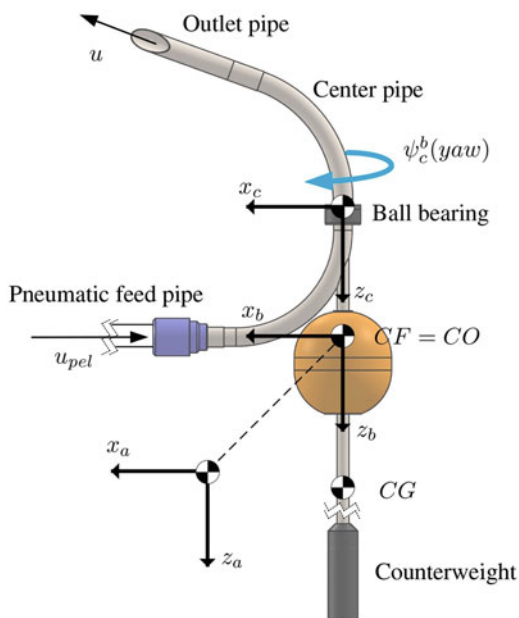
Fig. 9.4 Illustration of the basic pathway of feed in intensive salmon farming. (1) transport of raw materials (e.g., fish meal, soy meal, insect meal), (2) transport of extruded pellets to feeding barge with ship/trucks, (3) delivery of pellets from barge to cage through feeding hoses, (4) distribution of pellets with feed spreaders, finally making the pellets available to the fish

A feeding barge may contain up to 600 m. t. of feed after delivery, which tends to last around 1 week when production peaks in biomass in a conventional farming site with 15×50 m diameter cages.

9.2.4.2 From Barge to Cage

In the earliest phases of cage-based salmon farming, the fish were manually fed using buckets and bailers. However, for further industrialization it was necessary to move from manual to automated feeding, leading to the advent of the automated feeding systems that are predominant in salmon production today. These systems consist of several components that are placed inside the feeding barge and that together ensure that the pellets are transported from the feed silos to the cages. Feeding is typically controlled by a human operating a computer program where macro-scale control signals such as the amount of feed per time delivered to each cage is provided. This information is then fed to a computer system typically running on a programmable logic control (PLC) unit, which through logics and control functions generates proper analog and digital output signals that are delivered to the feeding system components. The most essential of these components include the doser, which is a valve delivering pellets at a certain rate into a duct, and a pneumatic blower that generates air pressure in the same duct. The pressure accelerates the pellets into tubes attached to a unit called a cage selector. The cage selector acts as a multiplexer in the sense that it can divert the stream of pellets delivered from the

Fig. 9.5 Example of rotary feed spreader describing the various degrees of freedom and components in such a system. (Reprinted from Skøien et al., 2018, Copyright (2018), with permission from Elsevier)



ducts inside the feeding barge to one of several tubes (up to 700 m in length) each extending to an individual cage.

Although there exist underwater systems for delivering the feed into the cage, the most common method by far is to use rotary surface spreaders (see example in Fig. 9.5). These systems are designed such that flow of pellets induces a rotary motion on the nozzle, effectually spreading the pellets in an annular ring around the spreader. Although spreaders are often completely mechanical devices with no actuators or motors, the spreading pattern can be modified by adjusting mechanical settings such as the nozzle angle and diameter, or the surface position of the spreader inside the cage, as well as the air flow rate from the blower.

If pellets are improperly stored or the system is improperly designed in relation to the feed pellet properties, the barge-to-cage stage of the feeding process can lead to challenges such as pellet breakage, meaning that the pellets are crushed or disintegrated before arriving at the cage, or blockage, where pipes or tubes are clogged by pellets. Such events can lead to excessive feed loss and temporary unwanted up-time, both of which can have large economic consequences for the farmer and will contribute to rendering the operation less sustainable. Common measures to avoid such situations include avoiding sharp bends in pipes or tubes, carefully adjusting the feed amount relative to the pneumatic pressure, avoiding too high or low pressures or sending brushes through the system to clean the pipes. Another potential challenge that may arise at this stage is uneven or unpredictable feed distribution patterns upon delivery to the cage. This may ultimately influence both productivity and fish welfare in that it is then more likely that disparities in feed intake and competition between individuals/groups in the cage may arise. Such

effects may ultimately result in reduced well-being and growth, as it is more difficult to ensure that they are provided enough nutrition to support their needs in growth and maintenance.

9.2.4.3 From Surface to Fish

Once the feed is released into the cage, the distribution is outside of human control and more at the mercy of the prevailing conditions at the site. Firstly, when being propelled from the nozzle, the pellets are susceptible to wind-driven effects that may alter their course before hitting the water surface. If the wind is very strong, this may even lead to pellets hitting outside the cage, which can to a certain extent be countered by reducing the pressure generated by the blower to allow the feed to land closer to the spreader. Once in the water, the hydrodynamic properties of the site come to play in determining the fate of the pellets. Whereas wave activity can also contribute to a certain drift and movement, especially for feed with low sinking rates, water current is the most important factor behind underwater pellet distribution. If sufficiently strong, currents can transport the pellets out through the net wall before they get eaten, leading to feed waste. This type of feed loss can be more difficult to predict and observe than wind driven loss, since observation underwater is more difficult than in air, but can to a certain extent be countered by, for example, moving the spreader toward the upstream edge of the cage.

Although the feeding schedule for a specific cage is often derived from feeding tables using factors such as the assumed total cage biomass, average fish size and temperature as inputs, feeding is also dynamically adjusted based on perceived appetite and feeding behavior. In earlier days, this was mainly based on direct observation of the cage, looking at features such as surface activity and amount of fish seen close to the surface. The current industrial trend toward larger cage units has rendered this method less useful, as increased cage size means that a proportionally smaller proportion of the fish are visible from the surface. Common industrial practice has therefore now shifted to using submerged moveable cameras that are aimed at the feed delivery area. This footage is typically fed back to the person controlling the feeding computer software on the barge or at a remote land-based feeding center, who then interprets how actively the fish are feeding and can adjust the feeding rates accordingly.

Despite recent advancements in industrial practices related to feeding, the underwater phase of feed delivery remains the part of the delivery line that is most detached from human control. It is also likely that most of the feed waste experienced in intensive fish farming occurs in this phase. Together, these aspects imply that technological advancements enabling closer human control of feed during the final underwater phase of feed delivery are likely to have large impacts on the continued industrial success of salmon farming. Better feed control can aid us in ensuring that the nutritional situation of the fish is ensured while minimizing the economic consequences and ecological/environmental footprint of the operation. Essentially, it can help us approach the ideal where all pellets are eaten by fish, and where all fish are able to find pellets when hungry.

9.2.5 Developmental Trends and New Concepts for Modern Fish Farming

An increased scarcity in near shore locations suitable for conventional cage-based salmon production is currently restricting the industrial growth in Norway. Fish producers have therefore begun to explore the possibilities of developing new concepts that can exploit previously unsuitable sites (e.g., due to environmental exposure or limited circulation) or be placed on land. This development is further stimulated by the introduction of the development permit scheme, where farmers can apply for additional production permits if they develop new concepts that are designed to specifically tackle the sustainability challenges in fish farming, especially where ectoparasites and pathogens are concerned. Since permits for salmon production have become increasingly hard to come by and expensive (often priced at more than \$10 M each), this has led to a significant increase in the development of new concepts.

Motivated by the benefits of moving to more exposed sites (Bjelland et al., 2015), many of these concepts are designed to handle higher degrees of exposure to waves, winds, and currents than traditional fish farms. These concepts range from upscaled cylindrical cages, either featuring a single larger production volume (e.g., Ocean Farm 1 by Salmar/Ocean Farming) or several sub-volumes within the same structure (e.g., Mariculture by Salmar/Mariculture) to ship-based designs with several inline production units (e.g., Havfarm by Nordlaks/NSK Ship design). However, they all have in common that they are built using principles from offshore-related industries such as oil and gas, and are hence built using steel and other rigid materials. Other new concepts developed in response to this arrangement are more similar to conventional cages in size but have specific properties designed to cope with one or several of the major challenges in fish farming. Some of these aim to achieve better control of the fish on an individual level (e.g., iFarm by Cermaq/Biosort). A third class of new emerging concepts are more specifically aimed toward limiting the contact between fish and parasites/pathogens by featuring semi-closed or fully closed production volumes.

9.3 Using Digital Technology to Improve Aquaculture Feeding Practices

In the aquaculture industry, automation and the application of technology has not reached the same level as seen in traditional industry production. This is probably partly because the industry has enjoyed high profit margins of late, reducing the need for increased production efficiency, but also because biological aspects such as behavior and genetics render a fish population in a sea-cage a highly complex system that may be more difficult to control than systems encountered in other industries. Zhou et al. (2018) reviewed methods and technologies for intelligent feeding control in aquaculture, outlining several of the components and tools currently available in research and industry. One of the main statements in that study was that the

assessment of fish appetite, feeding behavior, and growth are important fundamentals for realizing intelligent feeding algorithms (Zhou et al., 2018).

9.3.1 Precision Fish Farming: A Framework for Applying Digital Technology to Intensive Fish Farming

While Zhou et al. (2018) focused on aquaculture finfish production in general, we will in the following limit our focus to solutions potentially applicable to cage-based intensive production of marine fish. The structure of this technological review will be built upon the principles outlined in the precision fish farming (PFF) concept (Føre et al., 2018a). Precision livestock farming (PLF) is a term used to describe the introduction of technology and automation principles to better monitor the bioresponse in and assert control over livestock production (Berckmans, 2006). Over the last decades, PLF has received increased attention from the agricultural industry and research communities, a trend partly driven by technological development and a need for more efficient production. PFF is a recently introduced framework for adapting similar methods to fish production (Føre et al., 2018a). The coining of the term PFF was motivated by a need to formalize a framework for how technology and automation principles can be introduced to improve aquaculture operations while taking the biological premises into account. As the name implies, much of the philosophy behind PFF was adapted from PLF, but the initial seeds for the concept were sown even further back in time by the pioneering work of Jens G. Balchen and associates at the Norwegian University of Science and Technology (NTNU) and Stiftelsen for industriell og teknisk forskning (SINTEF) in the 1970s (Balchen, 2000).

Most work operations in the intensive salmon farming industry are still based on manually controlled mechanized or manual actions, and experience-based interpretation and decision making. Although the profit margins in the industry have been high for decades reducing the economic incentive for changes in how work operations are conducted, production challenges tend to scale with the size of the industry. It is thus unlikely that such labor intensive, manual processes will be sufficient for the future format of salmon farming.

While it is apparent that technology and automation play a role in improving this situation, envisioning a complete technological system able to handle an entire operation may be a daunting task due to all the sub-challenges and minor tasks that need to be considered. The PFF-idea acknowledges this by proposing that all operations in fish farms can be seen as a cycle of phases, starting with *Observing* the fish, then *Interpreting* the fish state from the observations, then *Deciding* a course of action, and finally conducting the chosen *Action* (Fig. 9.6). Finding technological solutions for handling the subtasks within each phase is easier than finding a holistic solution covering an entire operation. Conversely, the division into phases can also help technology providers to analyze how their products or services could be used in the industry. In sum, this means that the PFF framework can be used both as a guideline for fish farmers how to stepwise automate specific operations, and for

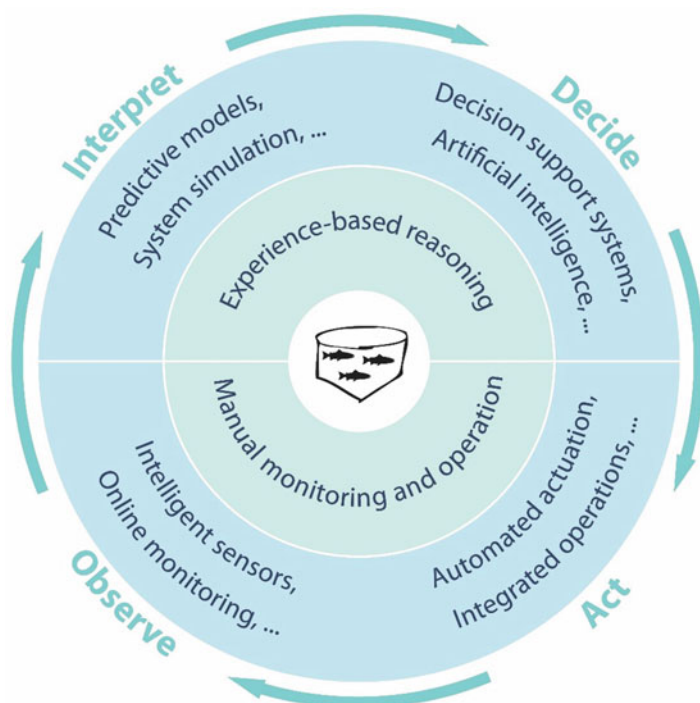


Fig. 9.6 The Precision Fish Farming (PFF) concept explained by describing the proposed transition from manual and experience based (inner green ring) to knowledge based and automated processes (outer blue ring) in the four cyclical phases of an operation (Observe, Interpret, Decide, Act). Green arrows denote the transitions between the phases. (Reproduced from Føre et al., 2018a, under CC BY license)

technology providers to see potential roles for their specific products within farming operations.

PFF can thus be used as a framework to help analyze how we can achieve more intelligent and optimized feeding in fish farming using technology. The first step of this process is to identify which indicators should be the output of the observe and interpret phases, and input to the decide phase. For the feeding process, feeding motivation might be the key indicator. Feeding motivation is known to affect fish behavior and depends on the physiological condition of the fish, suggesting that behavioral properties and physiological parameters known to be interlinked with appetite could be a place to start. The second step in the analysis is to assess the existing knowledge about the system and its dynamics, and eventual existing mathematical models that incorporate this knowledge. Models portraying behavior and physiology are clearly relevant when focusing on feeding. In addition, models portraying various aspects of feed delivery and distribution should be considered, as these can be used to describe feed availability and encounters between feed and fish, which are crucial factors when describing feed intake. It would then be natural to

evaluate the possibility of integrating or assimilating the observational data from sensors into the mathematical models to obtain a more reliable and complete estimate of the states in the cage and enable the derivation of precise estimates of appetite.

In the long run, it is also reasonable to assume that the actual feeding might become a feedback controlled automated process rather than being manually (or open-loop) controlled. This implies that a third step in the analysis should identify technology for closing the loop through, for example, automated feeding systems or vehicles.

9.3.2 Intelligent Sensors and Instrumentation: From Data to Information

9.3.2.1 Aim: Quantifying Key Properties in the Feeding Process

The first step in asserting control over an industrial process is to acquire the means to continuously measure the states of the process and their development over time. This implies a need for a reliable stream of data from sensors that describe the process objectively with sufficient accuracy. In intensive marine salmon aquaculture, the process of interest is the condition and development of the fish biomass inside the cages. Traditional measures for assessing the states of this process are largely limited to the subjective evaluation of fish states and behavior either through direct observation from the surface or through submerged video cameras. Achieving intelligent feeding in aquaculture therefore calls for the increased application of technology to objectively quantify how the fish look and behave. Most existing methods for monitoring fish underwater are based on optical or acoustic principles, ranging from local assessments using cameras, through wide range monitoring using echo sounders/sonars, to individual-based methods such as biosensors and telemetry (Fig. 9.7).

9.3.2.2 Optical Methods Research Frontier

Throughout the history of aquaculture, humans have mainly relied on their visual sense to collect information on how the fish are performing under culture. It thus follows that the most intuitive approach to acquiring objective and continuous information on cultured fish lies in applying technology that targets the same visual cues that are used in conventional manual monitoring.

Manual analyses of fish in sea-cages using optics has long been an established method in research, often in the form of short-term observations of random individuals (Oppedal et al., 2011), either as a supportive tool (e.g., Føre et al., 2011) or as a main source of information (e.g., Korsøen et al., 2009). Cameras have been used as a tool to assess feeding in farmed salmon. One early example of this was published by Kadri et al. (1991) who used cameras to manually assess movement speeds and patterns of salmon in a small sea-cage and linking these with

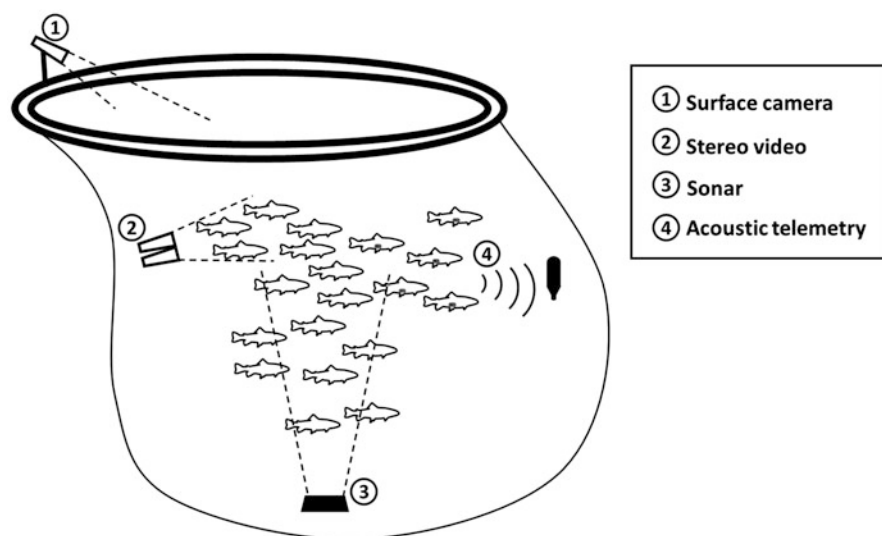


Fig. 9.7 Examples of existing monitoring tools applicable to cage-based fish farming. (Reproduced from Føre et al., 2018a, under CC BY license)

appetite. Further studies from the same research group later investigated aggression and response frequency toward feed in parr using similar methods (Kadri et al., 1997). In a similar study, Blyth et al. (1993) used cameras to relate feed intake with swimming speed in salmon.

With the advent of machine vision and other computer-based post-processing methods, the possibilities for quantifying various features of farmed fish based on camera footage increased drastically (Zion, 2012; Saberioon et al., 2017; Yang et al., 2021). The number of different methods and techniques applied in this area increases rapidly, and today includes a wide variety of different approaches including stereo-video for 3D monitoring of motion (e.g., Torisawa et al., 2011) or size (e.g., Lines et al., 2001), using entropy and fractal analyses to detect anomalous behaviors (e.g., Eguiraun et al., 2014) and using spectral analyses of hyperspectral images to determine skin condition and dietary composition (e.g., Saberioon et al., 2019). Further, while most studies are conducted using submerged cameras, there are also examples of studies using elevated cameras, for example, by running aerial photos of a cage through processing methods based on support vector machine (SVM) (Jovanovic et al., 2016) or deep learning networks (Jovanovic et al., 2018) to assess surface activity.

Some recent studies within this area have also targeted feeding behavior in cage-reared fish (see An et al., 2020 for a review of some of the commonly applied principles and methods). In a more applied study, Måløy et al. (2019) were able to distinguish the feeding behavior of salmon from other behaviors using deep learning methods applied to three different types of convolutional neural networks (Fig. 9.8). Since the authors of that study used a conventional mono-camera to collect their data

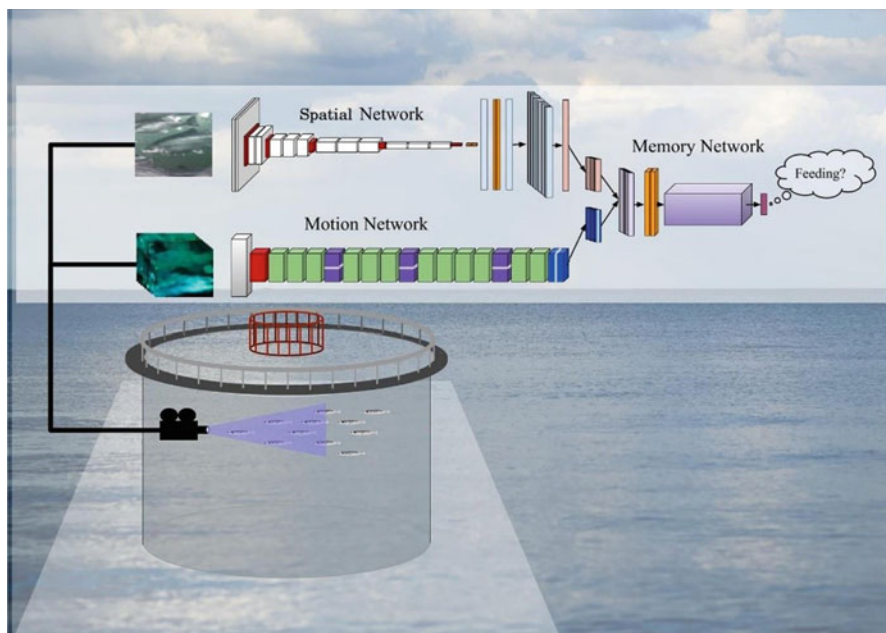


Fig. 9.8 Example from Måløy et al. (2019) on how deep-learning methods can be used to predict feeding behavior in farmed salmon. The approach collects data from a cage using a submerged camera and analyses both spatial distribution and motion in the footage. Outcomes from these analyses are then fed into a dual-stream recurrent network that makes the predictions. (Reproduced from Måløy et al., 2019, under CC BY license)

during the darkest period of the year, their success illustrates the potential of using methods from AI to acquire information on fish states even for sub-optimal data streams. Similar methods have also been used to assess feeding activity in indoor tanks (Liu et al., 2014; Zhou et al., 2019).

Machine vision methods have also been applied to study the physical aspects of the feeding process in fish farming, including the delivery of pellets to the cage volume and distribution of pellets within the cage volume. Although most assessments of pellet distribution on the cage surface have been based on manual sampling, Lien et al. (2019) developed machine vision methods for automatically detecting the splashes occurring when a pellet ejected from a feeder hits the water surface. They applied these methods to video footage obtained with an aerial platform hovering above a sea-cage to investigate the surface pellet distribution patterns produced by different spreader types and configurations. There have been more machine vision studies targeting underwater pellet distribution, probably because manual assessment of this phenomenon is more difficult than it is above the surface. An early study aspiring to detect and quantify underwater pellet distributions was published by Foster et al. (1995), using illumination that rendered the pellets as white objects in the video footage. By developing an algorithm that

detected white objects against a dark background, they were able to count pellets automatically. In a later study, Parsonage and Petrell (2003) used an upward facing camera and more advanced filtering to identify feeding pellets in salmon cages, effectually resulting in more robust detection, especially in the presence of fish and other objects in the footage. Skøien et al. (2014) had a different approach to assessing underwater pellet density. Through machine vision coupled with Kalman filtering and kinematic prediction of pellet trajectories, they achieved a higher accuracy than other studies, albeit at the cost of a larger and more complicated instrument.

Industrial Applications

Considering the ongoing rapid developments within computers and camera technology, it is no surprise that machine vision applications is one of the most technologically advanced areas within the aquaculture industry. The hardware required to realize a machine vision system has eventually become rather low cost, and the potential gains of applying intelligent algorithms to derive objective information from the images is therefore comparatively very high.

There are also products that use optical methods to automatically assess factors such as feed waste, feeding behavior, and biomass development, and use these to derive decision support data for the farmer.

9.3.2.3 Acoustics

Research Frontier

While electromagnetic waves such as light and radio signals are heavily attenuated in water, acoustic waves (or sound) travel and propagate much more efficiently in the wet element than in air. This is a phenomenon that has enabled marine animals, mammals in particular, to use sound for long range underwater communication, and that has led to major industrial innovations founded in acoustics in fisheries and other sectors such as defense technology, geophysics, and oil and gas. Acoustics are also well suited for acquiring data in fish farms, especially when turbidity, cage size, and population density are at levels rendering optical methods less effective due to limited visual range and obstruction of the visual field.

Acoustic monitoring methods can be divided into active and passive methods. Active acoustic devices emit acoustic pulses toward the region of interest and then actively listen for reflected acoustic energy from objects intercepting in the beam. Although much of the basic development within active acoustic devices has targeted other areas such as defense applications (e.g., Avera et al., 2002), seabed mapping (e.g., Barnhardt et al., 1998), and seismic surveying for oil and gas (e.g., Waters, 1981), considerable effort has also been put into developing such devices specialized for detecting fish in relation to capture fisheries (e.g., Rose et al., 2005) and stock monitoring (e.g., Handegard et al., 2013). It is thus reasonable to assume that such devices are suitable for aquaculture purposes too.

The most common and conventional active acoustic devices used to observe fish are echo sounders, which are typically equipped with a single transducer and that emit a single beam and listen for reflections from objects or particles within the beam. Echo sounders have been a tool in aquaculture research for decades, being used to observe how the spatial distribution of fish is affected by culture conditions (e.g., Fernö et al., 1995; Oppedal et al., 2011), farm management (e.g., Oppedal et al., 2001, 2007), and operations (e.g., Korsøen et al., 2009). Split beam sonars are a more advanced class of active hydroacoustic devices that are equipped with several transducers, and hence can not only detect distance to objects but also render their horizontal position in the beam. This potentially enables observing the movements of individual fish in sea-cages, as shown in several studies using different species (Arrhenius et al., 2000; Knudsen et al., 2004). On the high end of the scale are the multibeam devices that contain transducer arrays that simultaneously emit beams in different directions and thus are able to scan a larger volume with high resolution. Although multibeam devices are less common as a research tool than less advanced sonars, there have been recent studies using such devices to, for example, monitor swimming patterns and size (e.g., Zhang et al., 2014), and tail beat frequencies (e.g., Helminen et al., 2021) of farmed fish.

There have been studies using active acoustics targeting feeding in salmon cages. An early example was Bjordal et al. (1993) who used an echo sounder to observe the presence of feed beneath the feeding area in salmon cages and made attempts at controlling feed delivery based on these observations, essentially closing the loop. In Juell et al. (1993), the same authors applied acoustics to another facet of the feeding process by developing a “food detector” that acoustically detected pellets beneath the feeding area, enabling them to control feeding based on the amount of uneaten feed (Fig. 9.9). In a further study, Juell et al. (1994) also used echo sounders to assess how perceived hunger level and food availability affected the behavior of salmon.

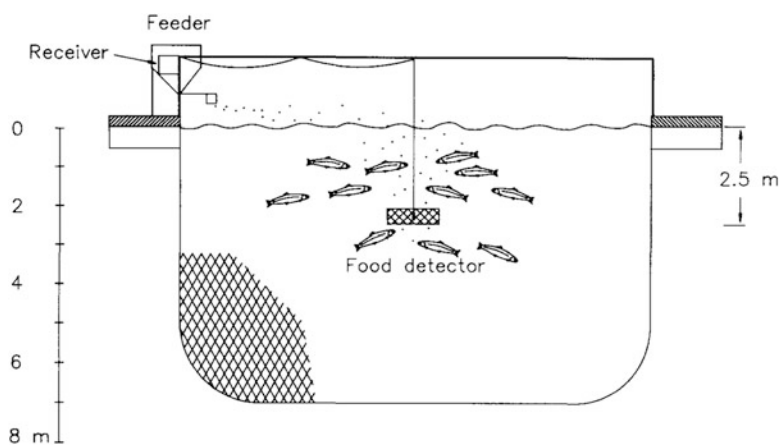


Fig. 9.9 Experimental setup employed by Juell et al. (1993) to test self-feeding using a food detector. (Reprinted from Juell et al., 1993, Copyright (1993), with permission from Elsevier)

Most previous studies using echo sounders have been based on manual analyses of the data, in the sense that the user observes the echogram or a numerical map equivalent of this, and from this derives what the fish are doing. This might change in the future, as the recent rapid growth of methods that may be categorized as artificial intelligence or machine learning has led to increased interest in applying such methods to data from active acoustic devices. Since an echogram is comparable with an optical image in terms of how the data is organized, methods for machine vision could potentially be adapted to processing acoustic data. Due to the massive capacity of computers in analyzing numerical data, it is now possible to quantify fish behaviors by applying AI methods such as deep learning on hydroacoustic data (e.g., Måløy, 2020). Such approaches are likely to be key elements in future observation methods for acquiring a deeper insight into what happens beneath the surface.

Passive acoustic monitoring (PAM) methods are based on using passive hydrophones (i.e., underwater microphones) that record sounds generated by various sources within its range. A PAM recording will typically result in a dataset describing the acoustic power as a function of frequency and time at the monitoring site, the unprocessed version of which is typically called the *soundscape*. Due to the efficient propagation of acoustic signals in water, a soundscape in the marine environment will feature contributions from a wide variety of sources both near and far, of either anthropogenic (e.g., boat traffic, marine constructions, seismic surveys), abiotic (e.g., sea state, precipitation, thermal noise), or biotic (e.g., animal communication, animal movements, and behavior) origin. If the biotic components of a soundscape can be identified and analyzed, it is possible to obtain some information on the presence of animals nearby, and their activities. Although much of the research in this area has focused on cetaceans, Kasumyan (2008) did a thorough review on the abilities for sound generation in different fish species. Their article described the mechanisms and organs fish use to generate sound, and was later complemented with another literature study, describing the ecological roles of sounds generated by fish (Kasumyan, 2009).

The most prominent example of applying PAM in aquaculture research is indeed related to feeding control and focused on developing a PAM system for detecting feeding activity in farmed turbot (Mallekh et al., 2003). This study found that the variance in the sound signal within a frequency range previously established as relevant for turbot behavior (6–8 kHz, Lagardere & Mallekh, 2000) was significantly linked with feeding activity and even ration size. Although there have not been similar studies aimed at feeding in salmonids, the sound production capabilities of six freshwater species, including four salmonids, were recently investigated by Rountree et al. (2018). This study concluded that most of the sounds generated by these species was due to air movement, and that it is possible to distinguish the species based on PAM analyses. For instance, it is possible that the process of a fish capturing and ingesting a pellet generates some sort of sound that might be possible to distinguish from the background soundscape. Furthermore, feed delivery is known to increase the swimming activity levels of farmed fish, a change in behavior that might be detectable through the changes in water pressure caused by movement through water.

Industrial Applications

The need for observing the fish in large sea-cages has increased as the industrial production volumes of intensive cage-based aquaculture have scaled up. This has led to the establishment of companies offering hydroacoustic solutions customized for aquaculture, including targeted monitoring of the feeding area and measurement of individual movement speeds using split beam solutions. In addition, established providers of sonars and echo sounders for fisheries are increasingly looking to develop their products toward aquaculture applications. Although there are fewer such initiatives targeting PAM, it is likely that both providers of active hydroacoustic systems and oceanic monitoring devices will explore this market in the future.

9.3.2.4 Biosensors and Telemetry

Research Frontier

While optical and acoustic methods are based on “remote sensing” in the sense that they do not require interaction with the animals, biosensor and telemetry methods are based on equipping the fish with electronic devices containing sensors for measuring variables in or near the fish (Cooke et al., 2011). These devices may either store the resulting data in internal storage mediums (Data Storage Tags, DST) or transmit them wirelessly to the user through acoustic/radio signals that are picked up by acoustic or radio receivers (Thorstad et al., 2013). Figure 9.10 illustrates different concepts related to the use of electronic tags in fish monitoring.

The origins of biosensors and telemetry applied to fish may be traced to wild fish research (e.g., Welsh & Bellwood, 2012; Taylor et al., 2017) and conservation efforts (Crossin et al., 2017), where the free migration of the fish render the use of

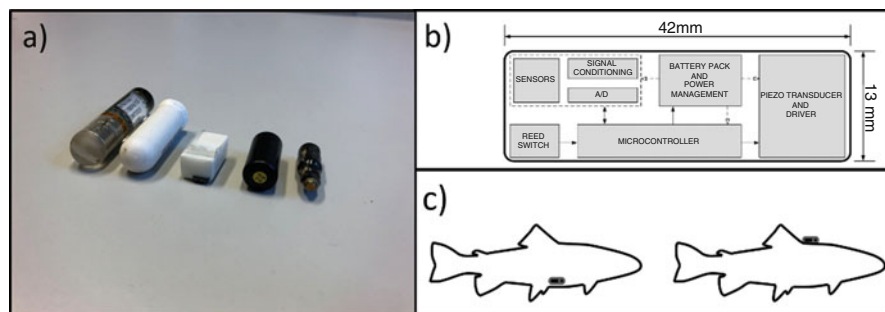


Fig. 9.10 The choice of tag type, shape, and size, and how they are provided to the fish depends on the aim of the study. (a) A selection of different logging (three leftmost) and acoustic (two rightmost) tags, (b) schematic view of the components in an acoustic tag (dashed arrow = energy flow, solid arrow = data flow), (c) fish are usually equipped with tags either by surgical implantation inside the body cavity (left) or by external attachment (right). (Sub-figure (b) Føre et al., 2011, Copyright (2011), with permission from Elsevier)

stationary equipment such as cameras and echo sounders less efficient. Although placing a device on or in the fish is considerably more invasive than the other methods, this also enables the measurement of properties difficult to measure remotely, such as physiological parameters (e.g., Cooke et al., 2004), and enables the collection of individual data histories over time. The list of parameters that have been measured using such devices include depth (e.g., Block et al., 1992), acceleration (e.g., Kawabe et al., 2003), muscle activity (e.g., Cooke et al., 2004), heart rate (e.g., Priede, 1983), and respiration (e.g., Martos-Sitcha et al., 2019). Biosensors and telemetry have seen a range of applications in aquaculture research including monitoring during crowding and transportation procedures (Brijs et al., 2018; Føre et al., 2018a, b), welfare evaluations (Hvas et al., 2020; Svendsen et al., 2021), and environmental responses (Johansson et al., 2009).

Biosensors and telemetry have recently been proposed as a useful component in the future practices for better monitoring animals in aquaculture, given that the practical challenges of the method are properly handled (Muñoz et al., 2020; Brijs et al., 2021; Macaulay et al., 2021). There have been some research efforts on monitoring feeding activity in fish farms using biosensors and telemetry. Early studies in this area focused on detecting the presence of fish inside or outside the proposed feeding area using hyperbolic positioning of acoustic tags (Juell & Westerberg, 1993; Begout & Lagardere, 1995, 2004). More recently, Alfredsen et al. (2007) sought to directly detect feed intake in Atlantic salmon by measuring the differential pressure between the opercular cavity of the fish and the surrounding water. This method was based on the premise that the fish generate negative pressure gradients to effectually suck the pellets into their mouth while feeding, and showed promising results in the laboratory. While this method could potentially provide an estimate of the actual number of pellets eaten by a fish, the need to measure the pressure inside the operculum makes equipping the fish with such tags difficult and invasive, especially when intended for use in sea-cages. Føre et al. (2011) sought a different avenue in using accelerometers and depth sensors to detect patterns in swimming activity and vertical movement observed during feeding in salmon. Although more indirect than the differential pressure approach, this tag type provided promising results in small-scale field trials (Fig. 9.11).

Scientific studies have shown that measuring physiological parameters may also shed light on fish-feeding activity. For instance, Cubitt et al. (2008) successfully applied quadratic and support vector machine (SVM) classifiers on electromyogram (EMG) data from rainbow trout to estimate hunger/satiation levels in the fish based on their muscular activity. Although without advanced processing methods, Lucas (1994) did a similar conjecture linking telemetry data on heart rate in pike with their feeding status. Since nutrition requirements, appetite, and hence feeding motivation in fish are intrinsically linked with their physiological state, measurements of physiological parameters may also be used as indicators of feeding behavior. Although not yet industrialized to the same level as conventional telemetry

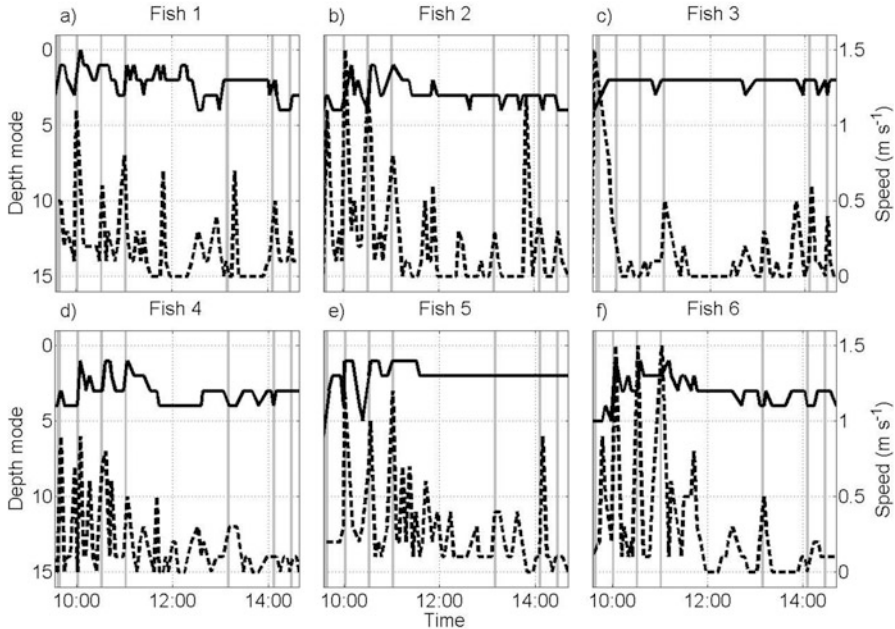


Fig. 9.11 Example data from observing feeding-related behavior for six fish in a small sea-cage using telemetry tags with depth. There appears to be a relationship between vertical movement speed (solid line), vertical positioning (dashed line), and feeding events (grey vertical fields) indicating motion toward the surface when feed is offered. (Unpublished data from the same study as published by Føre et al., 2011)

solutions, biosensor options for monitoring physiological and health-related parameters are currently developing fast (Endo & Wu, 2019).

Industrial Applications

Although there are currently several providers of both telemetry and biologging devices, their primary market is still within conservation and wild fish research. One of the main reasons for this is probably that such technologies are invasive in the sense that they require the fish to be captured and equipped with the devices to generate data. Biologgers also need to be recaptured to access the data, making them less suitable for real-time monitoring. In addition, telemetry and logging devices tend to incur a relatively high cost per monitored individual compared with remote-sensing technologies such as cameras and echo sounders. Nonetheless, several such systems have previously been successfully applied to farmed fish and provided unique insights into their dynamics through individual data histories. It is therefore likely that the application of such systems to monitor sentinel fish (i.e., a sub-selection of individuals in the cage population) can have a role in completing the observation toolbox in commercial cage-based aquaculture.

9.3.3 Modelling and Information Fusion: Unveiling the Unobservable

9.3.3.1 Aim: Simulate and Estimate States and Dynamics in Feeding That Are Difficult to Measure

When aspiring to control industrial processes, one is often faced with the situation that not all states and dynamics in the process are possible to measure directly through affordable existing sensor technology. In such cases, it is often useful to resort to the application of mathematical modelling, information fusion, and state estimation. Sensor fusion comprises methods for combining real-time data from different sensors/instruments to provide system information that is more reliable and complete than that possible to obtain with each data source by itself. State estimation is a technique that seeks to exploit both these features in combining mathematical models of the system with real-time inputs from sensors in estimator or observer structures. The model then accounts for both a priori knowledge and real-time data on the system, enabling further reduction of uncertainties and can even provide estimates of system states that are either difficult or impossible to measure directly.

9.3.3.2 Mathematical Modelling Research Frontier

Mathematical modelling is extensively used as a tool in monitoring and control purposes in many different industrial segments including oil and gas, vehicle navigation, and manufacturing (e.g., Monteiro et al., 2012; Rogers, 2007; Defersha & Chen, 2006). While most of the models used in these industries can be developed based on physical or chemical systems for which there exist well-founded empirical or theoretical equations, livestock applications require models that reflect several aspects of biological dynamics. This has been a subject in terrestrial livestock research for decades (e.g., Spedding et al., 1988) and has led to the emergence of models describing feeding dynamics (e.g., Fleming et al., 2020), behavior/migration (e.g., Guo et al., 2009), diseases (e.g., Brooks-Pollock et al., 2015), and herd dynamics in response to management strategies (e.g., Jalvingh et al., 1990) in terrestrial livestock production. The responses displayed by an animal toward some sort of external stimuli does not only depend on species, size, and the type of stimuli but also on more fuzzy elements such as the genetic heritage, social interactions, internal state, and life history of the animal. These elements are much less mapped and understood for fish than for terrestrial livestock, greatly complicating the development of generic models that can reflect, for example, the feeding patterns of salmon in sea-cage production. Similarly detailed models as those for terrestrial livestock are thus not defined for aquaculture. However, this also highlights the large potential of using models to better understand such systems, as it might be difficult to observe and assess the system states based on experience. Hence, modelling is likely to play a part in developing intelligent feeding in intensive aquaculture.

Getting feed pellets close enough to the fish is a precondition for feeding activity, hence a logical first step in modelling the feeding process in a sea-cage is to model the final stage of the feed delivery process. For cage-based fish farming, this includes modelling how pellets are delivered to the cage. This area was targeted by Skøien et al. (2015) who developed a model able to predict the surface distribution of pellets delivered by a pneumatic rotary feed spreader in a sea-cage by combining modelling approaches from robotics and ballistics. In a later study, this model was validated using experimental data on actual feed spreading patterns and expanded to accommodate a range of different rotary spreader configurations (Skøien et al., 2018). Once the feed has arrived at the cage, the next process that needs to be modelled is how the pellets distribute beneath the surface. This was first modelled by Alver et al. (2004) who developed a model of the 2D subsurface pellet distribution in a sea-cage using the transport equation incorporating the effects of water movement and turbulence (Fig. 9.12). This model was validated using experimental data and later expanded to 3D and made more realistic in terms of possible inputs (Alver et al., 2016). Using these models, it is thus possible to predict how different feeder configurations and environmental conditions contribute to spread feed in the production volume, and to what extent the pellets are available to the fish.

The next step in modelling the feeding process is to assess how the fish capture and assimilate the feed. Existing models of feed intake were reviewed by Sun et al. (2016) who identified both individual and group-based model formulations. These included more or less direct methods such as assessing feed intake based on measured gut content and feces production (e.g., Richter et al., 1999), models that predict feed intake based on an assumed energetic state or body weight (e.g., Cho &

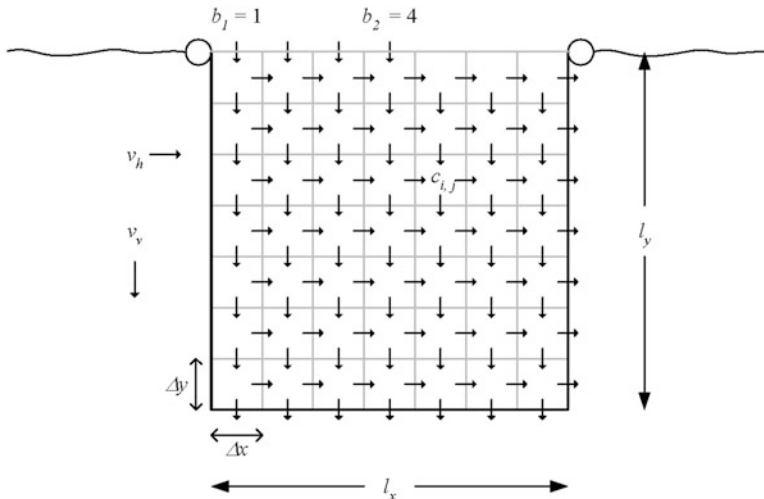


Fig. 9.12 2D-discretization of cage used to simulate the underwater distribution of pellets after being released at the surface by Alver et al. (2004). (Reprinted from Alver et al., 2004, Copyright (2004), with permission from Elsevier)

Bureau, 1998), and indirect methods based on chemical balance in the water (e.g., Trudel et al., 2000). Since obtaining measurements from the digestive tract in sea-cage aquaculture would require crowding and capturing individuals, the direct approaches are less likely to be useful in operational settings. Likewise, acquiring data by measuring the chemical balance in the water is likely to be challenging because the water in the cage is open to the surrounding environment, rendering the isolation of chemicals related to fish feces difficult. Hence, models based on energetics and weight are probably most relevant when aspiring to use models of feed intake in intelligent feeding applications. Such models are typically linked with some sort of growth modelling, which is probably the most modelled biological phenomenon in aquaculture as reviewed by Dumas et al. (2010). Some growth models are built as regression models seeking to link changes in weight to time or some other time-dependent variable, exemplified by polynomial models and the Von Bertalanffy model (Chen et al., 1992). On the other end of the scale are bioenergetic models seeking to describe how intake of nutrients is divided between different bodily functions such as somatic maintenance, reproduction, energy reserves, and structural growth. Examples of such models include Olsen and Balchen (1992) and various approaches based on the dynamic energy budget (DEB) formulation (Kooijman, 2000). Although the latter model format tends to be of a more mechanistic nature in aspiring to predict the stages between feed intake and body size, they are not necessarily more accurate at predicting end weights than regression type models (Dumas et al., 2010). Recent developments have also explored the utility of AI and neural networks in predicting feed intake in farmed fish (Chen et al., 2020).

Holistic models of the biological process of feeding in sea-cages that combine models of feed delivery to the cage, feed intake, and growth can be a potent tool in intelligent feeding applications in enabling the prediction of how the energy in the feed propagates from pellets to fish meat. In Alver et al. (2004, 2016) the authors used such an approach by using a simplified version of the model by Olsen and Balchen (1992) to predict feeding motivation, which, combined with the assumption that the fish were co-located with the feed distributed in the water, allowed predictions of feed intake. Combining this approach with a more advanced behavioral model could also have potency in also accounting for other behavioral dynamics. This was done by Føre et al. (2016) who combined the model in Alver et al. (2016) with an individual-based model of salmon behavior (Føre et al., 2009, 2013). Using this approach, the authors were able to validate the function of the outer loop of the holistic model (i.e., the relationship between feed delivered and growth) using growth data from a commercial sea-cage.

Industrial Applications

Although the industry has been and is using empirical growth models when scaling the gross feed outputs to the cages, there are few examples of industrial applications where dynamic models are prospected to be an integral part of feed delivery. A long-term aim of realizing this would be to integrate such models with sensory inputs from acoustic and optical systems deployed in the cage to achieve information fusion

on the fish behavior and distribution. This would have a primary application in being able to dynamically adjust the feeding schedule based on model outputs.

9.3.3.3 Sensor Fusion and State Estimation

Research Frontier

In related industries such as manufacturing (e.g., Lucke et al., 2008), subsea applications (e.g., Majumder et al., 2001), and agriculture (e.g., Khot et al., 2008; Hamouda & Msallam, 2019), sensor fusion and state estimation have become well-established tools for better exploiting monitoring technologies and existing knowledge. The basic challenge addressed by these techniques is that the state of complex processes can often only be partially measured, and that those measurements that are available are typically associated with uncertainty. Sensor fusion and state estimation techniques can allow the combination of separate measurements into a more comprehensive and accurate dataset, and the estimation of unmeasured states in a mathematical model of the process.

Although Balchen (2000) suggested a total system estimator based on Kalman filtering to better monitor fish in the sea, information fusion and estimation methods to combine information sources in aquaculture applications are not seeing widespread use in either aquaculture industry or research (Hassan & Hasan, 2016). However, due to the high number of animals, the largely uncontrolled environmental conditions and the biological factors in cage-based aquaculture, it is likely that such methods have a great potential as components in future intelligent feeding methods.

Although fusion and estimation methods are seeing more interest in the aquaculture industry and research (Hassan & Hasan, 2016), and virtual studies have been used to explore the potential of using sensor fusion to improve control in fish farming (Garcia et al., 2011), there are few examples of real application of fusion or estimation methods to study fish. Some of the earliest examples of applications that may be placed in this category were not studies focused on realizing sensor fusion as such, but rather arose as a necessity to obtain the desired information. For example, Armstrong et al. (1999) sought to study the space use of wild salmon juveniles and had to design a system integrating PIT-antennae with cameras to identify individuals in the video footage. More recently, research effort has been put into more technologically advanced studies aimed at fish in aquaculture-related settings, using methods resembling those seen in other industries. A notable example of such a study is found in Pinkiewicz et al. (2008) who used particle filtering and video to track fish movement in tanks. The same authors later developed a similar tracking method for sea-cages, using Kalman filtering to track the distribution, positions, movements, and sizes of salmon (Pinkiewicz et al., 2011). Although neither of these studies featured a dynamic system model, which is often a component in classical estimator applications, they were able to greatly reduce the uncertainty of parameters obtained by machine vision through data association using a Global Nearest Neighbor approach. At present there are no behavior models suitable for this purpose as individual-based approaches (e.g., Føre et al., 2009) do not have a state space amendable for Kalman filtering and other estimator techniques. This

highlights that developing the components and tools for full-fledged estimation of fish in sea-cages is a potential next step toward achieving a better overview of the dynamics in sea-cages, and hence toward achieving intelligent feeding.

Industrial Applications

Since there are few research applications using sensor fusion/estimation techniques today, it follows that industrial applications of these are limited. However, there are some initiatives that deserve some attention in the area of topside data assimilation and association. Examples of such applications include those that offer solutions where data is assimilated into a common platform, presenting the user with a holistic picture they can use to make more knowledge-based decisions and those that offer traceability solutions based on, for example, blockchain technology.

9.3.4 Automated Solutions and Autonomous Systems: Closing the Loop

9.3.4.1 Aim: Make Operational Actions Autonomous

While sensors, mathematical models, and their combination through fusion and estimation can help farmers to better monitor and assess the biological processes linked to feeding and growth in aquaculture, the act of converting such information into actual feeding schedules and strategies is still largely done by the individual farmers, and thus depends on their personal experience in farm management. Although this human-in-the-loop approach has proven efficient through decades of intensive fish farming, situations where humans cannot supervise the feeding process due to harsh weather or vast travelling distances may occur and are likely to become more frequent in the future due to the industrial trend in moving production to more exposed and remote sites (Bjelland et al., 2015). This challenge may in part be solved through remote feeding, where the person controlling the feeding system is not at the actual farming site, but rather monitors the process remotely with cameras. An alternative approach could be to use automated solutions that convert observations and monitoring information into control signals that actively steers the process toward a desired state, essentially closing the loop without the need for human intervention. Introducing such solutions would not only increase the automation level of feeding operations, but also render these operations less sensitive to variations in experience levels between individual farmers. Moreover, unmanned solutions for feeding can be implemented locally at the site, reducing their sensitivity to communication-related challenges such as latency, limited bandwidth, and electromagnetic interference compared with solutions based on remote control. In sum, improved automation in feeding can contribute to making fish husbandry and nutrition in aquaculture more optimized and repeatable and hence contribute to shifting the aquaculture industry toward a more knowledge-based regime. Automated solutions and autonomous tools would be key enabling technologies in achieving this, and we will in the following discuss how solutions from robotics and

feedback controlled and on-demand systems from research and industry could be exploited to this end.

9.3.4.2 Robotic Systems and Vehicles

Research Frontiers

While robotic systems specifically designed for feed distribution have been used in land-based small-scale applications in aquaculture (Von Borstel et al., 2013), they are not common in cage-based marine production. This is mainly because it is much more difficult to design such systems that can operate safely and reliably in the marine environment, than doing so in a land-based environment where the robot can operate in air. Moreover, the amounts of feed delivered to the cages and the rate of delivery requires heavy duty mechanical solutions that may be more difficult to robotize precisely. One exception is found in Reshma and Kumar (2016) who developed a theoretical concept for aerial drone-based feed delivery to fish cages, a concept that could work for small-scale production sites.

With the current rapid technological development, it is likely that we will see future applications that are more closely integrated with the feeding operation. Some explored concepts could already be turned toward improving control over the feeding process. For example, aerial drones could in combination with algorithms for automatically assessing surface activity (Jovanovic et al., 2016) or pellet distribution (Lien et al., 2019) provide information on the feeding response of the fish that in turn could be used to improve feeding control. Other systems such as ROVs (Remotely Operated Vehicles) could be used to obtain better control. Moreover, it is possible that underwater robots coupled with computer vision methods (e.g., Martinez et al., 2003) could serve as mobile observation points for monitoring the feeding activity of the fish, thereby providing a better overview of the feeding motivation in a larger part of the cage. If such systems were coupled with AI-methods able to automatically assess feeding activity (e.g., Måløy et al., 2019), they could even have the potential of conducting autonomous feeding monitoring, providing the farmer with a time variant proxy for fish appetite without needing to evaluate video footage manually.

Industrial Applications

The aquaculture industry is moving toward increased use of underwater robotics instead of human labor in tasks conducted in the sub-surface environment, particularly in the marine environment. This trend has been increasing over the last decades, much due to the increasing HSE-risks associated with moving operations to more exposed and larger sites, but also because the technological development in other industrial segments (particularly offshore oil and gas) has led to innovations that may also find usage in fish farming. However, adapting such robotic tools directly into fish farming operations is not always straight forward, as the movement from deep-sea to fish farm environments introduces new challenges that need be handled. For instance, the environment where the robot will conduct its missions will then feature live fish and flexible structures, effectually changing the boundary conditions for

how an operation may be conducted. This means that some operations may require tools specifically designed for that operation to succeed. Current industrial uses of robotics in mariculture vary from using largely conventional ROVs to inspect cage components (e.g., Rundtop & Frank, 2016), AUVs (Autonomous Underwater Vehicles) used for site surveys and other environmental monitoring tasks, to vehicles specially designed for net cleaning. However, there are so far no industrial examples of robots used in feeding operations.

9.3.4.3 Feedback Controlled/on Demand Feeding Systems

Research Frontier

Feedback control, where information about the current process output is used to formulate input signals to the process designed to steer the process to a desired state, is one of the mainstays of control theory and cybernetics. In fact, the use of the term “closing the loop” when addressing some kind of control challenge refers to exactly the application of feedback. Fully controlling the feeding process in intensive fish farming will require some sort of feedback from the process, as control purely based on prognoses and mathematical models will be ill suited to handle unforeseen changes in the responses of the fish, or environmental conditions. Such feedback can be realized by using process outputs obtained by either observing some property of the fish related to feeding behavior, distribution, or appetite, or by observing feed spills or spatial distribution to indirectly observe feed intake versus feed delivery.

Previous applications of feedback control in aquaculture have mainly focused on smaller laboratory-based cases featuring relatively simple organisms, such as model-based estimation and control of rotifer density in start-feeding cultures for cod larvae (e.g., Alver et al., 2004). Although there are fewer examples from science where such feedback control is applied to fish production, and feeding processes in particular, some studies have sought to address this area using acoustic measures or cameras. In a previously mentioned study, Bjordal et al. (1993) set up feedback from an echo sounder covering the upper five meters of the water column. The perceived fish density in the layers closest to the surface were then compared to a predefined density threshold to determine whether feeding should be continued or terminated, an automated solution that outperformed a fixed diet schedule applied to the same fish. In a contemporary study, Juell et al. (1993) used a customized feed detector to generate a feedback signal, achieving similar improvements over conventional feeding schedules. The feed detector used a high-frequency acoustic pulse to quantify the feed inside a delimited control volume, and the control system was designed to compare this value with a predefined threshold value to determine when feeding should be ended. A similar approach was tested by Blyth et al. (1993), who concluded that a measure of pellet wastage was a feedback value more suitable for controlling feeding than, for example, surface activity or swimming speed. Although they measured pellets using a sensor whose principle was not divulged in the study, this system was further explored in later studies (Kadri et al., 1998).

An alternative approach to feedback-control can be achieved through systems where the fish actively induce the delivery of feed. Since the feeding process in

practice is then controlled by the fish, the level of precision attainable through feedback control may be lower than when using more objective measures such as feed spills and behavioral observations, potentially leading to more feed wastage. In addition, implementing systems where individual fish need to interact with the feeding system in industrial scale may be very challenging, especially in facilities containing large populations of fish. However, the potential of achieving more efficient feeding in fish farming, there have been several studies exploring the feasibility of using self-feeding in aquaculture. In an early application of this principle, Alanara (1992) found that rainbow trout exhibited better growth when allowed to control feeding themselves through biting a rubber pendulum to release feed than when faced by conventional feeding regimes. Similarly, Paspatis and Boujard (1996) found that self-feeding of salmon where the fish activated a steel rod trigger led to more even growth and lowered feed waste. In a more recent study, Shi et al. (2017) used a system where the fish pulled a submerged bead to release feed, and found that although the system did not lead to improved growth compared with *ad libitum* feeding, feed waste was much lower, which coincides with the results found in earlier studies. Self-feeding systems have also been used in experiments with other cage-reared aquaculture species such as seabass (e.g., Rubio et al., 2004; Coves et al., 2006). If self-feeding systems are to be a preferred approach, a key challenge is to ensure a feed intake leading to a sufficiently high growth rate, as this is an equally important success factor as the reduction of feed waste.

Industrial Applications

Since it is obvious that efficient feedback control of feed delivery in fish farming will have a huge potential in realizing more efficient and environmentally friendly fish production (i.e., sufficient feed at the right time meaning better growth and lowered feed spills), the need for scientific validation of the efficacy of this concept is less crucial. This may potentially shorten the path from acquiring relevant measurements to being able to offer industrially viable feedback-controlled solutions. Although the farming industry may need some more convincing before revolutionizing their company practices in feeding (which after all is the most important management practice in fish farming), some technology providers are already starting to offer solutions that are approaching fully autonomous feeding, for example, through AI combined with acoustics or cameras.

9.4 Future Prospects and Developments

9.4.1 The Intelligent Feeding Methods of the Future

Feed utilization and production efficiency can be improved through direct measures such as developing feed with new physical/chemical properties, using different alloys or components in feeding systems and tubes and real-time feed characterization. However, we believe that the largest untapped potential in achieving more

intelligent feeding and nutrition in cage-based fish farming lies in applying technology to better understand and control the biological aspects of feeding in cages. In the following, we will try to summarize how we envision state-of-the-art technology can be used in future intelligent feeding methods.

9.4.1.1 Observing and Interpreting Fish States

To properly assume control over any process, it is important to first ensure that it is possible to fully monitor the state of the system. For feeding in fish farming, this includes being able to assess the feeding motivation and behavior of the fish, as well as the distribution of feed pellets in the cage volume.

The first step toward achieving this would be to develop algorithms for automatically analyzing data streams of raw data from sensors, optical footage, or acoustic echograms into numerical data that quantifies the features of interest. In the case of feeding, potential features of interest could include changes in swimming speed and orientation, vertical movements, changes in heart rate, and changes in blood glucose. Algorithms that target feeding-related features directly instead of first trying to describe the entire behavioral and physiological state and leaving the operator to interpret these could result in a much more focused and above all objective approach to monitoring and understanding feeding in sea-cages. For example, an optical system aimed at feeding could be designed such that it only generates information for the user if the swimming speed changes in a way that implies a transition between different stages of feeding behavior. The features in the video stream that would imply such transitions could be found using methods from machine learning using labelled data featuring video footage from the different stages. Although such methods often require large amounts of training and validation data to be successful, it is common to make such algorithms adaptive, in the sense that they are continuously improved when used, leading to increasing precision. In addition to instrument-specific algorithms, it may also be reasonable to combine the data from several sensors using sensor fusion principles, as it may be difficult to achieve a good enough description of the state through single measurements.

In some cases, the system state is not possible to observe through measurements alone, and it is then common to combine real-time measurements with mathematical models of the process in so-called estimator structures. This has proven to be a success recipe in other industrial segments, especially in situations where the installation of enough instruments to facilitate full state observation is either too difficult or expensive to be feasible. A precondition for using such methods is that a sufficiently accurate and realistic model of the system dynamics exists. For feeding in fish farming, such a model could reflect various aspects of feeding and nutrition, including feed distribution, feeding behavior, feed intake, and digestion. In an early example, Alver et al. (2004) suggested that the center of mass in the subsurface pellet distribution could be estimated by combining measurements of fish distribution with a model of spatial feed distribution model, and also proposed how this could be used for feedback control of the feeding process. For more precise control, one could further envision that this model could be set up to also simulate the fish population based on various inputs (e.g., feed delivery, temperature, fish size). If combined with

monitoring methods specifically designed to capture features relevant for feeding, such a model could result in an observer or estimator able to assess the feeding status of the entire population. The observer would produce estimates comparable with the measurements, and the deviations in these estimates would be used to correct the model state. Returning to the optical measurement example mentioned above, this would entail that the model needs to simulate fish movement during feeding and provide an output matching the criteria for speed changes used in the optical method. If successful, such a construction could combine real time data from a few individuals with a priori knowledge through the model to render the feeding process in salmon farming observable.

9.4.1.2 Deciding and Delivering

Once the full system state is possible to observe, it can be combined with information on other relevant concerns (e.g., remaining feed in silos, planned future operations) into a foundation for automating the decision making and feed delivery stages of feeding in intensive mariculture. Automated decision support systems (DSS) represent a possible technology to handle the decision stage and are currently seeing increasing use in other industrial segments. Such systems are often designed to combine real-time data from sensors and a priori knowledge from models in a common foundation for making informed decisions. This could either be realized by including these as separate data streams or by using the output of a state estimator in the event that this has been successfully implemented. In many cases, DSS also take experience data from human operators into account, which adds an operational dimension to the decision process. Since feeding fish is a highly complex process, this will most likely be wise to include in a DSS aimed at feeding, to also account for factors that are less clearly linked with measurable values and more closely linked with the intuition of the farmers.

Since all the aforementioned solutions would greatly increase the control over the feeding process, a future intelligent feeding method could enact feed delivery using the solutions that are commonly used today, for example, rotary spreaders, and still achieve large benefits in feed utilization and nutrition. However, modifying the delivery method could in some cases contribute to improving the situation further. For instance, underwater feeding systems could be introduced to reduce feed loss due to waves and wind, and to allow the fish to avoid the surface layers when conditions for growth are more beneficial deeper in the water column (e.g., when temperatures at the surface are very high or very low). Since underwater feeding most likely would not be able to spread the feed as much as during surface delivery, this could require multiple feeding points and instrumentation associated with these.

In cases where the prevailing currents are strong, another option could be to use mobile feeding points, either surface mounted or submerged. The feeding points could then be moved upstream to reduce the feed loss due to transport through the net wall, potentially greatly reducing the feed loss. Models of feed distribution such as that of Alver et al. (2016) could then be used to specify a path that reduces current-induced feed spills while still maintaining a feed distribution likely to stimulate efficient feeding in the fish. Feeding point mobility could either be facilitated

through permanently mounted winches and similar systems, or by using robotic free-swimming platforms.

Finally, although on-demand systems where the fish themselves actuate feed delivery may be complex to introduce to large-scale systems, they could serve a purpose in future feeding systems. This would be especially relevant in cases where a solid foundation in real-time measurements, models, and decision support is difficult to achieve. A potential way to cope with the challenges of scale could be to use multiple feeding points, such that the total demand is spatially spread. This challenge will be less important for smaller production units.

9.4.2 New Solutions for New Production Concepts

To fully explore the potential role of digital technologies in realizing the feeding methods of the future, it is important to also consider how such solutions could be applied in new emerging production concepts. It is likely that the feeding process in structures built for more exposed locations (e.g., Ocean Farm 1, Mariculture, Havfarm) will need to be done differently than in conventional cages. For instance, feeding a larger volume entails larger challenges in ensuring that all fish are fed. This could in part be mediated by increasing the ability to monitor the feeding activity of the fish using automated monitoring and estimation principles, as increased control depends on improved observational abilities. Another challenge that may be encountered when feeding at exposed sites is that larger waves and stronger winds and currents can lead to increased feed loss. Solutions based on sub-surface feeding could represent an avenue to tackle such challenges, as this could reduce the exposure to effects above and near the surface. Moreover, mobile feeding systems that are, for example, moved to the upstream area of the cage could contribute to reducing loss due to currents.

While concepts designed to treat fish more individually (e.g., iFarm) are very suitable for adapting management practices resembling those implied in PFF, these may also have challenges in achieving individual control of feed intake. Conventional feeding systems with a single feeding area may not be sufficient for this, as they may lead to dense congregations near the feeding points. This challenge could possibly be mediated by using multiple distributed or mobile feeding points, or possibly through on-demand systems where the fish are identified when they trigger the release of feed.

Although semi-closed solutions (e.g., Aquatraz) by design could lessen the feed loss in shielding parts of the volume to currents and waves, these solutions could probably also benefit from increasing feeding control. For fully closed solutions (e.g., Preline, “The egg”), however, it is likely that new methods for feeding should be introduced. Such solutions are typically based on flow through using water retrieved at depths well beneath where pathogens and parasites are found, and may also have some degree of water recirculation. In being closed, feed spills will not simply be released from the volume as in open net cages but can be collected at locations inside the volume. If quantified, this could offer possibilities in assessing

the actual feed consumption at the site accurately, which would be a very useful input to intelligent feeding algorithms. However, this also offers a challenge, since the amassment of uneaten feed and potential feces could lead to unwanted effects such as algae growth and buildup of chemical compounds that may be harmful for the fish. It is thus possible that feeding control through technology may be even more important in closed systems.

In addition to the new initiatives in marine aquaculture, there are also several ongoing prospects and concepts for producing salmon on land. The ambitions of these systems range from extending smolt production before transport to marine cages to conducting full production cycles on land. Similar to fully closed concepts for sea-based production, these concepts will need to cope with the excess feed and feces during production. However, land-based facilities have advantages over marine sites in the form of easily available infrastructure (e.g., power, network), and that they are placed in an environment that is less harsh and demanding for the continuous operation of advanced equipment. In that sense, it is probably possible to achieve a higher degree of control over the feeding process in land-based sites than in cage-based culture, and with production costs at land-based sites typically being considerably higher than at marine sites, this is possibly a necessary component in developing land-based production concepts that are equally profitable as sea-based sites.

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Smart Nutrition of Extensively Kept Ruminants

10

Luciano A. González, Janine Chang-Fung-Martel,
and J. Augusto Imaz

Abstract

The nutritional management of grazing livestock in extensive conditions is challenging because of the difficulty to measure diet selection, feed and nutrient intake, and excretion, energy expenditure, and ultimately animal performance. The large variability in space and time of weather, pasture characteristics, and animal requirements and performance pose an additional challenge. However, various sensor technologies exist today to measure key attributes related to feed availability and quality, energy and nutrient requirements, animal performance, and environmental footprint in near real-time. Requirements for maintenance are a function of body weight (LW), physical activities, and environmental conditions, which can be measured using automatic systems for LW determination, animal behaviour, and weather. Requirements for production (body growth, gestation, and lactation) can be measured directly or indirectly via automatic LW determination, and technologies for the detection of oestrus and birthing events. Feed efficiency could be measured using face masks, heart rate monitors, and open-circuit gas-quantification systems of gas exchanges (CO_2 , CH_4 , and O_2). Finally, mathematical nutrition models play a very important roll to integrate these technologies and predict hard to measure variables. Examples of such automatic model-data fusion approach are presented to demonstrate its potential as part of smart nutrition systems of extensively kept livestock. The combination of data collected automatically using digital technologies, data analytics, and mathematical prediction models have the potential to revolutionize animal nutrition of extensively reared livestock. This will improve productivity, animal welfare, and the sustainability of these systems.

L. A. González (✉) · J. Chang-Fung-Martel · J. A. Imaz

Sydney Institute of Agriculture and School of Life and Environmental Sciences, The University of Sydney, Camden, NSW, Australia

e-mail: luciano.gonzalez@sydney.edu.au

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10.1 Introduction

The management of extensively raised livestock poses multiple challenges compared to intensively raised livestock, due to the difficulty to measure and control feed availability and quality, feed and nutrient intake, feed and nutrient requirements, waste or excretion, and animal performance such as growth rate. Furthermore, grazing systems have inherent larger variability observed at both temporal and spatial scales for both animals and feed (Tedeschi et al., 2019). The large variability observed in feed and nutrient availability is a result of the plant species present and phenological stage, weather and soil characteristics, and management factors including fertilization, amongst other factors (Insua et al., 2019). Similarly, the large variability in animal feed and nutrient requirements are a result of differences in genetics, gender, age, degree of physiological maturity, and even the interaction of these factors with feed available which determines animal response (González et al., 2018). The variability in grazing behaviour including diet selection and physical activities are also important factors determining the energy balance of grazing livestock (Brosh et al., 2010). Therefore, optimizing cost of production, animal performance, production efficiency, animal welfare, and environmental management under extensive grazing conditions is challenging and often uncertain. The present chapter refers to grazing beef cattle and sheep for extensively raised livestock, without differentiating the extent of ‘extensiveness’. However, it is important to note that animal behaviour and nutritional processes could be different in very small (e.g., <1 ha), as opposed to very large, paddocks of several thousand hectares commonly found in places such as northern Australia (Pearson et al., 2021). As it is obvious, the suitability of different technologies may change with paddock size. For example, light sensors mounted on terrestrial or unmanned aerial vehicles (UAV) can be useful to monitor feed and nutrients available in small paddocks, but satellite imagery could be more suitable for large paddocks.

In extensively raised livestock, one of the most important key productivity indicators is stocking rate as an indicator of feed demands per unit of land, which must match the carrying capacity of the land to maintain productivity, profitability, and sustainability (O’Reagain et al., 2014; Odintsov Vaintrub et al., 2020). Precision livestock nutrition or precision livestock feeding is an integrated information-based system to optimize the supply and demand of nutrients to animals for a target performance, profitability, product characteristics, and environmental outcomes (González et al., 2018). Energy and nutrient demands of livestock depend on factors such as the number of animals, their LW, and their production level including

growth rate and weaning rate (Herrero-Jáuregui & Oesterheld, 2018). Carrying capacity is the number of animal units each unit of land can sustainably carry according to the amount of forage produced, which is in turn affected by the pasture species present, climate (rainfall), and soil fertility (Hall et al., 1998; O'Reagain et al., 2009). Technologies that can measure both feed or nutrient supply and demand, or variables related to them, could have enormous benefit to the grazing industries and help optimize livestock nutrition and production.

Important advances have been made in the last decade to measure remotely multiple nutritional processes and factors affecting the flow of nutrients and energy (González et al., 2018; Odintsov Vaintrub et al., 2020). Technologies exist today to monitor many of these processes ranging from the feed available to animals under extensive grazing conditions, the processes occurring inside the gastrointestinal tract, the use of energy and nutrients for maintenance and production, and finally the excretion or wastage of nutrients via faeces, urine, or methane from enteric fermentation (González et al., 2018). However, no review seems to be available focusing on extensive livestock grazing with examples on how sensor technologies and nutrition models can be used to improve the nutrition and productivity of both the animals and the land. The objective of the present chapter is to review recent developments in technologies and approaches to monitor and manage the nutrition of grazing animals in extensive conditions. The first part of the chapter presents a framework to understand the role of multiple technologies in animal nutrition and ways to integrate their data with mathematical nutrition models. Examples are provided on the use of different technologies and models within that framework to demonstrate the opportunities of the approach for extensive livestock production. It is important to note that some technologies are mostly used for research purposes at present time, although the technology is likely to be used under commercial settings in the near future, such as the GreenFeed (C-Lock Inc., USA) automated system to monitor methane and carbon dioxide emissions from ruminants. The present chapter does not attempt to infer what technologies are used or will be used for commercial applications because this may change in the future.

10.2 A Suggested Framework for Smart Nutrition of Extensively Raised Livestock

The opportunities for the livestock industries to capitalize on recent developments in digital technologies and sensors require approaches beyond just collecting and visualizing data (González et al., 2018). Nevertheless, the power of data visualization should not be undermined (Van Hertem et al., 2017). González et al. (2018) focused upon the opportunities presented by alternative approaches to just using the technologies or the data provided by them such as the integration of mathematical nutrition models, sensor data, and data science including machine learning, data fusion, and artificial intelligence. Mathematical nutrition models refer to those that simulate one or various nutritional mechanisms or processes involved in energy and nutrient supply and requirements of animals such as NASEM (2016) and Freer et al.

(2007) amongst others. It was highlighted that this approach may require the development of new nutrition models, the re-structure of existing models, or their re-parametrization. One of the reasons for this statement is that most models were neither developed using, nor aimed to use, data collected with the temporal and spatial resolution that sensor technologies can do nowadays.

González et al. (2018) provided an example of the rapid changes measured in the growth rate of grazing animals measured with automatic weighing systems, which were due to both changes in body components and rumen fill. However, most of the nutrition models have been drawn from research eliminating the effect of rumen fill through fasting animals for 12–16 h. Figure 10.1 describes such concepts where data collected from sensors and other farm data (e.g., data manually collected in the yards or using smartphone applications in the paddock) can be ‘fused’ or integrated to produce new data or information with greater value than the sum of the individual data streams (data fusion). The process of integration of such data can be achieved via multiple approaches, including machine learning, artificial intelligence, or even more basic statistical approaches like linear or logistic regression, or principal component analysis (Wolfert et al., 2017; Morota et al., 2018). However, it is important to highlight that data integration is not a requisite and single sensor data alone can be used for the model-data fusion framework as well. An example of this could be the use of LW data collected by automatic weighing stations to predict

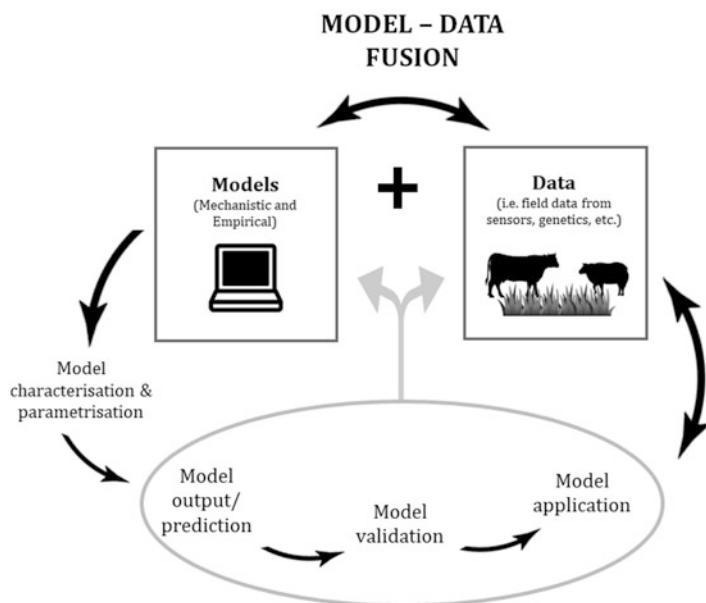


Fig. 10.1 Flowchart of an automated model-data fusion framework integrating technologies with existing models for the nutritional management of livestock. Two-way arrows emphasize the iterative process and interactive approach of the model-data fusion concept. (Adapted from Keenan et al., 2011)

energy and protein requirements of grazing animals according to measured LW and target growth rate as presented by González et al. (2014b). In the model-data fusion approach, sensor data can be used as input of mathematical nutrition models which could range from comprehensive mechanistic models such as NASEM (2016) and Freer et al. (2007) to simple empirical equations, such as the prediction of feed intake from LW and daily LW change (LWC) (Minson & McDonald, 1987). However, other studies have successfully used digital technologies such as Global Navigation Satellite Systems (GNSS) collars to estimate the efficiency of energy utilization for physical activities and energy expenditure for different activities (Brosh et al., 2007, 2010). Tedeschi et al. (2019) presented other frameworks based on the integration of mechanistic models and artificial intelligence to develop hybrid mechanistic machine-learning modelling techniques. Therefore, the options available to use the large amounts of data collected by sensor technologies are broad.

Once models and data have been integrated, predictions can have multiple dimensions in space, time, and utilization or objective. For example, predictions in space could range from predicting patch selection for grazing to predicting herd responses in different paddocks with different vegetation. Similarly, the dimension of time can range from predicting unobserved events or outcomes in the past, present (nowcasting), and future (forecasting) such as animal responses to feed supplementation including methane emissions from ruminants and aboveground forage intake. Furthermore, predictions could be made for the next day, week, month, or year adding to the complexity of the variables and processes which may require the application of various models (i.e., static time-point or dynamic models). Finally, the estimations made by models can feedback into new data being collected, into nutrition models, or both (Fig. 10.1), and this loop is expected to further improve the value of new data and refine the model parameters. Predicted values can also be used to evaluate the accuracy of the predictions as new data continues to be collected and used as input of models to further improve predictions. An example was presented by González et al. (2018) where model-data fusion was used to estimate the amount of feed supplementation required by grazing animals to reach a pre-determined production level and carcass endpoint based on predictions made by mechanistic models from remotely collected LW and LWC data. Both animal performance and supplement intake can be measured in real-time, and these data can be used by simulation models to calculate supplement conversion efficiency (kg LWC/kg supplement) on the left-hand side of Fig. 10.1. In addition, such results could also be used via the right-hand side of Fig. 10.1 to further refine the models using the new feed conversion parameters to estimate the amount of feed required to achieve a target final LW. Outcomes from applying these approaches can then feedback into the loop as adjustments in the amount of feed consumed can be done in real-time to re-formulate and optimize the desired outcomes. Nonetheless, it is important to highlight that this approach is theoretical and little research has been conducted to demonstrate the advantages or otherwise of model-data fusion.

The selection of key technologies to collect data to achieve a desired outcome or to respond to specific questions or hypothesis is also needed to extract greater value from digital technologies and nutrition models (González et al., 2018). A flowchart

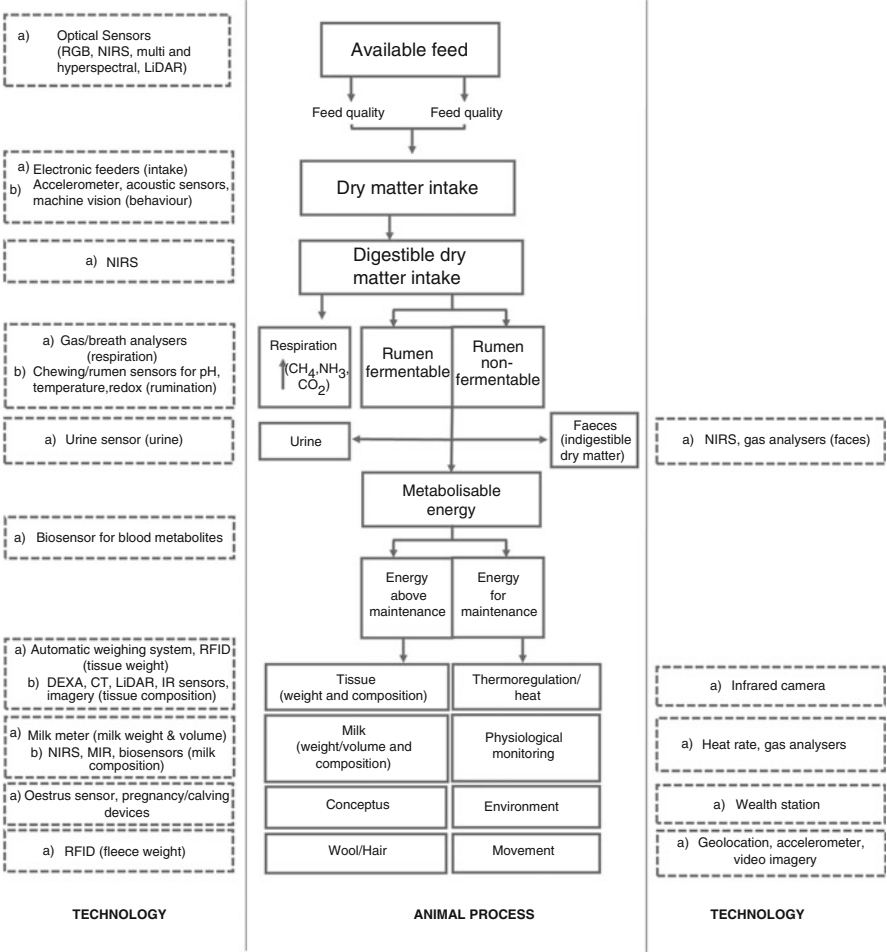


Fig. 10.2 A simplified hypothetical flowchart of nutrients through an animal (solid boxes) with potential technologies to measure key physiological processes (dashed boxes). *RGB* red, green, and blue, *NIRS* near-infrared spectroscopy, *LiDAR* light detection and ranging, *DEXA* dual energy X-ray absorptiometry, *RFID* radio frequency identification, *CT* computer tomography, *MIR* mid-infrared. (Adapted from González et al., 2018).

can be used to visualize where different technologies fit to obtain critical measurements throughout the nutritional processes involved in the flow of nutrients (Fig. 10.2; adapted from González et al., 2018). Figure 10.2 is not comprehensive but allows mapping the role that some technologies can play to provide critical information that allows understanding and quantifying the nutritional process. Some technologies may be more suited than others for a particular application depending on the objective or to address the most limiting factors to animal production, profitability, or environmental sustainability. For example, the increasing impact

of methane emissions in a carbon-constrained economy may result in placing larger emphasis on reducing methane emissions compared to increasing productivity, for which gas analysers such as the GreenFeed (C-Lock Inc., USA) could become more relevant to manage the nutrition of grazing ruminants. The following sections of this chapter will discuss some of the technologies available at key stages of the flow of nutrients in the animal body following the sequence of Fig. 10.2. Examples of applications and integration of data with prediction models will be presented to demonstrate the approach to aid in decision making and improve the nutritional management of extensive livestock systems.

10.3 Feed Availability and Quality

Pasture growth rate, biomass, and quality are key attributes of importance in extensive livestock production, which are highly dependent on weather, soil, and management, and determine livestock production, sustainability, and welfare throughout the year (Ash et al., 2015; O'Reagain et al., 2009). These attributes of the vegetation available to animals are critical for managing stocking rate, length of the grazing periods, pasture utilization rate or grazing intensity, and animal performance. Pasture growth rate is normally measured in kg of DM/day/ha, biomass in kg of DM/ha, and quality has often been measured through dry matter digestibility (DMD) and the concentration of nutrients such as crude protein (CP), neutral detergent fibre (NDF), or minerals in % of DM. This section describes some of the most used and promising technologies to monitor the vegetation in grazing systems.

10.3.1 Vegetation Reflectance and Vegetation Indexes

The most widely used technologies to monitor the vegetation in extensive rangelands are based on measuring ground reflectance or absorbance of light at various sections of the light spectrum (Ali et al., 2016). The reflectance of the vegetation depends on the type of forage such as green in actively growing vegetation or brown in senescent vegetation (visible section of the spectrum), or its chemical composition (e.g., infrared region; Wachendorf et al., 2018). Sensors or cameras to measure reflectance can be mounted on fixed platforms on the landscape (Flynn et al., 2008; Hancock et al., 2015), manned ground or aerial vehicles (Insua et al., 2019), unmanned ground or aerial vehicles (Oliveira et al., 2020; Wijesingha et al., 2020), or satellites (Edirisinghe et al., 2011). There are obvious advantages and disadvantages for each platform. However, for extensive grazing conditions satellites are preferred because of the large coverage (worldwide) and area of each overpass (several km swath width), low cost, and appropriate temporal and spatial resolution. However, satellite imagery is affected by cloud cover which can result in significant data loss during wet seasons. In contrast, ground or aerial vehicles are less dependent of cloud cover, have high spatial resolution but lower coverage (Wijesingha et al., 2020).

Spatial, temporal, and spectral resolution are the most important considerations of these sensors in different platforms (Wachendorf et al., 2018). Spatial resolution refers to the pixel size projected on the ground and can also refer to image or swath size. Temporal resolution refers to the frequency at which data can be obtained (e.g., number of days between satellite visit of the same point on earth), and spectral resolution refers to the number and width of the spectral bands that can be recorded with the sensor (Wijesingha et al., 2020). Sensors can be classified as true colour or red, green, blue (RGB) for sensors measuring reflectance in the visible part of the spectrum, multispectral sensors that can measure at multiple parts of the spectrum most often including measurements in the infrared and near-infrared wavelengths, or hyperspectral sensors with the ability to measure reflectance with high spectral resolution such as bands every 10 nm (Paoletti et al., 2018; Wachendorf et al., 2018).

There are multiple vegetation indexes that can be calculated from the reflectance measured at each spectral band, which reflect the characteristics of the forage such as greenness or chemical composition (Ali et al., 2016; Wachendorf et al., 2018). Normalized difference vegetation index (NDVI) or greenness index measures the reflection from actively growing plants, and it is widely used as an indicator of green forage biomass, plant growth rate, quality, and pasture health (Ali et al., 2016). The NDVI also shows high correlation with the DMD and CP of pastures (Ausseil et al., 2011). Vegetation indexes can capture both temporal and spatial changes in vegetation biomass and quality. However, many of these indexes are not suitable to measure biomass of dry pastures and require calibration equations that may be site and sensor specific (Wachendorf et al., 2018). An example of an image to show the spatial variability obtained from a drone on a rotational grazing system is shown in Fig. 10.3, where both the RGB and NDVI values are shown for each pixel.

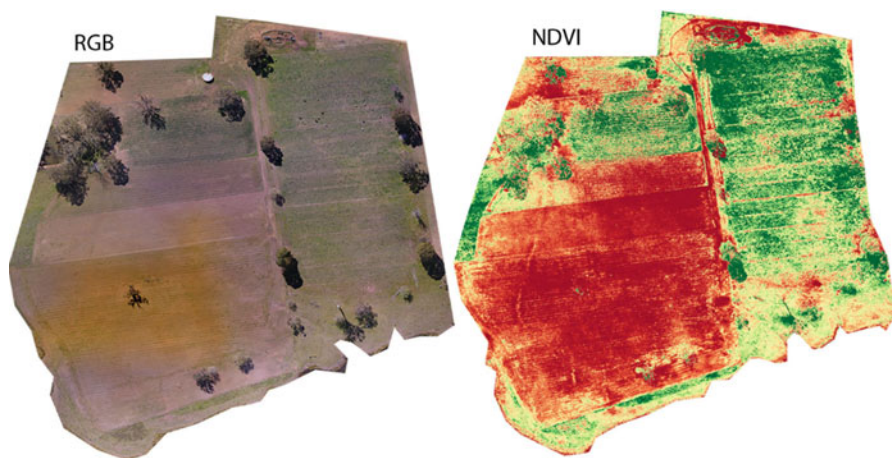


Fig. 10.3 Drone imagery of pastures in true colour (Red, Green, and Blue (RGB)) and normalized difference vegetation index (NDVI) under a rotational grazing system with beef cattle to show the ability of the technology to capture spatial variability in actively growing forage. Green colour indicates paddocks or areas within a paddock with high accumulation of green forage compared to red colours which indicate very low forage availability or bare ground

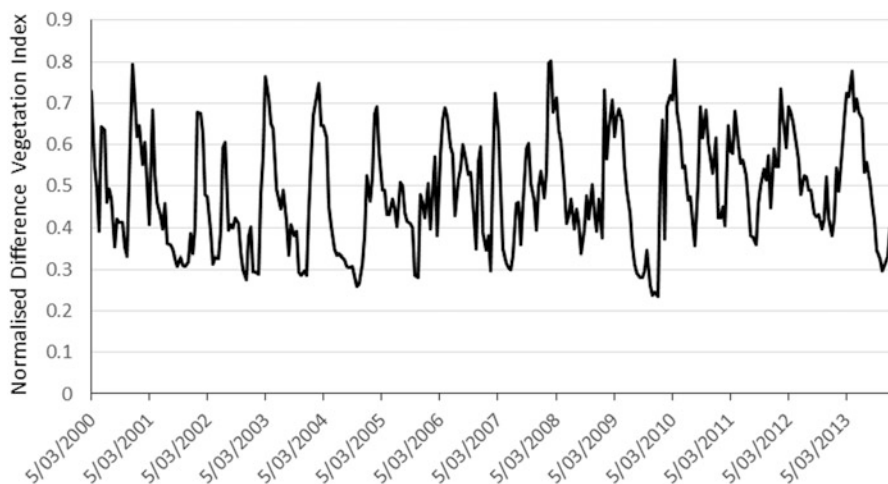


Fig. 10.4 Normalized difference vegetation index (NDVI) or greenness index of tropical pastures in northern Australia over a period of 3 years, demonstrating the ability of satellite imagery to provide detailed temporal changes that reflect the nutritional status of grazing livestock. Low NDVI values indicate dry seasons and high indicate wet season with green forage accumulation

In addition, these spectral sensors mounted on satellites can provide frequent data with some satellites offering free RGB imagery daily (e.g., <https://www.planet.com/>) or free multispectral imagery every 5 days (e.g., <https://eos.com/sentinel-2/>) to capture very detailed information of temporal changes in green forage biomass. An example of the ability of these technologies to provide detailed temporal changes through vegetation indexes is shown in Fig. 10.4 over tropical pastures in northern Australia (Rockhampton, Queensland) using MODIS satellite (<https://modis.gsfc.nasa.gov/data/dataproduct/mod13.php>).

10.3.2 Biomass and Growth Rate of Pastures

An early example of the utilization of both satellite imagery and data fusion for rangeland monitoring with applications in the nutritional management of livestock was presented by Hill et al. (2004). The authors used satellite imagery to calculate vegetation indexes and then integrated these with weather data to estimate pasture growth rate for budgeting feed available for livestock and managing stocking rate. Examples of model-data fusion approaches have also been used in pastures to improve the estimation of pasture biomass using remote sensing data from proximal hyperspectral sensing, Sentinel-2 satellite, and a radiative transfer model through the calculation of leaf area index (Punalekar et al., 2018). A simpler approach was used by Gargiulo et al. (2020) with Sentinel-2 data being used to calculate NDVI over time and then regressed the slope of the NDVI values against time to as an estimation of pasture growth rate ($R^2 = 0.74\text{--}0.94$). However, biomass estimation from NDVI

showed low precision in latter study ($R^2 = 0.61$). Landsat satellite imagery has also been used to assess the effect of grazing management and climate on pasture vegetation index, which was recommended for both research and commercial applications (Donald et al., 2013). These examples show the potential of different modelling approaches and model-data fusion applied to pastures grazed by animals with applications to monitor feed and nutrient on offer. It is important to note that ultrasonic sensors and light detection and ranging (LiDAR) have also been used to measure pasture biomass with acceptable precision as reviewed by Wachendorf et al. (2018). These sensors work by emitting ultrasonic sound waves or infrared light and then measuring the time it takes to be reflected by the pasture. This time is then used to calculate the distance between the target object (pasture) and the sensor providing a cloud of points that allow estimating forage height and density, and therefore biomass (Wachendorf et al., 2018). However, these sensors are not mounted on satellites for applications in extensive grazing and are mostly used in ground or aerial vehicles.

10.3.3 Pasture Quality

Scientific evidence supports the use of spectral data to measure the quality attributes of pastures for grazing animals despite an apparent lack of commercially available systems. Research by Ausseil et al. (2011) reported that ME, organic matter digestibility, and CP concentration of pastures could be predicted from satellite-derived vegetation indices with $R^2 > 68\%$. These relationships between vegetation indices and pasture quality and quantity can also be reflected in the growth of the animals (Pearson et al., 2021). Recently, Insua et al. (2019) used a model-data fusion approach integrating UAV spectral data with mechanistic (process-based) models of plant growth to predict pasture growth rate, digestibility, and morphology. The latter authors predicted DMD of pasture from changes in NDF concentration according to plant morphology from leaf growth and senescence, and leaf number and length accounting for the severity and frequency of grazing. The authors found that the model-data fusion approach was accurate to predict the spatial and temporal changes in pasture biomass, neutral detergent fibre, digestibility of neutral detergent fibre, and digestibility of dry matter with concordance correlation coefficients of 0.94, 0.71, 0.92, and 0.93, respectively. Schut et al. (2006) also demonstrated the ability of imaging spectroscopy to measure the concentration of N, P, K, crude fibre, NDF, acid detergent fibre, and digestibility of *Lolium perenne* and grass-clover swards. Other researchers used a data fusion approach to demonstrate that the integration of spectral satellite or hyperspectral proximal sensing and ultrasonic data streams improved the predictions of biomass, CP, and acid detergent fibre (ADF) by over 35% in highly heterogeneous pastures (Mockel et al., 2017; Safari et al., 2016).

The literature cited in this section demonstrates that metrics of forage plants relevant to manage the nutrition of animals grazing in extensive rangelands can be measured remotely. These metrics include biomass, growth rate, chemical

composition, and digestibility or ME concentration using multispectral and hyperspectral sensors, remote and proximal sensing. The metrics can then be used by mathematical nutrition models such as NASEM (2016) and Freer et al. (2007) to predict feed and nutrient intake, and performance of grazing livestock. However, the challenge still exists in developing the prediction equations to convert the spectral data into the relevant metrics required for the nutritional management of livestock. Unfortunately, these equations are time consuming and expensive to obtain, and likely to be specific for different pastures, regions, and sensors. The standardization of field data collection, data sharing, and alliances between research groups could result in generalized calibration equations to benefit the grazing industries.

10.4 Energy and Nutrient Requirements

The feed and nutrient requirements of animals can be partitioned into those required for maintenance and production (Freer et al., 2007; NASEM, 2016). The largest influence on feed and nutrient requirements of livestock grazing in extensive conditions comes from LW, LWC, physical activities, and the need to maintain body temperature in some regions where ambient temperature is challenging for the animals. In addition, energy and nutrient requirements for wool production can also be significant in wool sheep breeds, such as Merino (Freer et al., 2007). Therefore, LW is one of the most critical measures to estimate feed and nutrient requirements of extensively raised livestock (González et al., 2018). The importance of animal behaviour on energy requirements for grazing livestock has also been highlighted in a recent review (Tedeschi et al., 2019). Distance travelled by animals searching for feed and water in extensive conditions can also be significant (Brosh et al., 2010). This section describes some of the technologies to measure or predict energy and nutrient requirements for maintenance driven by LW and physical activity of the animal. Feed and nutrient requirements are affected by growth rate, the composition of growth, gestation, and lactation, and this is the focus of the second part of this section.

10.4.1 Nutrient Requirements for Maintenance

The energy and nutrient requirements for maintenance under extensive grazing conditions will be mostly influenced by the LW and the physical activities performed by the animal (Tedeschi et al., 2019). Therefore, remote monitoring of LW and animal behaviour may be amongst the most important variables to monitor. Many nutrition models estimate energy requirements for maintenance as total heat production which can be partitioned in heat for basal metabolism, muscular activity required for physical activity, action of digestive enzymes, ruminal fermentation, heat associated with the metabolic processes of product formation from absorbed metabolites, thermal regulation, and waste formation and excretion (NASEM, 2016; Tedeschi et al., 2019). This section describes some of the technologies and

approaches available to measure LW, physical activities and behavioural time budgets, and gas exchange to measure heat production in extensively kept livestock.

10.4.1.1 Remote Monitoring of Body Weight and Composition

Technologies exist today to measure LW and growth rate of animals in the paddock without the need of mustering (González-García et al., 2018; González et al., 2014b). These technologies enable real-time monitoring of the temporal and inter-individual variability in LW and the effects of environmental and management factors on the growth path (Brown et al., 2014; Imaz et al., 2020b). In-paddock automatic weighing (i.e., walk-over-weighing scales, WOW) and imaging techniques (2D and 3D) are a group of technologies to measure LW and composition of animals. Automatic weighing scales were developed in the dairy industry decades ago (Filby et al., 1979), nevertheless their utility for extensively managed cattle and sheep was demonstrated only recently (González et al., 2014b, 2018; van Straten et al., 2009; Zachut & Moallem, 2017). Additionally, imaging techniques have been used in cattle and small ruminants (Fernandes et al., 2020). Images are used to determine LW, or a range of body measures to predict LW and composition, although most have been demonstrated in confined or intensive production systems (Fernandes et al., 2020). Interestingly, the use of images in animal science has had a fast growth in the last few years aided by the current development of digital cameras and computer-based software for image analyses (Gjergji et al., 2020).

Automatic weighing scales collect LW data as animals walk a strategically placed scale which can be a walk-through or walk-in system (Imaz et al., 2020a; Mendes et al., 2011) which weighs the animals while they walk, drink water, or eat supplement, respectively. The automatic weighing system contains a radio-frequency identification (RFID) reader enabling measurements on individual animals, a weighing platform with load cells, a data processing and storage device, and wireless data transmission. The most common system of identification in livestock is RFID utilizing low-frequency radio signals to transfer information between a transponder and an antenna that collects the signal and transfers it to a decoder (McAllister et al., 2000). This technology is the backbone of many other technologies because these are the means to assign a piece of information measured by other sensors to an animal. Nowadays, several companies offer integrated platforms enabling not only animal weighing (Tru-Test Remote WoW; Simanungkalit et al., 2020), but also validated systems for measuring feed intake, feeding behaviour, and water consumption such as GrowSafe (Mendes et al., 2011; Wang et al., 2006) and Intergado (Chizzotti et al., 2015; Oliveira et al., 2018).

The frequency of data acquisition is crucial to drive the potential accuracy to describe the growth path of animals using remotely collected LW data (Imaz et al., 2020a). Research has demonstrated that more frequent data collection can increase the ability to capture detailed information to describe the effect of environmental and managerial factors (Imaz et al., 2019, 2020b). The number of records obtained using automatic weighing can be affected by different factors including the location of the WOW within the farm, setup of the system and configuration, type of production system (e.g., dairy, beef cattle), animal category (e.g., mature, or young cattle), and

nutritional management. A review of 9 studies involving cattle and sheep managed extensively showed that the number of records varied from 0.15 to 3.74 per animal/day (Aldridge et al., 2017; Brown et al., 2014; González et al., 2014b; Imaz et al., 2019, 2020b; Menzies et al., 2018; Simanungkalit et al., 2020). Only two studies presented the interval between valid LW records which were 2.48, 1.94, 1.45, and 0.76 days for calves, mature cows, weaners, and steers, respectively (González et al., 2014b; Imaz et al., 2020a). In addition, 7 studies reviewed in grazing beef utilized water as main attractant and 4 of them also included liquid molasses, molasses-lick blocks, and salt and vitaminized minerals (González et al., 2014b; Imaz et al., 2020b; Segerkvist et al., 2020; Simanungkalit et al., 2020). Menzies et al. (2018) reported a tendency for cows to come to water less frequently during the parturition.

In grazing sheep, González-García et al. (2018) and Brown et al. (2014) successfully collected LW data from ewes and lambs. However, a flock of 196 naïve sheep (not previously experienced with WOW) required approximately 90 days to obtain records for 80% of the flock using water as the main attractant (Brown et al., 2014). Interestingly, non-naïve sheep in combination with water and supplement as attractants required less than 15 days to achieve a similar percentage of the flock. However, LW data from only 20% of the flock was recorded in less than 55 days when naïve sheep were incentivized to walk over the system using salt blocks instead of water, or its combination. These results indicate that multiple factors affect the usage (i.e., attendance) of weighing systems such as feed available, type of attractant, paddock size, number of animals in the group, nutritional management, and environmental conditions (e.g., rain).

Definition of the body of animals can be collected in 2D and 3D using still images or video analysis to determine LW, animal performance, and body composition in live animals (Gomes et al., 2016; Song et al., 2018; Weber et al., 2020). This recent increase in the use of image analysis was particularly triggered by computer-aided analyses such as machine learning (Miller et al., 2019). Imaging techniques can be used to collect data with minimum equipment required in contrast to the weighing scales needed by WOW. Nevertheless, most studies were performed in confined conditions (Fernandes et al., 2020) and little to no research can be found in beef and sheep raised extensively (Miller et al., 2019). Findings suggest that such technologies offer potential to measure animal performance in extensive conditions, but grazing behaviour, the frequency of visits to the point where the images are collected, and environmental conditions may affect the quantity and quality, and thus the accuracy of body measurements.

Studies reported modest to high correlations between body measures obtained from 2D and 3D imagery and LW in beef and dairy cattle (Le Cozler et al., 2019; Ozkaya et al., 2016; Song et al., 2018; Stajanko et al., 2008; Tasdemir et al., 2011; Weber et al., 2020). Ozkaya et al. (2016) predicted LW from body area ($R^2 = 0.61$) and the accuracy of such predictions were improved ($R^2 = 0.88$) when combined with body measures such as wither height, body length, and chest girth in Limousine cattle. Similarly, Weber et al. (2020) estimated LW ($R^2 = 0.75$) from 2D images of the dorsal area of confined Nellore (*Bos indicus* cattle). The latter authors suggested that automatic segmentation techniques and previous LW data from animals (e.g.,

static weighing operations) could improve the accuracy of LW prediction. Interestingly, Tasdemir et al. (2011) found a high correlation ($r \sim 0.98$) between LW, predicted from several body measures, and LW measured by weighing the animals. The use of 3D imagery seems to present similar results to 2D imagery in terms of accuracy and sources of errors affecting LW predictions, although most research has been done in dairy cows (Song et al., 2018). Le Cozler et al. (2019) found that the correlation between biometric measurements taken manually and those measured with a 3D scanner ranged from 0.62 to 0.89. The study stressed that errors in manual measurements may also exist because they are extremely difficult to perform accurately on live animals.

In addition to LW, body condition score and body composition are important to determine animal requirements (Marcondes et al., 2012). For instance, animals with similar LW could differ in the proportion of fat and muscle due to nutritional status, age, and genetic factors including breed and frame (Owens et al., 1995). This is important in cattle and sheep managed extensively, because animals may lose large amount of LW during winter or dry seasons and regain body condition in the spring or wet seasons. Gomes et al. (2016) reported large differences in the ability to predict empty body fat in Angus and Nelore cattle using 3D digital image analyses. The models developed estimated empty body fat with moderate accuracy ($R^2 = 0.45$) in Angus; however, no significant associations between body fat and camera-derived measures were found in Nellore cattle. Similarly, Hyslop et al. (2008, 2009) used 2D digital imaging in Limousin and Angus crossbred finishing steers to estimate LW ($R^2 = 0.81$), cold carcass weight ($R^2 = 0.81$), bone out proportion ($R^2 = 0.91$), and meat and fat proportions ($R^2 = 0.61$).

Miller et al. (2019) integrated an on-farm system with an automated 3D camera placed at the water trough with machine learning to predict carcass parameters in finishing beef cattle. Sixty potential predictor variables were automatically extracted from the live animal 3D images (lengths, heights, widths, areas, volumes, and ratios) used to develop predictive models for LW and carcass characteristics. The predictions of carcass yield, conformation and fat ranged from R^2 of 0.55–0.70. Similar approach and results were observed by McPhee et al. (2017) utilizing a 3D camera along with machine learning to assess rump fat and muscle score in Angus breeding cows and steers. However, the authors highlighted the need of building broad databases, including *Bos indicus* and continental cattle, to strengthen the ability of machine learning to predict outcomes around body composition in cattle.

The continuous monitoring of LW enables a more accurate determination of animal requirements for maintenance over time and amongst individuals. For instance, grazing animals may go through periods of undernutrition as forage in a paddock is depleted and matures (Burns & Sollenberger, 2002). Compensatory growth may occur depending on age, animal category, and duration and severity of the feed deprivation (Ryan, 1990). During such periods of undernutrition, LW loss could range from a modest increase to severe LW loss and animals may adapt to a lower nutritive status by stunting, if the restriction is maintained over time (Ryan, 1990). A frequent remote weighing assessment offers applications to identify timely the effects of undernutrition and deliver supplementary feed only when it is required.

Increasing the frequency of LW data collection could also enable determination of the duration and magnitude of compensatory growth in cattle. Similarly, a large variability in the growth path of individual animals can be detected and provide a different nutritional management targeting only those animals showing lower performance than expected. A simultaneous assessment of LW and body composition could be a powerful tool to predict slaughter endpoints from different breeds, feeding regimes, and days on feed. However, a relatively low number of studies have been published, in part, due to the constraints of physically separate muscle and fat from slaughtered animals to assess their proportion. The growth of novel technologies with potential to monitor body composition and LW offers unprecedented room to explore associations between desirable body composition traits, LW, and predict these outcomes in real-time.

10.4.1.2 Requirements for Physical Activities

A large proportion of the energy and nutrients consumed by grazing animals under extensive conditions can be used for physical activities such as grazing, walking, resting, and ruminating (Tedeschi et al., 2019). Walking or travelling is the most energy-consuming activity (Tedeschi et al., 2019) and thus it has sometimes been considered a loss of efficiency. Nutrient requirements for physical activities have been measured under experimental conditions mostly using indirect calorimetry, where the consumption of O_2 and production of CO_2 are measured either using respiration chambers, portable masks (Brosh et al., 2010), or more recently open-circuit gas quantification systems such as GreenFeed (C-Lock Inc., USA; Herd et al., 2020). These conversion factors such as MJ of ME/km travelled can then be used as part of mechanistic nutrition models to drive the partitioning of energy and nutrients for different biological processes (Freer et al., 2007; NASEM, 2016). Early research has demonstrated that accounting for body composition and composition of growth in cattle can improve the prediction of feed intake of individual animals (Guiroy et al., 2001). Similarly, large differences between animals exist in the time budgets, behaviour, and energy expenditure which could also be used to improve the predictions of feed efficiency for individual animals.

Fortunately, many sensors have been developed in the last few years to allow estimating the energy expenditure of individual animals such as GNSS devices to measure geolocation and thus distance travelled, and accelerometers to measure grazing, ruminating, and resting time budgets (González et al., 2015). These technologies have been used successfully in an integrated way by Brosh et al. (2007, 2010), along with heart rate monitors and portable masks to measure the oxygen consumption of each heart bit. Heart rate is then measured for each behaviour to finally determine energy expenditure of each activity. Although this approach has only been used for research, the reduction in cost, size, and weight of new devices to monitor animal behaviour may allow scaling up animal monitoring at large scale under commercial conditions.

An example of a practical application of such technologies to help designing an intensive rotational grazing system is presented herein (Fig. 10.5). We used GNSS collars to determine the distance travelled by animals in a cell grazing system under

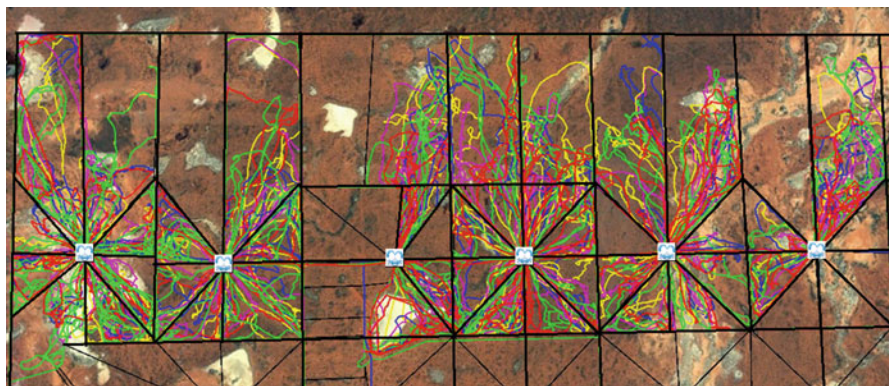



Fig. 10.5 Tracks of five steers grazing *Acacia aneura* vegetation communities in a developing cell grazing system with small 180-has and large 1000-has paddocks in semiarid Australia (Gonzalez, unpublished data). Each coloured line refers to the GPS track of an individual steer over time, fences are the black lines, and  shows the water troughs

development in semiarid southwestern Queensland (Australia) where woody vegetation with high concentration of tannins ($\sim 5\text{--}7\%$ of DM) such as mulga (*Acacia aneura*) plays an important role in animal nutrition. The landscape has traditionally been grazed with cattle and sheep with continuous grazing in large paddocks often exceeding 8000 hectares with only 1 or 2 water points. This may result in uneven grazing distribution because animals stay close to the water points, potentially leaving a large proportion of forage not grazed, and thus resulting in low stocking rate and productivity. Cell grazing systems and regenerative agriculture have become popular in Australia and elsewhere because of the potential to improve productivity and sustainability although the scientific evidence is conflicting (Briske et al., 2011). Cell grazing requires a large investment in fencing and water point development to break up large into smaller paddocks that can be grazed for only 1 or 2 days and allow resting for many months. Figure 10.5 shows tracks of five animals moving throughout a section of the property being developed for cell grazing. The small paddocks have an area of approximately 180 hectares (length of 2 km) and the large paddocks of approximately 1000 hectares (length of 6 km), and a water point every 4 km at the intersection of the paddocks. Figure 10.5 suggests that animals do not utilize the back of the large paddocks further from water and prefer to stay within approximately 2 km of the water point.

A large day-to-day and animal-to-animal variation was observed in the distance travelled per day which ranged from 2.72 to 29.34 km/day (data not shown). Interestingly, animals travelled 2.64 km/day more in large paddocks compared to small paddocks (Table 10.1). Using the equations presented by Freer et al. (2007), animals in the large paddocks required 4.15 MJ of ME/day more for travel compared to small paddocks. Faecal samples were also obtained from these animals to measure DMD, CP, and grass vs. non-grass proportion of the diet consumed using NIRS technology (Dixon & Coates, 2009; Coates & Dixon, 2011). The ME concentration

Table 10.1 Distance travelled and activity level from electronic collars, estimated energy expenditure for travel, and diet selection of steers grazing mulga vegetation communities in a developing intensive rotational grazing system with small (180 has) and large paddocks (1000 has) of SW Queensland, Australia

	Paddock size		<i>P</i> -value
	Large	Small	
Distance travelled, km/day	11.61 ± 0.376	8.97 ± 0.285	<0.001
Activity X-axis, count	46.22 ± 0.796	41.44 ± 0.602	< 0.001
Metabolizable energy walk, MJ/day	18.60 ± 0.593	14.45 ± 0.449	<0.001
Feed required travel, kg DM/day	2.43 ± 0.079	1.95 ± 0.065	<0.001
Diet DMD, % DM	56.26 ± 0.377	56.20 ± 0.311	0.91
Diet CP, % DM	12.32 ± 0.220	12.81 ± 0.181	0.09
Digestible DMI, g DM/kg LW	11.36 ± 0.104	10.16 ± 0.094	< 0.001
Faecal N, % DM	1.68 ± 0.028	1.83 ± 0.023	<0.001
Grass intake, % DMI	31.92 ± 0.994	16.68 ± 0.658	<0.001
Non-grass intake, % DMI	68.08 ± 0.994	83.32 ± 0.658	<0.001
Mulga intake, % DMI	29.15 ± 1.679	43.90 ± 1.111	<0.001

of the diet consumed was then used to calculate the required feed intake for walking, which suggested that steers in large paddocks may need to use 0.48 kg dry matter intake (DMI)/day for the extra walking.

It is also important to note that paddock size affected stocking density in this study, which may not only affect distance travelled by animals but could also affect diet selection and intake of plants with secondary compounds that may reduce animal performance (Briske et al., 2011). Faecal NIRS results of the study in Queensland indicated that animals tended to consume a diet with higher CP ($P = 0.09$) and excreted higher N concentration in faeces ($P < 0.001$) in small compared to large paddocks (Table 10.1). These results may be explained by higher selection of mulga in the diet of steers in small paddocks (Table 10.1), which comprises a large proportion of the diet in this landscape and contains approximately 13% CP and up to 6% of condensed tannins (data not shown). This example highlights the potential of NIRS technology to monitor diet quality and selection which can then be used to improve animal nutrition, productivity, and sustainability. The technology could expand its commercial use and applications considering the development of simple, practical, and cheap NIRS sensors such as those used by Coombs et al. (2021a).

The above data presents an example of potential applications and approaches when using sensor technologies to monitor animal behaviour in extensive grazing conditions. These technologies offer a great opportunity to remotely monitor animal behaviour and manage them in extensive grazing. Furthermore, these technologies can measure behaviours with multiple applications in the nutrition of livestock in extensive conditions including grazing patch selection, time budgets (Brosh et al., 2010; González et al., 2015), energy requirements for physical activities (Brosh et al., 2010), and the response of animals to declining pasture availability (Manning et al., 2017).

10.4.1.3 Total Heat Production or Maintenance Requirements

The indirect calorimetric method used by Brosh et al. (2006, 2007) for grazing animals with face masks to measure gas exchange and GNSS collars to measure animal behaviour showed great utility to measure total and partial heat production or energy requirements for each activity. However, the technique is labour intensive and impractical to use in many animals. Interestingly, gas exchange can now be measured in a larger number of animals and in a simpler way using open-circuit gas exchange systems such as GreenFeed (Caetano et al., 2018). The newer GreenFeed models (C-Lock Inc., South Dakota, USA) can measure the production or consumption of CO₂, O₂, NH₃, CH₄, and H₂, of exhaled breath so heat production can be estimated from data collected when animals visit the unit to eat supplementary feed. The technology has shown high accuracy to measure daily methane emissions (g of CH₄/hd/day) when animals attend a feed dispenser in both intensive and extensive conditions (Alemu et al., 2017; Arbre et al., 2016). This opens many opportunities to estimate energy requirements for maintenance in grazing livestock, which could also be integrated with nutrition models such as those presented by Tedeschi et al. (2019). Recently, the GreenFeed system has been used to estimate heat production of individual animals from O₂ consumption and CO₂ and CH₄ production using the indirect calorimetry method (Gunter & Beck, 2018; Herd et al., 2020; Pereira et al., 2014). However, this method requires the estimation of ME used for production which can be obtained from measuring LW, growth rate, and composition of growth using the model-data fusion approach as demonstrated by Herd et al. (2020).

10.4.2 Energy and Nutrient Requirements for Production

The requirements for production are determined by body growth rate, composition of body growth, gestation stage, foetus weight and number of foetuses, lactation with its components of milk production and chemical composition, and wool growth (Freer et al., 2007; NASEM, 2016). This section describes options for remote monitoring of these processes with some examples suitable for the smart nutrition in extensive livestock production.

10.4.2.1 Requirements for Body Growth

The energy and nutrients required for body growth depend on several factors, but mainly on growth rate and composition of growth (fat and muscle; NASEM, 2016). One practical option to monitor, predict, and manage the nutritional requirements for growth of grazing livestock is to measure LW, growth rate, and body composition or body condition using remote monitoring tools described above. The efficiency at which an animal converts feed and nutrients into body growth is very challenging to estimate under grazing conditions because feed intake cannot be measured. The use of mathematical prediction models of energy balance aided by automatic determination of body growth and composition are probably the most practical way to monitor energy and nutrient requirements for a target or observed body growth (Guiroy et al., 2001; González et al., 2018). Figure 10.6 shows an example of using automatically

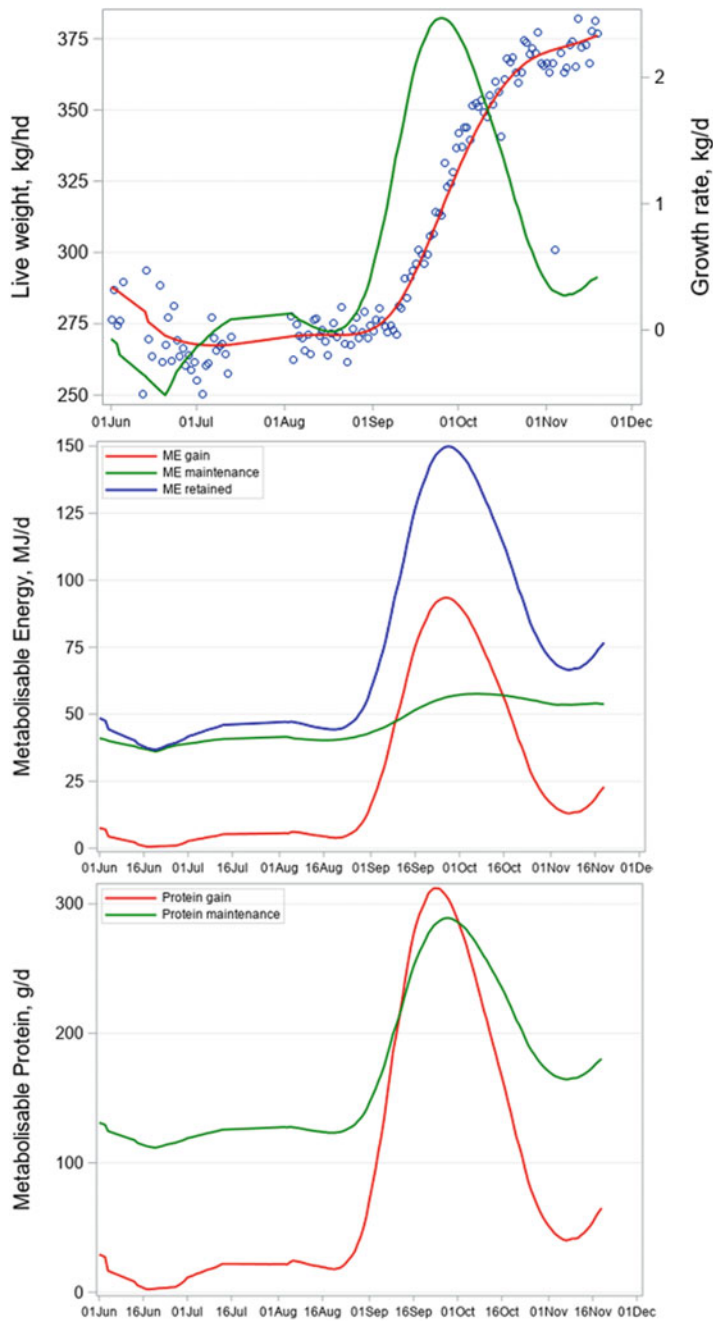


Fig. 10.6 Remotely collected body weight and growth rate, and model-estimated metabolizable energy and protein required for maintenance and growth of steers grazing natural pastures in southern Australia. The top panel shows live weight recorded by automatic weighing systems in the paddock (blue circles), predicted live weight after smoothing (red line), and estimated growth rate (green line)

collected data of both LW and growth rate to estimate the ME and nutrients required for growth described by Freer et al. (2007). The graphs show the average LW and daily LWC of a group of 12 steers grazing natural pastures throughout the winter and weighed at the water point with a WOW scale. Animals were assumed to walk 5 km/day and have an average body condition score (BCS). The energy and nutrients required for body growth can then be added to the requirements for maintenance and other production activities, such as gestation and lactation to obtain total ME and nutrient requirements. The efficiency with which animals use energy for maintenance and production remain a rough estimation using the coefficients calculated by the nutrition models. However, new technologies such as those that measure gas exchanges of individual animals could be of great assistance to estimate the coefficients for individual animals. Similarly, body composition is most often predicted from BCS, but new technologies could change the way this is done as reviewed above.

Another example to extract the value of LW data remotely collected using the model-data fusion approach was presented by González et al. (2018). The authors used a very similar approach to that presented above, but instead predicted energy balance with the equations presented by Freer et al. (2007). The amount and dates to deliver feed supplementation was then estimated daily to cover the energy deficit of animals losing LW so that energy balance becomes zero (maintain LW). The simulation demonstrated that the date to start and end feed supplementation, and the amount to be provided each day based on the extent of LW loss could be predicted. The same approach can be applied to determine the amount of feed supplementation to achieve a target performance, but substitution rate or additive effects should also be considered (Tedeschi et al., 2019). Large differences in the amount of LW loss and hay required was evident between animals and the approach demonstrated potential to manage day-to-day and animal-to-animal variability in animal performance. However, this approach has not been demonstrated to be feasible to date and further research is required to explore its feasibility.

10.4.2.2 Requirements for Gestation

The main factors affecting nutrient requirements for gestation are gestation stage (day of gestation), number of foetuses, and size or birth weight of the offspring (Freer et al., 2007). Technologies for remote monitoring of these attributes would have tremendous benefit to the livestock industries worldwide. Remote detection or monitoring tools of oestrus, conception date, and even simpler information such as pregnancy status over time are needed. It is common in extensive livestock production systems to segregate females into different groups according to the number of foetuses and gestation stage upon pregnancy testing to facilitate their nutritional management (Edwards et al., 2011; Young et al., 2016). The requirements of energy and nutrients increase with day of gestation, number of foetuses, and birth weight of the offspring, and therefore female segregation aims to manage LW through more precise nutritional management during gestation according to these factors. Furthermore, nutritional management during gestation also increases survival and performance of the offspring (Holst et al., 1986).

Technologies exist today to detect oestrus events in livestock from various mechanisms, such as pressure sensors near the tail head, accelerometers in ear tags, collars, or pedometers (Alhamada et al., 2016; Mottram, 2016). However, the accuracy of these or alternative devices to detect pregnancy status and date of conception has not been assessed. There are no technologies available for the extensive livestock industries that can measure pregnancy status or number of foetuses remotely. Nevertheless, automatic determination of LW can be used to monitor the nutritional status of livestock in extensive conditions throughout gestation (González et al., 2018). In addition, remote weighing can also be used to monitor and manage reproduction in extensive livestock because of the close relationship between body reserves, LW, and pregnancy and weaning rates (Tait et al., 2017). van Straten et al. (2009) also demonstrated that the percentage of post-calving LW loss has a negative impact on future reproductive performance in dairy cows, which suggests that remote monitoring of LW may have huge applications to manage reproduction through nutritional interventions.

Unpublished data from a study with 38 breeding Charolais cows automatically weighed in southern Australia over 5 years (Imaz et al., 2020a) has been used to calculate the LW trajectories of pregnant and empty cows throughout the year. Calving occurred in July and August (week 27–35) and weaning at approximately 6 months. The LW and LWC was analysed using a mixed-effects linear regression model with calving status as fixed effect (calved and not calved), week number as a repeated measure on each animal ID, and year as a random effect. All animals were managed as a group with the same treatments and grazed native pastures and oat crops and were provided feed supplementation when required. Results showed that cows that calved were 48 kg heavier than cows which did not calve on week 23 (calving \times week $P < 0.05$; Fig. 10.7). In contrast, cows that calved were up to 33 kg lighter than cows that did not calve throughout the post-calving lactation period (week 52). These results demonstrate that remote weighing can be effectively used to detect LW changes due to gestation and therefore could be used to manage the nutrition of pregnant females (González et al., 2018). For example, many simulation models predict the weight of the gravid uterus from foetal age or time since conception and expected birth weight of the calf at average condition of both the cow and foetus. The weight of the gravid uterus can be added to the LW of the cow at average condition which could become the target LW of the cow in optimal BCS to be managed through more precise nutrition. However, further research needs to be done to determine thresholds or trigger points when animals fail to put on the required LW for a healthy and productive calf and cow. For example, there is a need to establish the optimal and minimum LWC expected throughout gestation for the technology to be used as a monitoring tool to manage the nutrition of pregnant females with a concept similar to that explained above.

10.4.2.3 Requirements for Lactation

Nutrient requirements for lactation require information of daily milk production and chemical composition such as CP, fat, and milk solids (Freer et al., 2007). However, these measurements cannot be obtained in extensive grazing systems, because of the

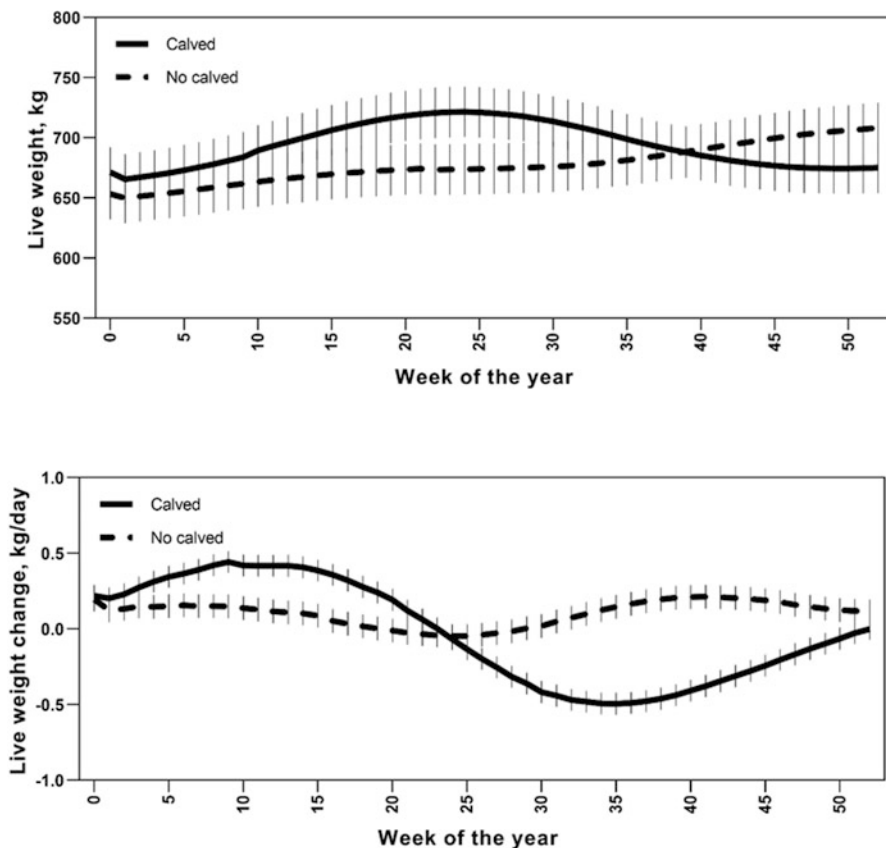


Fig. 10.7 Trajectory of live weight and live weight change (growth rate) of grazing Charolais cows that calved and cows that did not calve over a period of a year. Calving occurred between July and August and weaning between January and February

impracticality and cost. One option is to predict these requirements using models according to stage of lactation and other factors that could account for milk production and composition such as breed, LW, maternal ability as done with estimated breeding values for milk production, or calf weight and growth rate (Freer et al., 2007; NASEM, 2016). These models often require input information such as lactation stage (which is a function of birthing date), genetics determining milk production, and BCS of the cow amongst other factors. Remote determination of birthing date, calf birth weight, and lactation stage are important aspects to determine the nutritional requirements and management of females. Furthermore, weaning rate in a herd or flock is a major contributor to feed requirements or demand. In extensive grazing systems, birthing date and lactation status can be difficult to measure due to the limited contact between people and animals. Several sensors have been developed and trialled to measure birthing events in cattle, but their practicality, cost, and

accuracy are still limited under extensive grazing conditions. The suitability of a sensor or method to measure birthing events depends on the environmental conditions, management such as mustering practices, and stage of gestation when the monitoring occurs (Pearson et al., 2020). Recent research with beef cattle in extensive grazing conditions that used two commercially available vaginal implant tags (VIT) have highlighted some of the limitations associated with the length of time the VIT can last in the vagina being less than 3 months, early expulsion leading to false alerts, and high cost of the current devices (Pearson et al., 2020).

Several other sensors have been trialled for the determination of birthing events such as GNSS devices and accelerometers embedded in ear tags, collars, and pedometers (Fogarty et al., 2021; Pearson et al., 2020). These devices can measure animal behaviour with high detail, producing metrics such as speed and distance of travel, time budgets for grazing, rumination, and resting amongst others (Chang et al., 2020). Fogarty et al. (2021) review highlighted calf grooming, rumination, and postural changes as potential indicators of calving and emphasized the large variability between animals. However, the behaviour of animals in extensive conditions is complex and affected by many factors which may result in low specificity to detect birthing using these behaviours. A recent study that integrated GNSS, accelerometer, and weather data detected less than 55% of the lambing events in ewes within 3 h of birth (Fogarty et al., 2021). Another study with beef and dairy cattle applied machine-learning techniques to data obtained from collars with accelerometers and accelerometers attached to the tail to detect calving events (Miller et al., 2020). The accelerometer was able to detect calving in beef and dairy cattle with 18.7% and 26.7% of error, respectively. Therefore, the accuracy of these sensors to detect birthing events has been generally low, particularly when used under extensive conditions where females can remain active even on the day of birthing (Fogarty et al., 2021; Pearson et al., 2020).

Another method trialled for remote detection of birth events is the use of automatic weighing systems to measure LW loss of females upon expulsion of the foetus, amniotic fluid, and placenta. Aldridge et al. (2017) and Menzies et al. (2018) investigated the prediction of calving date in extensively managed breeding herds using WOW. In these studies, calving date was predicted with 59% ($n = 232$) to 63% ($n = 40$) accuracy using weighing data from late gestation to post-calving. The low accuracy to detect calving was due in part to large variability between cows in LW loss with calving and low frequency of data collected around birthing events. Figure 10.8 shows examples of two grazing cows with large and small LW loss at the time of calving to demonstrate the concept (Chang et al., 2021). This research has also demonstrated that calf birth weight could be predicted from the extent of LW loss of the cow ($P < 0.05$; $R^2 = 0.56$), which could also help to manage the nutrition of cows nursing heavy calves.

Once a birthing event is detected automatically, it is important to know if the offspring has survived to tailor the nutrition to the requirements of a dry or lactating female in the paddock. The nutritional requirements of the dam will be partly determined by the amount of milk produced, which is correlated to the weight of the offspring (Gleddie & Berg, 1968). Furthermore, sheep would require the

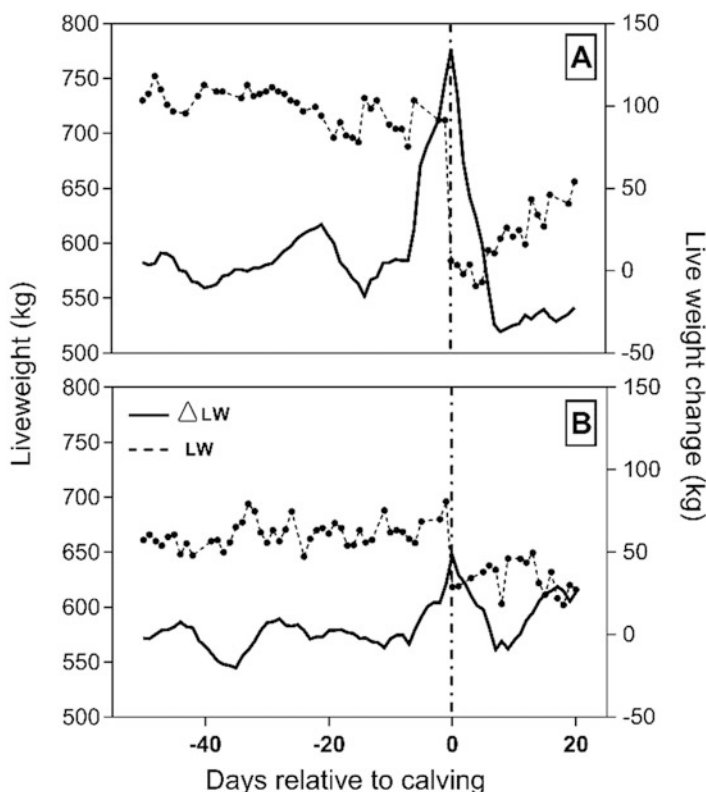
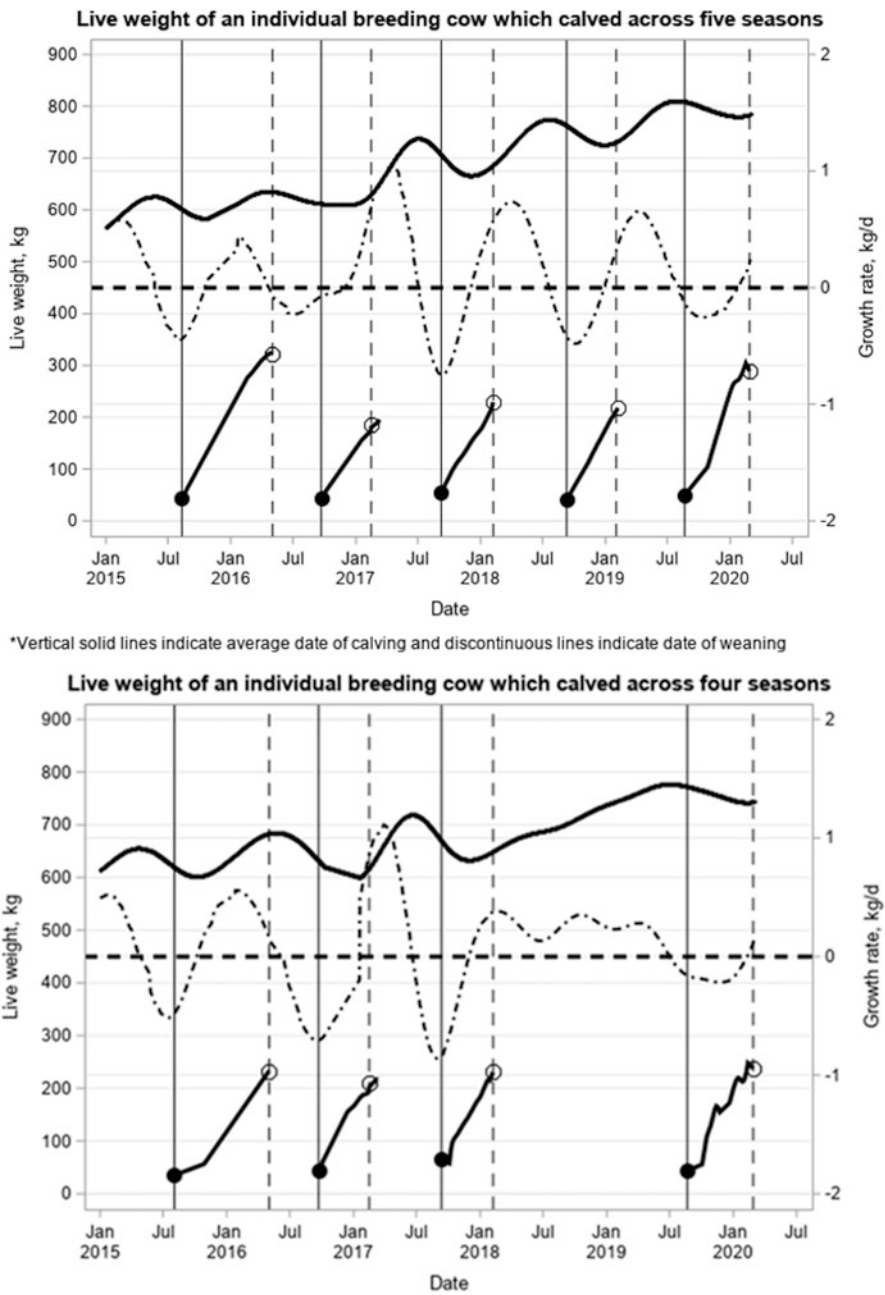


Fig. 10.8 Live weight (circles with dash) and live weight change (solid line) of two (A, B) grazing cows at the time of parturition as measured with automatic weighing systems (Chang et al., 2021). Live weight change was 135 kg for cow A and 51 kg for cow B

determination of the number of lambs being raised because this has a large influence in the nutritional requirements of the dam (Freer et al., 2007). It is common to see females losing LW during lactation, even with a good plane of nutrition because energy and nutrient requirements for milk production can exceed feed intake capacity depending on multiple factors (Freer et al., 2007). Therefore, LW changes of both the cow and calves could be used to remotely determine lactation status and nutritional requirements and manage the nutrition of lactating females. Figure 10.9 shows the LW trajectory of a Charolais cow that weaned a calf every year out of 5 years, and a cow that missed calving in year 4 under grazing conditions. Cows lose LW after calving when lactating and the extent of LW loss was negatively correlated to the weight of the calf weaned ($P < 0.05$; data not shown). In contrast, dry, non-lactating cows maintained or gained LW during the calving season (Gleddie & Berg, 1968). These examples demonstrate the ability of automatic weight determination to monitor the relationship between nutritional demands and LW of cows during lactation in extensive conditions.



*Vertical solid lines indicate average date of calving and discontinuous lines indicate date of weaning

Fig. 10.9 Live weight (solid line) and growth rate (dotted line) of a breeding cow that weaned a calf for five consecutive years (top panel) and another cow that did not calve in year 4 (bottom panel). The weight of their calves is shown as a solid line with closed (birth) and open circles (weaning). (Imaz and Gonzalez, unpublished data)

10.5 Feed, Energy, and Nutrient Intake

Measuring feed and nutrient intake in grazing livestock has been the subject of research for over a century. However, there is still no technology or methodology to measure feed and nutrient intake of individual grazing animals with high accuracy, in a practical and economical way, and at large scale, despite incredible advancements in sensor technologies during the last few years. Multiple reviews in the last few years have covered this topic of feed and nutrient intake of grazing animals and the reader is referred to these (Galyean et al., 2016, 2018; Greenwood et al., 2018; Smith et al., 2021; Tedeschi et al., 2021). The challenge with the grazing animal is twofold: (1) to measure the weight of DM consumed, and (2) to measure diet selection and quality such as digestibility, fibre, and CP concentration. Pastures in extensive conditions are generally heterogeneous with large variability in the plant species and chemical composition across time and space, and such changes that can occur very rapidly (Smith et al., 2021). In general, technological approaches to measure feed and nutrient intake in animals are based on either measuring pasture or feed disappearance, or animal factors related to intake, such as chewing behaviour (Smith et al., 2021).

Methods to measure feed intake from pasture disappearance are like those mentioned above to measure pasture biomass and quality and include surface reflectance using cameras such as RGB, multispectral and hyperspectral cameras (Wachendorf et al., 2018). Other methods such as LiDAR, lasers, photogrammetry, and ultrasonic sensors measure pasture height and density, however there is limited research to judge the utility or accuracy of these techniques to measure DMI. However, the challenge with these sensors is still the lack of accuracy to detect intake and quality of the forage consumed by individual animals grazing in a group. This section describes the main technologies to measure feed intake and diet selection and quality based on on-animal sensors to measure behaviour, analysis of faecal samples for diet quality using NIRS, and gas exchange from animals to measure ME intake.

10.5.1 On-Animal Sensors to Measure Behaviour

On-animal sensors are the subject of ongoing research around the globe to measure feed and nutrient intake (Smith et al., 2021). These sensors measure variables related to feed intake such as grazing time, chewing time, biting rate, and bite size. Most of the sensor technologies nowadays are based on accelerometers attached to an ear tag, collar, or halter. However, other technologies with the capability to measure bite size include noseband pressure sensors (Braun et al., 2015a, b; Champion et al., 2004; Rombach et al., 2019; Werner et al., 2018; Zehner et al., 2017). Acoustic sensors have also shown promise to measure chewing behaviour from metrics such as biting and chewing rate and energy (Benvenuti et al., 2016; Galli et al., 2011; Navon et al., 2013). These sensors can also be combined with GNSS to record the location of the animals in the landscape helping in the classification of behaviours (Arablouei et al.,

2021; González et al., 2015). Greenwood et al. (2018) used collars with GNSS and accelerometers to measure grazing, ruminating, walking, and resting, and reported that sensor data explained 53% of the variability in pasture intake calculated with rising plate meter. Most previous research have demonstrated that sensor technologies that measure animal behaviour as a proxy of feed intake have low precision and accuracy, or high precision can be achieved under controlled experimental conditions, but the algorithms are not robust to be applied under conditions in which these were not developed. Therefore, alternative methods such as the use of sensor data and mathematical nutrition models will be used while the search for robust technologies and data processing methods continues.

Data transmission is also important in extensive grazing conditions to measure animal behaviour and accessing the data in real-time from long distances. This challenge applies to all technologies although the size of the components is not a limitation for some technologies that are not moving through the landscape such as automatic weighing stations. Mobile cellular networks are often used where available because of the low cost, speed, and amount of data that can be transferred. However, other methods may be needed in where cellular networks are not available, such as sensors that can transmit data directly via satellites (Pearson et al., 2020) and via LoRa and LoRaWAN (long-range, low-power WAN) have also become very popular in the Australian rangelands (Casas et al., 2021).

10.5.2 Faecal Near-Infrared Spectroscopy (NIRS)

Faecal NIRS has been developed for many years for use in animal production to measure the diet consumed by animals (Boval et al., 2004; Coates, 2000). This is a very important aspect in animal nutrition of grazing systems because faecal NIRS measures the diet selected by the animals, rather than the diet available to the animals (Dixon & Coates, 2009). Several measures can be obtained from faecal NIRS including feed intake, dry matter digestibility (DMD), crude protein (CP), and fibre and minerals concentrations (Boval et al., 2004). Under grazing conditions, pasture growth rate, biomass, and quality change rapidly reflecting weather patterns as demonstrated above. This affects the nutritional quality of pastures and thus forage, energy, and nutrient intake. A long-term grazing trial performed in northern Australia (near Charter Towers, Queensland) used faecal NIRS obtained from a representative sample of each trial paddock approximately every 3 weeks to monitor DMD and CP of growing steers (O'Reagain et al., 2009, 2014). The results clearly demonstrated the effect of weather patterns and pasture quality on energy and protein concentration of the diet selected by the animals (Fig. 10.10). Weather patterns of the region are characterized by a wet season normally starting between December and January and lasting for 3–4 months with the rest of the year receiving no to little rainfall. A spike of up to 65% DMD and 13% CP occurs with the break of the wet season, which then decreases as the pasture dries off to reach values below 45% DMD and 2% CP during the dry season.

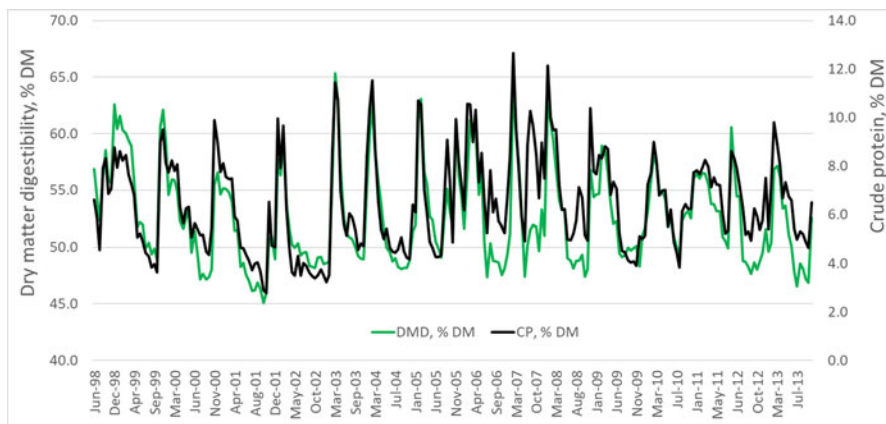


Fig. 10.10 Dry matter digestibility (DMD, % DM) and crude protein content (% DM) of the diet selected by cattle grazing tropical pastures near Charter Towers, Queensland, over a 15-year period showing the seasonal variation in diet quality. (O'Reagain et al., unpublished)

Faecal NIRS is used commercially in Australia to manage the nutrition of grazing beef cattle so urea, protein, or energy supplementation can be triggered at the appropriate time of the year (Dixon & Coates, 2009). This information can also be used to predict DMI, metabolizable energy intake (MEI), and CP intake (CPI) using various models such as those published by NASEM (2016), González et al. (2012), and Freer et al. (2007). Examples of model-data fusion using remotely collected LW data, faecal NIRS, and nutrition models have previously been presented by González et al. (2014a, 2018). The approach of using results from faecal NIRS to predict DMI, MEI, and CPI from mathematical nutrition models is expected to produce more accurate predictions compared to those made from forage analysis because faecal NIRS measures the diet selected by the animal. The NIRS sensors have advanced in the last few years significantly reducing the cost, size, and weight to currently become smartphone sensors which have yielded results with comparable accuracy compared to expensive benchtop NIRS devices (Coombs et al., 2021b; Dixit et al., 2020). These sensors and the development of prediction equations to use the data they provide could expand the utilization of this technology and simplify many of the measurements that are difficult to make such as diet digestibility, protein content, and proportion of diet components including grass and non-grass component.

10.5.3 Metabolizable Energy Intake

Measuring feed efficiency under grazing conditions did not seem possible until recently because of the lack of methods to measure feed intake and diet quality at pasture. Recently, the GreenFeed system has been used to estimate heat production of individual animals from O_2 consumption and CO_2 and CH_4 production using the indirect calorimetric method (Gunter & Beck, 2018; Herd et al., 2020; Pereira et al.,

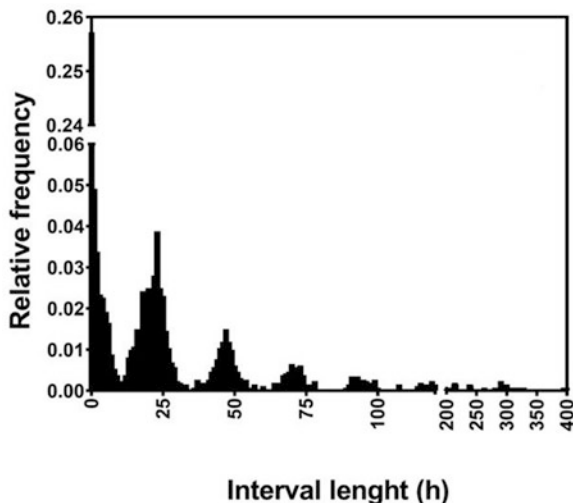
2014). This methodology can then be used to estimate ME intake if ME retained (MER) for production can be measured or estimated, which requires body weight, weight gain, composition of growth, and milk production and composition (Bosh et al., 2010; Herd et al., 2020). A model-data fusion approach has been used to estimate MER because of the difficulty to measure this in grazing conditions. Herd et al. (2020) estimated MER using nutrition models that use LW, average daily gain (ADG), and ultrasound fat thickness in live animals. These authors reported that ME intake predicted from emissions measured by the GreedFeed system plus energy retained in LW gain accounted for 85% of the variability in ME intake from feed intake and digestibility. This approach could then be used to identify more efficient animals at pasture from real-time measurements of CH₄, CO₂, and O₂ (Pereira et al., 2014).

10.5.4 Supplement Intake of Grazing Animals

The monitoring and control of supplement intake is amongst the most important practices to manage the nutrition, production, and the environmental footprint of livestock under grazing conditions. Feed supplementation of grazing animals is done for many purposes, such as covering nutrient deficiencies, improve growth rate and LW, reduce the impact of anti-nutritive factors, improve weaning weight, improve fertility, reduce mortality, and improve animal welfare under tough conditions such as drought. The nutritional management of grazing cattle and sheep is frequently orientated to increase growth rate and weaning rate using energy and protein supplementation because these are the most common limiting factors (Caton & Dhuyvetter, 1997; Poppi & McLennan, 1995). The response to supplementation depends on multiple factors such as type of supplement and chemical composition (mineral, energy, protein), mode of delivery (lick blocks, loose), processing of ingredients, and infrastructure (feeders, bunks, on the ground) amongst others. The consumption of supplements has been traditionally controlled using salt, increasing the hardness of lick blocks, or delivering restricted amount to avoid consumption above certain quantities (Tedeschi et al., 2019).

However, there have been multiple developments in the last few years to measure and control supplement intake of grazing animals using electronic feeders of different designs such as electronic hoppers that drop a predetermined volume of pellets, feeders on load bars that recognize the RFID to measure the intake of each visit by animals, and electronic feeders with pneumatic gates (González et al., 2018; Imaz et al., 2020b). One of the unique characteristics of supplement intake in grazing animals has been the large variability in supplement intake both between animals and over time depending on the forage available in the paddock and the type of supplement delivered (Imaz et al., 2019). Feeding behaviour around feed supplementation in grazing animals is markedly different from animals consuming a total mixed ration. Unpublished data from previously published studies (Imaz et al., 2020b) has been used to analyse the frequency distribution of the length of time between successive visits to the supplement of grazing growing cattle (Fig. 10.11).

Fig. 10.11 Histogram of the length of the interval between any two consecutive supplement feeding events in grazing cattle



This frequency distribution is markedly different from the 2 or 3 populations of intervals that dictate hunger and satiety in animals fed total mixed ration (Yeates et al., 2001). It is unclear what each population of intervals mean or reflect but could also have implications for the nutritional management of animals in grazing conditions to achieve the target performance or supplement intake (Imaz et al., 2020b). Furthermore, the large variability in supplement intake between animals (Imaz et al., 2020b) and over time (Reuter et al., 2017) suggests that controlling supplement intake of individual animals could improve group productivity. However, no published papers have demonstrated this approach in grazing animals and the opportunities with controlling individual feed intake are unclear to date.

These electronic feeders could help defining effective supplementation strategies for grazing livestock including type of supplement, frequency of delivery, amount of supplement, and animal response (Caton & Dhuyvetter, 1997; Farmer et al., 2001; Löest et al., 2001).

10.6 Feed and Nutrient Excretion

Information of the amount or concentration of nutrients being excreted by animals has several applications in the livestock industries because it can determine the proportion or amount of nutrients retained if intake is known and because the excretion of nutrients can have significant impacts on the environmental footprint of livestock production (Dijkstra et al., 2011). Nutrient excretion occurs mainly via urine, faeces, and exhaled gaseous emissions, such as methane, even though nutrients can also be excreted via sweating or saliva, which is considered insignificant for the present review. Technologies to measure the volume, weight, and nutrient concentration of each of these excretions are available and have the potential

to be adopted in extensive grazing. Many livestock industries around the world are constrained by the amount of waste and nutrient concentration in the waste produced, because of the risk for environmental pollution and the need to manage the waste appropriately (Velthof et al., 2015).

Faecal NIRS can also be used to measure the concentration of nutrients being excreted in addition to predicting their concentration of the consumed diet (Dixon & Coates, 2009; Jancewicz et al., 2016; Tolleson & Angerer, 2021). This is an area of great interest due to the need to manage the environmental stewardship of livestock production and faecal NIRS is one of the most practical ways to measure the concentration of nutrients such as N and P in faeces for grazing livestock. Faecal NIRS analysis can also provide information of the concentration of N in faeces which shows a similar pattern to diet N and DM according to seasonal changes (data not shown).

Urine sensors have also been developed to detect urination events, volume, and N concentration in cattle with high accuracy and precision (Marshall et al., 2021; Misselbrook et al., 2016). In addition to providing a tool to manage the environmental footprint of grazing animals, these tools could also be used to manage their nutrition because of the relationship that exists between nutrient concentration in faeces and urine and nutrient intake (Dixon & Coates, 2009; Marshall et al., 2021). Further development of these technologies could also find application for the environmental management of livestock production although pollution from faeces and urine is not expected to be an important issue in extensive livestock production.

Another area of tremendous interest at present is measuring methane emissions from grazing ruminants which can be measured at the individual or group level under grazing conditions. Information on greenhouse emissions of grazing animals can be used to manage their nutrition aiming to improve productivity and reducing GHG emissions. Jones et al. (2011) used open path lasers to measure the concentration of gases in the air and derive emissions factors of grazing Angus cows that were pregnant in the summer with 55% DMD of the pasture, and nursing calves in the winter when pastures had 81% DMD. The authors reported that the technology was able to detect lower CH₄ emissions in animals fed low compared to those fed high-quality diets, and in cows with low compared to high estimated breeding values (EBV) for residual feed intake.

Using the GreenFeed system at pasture, Velazco et al. (2017) reported a negative association between daily CH₄ production and EBV for residual feed intake, and a positive association between CH₄ and LW and ADG. A vast body of evidence exists on the use of the GreenFeed system to measure gas emissions at pasture and therefore this technology seems promising for a range of applications in the process of quantifying and mitigating greenhouse emissions and selecting animals for feed efficiency (Herd et al., 2014; Todd et al., 2018). This technology is expected to be a valuable tool to understand emissions in extensive grazing conditions, particularly in those rangeland environments where diet selection is difficult to replicate and many plants with secondary compounds could exist.

10.7 Smart Animal Nutrition and Production in Extensive Conditions

There are several options to improve the nutritional management of grazing animals using smart methodologies and technologies. These options can be divided into those that: (1) manage the nutrition of the entire herd or flock to achieve the desired outcomes at the group level such as improving the performance of the herd, profitability, or reducing methane emissions, (2) improve the nutritional management of groups of animals within a herd or flock, and (3) improve the nutritional management of individual animals.

Several examples were provided above on the power of integrating multi-sensor data and models to increase the value of the information and the decision-making process. However, there are not many examples in the literature that have demonstrated how technologies can be used to manipulate animal nutrition under extensive grazing conditions above and beyond a scenario without technologies. In-paddock weighing and electronic feeding systems with feed control can enable individual animal feeding under grazing conditions (González et al., 2018). Imaz et al. (2019, 2020b) used a combination of automated LW monitoring, electronic feeders with the capacity to monitor and control supplement intake, and auto-drafting gates to draft animals to different sections of a yard enclosing the water point according to RFID or weight. The approach was useful to understand the dynamic relationships between forage biomass and quality, attendance to the WOW and supplement intake. Smart livestock nutrition could be done either using the electronic feeders with pneumatic gates, the auto-drafter, or both. These technologies allow identifying animals with high or low performance but more importantly allow controlling the nutrition of individual animals according to growth potential, breed, target carcass endpoint, and a target environmental footprint amongst other opportunities. However, a more complex situation could arise with feed supplementation having a strong interaction with forage biomass in the paddock, which could lead to 'true' supplementation where pasture intake is not reduced, substitution where pasture intake is reduced as supplement intake increases, and complementation where pasture intake is increased such as in the case of urea supplementation with low-quality forages (Löest et al., 2001; Tedeschi et al., 2019). This is further complicated by the constantly changing pasture biomass and quality due to animal selection, plant growth and senescence, and environmental conditions. Traditionally, feed supplementation at pasture has been done targeting a predetermined intake and performance at the group level (Tedeschi et al., 2019). However, smart nutrition of grazing livestock should consider the response of animals to declining pasture availability and quality and the monitoring and control of feed intake of individual animals under extensive conditions. The challenge with feed supplementation at pasture is to provide the supplement at the right time, the right amount, and to the right animals (González et al., 2018). Little research exists to date demonstrating the feasibility to control the amount of supplement intake of individual animals in extensive grazing conditions. Wyffels et al. (2020) presented an interesting example of the integration of technologies (electronic feeders and GPS collars) to study the

behavioural change of cows when provided feed supplementation while grazing winter mixed grass prairie. The authors reported high variation between individual animals, a reduction in grazing time, and an increase in distance travelled as supplement intake increased. Therefore, these technologies also showed the ability to improve the understanding of factors that can be affected by nutritional interventions and manage them more precisely.

The manipulation or control of growth rate using digital technologies and data analytics offer a great potential to control the time animals take to reach market specifications such slaughter weight, carcass composition and quality at slaughter, or both. The technologies and approaches described in this chapter, and many other alternatives, could be used to optimize productivity, profitability, and environmental outcomes. Growth rate of grazing animals can be manipulated using multiple nutritional and non-nutritional strategies such as hormonal growth promotants, which also interact with nutritional management. Increasing growth rate to reach market weight earlier could have a tremendous impact on profitability and intensity of greenhouse emissions as demonstrated with data presented in this chapter and González et al. (2018). The concept of providing feed supplementation to grazing animals at the precise time and amount either to a group or individual animals to achieve target growth rate and slaughter time is the most obvious. In addition, auto-drafters or electronic feeders could also be used to provide the type of supplement required to individual animals or groups such as providing energy and protein supplements to lactating cows or roughage to dry cows with lower requirements. The authors also envision supplementation strategies supplying key metabolites under certain instances such as methionine or choline to high-producing dairy cows or animals under negative energy balance or stress (Vailati-Riboni et al., 2017).

10.8 Conclusion

Recent developments and the on-going refinement of technologies and methodologies to monitor performance and nutritional processes of extensive livestock production open incredible opportunities to improve production, welfare, profitability, and sustainability. Key technologies for precision livestock nutrition in these conditions include those for body weight and composition determination, forage biomass and quality, supplement intake, and gas metabolic gas production. The integration of sensor data with mathematical models seems to be gaining popularity because of synergies between these. This approach could make a significant contribution to improve the nutritional management of extensively managed livestock, and thus productivity, profitability, animal welfare, and environmental footprint. Areas of future research and development include those related to improving the estimation of feed and nutrient intake, and the development of mathematical models adapted to use data collected at high frequency and detail for individual animals.

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The Potential Contribution of Smart Animal Nutrition in Reducing the Environmental Impacts of Livestock Systems

11

Stephen George Mackenzie

Abstract

The aim of this chapter is to evaluate the role Smart Animal Nutrition can play in improving the environmental sustainability of livestock production, focusing on the quantitative evidence presented to date of environmental impact mitigation. The modelling challenges for quantifying the potential environmental benefits of Smart Nutrition technologies are discussed first, with a focus on life cycle assessment (LCA) modelling. How LCA models treat new technologies, and the functional units by which livestock products are evaluated, are important areas for further methodological development for the evaluation of Smart Nutrition Technologies. A handful of LCA evaluations of Smart Nutrition technologies exist to date, mainly focused on precision feeding technologies in pig and poultry systems. These studies have consistently found that Smart Nutrition technologies can mitigate environmental impacts of these systems to some extent. Beyond these systematic evaluations using LCA modelling, a wider range of studies presenting important experimental evidence that Smart Nutrition can tackle vital hotspots of environmental impact from animal production such as methane emissions from ruminants are considered. Beyond the empirical evidence of mitigation potential presented to date, this chapter discusses the potential to consider directly environmental impact objectives in the application of Smart Nutrition technologies. The application of LCA modelling for this purpose with respect to breeding, feeding, and environmental management of livestock has

S. G. Mackenzie (✉)

The Global Academy of Agriculture and Food Security, The Royal (Dick) School of Veterinary Studies, The University of Edinburgh, Edinburgh, UK

Waste and Resources Action Programme (WRAP), Banbury, UK

e-mail: stephen.mackenzie@wrap.org.uk

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started to be demonstrated conceptually. Novel applications of complementary modelling frameworks will be vital for livestock production as it looks to meet its key sustainability challenges.

Keywords

Environmental impact · Environmental impact mitigation · LCA · LCA methodologies · LCA livestock · Methane · Nutrient excretion · Precision feeding · Smart technologies · Smart nutrition · Sustainable diets · Sustainable feed · Sustainable livestock

11.1 Introduction

For more than a decade, since the release of *Livestock's Long Shadow* (Steinfeld et al., 2006) the livestock industry has been under intense pressure to reduce its negative environmental impacts and produce animal products sustainably, while at the same time meeting the increased demand for livestock products (Thornton, 2010; FAO, 2017). Many scientists and activists are now calling for drastic reductions in meat consumption, and personal choices around eating meat are now viewed by some as the most important decisions that individuals make with respect to the environmental impact of their consumption habits (Poore & Nemecek, 2018; Springmann et al., 2018). Although it should be noted others still suggest personal choices in areas such as transport are more sensitive with respect to greenhouse gas (GHG) emissions than food consumption habits (Ivanova et al., 2020). In many areas of the global north, the industry is also facing significant competition from cultured meat and meat replacement products, soya-based proteins, fungal-based protein products, and cultured animal cells. A significant selling point of these products is that their consumption is less environmentally damaging (CBInsights, 2017; Rick Morgan, 2018) and more socially acceptable given that its mass production is not associated with the ethical issues around animal welfare (Coleman et al., 2015). In contrast with these calls to reduce meat consumption, current global production trends are the opposite with meat production output having tripled globally since 1970 and set to continue rising towards 2050 to meet growing consumer demand in rapidly growing economies such as China and India (FAO, 2017). Faced with competing pressures to meet global demand and become more environmentally sustainable there is significant interest, hope, and an increasing number of claims that technological innovation within the livestock sector can rise to these challenges (Makkar, 2016; Berckmans, 2017; Lovarelli et al., 2020).

The production of feed for animals is the source of around 20% of the GHG emissions caused by food production in total when accounting for land use change (Ritchie, 2019). Feed production is the source of around half of GHG emissions from pork (48%) and poultry production (57%). For cattle, feed production contributes 36% of the total GHG emissions, as enteric methane production constitutes the majority of GHGs from these systems (Gerber et al., 2013). Moreover, feed inputs

can have significant influence on enteric emissions as well as levels of nutrient excretion and the resulting environmentally sensitive emissions in the management of manure in livestock production systems. For example, pig production and its associated manure is regarded among the largest contributors to acidification of ecosystems and eutrophication of fresh water bodies, arising from livestock (de Vries & de Boer, 2010; McAuliffe et al., 2016). Specific case studies have shown that manipulating diet formulations can reduce overall acidification by up to 17% in pig production and 10% in broiler production compared to least cost diets (Mackenzie et al., 2016a; Tallentire et al., 2017).

With feeding practices so sensitive for the environmental impacts of animal production, it is little wonder that a significant body of research has tried to identify strategies for altering feed inputs to reduce the environmental impact of livestock production (Wanapat et al., 2015; Mackenzie et al., 2016a; Tallentire et al., 2018; Garcia-Launay et al., 2018). Within this area of research, an important and expanding line of enquiry has been to ask “what is the potential of Smart Animal Nutrition to mitigate negative environmental impacts caused by livestock production and thus improve the sustainability of the industry?” (e.g. Banhazi et al., 2012; Fischer et al., 2020; Pomar & Remus, 2019). What constitutes “Smart Animal Nutrition” has several potential definitions and perspectives on this are discussed at length throughout this book. For the scope of this chapter, we will simply discuss innovations that represent technological advances in livestock feeding. The potential environmental impacts of physical on-farm technologies such as precision feeding and smart grazing systems are discussed, as well as how environmental impact considerations can be integrated directly into traditional feed formulation algorithms.

The focus of this chapter will be to analyse and discuss relevant research presented to date that can begin to answer this question. However, first it is important to discuss the available methods and modelling challenges for quantifying any potential environmental benefits that may arise from Smart Animal Nutrition.

11.2 How to Quantify the Potential Environmental Impacts of Smart Nutrition

As interest and scrutiny has grown regarding the environmental impacts of livestock production, so has the level of research effort to establish relevant methods that quantify the impacts of the sector. These efforts range from establishing, for example, the overall impacts of pig or beef production systems at the global or national scale, down to the impact of individual products such as cheese or chicken as bought by consumers (MacLeod et al., 2013; Opio et al., 2013; Eshel et al., 2014; Poore & Nemecek, 2018). While a plethora of methods to assess environmental impact exist that can be applied to food production systems (Cerutti et al., 2011), the life cycle assessment (LCA) framework has become a widely accepted way to holistically assess the environmental impact of livestock systems (Peyraud & Macleod, 2020).

11.2.1 Life Cycle Assessment and Livestock Systems

An LCA is an analysis technique to assess environmental impacts associated with some (cradle to gate) or all (cradle to grave) stages of a product's life. Depending on the system in question, these stages include raw material extraction through materials processing, manufacture, distribution, use, and disposal (definition adapted from (Muralikrishna & Manickam, 2017)). Originally developed for industrial processes, LCA quantifies the impacts arising over the life cycle of a product or service (per unit of product) and allows to compare production methods, looking at the incoming and outgoing flows (Curran, 2012). While LCA is commonly used to evaluate the environmental impact of a system per unit of productive output, the methodology has been shown to be scalable to the evaluation of systems at the global level (MacLeod et al., 2018). There are several books and encyclopaedia entries that cover the basic concepts of LCA (Guinée, 2002; Curran, 2012; Muralikrishna & Manickam, 2017), so please refer to these for detailed theoretical discussion and first principles behind the method. Several international standards including ISO 14044, ISO 14046, ISO 14067, and PAS 2050 have been established to standardise methodologies for LCA models as well as specific environmental impact calculations such as Carbon Footprinting and Water Footprinting. To demonstrate how LCA is applied when modelling livestock systems, Fig. 11.1 provides an outline of the system components to be considered when designing an LCA model of pig production as set out by the FAO technical advisory group on the subject in 2018 (FAO, 2018). Subsequently, Fig. 11.2 shows the model components of a cradle to farm-gate LCA and the specific emission sources considered in an assessment of the environmental impact of housing technologies in pig production systems (Pexas et al., 2019).

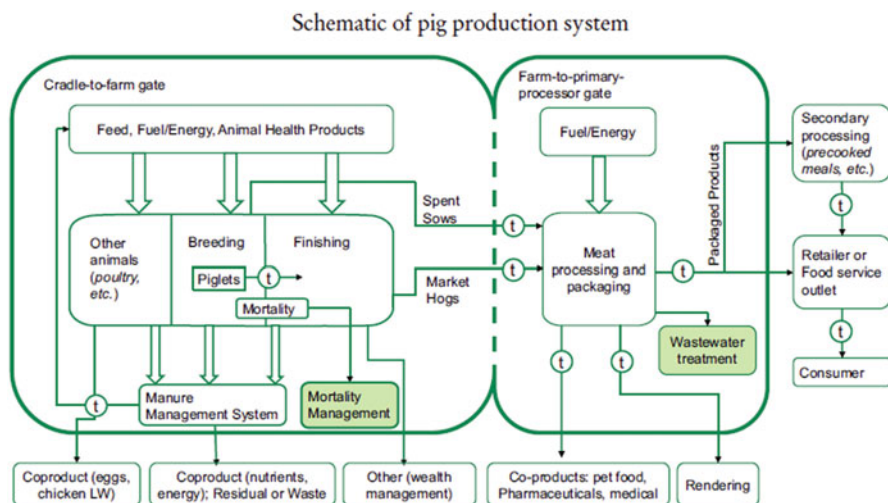


Fig. 11.1 The components of pig farming systems to be considered when designing system boundaries of LCA studies of pig production. (Reproduced from FAO assessment guidelines for the assessment of environmental performance of pig supply chains (FAO, 2018))

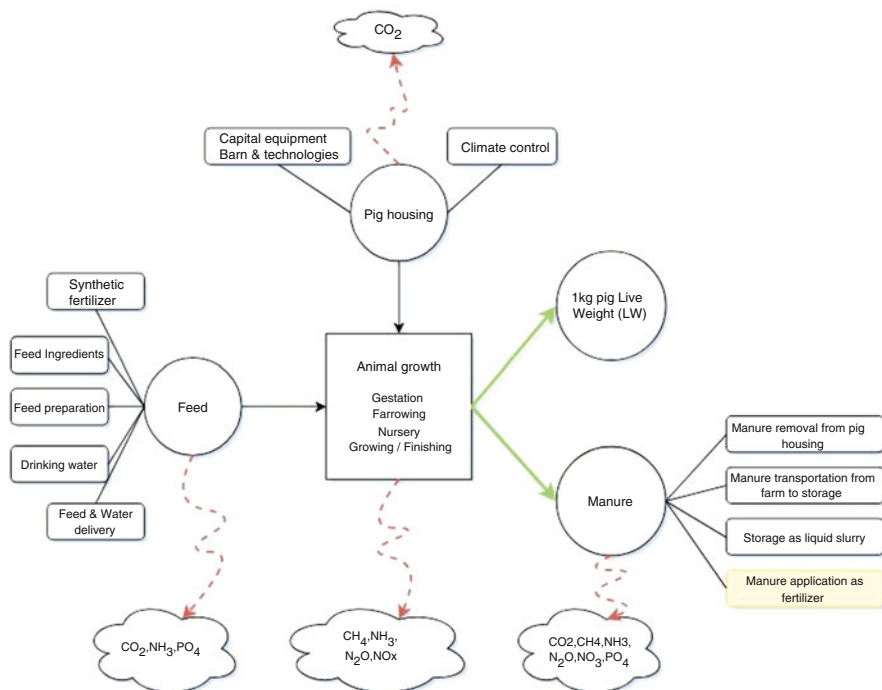


Fig. 11.2 The model components of a cradle to farm-gate LCA and the specific emission sources considered in an assessment of the environmental impact of housing technologies in pig production systems. (Reproduced from Pexas et al., 2019)

The widespread extent to which the methodology has now been used to evaluate the impacts of livestock systems was highlighted in a recent meta-analysis of LCA studies of food production which included 570 LCA studies of different livestock systems and excluded many more (Poore & Nemecek, 2018). The findings of that review and others (e.g. de Vries & de Boer, 2010; Clune et al., 2017) have been consistent – that is, 1 kg of beef caused greater greenhouse gas emissions and used more land overall than other livestock products. Beef production is then followed by production of 1 kg of pork, chicken, eggs, and milk with respect to the intensity of GHGs and land use per unit of product. Despite this, reviews on the subject have highlighted the huge range in methods applied when conducting LCA of livestock systems, which represents a significant barrier to the credibility of individual studies and wider understanding of their findings. This inconsistency led to several FAO technical advisory groups being established; these groups subsequently published a series of methodological recommendations for applying LCA to different livestock systems, as well as important parts of the livestock supply chain such as feed production (e.g. FAO, 2016a, b, 2018). These guidelines are important reference, as they represent a form of consensus on how to apply LCA to specific livestock systems and should provide some methodological consistency on how LCA is

applied to livestock systems. Importantly, the FAO guidelines are very clear that LCA of livestock systems should account for multiple impact categories. There is slight variation between the documents for different species but generally these include: GHGs, water use, land use, acidification, and eutrophication (FAO, 2016a, c, 2018). As set out clearly by the Our World in Data project, food production systems are responsible for much larger relative proportions of global water use (70%), land use (50%), and eutrophication (78%) than GHGs (26%) (Ritchie, 2019). Livestock systems contribute a significant amount to all these issues and any assessment aiming to show that innovations are improving the environmental sustainability of livestock production needs to demonstrate this beyond the narrow frame of GHGs. There are, of course, methodological areas of debate as application of LCA in this area becomes more sophisticated and widespread. Those that are particularly relevant when considering the impacts of Smart Animal Nutrition are discussed below.

11.2.2 Functional Units

LCA models are designed to contrast different scenarios to provide the same “function”, whether the model compares different products or different methods to produce the same product (Weidema et al., 2004). As such, a functional unit is chosen in each scenario to represent the function that a production system serves. The currently accepted convention, and standard way of representing functional unit in LCA of meat production systems, is to use a variation on edible meat or carcass weight with no further properties describing the nutritional quality of the meat produced (e.g. ADAS, 2015; FAO, 2016a, 2018). This means potentially important chemical and physical characteristics of outputs from different production systems are not considered and cannot be compared. This situation contrasts with the standard functional unit used in dairy LCA of fat and protein-corrected milk (FPCM) (FAO, 2016a) using methods such as that set out by Bartl et al. (2011). A few studies of dairy systems build further on this to include either FPCM produced per land occupied or to include the meat produced and sold from dairy systems in the functional unit, but the vast majority use a mass or volume measurement of FPCM (FAO, 2016a).

More broadly in LCA of food production systems, there has been a trend towards developing nutritional functional units based on a set of nutritional properties for food products, which match guidelines for human dietary requirements (Saarinen et al., 2017). For LCA of livestock production systems, McAuliffe et al. (2018a, b) presented such a methodology based on using important nutritional properties for high-protein foods adapted from the methods of Saarinen et al. (2017) for Finnish food systems. Adoption of such methods is in its early stages in livestock LCA, but it can significantly impact on how environmentally sustainable different production systems are viewed to be (Centre for Innovation and Excellence in Livestock, 2020). As a methodical approach, nutritional functional units used in an LCA, for example, of pig farming systems will value production systems whose animals have carcass

compositions more suited to human dietary requirements (for instance by having higher lean meat content). This framing for the analysis of environmental impacts may highlight further benefits from Smart Nutrition beyond simply increasing productivity in livestock systems. Figure 11.3, reproduced from the Our World in Data platform, shows how functional units can change the outcome of LCA comparisons of animal products.

11.2.3 Applying LCA to New Technologies

Interest in the potential benefits of novel technologies for the sustainability of production systems, as well as the need to examine any claims made by those with commercial interests, means that LCA studies are often used to quantify their potential environmental impacts. Livestock systems are no exception, with many studies investigating the potential implications of novel technologies in feeding (e.g. Andretta et al., 2017), breeding (e.g. Ottosen et al., 2019), and environmental management (e.g. Pexas et al., 2021) for the environmental impacts of production systems. Smart Nutrition technologies, and many of the studies discussed in this chapter, fall into this category. How LCA deals with emerging technologies and how to evaluate them in a consistent manner has been the topic of several recent reviews and discussions papers (Arvidsson et al., 2018; Thonemann et al., 2020; Bergerson et al., 2020; Moni et al., 2020; van der Giesen et al., 2020). Some of the major challenges of examining emerging technologies through LCA identified in these reviews that are particularly relevant to the case of Smart Nutrition technologies are listed in the following text.

11.2.3.1 How to Scale Up a Model for a Product or Technology When the Available Data Is Likely Based on Small-Scale Pilots?

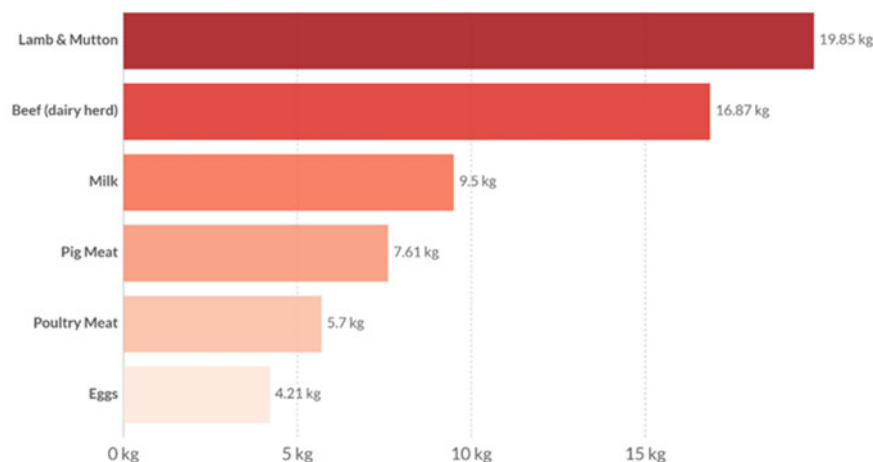
Bergerson et al. (2020) outlined four classifications for analysing new technologies through LCA depending on the maturity level of both the technology and the potential market that it is entering, outlining the major issues to consider in each case. Most new technologies for livestock production systems would fit the classification of “low maturity” technologies operating in a “high maturity” market under this rubric, given that demand for livestock products and thus material inputs to livestock production systems is well established. Smart Nutrition technologies fit well in this classification; as such, it is important to be aware of the particular challenges encountered for this type of assessment.

Bergerson et al. (2020) identified that in such cases, the largest source of uncertainty in LCA calculations comes from necessary assumptions of how the technology will change from small-scale pilots to widespread commercial implementation. In the case of livestock LCA this issue arises, for example, in attempts to evaluate the potential impact of newly marketed feed ingredients, such as insect meal or algae in animal diets when these ingredients are only being produced on a pilot scale (Halloran et al., 2016; Tallentire et al., 2018). Moni et al. (2020) propose nine levels of classification of “technology readiness levels” and strategies for dealing

Greenhouse gas emissions per 100 grams of protein

Greenhouse gas emissions are measured in kilograms of carbon dioxide equivalents (kgCO₂eq) per 100 grams of protein. This means non-CO₂ greenhouse gases are included and weighted by their relative warming impact.

Our World
in Data



Source: Poore, J., & Nemecek, T. (2018). Additional calculations by Our World in Data.

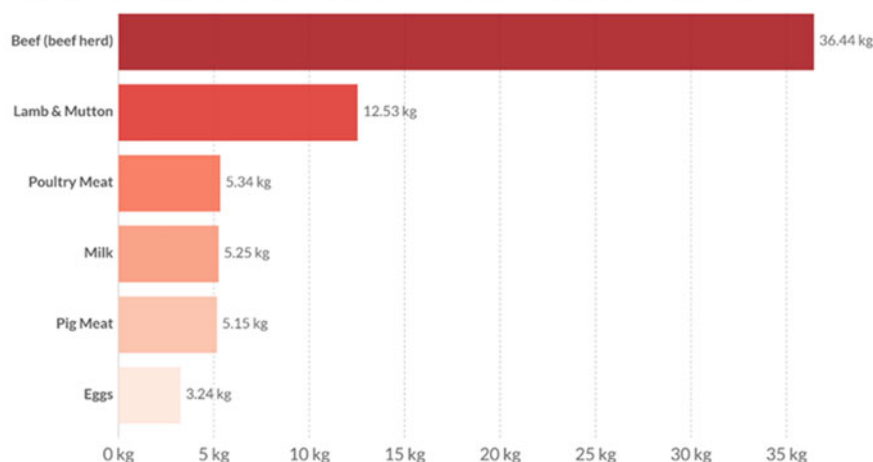
Note: Data represents the global average greenhouse gas emissions of food products based on a large meta-analysis of food production covering 38,700 commercially viable farms in 119 countries.

OurWorldInData.org/environmental-impacts-of-food • CC BY

Greenhouse gas emissions per 1000 kilocalories

Greenhouse gas emissions are measured in kilograms of carbon dioxide equivalents (kgCO₂eq) per 1000 kilocalories. This means non-CO₂ greenhouse gases are included and weighted by their relative warming impact.

Our World
in Data



Source: Poore, J., & Nemecek, T. (2018). Additional calculations by Our World in Data.

Note: Data represents the global average greenhouse gas emissions of food products based on a large meta-analysis of food production covering 38,700 commercially viable farms in 119 countries.

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Fig. 11.3 A ranking of the greenhouse gas emissions caused by various livestock products when the functional unit is 100 g of protein or 1000 kcal energy, respectively. (Reproduced from Ritchie, 2019)

with cases at different levels on this scale in LCA studies. The overriding issue at most levels on this scale of technological and market maturity is how to overcome large uncertainties when projecting scaled up production models. Assumptions made in this area of an LCA model are likely to be sensitive to the outcomes and the existence of these highly sensitive and uncertain parameters can undermine the credibility of ex-ante LCA models of emerging technologies (Bergerson et al., 2020). In the case of using emerging products as ingredients in animal diets, LCA modellers run into further difficulty as lack of widespread use of an ingredient means its implications for animal performance may also be uncertain with data coming from small-scale experiments. Attempts to identify solutions to this issue in LCA modelling have been wide-ranging and there is little consensus on a consistent methodological framework to follow (Thonemann et al., 2020). Generally, there is consensus that (a) greater levels of uncertainty should be attached to any scenarios scaling up technologies at an early stage in their development (van der Giesen et al., 2020), (b) methods from chemical engineering to scale up process models could be usefully applied more widely to address this issue in LCA studies (Piccinno et al., 2016), and (c) that scenarios constructed for this purpose should be defined through consultation of experts on the technologies in question wherever possible (van der Giesen et al., 2020).

11.2.3.2 How to Account for Changes Over Time in the Background Databases Used in LCA Modelling?

Most LCA models have a foreground system, which is the focus of the study, where possible primary data is utilised as much as possible to ensure subsequent modelling is as representative and accurate as possible. For example, in the case of livestock systems, this may include animal performance data, data recording on farm emissions (e.g. ammonia or methane), and the ingredient composition of animal diets, on farm energy use and on farm water use. However, to maintain a reasonable scope for any LCA study, secondary data sources are, out of necessity, utilised to model processes outside the foreground system both upstream and downstream in the supply chain. For example, in LCA of livestock systems this can include the production feed materials. If there is primary data on crop production available, then secondary data will likely be used to model the production of chemical fertilisers as inputs to crop production. In the extremely unlikely case that primary data can be utilised to model fertiliser production, secondary databases would almost certainly be used to model generation of electricity as an input to fertiliser production along with many other processes in the LCA model.

The use of these background databases is a tricky area for any LCA that tries to compare current production systems with those of either the past or future. Several papers on how to treat emerging technologies in LCA have identified the need to ensure consistency between foreground and background data in LCA models of emerging technologies (Arvidsson et al., 2018; Moni et al., 2020; van der Giesen et al., 2020). For instance “*background data, should represent the future situation*

for when any new technology is defined to be commercially operational” according to van der Giesen et al. (2020). Many general discussions on the subject have emphasised how important this is, given that background data will often constitute at least 95% of unit processes modelled in an LCA, with the sensitivity of these data varying greatly between different models. However, to follow this suggestion in LCA of livestock systems is easier said than done. Is it realistic to expect LCA modellers to predict the relative changes to crop production systems, or going back up the supply chain, fertiliser production, and energy generation when looking to model future scenarios for livestock production?

Currently, there is not an off the shelf database where researchers can source such scenarios readily. Arvidsson et al. (2018) acknowledge that there are practical issues to consider for this aspect of LCA modelling and suggest that where possible, impacts relating to background are omitted or reported separately when evaluating emerging technologies in LCA. While such a recommendation may make sense in certain cases, it hardly seems relevant for the case of Smart Nutrition in LCA where, for example, the entire benefit of the technology being evaluated may come from altering the composition of animal diets to achieve increased animal performance. Impacts modelled using secondary datasets in the production of feed materials cannot be easily separated in such a modelling exercise and may influence any projected environmental impact reductions from the technology in question. This is not an easy issue to deal with in LCA modelling of livestock systems, however one recommendation this chapter would make is to utilise a suitable uncertainty analysis to mitigate the problem. Some uncertainty analysis methods separate uncertainty that is unique to each scenario being modelled from that which is shared (Leinonen et al., 2012; Groen et al., 2014; Mackenzie et al., 2015). As such, a range of scenarios in the background and foreground data can be included (e.g. in crop yields) in the LCA. The use of techniques such as Monte-Carlo simulations for two scenarios run in parallel can allow researchers to account for such uncertainty and still get useful answers as to the likelihood that Smart Nutrition technologies will provide environmental impact reductions even accounting for these uncertainties (Mackenzie et al., 2016b).

The methodological challenges discussed above are relevant for the future design of LCA studies to investigate the potential of Smart Nutrition to improve the environmental sustainability of livestock systems. However, they represent on-going methodological debates in the wider LCA community and there are few published examples to date where such methodological issues have been addressed in LCA evaluations of Smart Nutrition technologies in livestock. This should be taken into account when reading later discussion in this chapter of the LCA studies that have been carried on Smart Nutrition in livestock. However, researchers have begun to quantify the benefits of Smart Nutrition technologies using both LCA and other methodologies, with the technologies for precision feeding in pigs and poultry an interesting case in point.

11.3 Precision Feeding in Pig and Poultry Production

Precision feeding is a technology that is viewed as having the potential to mitigate environmental impacts from pig and poultry production systems while also delivering economic benefits (Pomar et al., 2011; Banhazi et al., 2012; Andretta et al., 2017; Tullo et al., 2019; Misiura et al., 2021a). Precision feeding differs from traditional (phase) feed formulation strategies where all the animals within a population receive the same diet throughout the entire feeding phase (e.g. using the mean of the population to define the nutrient requirements and thus diet specifications (Symeou et al., 2015)). In precision feeding systems, diets are tailored to individual specifications for each animal based on measurements such as body weight, feed intake, and average daily gain (Remus, 2018). Generally, in pig and poultry systems the most practical way of tailoring diets for individuals is to deliver a mix of two (or in some recent cases more) pre-formulated feeds to meet a bespoke set of nutritional requirements based on these measurements. There have been several examples of precision feeding systems for pig and poultry production presented in scientific literature in recent years (Pomar et al., 2009; Banhazi et al., 2012; Zuidhof et al., 2017; Remus, 2018; Gaillard et al., 2020).

At the time of writing, two LCA studies have been conducted to determine the potential of precision feeding to reduce the environmental impact of pig production systems (Andretta et al., 2017; Monteiro et al., 2017). Andretta et al. (2017) analysed precision feeding for Brazilian pig production. They compared a conventional three-phase feeding program for grower/finisher pigs with precision feeding individual (PFI) animals with daily specifications. The PFI scenario reduced GHGs by up to 6%, reductions in acidification and eutrophication of up to 5% were also observed across several regional scenarios for Brazilian pig production compared to conventional phase feeding. Monteiro et al. (2017) used LCA and an established pig nutrition model (InraPorc) to compare two-phase conventional feeding strategies with precision feeding of grower/finisher pigs in both French and Brazilian pig production systems. They concluded precision feeding produced average reductions in GHGs (6.1%), acidification (12.7%), and eutrophication (10.7%) in comparison to two-phase feeding. Some of the differences in the potential acidification and eutrophication reductions between the two studies may be explained by the fact that Monteiro et al. (2017) tested precision feeding against a baseline of two-phase conventional feeding compared with a three-phase conventional feeding scenario in Andretta et al. (2017). The three-phase feeding strategy itself would likely reduce P and N excretion in comparison to the two-phase scenario. However, the relative small difference in impacts between the two-phase and four-phase conventional feeding scenarios of Monteiro et al. (2017) shows that this does not entirely explain the difference in their results for acidification and eutrophication. Both studies used functional units of 1 kg and 1 tonne of live weight pig at the farm gate, and it was against this output that all impacts were modelled for the conventional and precision feeding scenarios. As discussed earlier in the chapter, this approach means that any consequences from precision feeding for carcass composition that may occur, for example, by increasing leanness (Lovato et al., 2017; Remus, 2018; Remus et al.,

2019) could not be accounted for. This means that as they are currently implemented, LCA studies of precision feeding systems may not account for key improvements to the animal products being produced in terms of nutritional value. An alteration of functional unit to, for example, environmental impact per 100 g protein produced might at least begin to capture such changes, see Sect. 11.2.2 for further discussion on functional units.

In addition to complete LCA studies, several investigations into precision feeding have demonstrated improvements to key performance metrics that are known to be sensitive variables for the environmental impacts of pig and poultry production systems. Feed conversion ratio in the grower finisher phase, along with N and P intake in diets, have been shown to be highly sensitive production variables for the environmental impact of pig production in local sensitivity analyses of LCA models (Mackenzie et al., 2015; Groen et al., 2016). The relative importance of N intake for environmental impacts from pig systems was further emphasised in a recent global sensitivity analysis of a pig production system model, where it was shown to account for 64% of variance in acidification and 52% of variance in eutrophication (Cadaro et al., 2018). As such, to a certain extent, demonstrations that precision feeding is able to either improve feed efficiency or reduce N and P intake/excretion can be taken as good proxy indicators that precision feeding has the ability to reduce the environmental impacts of pig and poultry production systems. There is evidence that precision feeding can result in significant improvements to both feed efficiency and nutrient utilisation in both pig and poultry production. For example, precision feeding systems in grower/finisher pigs have been shown to have the potential to reduce N and P intake and excretion by around 25% while still meeting daily nutrient requirements for individual pigs and reducing overall feed costs (Pomar & Remus, 2019; Gaillard et al., 2020).

For poultry production systems, fewer peer-reviewed studies have been published in this area than for pigs. In experiments conducted on broiler breeders, precision feeding was able to marginally improve feed conversion ratios, reduce body weight variability across the flock, and increase breast muscle in pullets compared to conventional feeding (Zuidhof, 2018, 2020; Zukiwsky et al., 2021). The utilisation of protein in feed tends to be slightly more efficient and more consistent in broiler and layer systems when compared to pig production (Flachowsky & Kamphues, 2012; Pomar & Remus, 2019). Due to this reduced variability in protein utilisation, the potential for reducing N excretion by precision feeding in poultry systems is likely a little lower than in pig production.

However, in terms of overall potential reductions to GHGs, acidification and eutrophication estimated by the two LCA studies conducted to date (Andretta et al., 2017; Monteiro et al., 2017) should be kept in mind for context when discussing these. In general, the overall potential of precision feeding to reduce environmental impacts from these systems should be viewed as a potential marginal improvement rather than a step-change. Nobody has yet presented peer-reviewed evidence that precision feeding can reduce environmental impacts caused by pig and poultry production systems by more than 13% in any major impact category. For GHGs, the maximum reduction shown to date is 6%. However, precision feeding still has

real potential to deliver both reductions to overall environmental impacts along with economic benefits for the sector representing a potential win-win technology when viewed through both lenses. Importantly, for the prospects of precision feeding providing environmental sustainability benefits, promising data has been presented for pigs suggesting, if not conclusively, that improvements to protein retention efficiency are sustained even under conditions of heat stress (dos Santos et al., 2018). An ability to improve performance at raised temperatures will be key to the technologies rolled out in growing markets such as Brazil, India, and South Africa where average temperatures are relatively high, but also to its robustness in delivering both economic and environmental benefits around the globe in the face of rising temperatures due to climate change.

11.4 Smart Nutrition in Ruminant Systems

Fundamental differences in biology and husbandry between ruminants and monogastric animals mean that Smart Nutrition technologies take different forms in ruminant production systems compared to those for pigs and poultry. The overall commercial value of each animal is much higher in ruminant systems, particularly in the case of dairy production, than for pigs and poultry. As such, the dairy sector has had a longer history developing and implementing precision livestock farming technologies than pig and poultry production (Rowe et al., 2019). This means a huge variety of measurements and data are available to researchers in pursuit of smart solutions to reduce environmental impacts in ruminant production, as demonstrated in Fig. 11.4, which shows a schematic of nutrient flows in dairy systems and the available technologies to measure key nutritional processes (Gonzalez et al., 2018).

Specific concerns regarding environmental impacts and the potential nutritional routes to mitigation also have different emphasis for ruminant production systems compared to those of monogastric animals. Cattle production systems are responsible for the majority (around 65%) of GHGs from livestock production (Gerber et al., 2013) and dairy production systems are by far the most intensive of any livestock production system in terms of water use per 100 g of protein (Poore & Nemecek, 2018). As such, the discourse on pathways to environmental sustainability is much more focused on reducing their GHGs and particularly enteric methane production for ruminants. The potential of individual ingredients or dietary supplements to reduce methane emissions in feedlot cattle systems has now become the focus of intense research activity. The most eye catching findings to date have suggested that the addition of *Asparagopsis taxiformis* (red seaweed) can reduce methane enteric methane production by as much as 80% in feedlot systems (Roque et al., 2021). It should be noted that while initial findings such as these are promising, investigations into the methane reduction potential of seaweed as a dietary additive are at an early stage, with a recent systematic review on the subject finding only five peer-reviewed trials using seaweed in cattle diets (Honan et al., 2021) and commercial scale production of seaweed for cattle diets still just an ambition (Roque et al., 2021).



Fig. 11.4 A schematic of nutrient flows in dairy systems and the available technologies to measure key nutritional processes. (Reproduced with permission from Gonzalez et al., 2018)

Beyond seaweed, there is a huge range of supplements with methane reducing potential under investigation and commercial development, some of which have advanced much further on the road to commercialisation. For example, 3-nitroxypopropanol (3NOP, sometimes marketed as Bovaer) has been shown to reduce methane yield for beef ($-17\% \pm 4\%$) and dairy ($-39\% \pm 6\%$) feedlot systems (Dijkstra et al., 2018) and has been shown to reduce methane production in feedlot systems in over 15 peer-reviewed studies (Honan et al., 2021). Both 3NOP (estimated cost £38 per head annually) and Nitrate (£27 per head annually) supplementation of cattle diets were cited in recent evidence submitted to support the 6th UK carbon budget as realistic, scalable pathways for methane reduction in UK dairy production (Eory et al., 2020). Producers of such supplements in some cases plan to capitalise on expanding participation in carbon markets in order to make their products commercially viable. For example, the producers of Mootral© (an additive made from garlic and citrus extracts) are now able to sell “CowCredits” deemed to be equal to 1 tonne of methane emissions per animal supplemented with Mootral© annually, under a methodology approved by the Verified Carbon Standard programme. CowCredits were given permission to trade on the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) market in 2021 and were launched at a price of €70 per tonne of CO₂ (Bloomberg, 2021).

Beyond supplementation of individual ingredients, significant focus has been placed on utilising Smart Technologies in ruminant nutrition to reduce enteric methane emissions (Gonzalez et al., 2018). The use of precision feeding to restrict the food intake of lactating Holstein cows has been shown to reduce their methane emissions of less efficient animals within the herd (Fischer et al., 2020). Their experiment identified the 10% of the herd with the lowest residual feed intake (RFI) through individual animal feed intake and performance monitoring. They then restricted feed intake across the herd to the levels of the lowest 10% in terms of RFI. This treatment resulted in a 10% reduction in the g/day of methane emitted from the least efficient animals. However, it is unlikely this would translate into an overall reduction in GHGs from the production system if analysed in an LCA. Restricted feeding actually resulted in an increase in the methane emissions per litre of FPCM as milk yield reduced by greater than 10% compared to ad libitum feeding. Aside from targeting methane reductions specifically, there has been significant focus on applying strategies of individualised feeding to ruminant systems to improve the productive performance of both beef and dairy cows. For example, White and Capper (2014) demonstrated that formulating diets weekly to account for variability in outdoor temperature was able to increase milk yield, dry matter intake, and the feed efficiency when compared to less frequent formulations. In effect, this strategy was able to meet the energy requirements of dairy cows more precisely by accounting for the impact of temperature on their metabolism, thus making the farm more productive and profitable. This example highlights a difference between the application of precision feeding in ruminant systems compared to pig and poultry production, as in the latter two temperatures are often controlled as much as possible.

The technologies investigated by White and Capper (2014) and Fischer et al. (2020) are case studies of systems where feed is provided to dairy cattle in a way that is analogous to pig and poultry systems. However, grazing systems account for a significant proportion of beef, dairy, and lamb production around the world, with livestock grazing around 25% of the global land surface (FAO, 2020). As such, the potential of Smart Nutrition applications to reduce the environmental impact of these systems is a vital subject that requires significant investment.

11.4.1 Smart Grazing Systems

While for extensive grazing systems it may have traditionally been impractical to take important measurements such as animal live weight on a frequent basis, remote sensing technologies now mean that such data can be collected daily without the need for humans to handle animals (e.g. Imaz et al., 2020). The availability of such information opens the door to a greater range of interventions to enhance productive performance and drive down GHG emissions from grazing production systems. When reviewing pathways to methane emission reductions in grazing beef systems, Thompson and Rowntree (2020) identified the use of nutritional supplements to improve the efficiency of feed energy use as an important pathway for methane emission reductions. For example, supplementation of concentrates to improve the productive performance of grazing animals is a well-established practice and has been shown to have the potential to reduce methane intensity ($\text{g CH}_4/\text{kg product}$) by up to 27% and 31% in beef and dairy systems, respectively (van Gastelen et al., 2019). However, the availability of real-time individualised data on live weight open up the possibility to reduce methane emissions further. This could be achieved, for example, by targeting animals performing less well within the herd with greater nutritional supplementation of concentrates in the diet. Another important pathway for methane reduction identified by Thompson and Rowntree (2020) was to improve forage quality through a combination of considering both the type and maturity of forages being offered. Zubieta et al. (2021) suggest that through proper consideration of herbage mass in pasture and striking the optimum balance between herbage mass accumulation and quality in tropical grazing pastures, significant reductions in methane intensity are possible. In combination with appropriate stocking densities and rotational grazing there is potential to reduce the rate of methane produced by grazing cattle and sheep to $0.2 \text{ kg CH}_4/\text{kg LW gain}$, a potential 55% reduction (Zubieta et al., 2021). Again, Smart Technologies have the potential to revolutionise this area and make such reductions in the methane intensity, and thus the GHGs caused by grazing systems a reality. For example, in temperate climates, above ground hyperspectral imagery (HSI) and multispectral imagery (MSI) collected from unmanned aircraft, satellite images, and handheld cameras can now be utilised to predict above ground biomass and crude protein content in real time for a grazing paddock (Askari et al., 2019). In semi-arid climates unmanned aircraft and satellite images can be used to estimate available forage mass and soil water content so that available soil nutrients and water are utilised productively without degrading available resources in the long term (DiMaggio et al., 2020; Kimura & Moriyama, 2020).

While there are currently no LCA studies that have systematically evaluated the GHG reducing potential of Smart Technologies in grazing systems, this is a research avenue likely to be explored extensively in the next few years. For instance, McAuliffe et al. (2018b) analysed the GHGs caused by individual animals in grazing beef systems, suggesting that LCA models projecting aggregate emissions based on average performance were underestimating GHGs in some cases. They suggest this is due to insufficient consideration given to poorly performing animals, whose emissions were exponentially greater as average daily gain decreased. The modelling framework they established could be applied to investigate various Smart Technologies in grazing systems that aim to improve the nutritional performance of ruminants and reduce environmental impacts, as it has the ability to capture the reductions these technologies make to the environmental impacts of poorly performing animals within the herd.

An important methodological point to consider with respect to GHGs from grazing systems is the recent emergence of the new metric GWP* (Allen et al., 2018; Lynch et al., 2020). The method is an adaptation of the GWP100, which calculates the Global Warming Potential of all emissions over a 100-year timescale and has become the standard for expressing GHG emissions in the scientific literature (Lynch, 2019; Thompson & Rowntree, 2020). In summary, GWP* differs in how it calculates the contribution of short-lived climate pollutant emissions, such as methane and nitrous oxide to global warming, and under this methodology their potency is determined predominantly by changes in their emission rate. The methodology is more explicit in disaggregating CO₂ and non-CO₂ GHGs and calculates peak temperatures caused by GHG emissions using a “*linear combination of cumulative CO₂ emissions to the time of peak warming and non-CO₂ radiative forcing immediately prior to that time*” (Allen et al., 2018). This has important potential implications for how GHGs are calculated for grazing ruminants as the method treats methane emissions as significantly less potent in GHG terms in cases where emission levels are stable compared to GWP100. Through specific application of the method at various scales (sector level, national level, farm level), it may be possible through a cumulative and sustained shrinking of the methane emissions that some grazing systems are viewed as having minimal contribution to global warming. This is unlikely to be the case for feedlot ruminant production or monogastric production systems where the production of feed for animals is associated with significant levels of GHGs (Poore & Nemecek, 2018), including, for example, the burning of fossil fuels to produce fertiliser which produces CO₂ directly. However, as authorities on the GWP* methodology have noted, the longer we fail to reduce GHGs globally, increasing the cumulative stock of CO₂ emitted, the smaller the possible rate of sustainable methane emissions (Lynch et al., 2020).

Smart Nutrition technologies represent an important avenue of innovation in future livestock production systems and in many cases reduce environmental impacts from these systems as a by-product of achieving economic objectives. However, as discussed next there is increasing interest in using technological innovations specifically for the purpose of improving the environmental sustainability of livestock production.

11.5 Nutritional Strategies that Target Reductions in Environmental Impacts

As Gonzalez et al. (2018) described in relation to ruminants, combining precision nutrition technologies with simulation modelling has the potential to make individual technologies much more powerful in modern livestock farming. The interest in this area of science has been heightened by the perceived potential of these data driven technologies to improve economic outcomes for livestock producers and companies (e.g. White & Capper, 2014). With application of the right modelling frameworks, livestock production systems optimised for reduced environmental impacts can also be designed. However, there will of course be trade-offs between economic and environmental objectives, particularly when markets do not include any valuation of the true external cost to society caused by environmental impacts (Moran, 2021). The challenge of aligning economic and environmental objectives as closely as possible presents itself starkly to livestock producers, policy makers, and investors at present. Overcoming this challenge will not be possible without models that systematically quantify the environmental impacts of livestock systems and use this information directly in decision-making. Researchers have begun to demonstrate that through integration of LCA models into more conventional modelling frameworks for breeding (Macleod et al., 2019; Ottosen et al., 2019) and feeding (Mackenzie et al., 2016a; Tallentire et al., 2017; Garcia-Launay et al., 2018; Marques et al., 2022), it is possible to minimise the environmental impacts of livestock production systems through linear optimisation algorithms. Figure 11.5 shows a simple representation of this for combining an LCA model and a traditional diet formulation algorithm in pig systems as presented in Mackenzie et al. (2016a).

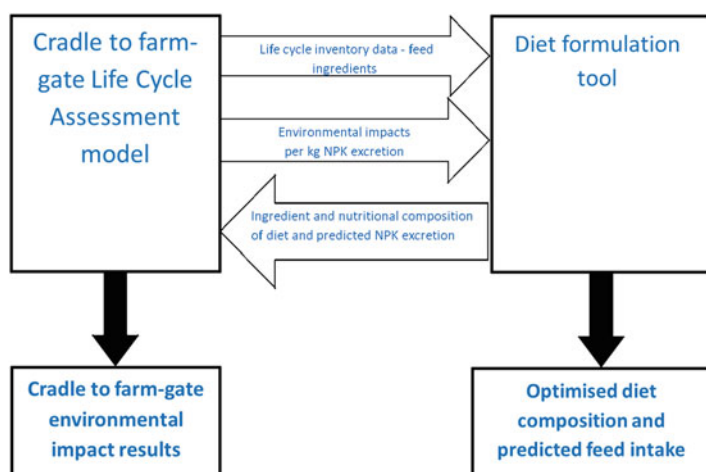


Fig. 11.5 A schematic of combining an LCA model with a diet formulation algorithm to formulate livestock diets for objectives that explicitly consider the environmental impacts of the system. (Adapted from Mackenzie et al., 2016a)

In that exercise, by accounting for the environmental impacts from producing feed ingredients and nutrient excretion, diets were formulated for environmental impact objectives including minimising GWP100, eutrophication, and acidification. That study showed that in some Canadian pig production systems GWP100 could be reduced by as much as 25%. Garcia-Launay et al. (2018) among others have adopted similar approaches to show the cost benefit trade-offs in formulating diets to reduce environmental impacts in pigs, which give insights regarding the cost of environmentally sustainable animal diets, although their work did not account for the impacts of nutrients excreted in manure. Marques et al. (2022) recently integrated the linear optimisation of diets for both multiple environmental and economic objectives with a nonlinear profit-maximising diet model for French feedlot beef systems. In their scenarios a combination of improved animal performance, reduced upstream GHG emissions in the feed supply chain and reduced on farm methane emissions contributed to a maximum 8% reduction in system level GHGs per kg carcass weight, when optimising solely to minimise GHGs. The trade-off for this reduction in GHGs was a 13% drop in overall profitability of the simulated farm. Their analysis also showed that a 4% overall potential reduction in GHGs can be achieved at a cost of €22/kg CO₂ eq/kg carcass weight or around €56/tonne CO₂ eq. This example makes for an interesting comparison with the €70/tonne CO₂ eq CowCredits for supplementation of Mootral© discussed previously in Sect. 11.4. Achieving reductions in GHGs through diet optimisation can be more cost effective in some cases compared to implementing specific technologies like feed supplements, but there are currently no direct economic incentives for producers to reduce GHGs through this route. Marques et al. (2022) did not account for the potential of including new ingredients that can reduce enteric methane emissions such as red seaweed, 3NOP, or Mootral© in their diet formulation algorithms.

The potential of improving precision feeding outcomes based on targeted breeding strategies in livestock animals has been proposed as a route to much greater reductions in environmental impacts than those observed to date (Pomar & Remus, 2019; van der Peet-Schwering et al., 2020; Misiura et al., 2021b). Research on the potential to reduce the environmental impacts of livestock systems has already demonstrated that when combined, appropriately designed feeding and breeding strategies can result in large reductions of the targeted environmental impact. For example, Tallentire et al. (2018) formulated broiler diets to test the potential of combined feeding and breeding strategies to reduce the environmental impacts of broiler production systems. The results of that study demonstrated that even if slow growing birds were selected over time to meet welfare standards, reductions of up to 55% in GWP100 could be achieved by formulating diets to minimise this impact category. A similar approach was recently applied to pig production systems by Soleimani and Gilbert (2021), although in that case they demonstrated the concept of designing diets for pigs of two different genetic trait profiles of pigs within the same production system and modelled the individual responses to this within a herd. Using this approach, they were able to demonstrate moderate overall reductions of up to 11% for GWP100, acidification, and land use by using multi-objective functions to reduce overall environmental impacts, the trade-off being increased levels of

eutrophication. Their results showed greater potential to reduce environmental impacts in pigs with the lower levels of RFI. The work by Soleimani and Gilbert (2021) generally represents a step towards explicitly accounting for environmental impacts when formulating diets to specifications for individual animal genetic profiles. As the concept of precision feeding and individualised feeding programmes become more commonplace in livestock systems, integrating them with LCA frameworks could enable them to realise their true potential to reduce the environmental impact of livestock production systems by design.

Furthermore, retrospective analyses have identified that significant improvements to the environmental impact intensity of livestock products have been achieved over time (Putman et al., 2017, 2018; Pelletier, 2018; Ottosen et al., 2021). These trends are often attributed to genetic improvements in production animals due to effective breeding strategies, alongside improved management and nutritional provision by producers. However, an analysis by Ottosen et al. (2021) of the causes behind the reductions in the environmental impact intensity of British pig production systems found that a trend in the market price and availability of feed ingredients which altered the diets being fed to pigs were also an important factor in driving impact reductions. These findings further emphasise that breeding strategies and improving feed efficiency alone may not necessarily bring significant further reductions to the environmental impacts of livestock systems. Careful consideration of the environmental impacts of ingredients used in animal diets and the consequences of forage offered to grazing livestock will need to be considered in order to make large improvements to the environmental sustainability of livestock systems.

11.6 Conclusions

A plethora of technological applications of Smart Nutrition are being developed across livestock systems, made possible by advances in remote sensing, the automated real-time analysis of image and sounds, and greater understanding of animal genetics. Many of these technologies are expected to improve the environmental sustainability of livestock farming systems. Systematic evaluation of these claims and the true potential of these technologies to mitigate environmental impacts using LCA modelling is in its infancy with only a handful of complete LCA evaluations of Smart Nutrition technologies found in the research for this chapter. The evaluations completed to date have consistently found that even through conventional application to maximise the economic returns for producers, Smart Nutrition technologies can mitigate to some extent environmental impacts. It is likely that as application of Smart Nutrition technologies widen, more studies will be conducted to assess their mitigation potential using LCA.

Broadly speaking, the LCA modelling frameworks to evaluate livestock systems are now established, although further methodological development is expected both in how LCA models treat new technologies and the accepted functional units by which livestock products are evaluated. Furthermore, the development and acceptance of methodologies such as GWP* with respect to the global warming potential

of short-term greenhouse gases may alter sustainability objectives for grazing livestock systems and mean less focus being placed solely on the reduction of enteric methane emissions.

As discussed in Sect. 11.5 of this chapter, there is potential to go further and directly consider environmental impact objectives in the application of Smart Nutrition. This potential is largely unrealised in commercial settings at the time of writing, but such applications may prove powerful for those looking to use Smart Nutrition as a way to revolutionise the sustainability of livestock production systems. This chapter has looked at the potential application of precision livestock technologies through the lens of Smart Nutrition. However, the potential to utilise LCA models to optimise breeding, feeding, and environmental management of livestock has begun to be demonstrated in various research papers. Such novel applications and combinations of different modelling frameworks will be important tools in the arsenal of the livestock sector as it looks to meet the important sustainability challenges facing it to play its part in future food systems.

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