Chapter 3

Herdsman+: artificial intelligence enabled systems and services for livestock farming

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Abstract

The application of artificial intelligence coupled with the growth in the availability of cost-effective low power computing platforms, has accelerated the adoption of on-farm technologies that support the decision making of farmers. An exemplar of the evolution is encapsulated by the development of activity monitors for dairy cattle, migrating from simple step counting devices designed to identify the onset of oestrus to systems that continuously monitor individual cattle and provide insights into the time spent eating, ruminating, calving and other key welfare events such as lameness and mastitis. The chapter illustrates how the use of digital technologies has brought benefit to the livestock farming industry, presenting the current state-of-the-art with emphasis on accentuating the potential for cloud based platforms to support the integration of multiple on-farm data streams, the foundation for the provision of a mix of data-driven animal-centric services that bring further benefits to the livestock community.

Keywords: agricultural engineering, precision livestock systems, decision support applications, internet-of-things (IoT), wireless sensor networks (WSNs), artificial intelligence (AI), machine learning (ML)

3.1 Introduction

The widescale use of digitally enabled devices such as heat detection collars, leg tags, ear tags and boluses (Afimilk, 2015; Fullwood, 2018; McGowan *et al.*, 2007; National Milk Records, 2018; Roelofs and Van der Kooij, 2015; Wolfger *et al.*, 2015) has revolutionised the dairy sector. Such devices are now in common usage. Building on this deployment using cloud hosted platforms to integrate multiple measurement streams offers the potential to improve the performance of individual measurement devices and create a platform to deliver a much broader range of services.

An illustration of the on-farm environment is shown in Figure 3.1. Information from a range of measurement devices for example cattle collars, milking station and feed wagon are communicated to a cloud hosted platform. Currently, these systems are vendor specific and are designed to operate in isolation with optional cloud hosting to facilitate access through channel, e.g. smart phone, for farm operatives. Cloud based implementations are reliant on robust internet access which in rural settings is highly variable.

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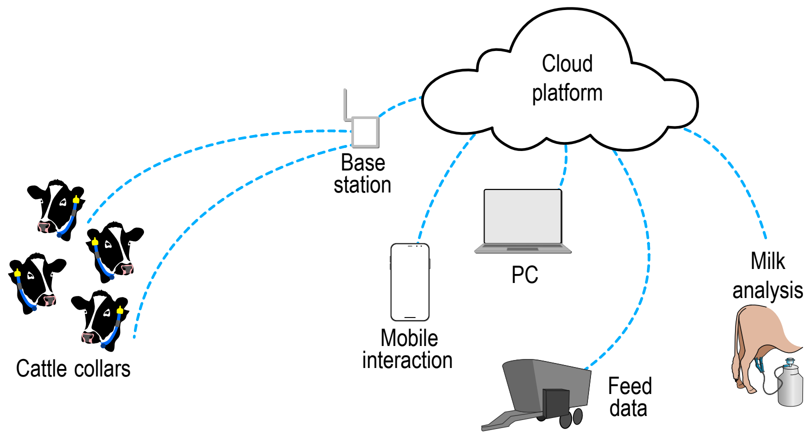

Figure 3.1. Schematic of internet enabled farm.

While value from each system can be identified, the approach falls short to fully address the requirements of the farmer, presenting challenges of mastering a range of custom interfaces and often requiring multiple data entries. To better serve the end-user, independent solution providers[2,3] are beginning to offer hosting services that address the needs of multi-vendor sensor integration. The effective integration of multiple data sources eliminates the need to master the operational features of multiple interfaces and is the foundation for developing richer insights within the farm environment – the basis of concepts encapsulated by Herdsman+.[4] This chapter reviews the evolution of these sensor device and demonstrates the Herdsman+ approach which is predicated on mining data from multiple sources to derive better information and provide new services to the community.

3.2 Oestrus detection in dairy cattle

Methods for automating the process of monitoring the behaviour of cattle have become increasingly important given the recent trend characterising the dairy industry. A striking example of the pressure the sector is experiencing is the UK community, which as witness a steady decline in the number of milk producers from 2.6 million in 1996, to 1.9 million in 2015 (AHDB Dairy, 2016). Similarly, the number of dairy producers has fallen from 35,741 in 1995, to 13,815 in 2014. In tandem with this, the average herd size has risen, as those holdings with smaller herds have left the industry. In 2014, the average number of cows per herd was 133, compared to 97 in 2004 (AHDB Dairy, 2016). Further, the period over which the average herd size has grown has been accompanied by an increase in average milk yield per cow.

A direct consequence of the dynamics of the sector is a change in traditional practices and established methods. The time available to farmers to observe the herd has reduced and thus increasingly, farmers are relying on technology to undertake routine tasks traditionally executed through visual

2 https://www.365farmnet.com/en/
3 https://glas-data.co.uk/
4 https://www.iof2020.eu/

inspection. The most striking corroboration of the increase in the level of adoption of on-farm technology solutions is the reliance on oestrus, or 'heat', detection collars and pedometers to assist in the optimisation of pregnancy rates (Afimilk, 2015; Fullwood, 2018; McGowan *et al.*, 2007; National Milk Records, 2018; Roelofs and Van der Kooij, 2015; Wolfger *et al.*, 2015).

The success of automated heat detection systems has been driven by two factors. Pressures to reduce operating costs have forced consolidation and thus modern farms are larger, operate with fewer staff which, while effectively limiting the time to observe their animals. In parallel, the sector has witnessed a steady decline in cattle fertility (Gröhn and Rajala-Schultz, 2000; Lucy 2001). While the reasons are complex, deficiencies in oestrus detection are a significant contributory factor. The resultant fall in pregnancy rates costs the sector directly through the loss of revenue from milk production. An eligible cow that is not bred (or is incorrectly bred) has a resultant loss of approximately 21 days of milk production, equivalent to £140 per cow assuming a representative price per litre. An examination of farm fertility carried out in 1994 over 4,550 herds in the US, found a mean heat detection accuracy 38% (Lucy, 2001). In contrast, technological solutions (collars and leg tags) are reported to perform with success rates upwards of 80-90% (Mayo *et al.*, 2019).

3.3 Internet of things: low power processors and radio technologies

Oestrus (heat) detection systems are exemplars of the successful application of wireless sensor technology that addresses a specific problem and enables an 'Internet of Things' methodology to deliver greater value. Low power sensor technologies, usually Micro-Machined Electromechanical (MEMs) accelerometers, are combined with low power processors and wireless radio chipsets to provide a monitoring capability that operates 24 hours per day over an extended period of time (5 to 10 years). To determine when a cow is on heat the activity of the animal is measured since cattle in heat (oestrus) become restless (Kiddy, 1977; Van Vliet and Van Eerdenburg, 1996). Machine learning or statistical approaches can identify outlier behaviour that aligns with the onset of heat (Eradus *et al.*, 1992; Martiskainen *et al.*, 2009). Measurement of this change in activity is readily achieved using MEMs accelerometers (Pastell *et al.*, 2009; Robert *et al.*, 2009). The precision of the diagnosis can be enhanced by incorporating other behaviours, e.g. feeding or rumination. To identify these, the frequency content of the accelerations can be informative, consequently three axis accelerations are sampled at rates of 10 Hz or more (Michie *et al.*, 2017). This generates significant amounts of data that is not practical to transmit back to a central point as is illustrated in the following example.

Early on in the development of SilentHerdsman, a detailed investigation of the radio transmission characteristics in the on farm environment was undertaken (Kwong *et al.*, 2009a,b, 2012). The studies examined the influence of radio carrier frequency, antenna location and the influence of cattle on the propagation characteristics. An individual cow represents a significant barrier to radio propagation. At 2.4 GHz, a common radio frequency for Industrial Scientific and Medical (ISM) use (OFCOM, 2021), penetration through body fat is around 10 cm and wet skin attenuates even more significantly. This means that cattle in the vicinity of a radio collar would have a strong possibility of blocking any radio transmissions. The radio transmission improves with the inverse of the carrier frequency however, the associated bandwidth of the receiver drops to a similar degree. A compromise was required between transmission range and data transmission capacity. The studies undertook both analytical and experimental analysis of the farm environment and demonstrated that much of the impact that comes from the animal body mass could be mitigated through appropriate location of the base station. Hence a recommendation was made to locate base stations at a height of 2.5 m or more where possible.

During the course of the above investigation, the challenges of the operational environment from mechanical damage were highlighted. Almost all of the initial prototype devices were damaged by the fatigue associated with the constant motion of the collars and the fact that the electronic units were continually knocked against metal enclosure during cattle's daily routine, particularly during periods like feeding. This was resolved when the units were engineered for production and all elements of significant mass (e.g. battery) were firmly soldered to the motherboard and glued in place for additional protection.

The wireless radio protocols for communicating between the collar, or leg tag, and a base station are designed to transmit small messages and therefore constrain the amount of data that can normally be transmitted. For example, IEEE 802.15.4 standard (IEEE, 2018) for low power wireless radio supports a physical layer that generally transmits at 250 kb/s, 40 kb/s or 20 kb/s. The packet structure has an overhead of 0-6 bytes for management and a data payload of up to 128 bytes of information. This small packet size is well suited to the on farm environment as analysed in 21-23 because it increases the probability that the radio transmission will be successful. It is more likely that the radio will find a short timeslot when it can transmit its data as opposed to negotiating a long time period to upload large amounts of data. It does however, constrain the amount of data that can realistically be transmitted but again this is beneficial within the operational constraints since this minimises the power consumption and hence optimises collar/tag operational lifetime.

For the sake of illustration, we can consider the highest data transmission rate 250 kb/s. In practice not all of this channel capacity is available to an individual user. The wireless protocol will cater for acknowledgements between the transmitting node and the receiving node which will consume some capacity and also the devices will have to listen and wait for a clear channel to transmit. If it is assumed that half of the channel capacity can be used an approximate maximum data transmission can be estimated. To simplify further it can be assumed that we are only concerned with the maximum payload of 128 bytes.

The transmission of unprocessed data (three axis accelerometer measurements at a sample frequency of 10 Hz or more) would require 3 × 10 bits × 10 samples per second, or 300 bits/s. Over the course of a day this will equate to 3.24 Mbytes of data (25.9 Mbits). Under perfect operating conditions where the radio simply broadcasts all of the data which is received without acknowledgement and the need for retransmission, this would require that the radio was transmitting for 207 seconds per day or 3.5 minutes. An approximate current consumption for a transceiver in transmit mode is in the region of 10 to 20 mA (e.g. Texas Instruments, 2021). Therefore, each collar (or tag) will consume between 35 and 70 mAh of power per day. The capacity of an AA battery is around 2,500 mAh meaning that to meet the power requirements of the radio alone, the battery would have to be changed every 35 to 70 days. If the issue of battery life is considered from an on-farm operational perspective, an AA battery with a capacity of 2,500 mAh is required to last at least 5 years, approximately equivalent to the average lifetime of a productive dairy cow, without charging. The restriction translates into an average power consumption limit of no more than 500 mAh/year, an average current draw from the battery of less than 50 μA.

Thus, to meet the operational lifetime requirement, innovative management of the limited power resources is a necessity. The solution must exploit the low power sleep modes of the processor, radio and accelerometer and process the measurement data directly on the collar processor to reduce/compress the amount of data that needs to be transmitted – an example of 'edge computing' – and only transport periodic status updates at hourly intervals. Alternatively, the measurement data can be pre-processed into features that describe the dominant signal characteristics over a predefined period of time before transmission (Michie *et al.*, 2017). In this manner substantial savings in radio transmission power consumption are obtainable and battery lifetimes of 5-10 years are common (e.g. Afimilk, 2015; Fullwood, 2018; National Milk Records, 2018). Information generated in this way can then be processed on a central farm computer or on the cloud to represent the measurement data in a manner that is meaningful to the farm operative to support their daily decision making.

3.4 Automated measurement of animal welfare

Heat detection systems are now readily accepted within the dairy industry as yielding a significant return-on-investment to the extent that there is strong competition to differentiate products through the provision of additional features that give enhanced insight into welfare events. Closely coupled are the demands both from milk processors and consumers for higher levels of animal welfare with supermarkets migrating to pricing frameworks where a premium is paid on the ability to demonstrate and validate positive welfare practices. Measurement technology has a role to play providing a continual record of animal conditions.

Monitoring the time that cattle spend feeding is considered an excellent proxy for establishing a view of overall health (Phillips, 1993). Cows that are sick will eat less, and/or spend less time eating. Similarly, rumination patterns and the time spent ruminating add valuable insights into cattle welfare (Borges, 2012; Pahl *et al.*, 2015; Phillips, 1993; Reith and Hoy, 2012; Stangaferro *et al.*, 2016; Welch and Smith, 1970) aiding to identify, for example the onset. Rumination typically takes place when the cow is at rest, often lying down. Boluses of feed partially digested by gut enzymes, are regurgitated and remasticated to aid digestion, a process characterized by a rhythmic chewing action lasting for around 50 seconds per bolus (Phillips, 1993). The rhythmic motion of chewing action, can be identified from the concomitant motion of the neck muscles facilitating the use of accelerometers to estimate the time spent ruminating (and feeding). A healthy dairy cow ruminates for 500 to 600 minutes per day; any significant departure from that time will generate a 'welfare alert', a trigger to investigate the animal further.

The detail of process of extracting the rumination information is not the main subject of this chapter but for illustration Figure 3.2 shows an example of a rumination sequence measured using a pressure sensitive halter (Michie *et al.*, 2017) monitoring jaw motion during rumination (bottom trace) along with corresponding measurements of accelerometer data made using a collar taken at the same instance in time. The data demonstrates that the rumination signal has a strong and identifiable

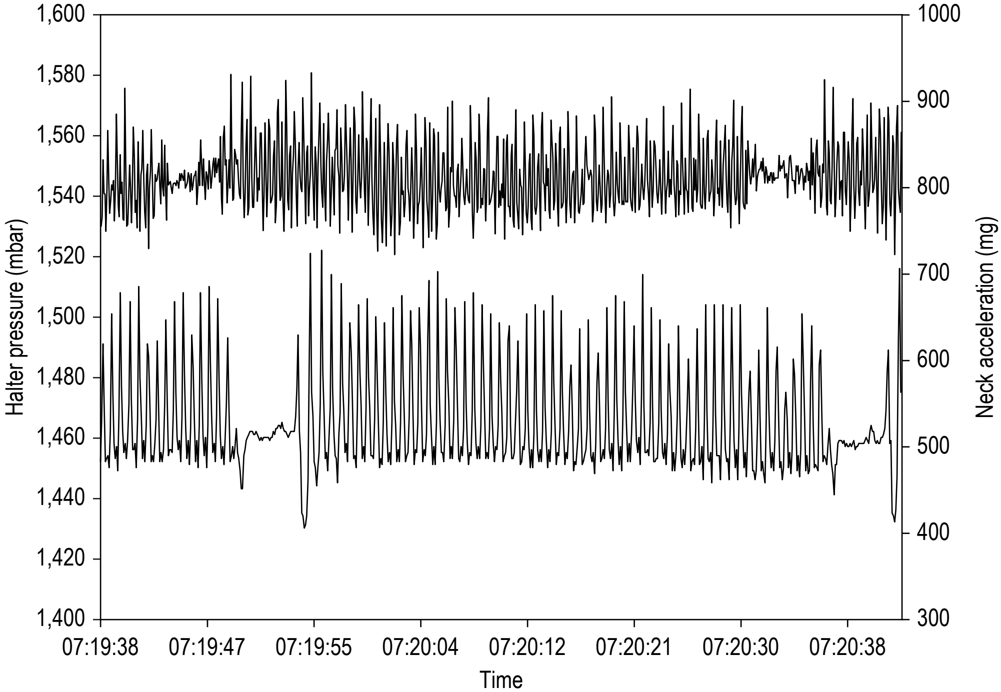

Figure 3.2. Rumination signature measured using a neck mounted accelerometer (upper trace) and a pressure halter (lower trace).

frequency content (rhythmic content). Processing on the collar to identify this rhythmic process enables rumination periods to be readily identified and transmitted without significant power consumption that would compromise battery lifetime (Andriamandroso *et al.*, 2017; Pavlovic *et al.*, 2020; Smith *et al.*, 2016; Watanabe *et al.*, 2008).

The value of such measurements is illustrated Figure 3.3 which shows a representative measurement from Afimilk SilentHerdsman (National Milk Records, 2018). A running average of the feeding/rumination patterns was used to identify when changes from normal behaviour occur for a specific animal and used to trigger alerts when they deviate from the norm.

Figure 3.3 illustrates the case where both rumination and feeding patterns have dropped below 25% of their running average. This is an indication of a significant illness event, in this case 'milk fever' resulting from a reduction of blood calcium in the early stages of lactation. If the cow is not assisted through dietary management, milk fever can produce a range of symptoms and ultimately death. Early diagnosis is therefore of critical importance and is evidently facilitated with the use of collar-based systems. However, it must be stressed that the system is best viewed as provisioning decision support with the final diagnosis delegated to the veterinarian.

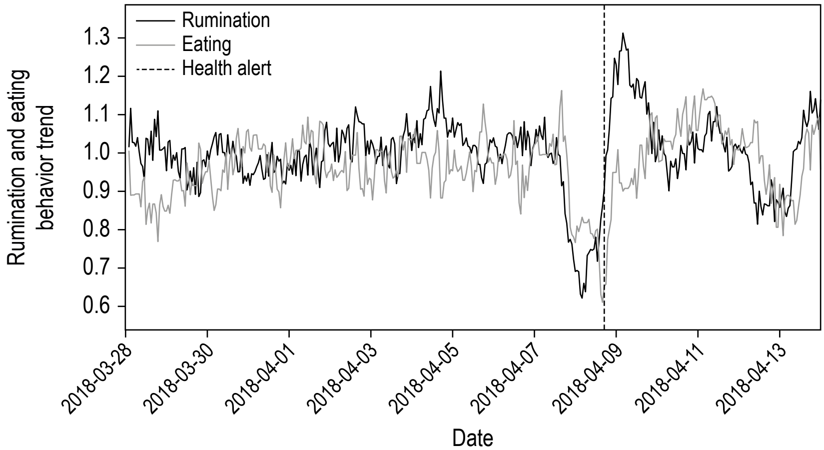

Figure 3.3. Feeding and rumination patterns taken from Afimilk Silentherdsman showing sharp reduction reflective of illness.

3.5 Heat stress

The onset of heat stress, proven to compromise productivity, occurs when the heat load experienced by an animal exceeds that which it is capable of managing (Schirmann *et al.*, 2013). Methods to detect heat stress have often focused on direct body temperature measurement, e.g. a study utilising rumen temperature measurements under conditions of high heat load was performed on Aberdeen Angus and Braham steers (Polsky and Von Keyserlingk, 2017) with some animals, allowed access to shade. The Aberdeen Angus cattle with access to shade showed rumen temperatures 0.5-0.53 °C lower than those denied shade; no measurable difference was observed on Braham steers, well known for their heat tolerance.

During periods of heat stress the animal is no longer able to regulate its internal temperature to within a comfortable degree (Schirmann *et al.*, 2013). The stimulus is commonly a high ambient temperature often combined with high humidity (Lees *et al.*, 2018) and is known to compromise productivity. The physiological responses to cope with heat stress include increased Respiration Rate (RR), panting and sweating. A dairy cow would typically display a resting RR of 26-50 breaths per minute but when stressed, the rate will increase and can exceed 100 breaths per minute. Increases in RR is often accompanied by a laboured breathing/panting and this motion is detectable using accelerometers.

Figure 3.4 illustrates a measurement made on a single cow over a period of 24 h where the ambient conditions were conducive to the onset of heat stress. The analysis is based on a measurement of the harmonic content of the signals to produce an indication that that cow was experiencing heat stress (Schlattler, 1987).

Signs of the onset of heat stress can be observed at relatively low ambient temperatures; cattle begin to show reduced feed intake when the air temperature is above 23 °C and when the humidity is

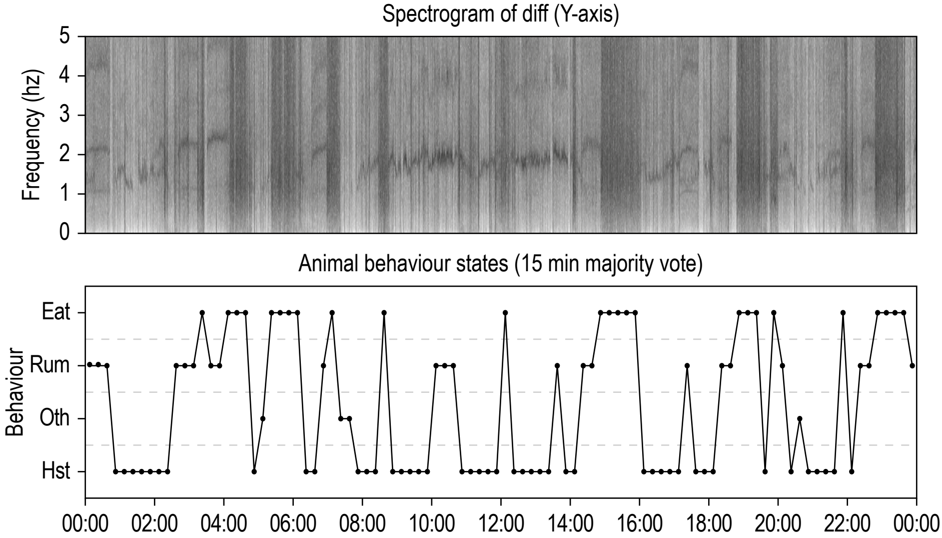

Figure 3.4. Spectrogram and 15 min aggregate of behaviour classification.

greater than 80% (Schirmann *et al.*, 2013). High humidity inhibits self-cooling by evaporation and reduces the ability to self-regulate through sweating. An empirically derived Temperature Humidity Index (THI) is an accepted metric with which to estimate the potential for the onset of heat stress (Lees *et al.*, 2018):

$$THI = 0.8T + (RH\% \times (T - 14.4)) + 46.4 \quad (1)$$

where T is the daily maximum temperature (°C) and RH% is the mean daily relative humidity percentage. Friesian cattle for example, experience heat stress at a THI level of 68 or more (21 °C and RH=75%); Figure 3.5 displays boxplots of activity budgets for 10 cattle under observation over the month of July where daily temperature was routinely above 30 °C and the THI was between 70 and 90. The times spent exhibiting signs of heat stress, where their respiration rates exceed 60 bpm are significant and are comparable with all other behaviours (Schlattler, 1987). Knowledge of this information can inform farmers to take mitigating action, e.g. activate sprinkler systems.

Although the determination that an animal showing signs of heat stress was made using accelerometer measurements, it is corroborated by knowledge of the local ambient conditions, consistent with the broader value proposition derived from correlations between multiple data enhancing insights into welfare conditions; the basis of the premise underpinning Herdsman+.

3.6 Herdsman+ sensor integration to improve mastitis detection in dairy cattle

The functionality of collar-based technology clearly enables a service whereby farmers are alerted to the onset of heat, and or an impending illness. Integration of data from collars with other sensor

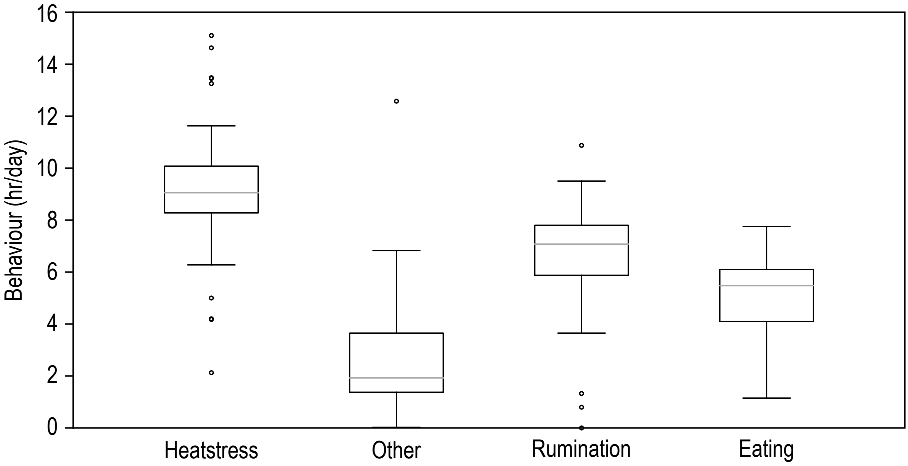

Figure 3.5. Estimates of daily time budgets over the observation period.

modalities enables improved and potentially more specific diagnosis of illness events. An example of the Herdsman+ principles is the diagnosis of mastitis by combining Silent Herdsman collar data with information from a robotic milking station.

Cattle attend robotic milkers typically three or more times daily according to their own needs. The robot therefore offers an excellent platform for assessing cow welfare during milking periods. Dry cows and heifers require additional measurement technology, e.g. collars, to facilitate year round observation. Measurements of key milk constituents, typically fat content and conductivity, through in-line sensors integral to the milking station, presents an ideal opportunity to obtain a daily signature that can be used to identify the possible onset of a damaging illness, e.g. mastitis. Early detection enables early treatment and minimizes the need for antibiotics. Despite providing important data, there are instances where sensors can produce misleading readings and in general, additional sensor modalities can provide mitigating insight.

Conductivity analysis from a Fullwood (Fullwood, 2018) milking robot was used in tandem with accelerometer derived data from the Afimilk Silent Herdsman collar to improve measurement reliability. Figure 3.6 shows a measurement trace from the milker that displays an increase in conductivity over all four quarters over a period of three days around the 12th December 2016. This change in conductivity generated a mastitis alert. The associated collar derived welfare indicators (feeding and rumination) indicate the onset of oestrus around the 22nd November (apparent rise in feeding due to increased restlessness, licking and nuzzling accompanied with a fall in rumination) but after this time the indicators are stable. A cow with mastitis would normally feed and ruminate to a lesser degree suggesting that mastitis is not present. The conductivity was in fact due to a fertility treatment and all cattle within the group displayed the same response. Hence the raised conductivity was ignored since feeding/rumination behaviour analysis indicated that there was no significant welfare issue.

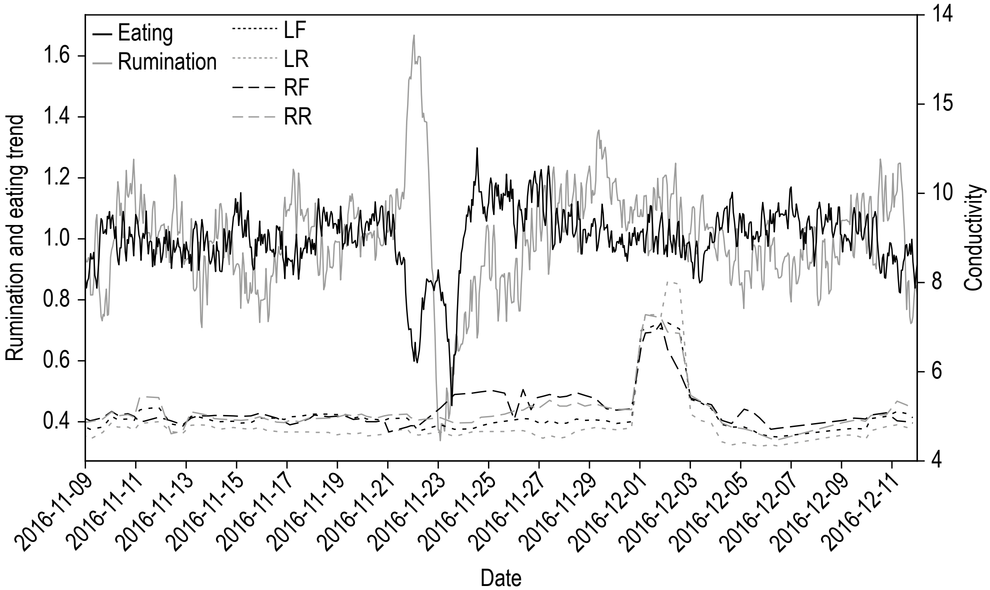

Figure 3.6. Illustration of False Alarm Milking Robot and associated collar signals.

An example of a genuine mastitis response is shown in the measurement combinations below in Figure 3.7.

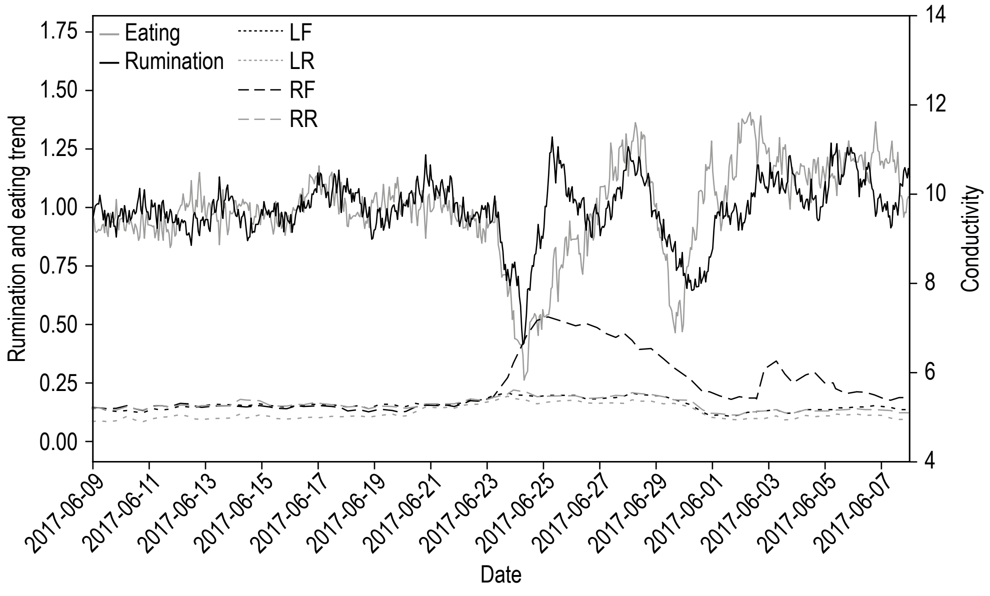

Figure 3.7. Acceleration derived Feeding/Rumination signals and milk conductivity measurements.

In contrast, to the precious case, the sharp drop in time spent feeding/rumination is a consequence of a genuine mastitis infection. Rumination and feeding have dropped by more than 25% the day prior to a rise in conductivity. The changes in feeding and rumination were identified the day prior to a rise in milk conductivity remaining erratic after treatment indicating that the animal was fighting the condition (Schlattler, 1987).

3.7 Optimising feeding for cattle

Optimising animal welfare through a combination of measurement data provides clear on-farm operational benefits and supports strategic decision making, for example when to cull or take finishing cattle to market. Producing high quality food from either beef or dairy cattle presents significant challenges. One of the main costs of milk or beef production is attributed to the animal feed and maintaining a balanced diet across the herd without waste/excess feed is also a key challenge. Ideally, knowledge of the feed intake of every animal informs the assessment in respect of nutritional balancing and determining productivity.

Significant advances have been made in terms of delivering consistent mixes of feed across the herd through the use of feeder-mixer wagons (Michie *et al.*, 2020). The composition of the feed mix data from the wagons is cloud hosted recording the nutritional history and gating the establishment of a relationship with welfare. More recently, manufacturers have integrated spectroscopic analysis equipment into the feeder wagon giving real real-time information on the nutritional value of feed delivered.[5] These advances enable the consideration of precision feeding to be considered.

Precision feeding describes the process where animals are optimally fed to match their calorific intake and nutritional balance to optimize both milk production and the desired milk composition (e.g. fat, protein and lactose percentages). Measuring individual feed intake in a practical manner is difficult to achieve. Feeding and rumination times from collars offer the potential to close this loop provided that time spent feeding is sufficiently correlated with feed intake and the feeding behaviour is captured adequately using a collar. Each animal has an individual feeding preference which can change with time further compounding the issue.

A calibration experiment was undertaken (Barbi *et al.*, 2010; Schlattler, 1987) to determine the potential to use feed intake estimates, calculated using measurements of the time an animal spends feeding, to produce information that is useful to a farmer. Given that feeding behaviour derived from accelerometer measurements (collar or ear tag), is vulnerable to potential errors the experiment was performed using electronic feeders. Although not as practical in a production setting as a collar-based solution, the approach eliminates one source of error viz the misclassification of a feeding event from a collar or ear tag signature and gives an indication of the potential utility of such measurements.

The work was carried out within a beef cattle finishing farm. 32 beef finishing cattle were divided into two groups of 16 and given diets of different composition. The feeds, prepared as Total Mixed Rations (TMR)) using a mixing wagon, consisted of (g/kg dry matter) forage to concentrate ratios

5 https://www.alltech.com/keenan/new-machines.

of either 494:508 (FORAGE) or 80:920 (CONC) selected as representative of commercial diets. Each animal was tagged with a unique radio frequency ear tag that was used to record the time spent at an individual feeding station and the feed intake (kg removed from the feeding station) during a feeding bout. This information enabled the correlation between feed time budgets and feed intake to be confirmed. The feeding behaviour variation across the herd was observed over the course of the trial and is displayed in Figure 3.8. Evident are the significant differences between animals; some animals tend to feed often and consume small meals whereas others consume large meals less frequently.

Support Vector Regression (SVR) was applied to the data to establish a relationship between feed intake using data readily accessible on a production farm in combination with time spent feeding (Barbi *et al.*, 2010; Schlattler, 1987). The relationship was formulated for the two diets (CONC and FORGAGE) and the one breed (cross-bred Limousin). The SVR model used a range of inputs that are readily available on a farm to estimate feed intake:

- total number of visits to the feeder (NVISITS);
- feeding duration (TFEED);
- average length of time during each visit to the feeder (TPERVISIT);
- DIET (FORAGE or CONC);
- age (days);
- liveweight (kg).

The data were randomly sampled to generate a training set of 75% of the data with the remaining 25% used for validation. The performance of each model – the target variable being the daily feed

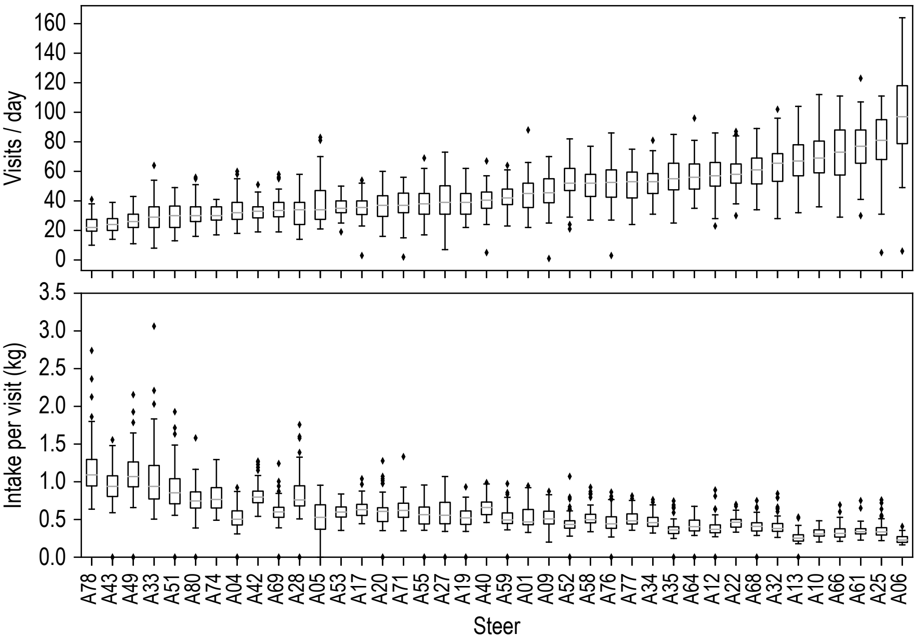

Figure 3.8. Variation in feeding profiles across a herd.

intake – was evaluated through 5-fold Monte-Carlo cross-validation. The SVR feed input prediction was used to predict the feed conversion efficiency (FCR) of the herd. FCR is an accepted measure of the efficiency of an animal to convert feed into an output of value; in the case under consideration the feed is converted to beef as the animal grows and the FCR is a measure of how much feed is consumed to produce 1 kg of body mass. The FCR is calculated for each animal using Equation 2 where the mass of feed consumed has been adjusted to remove the water content and reflect only the dry matter.

$$\text{FCR} = \text{Feed Consumed}_{\text{DRY MATTER}} / \text{Increase in Body Weight} \tag{2}$$

Figure 3.9 shows the calculated FCR both from direct measurements and the estimates of feed intake for both the FORAGE and CONC diets; there is clear evidence of a good agreement between the estimated and actual FCR values.

The correlation between the calculated FCR using actual values and estimated values of feed intake was calculated to have R^2=0.93 (CONC) and R^2=0.83 (FORAGE). Using this data, the performance of each animal, as captured by the FCR, was predicted and compared to actual performance. Animals were categorised into three groupings; the 'top' performing animals with the lowest FCR value, i.e. animals that gained the most weight per kg of feed; the 'bottom' grouping represents animals that require the greatest amount of feed per kg of growth; and the 'average' group represents the remainder of the herd. Each grouping contained 26 animals (Table 3.1).

In the case of the 'top' category, the estimated feed intake data correctly identified 18 of the 'top' and mis-classified 8 as 'average' performers. Similarly, for the 'average' category 15 were correctly identified, 8 were classed as 'top' and 3 as poor performing. Finally, in the case of the 'poor' category, 23 were correctly identified with 3 identified as average performers. No lowest performing animals

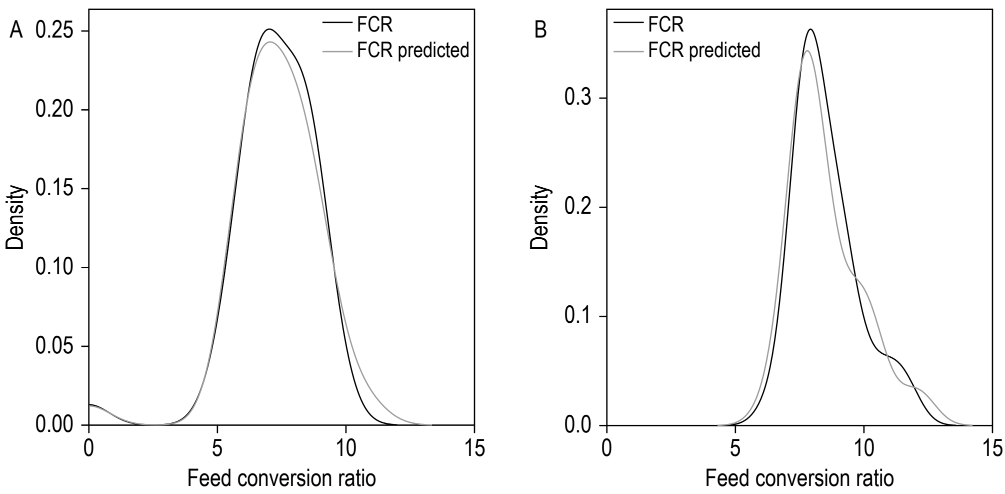

Figure 3.9. Feed conversion ratio (FCR) from direct intake measurements and from estimated intake; (A) FORAGE, (B) CONC.

Table 3.1. Prediction of cattle feed intake performance.

		Predicted performance			
		Top	Average	Poor	Total
Actual performance	Good	18	8	0	26
	Average	8	15	3	26
	Poor	0	3	23	26

were incorrectly categorised as ‘top’ performers and similarly no ‘top’ performing animals were categorized as ‘poor’.

3.8 Future trends/applications

As the sector matures and develops the addition of other measurement technology, e.g. radar based gait measurement devices or more extensive use of image processing is inevitable. So too is the greater integration of sensor systems facilitated by cloud-based platforms. Enhanced rural connectivity supported by the emergence of new radio standards such as 5G communications providing low latency communications with cloud environments may increase the sophistication of analysis that can be carried out on the measurement data. This will lead to greater accuracy in sensor performance and more precise diagnosis of specific illness. Alternatively maintaining on sensor processing but with more advanced processors combined with longer range communications technology such as Narrow band IoT may enable vendors to produce systems that can be deployed without the need for farm-based infrastructure. The later evolution will significantly disrupt the current commercial practices of existing vendors enabling other entrants to sell directly to the farmer offering services hosted predominately from cloud platforms.

3.9 Conclusions

The increasing uptake of monitoring technologies and systems that furnish farmers with real-time information on animal behaviour has supported the wide-scale implementation of a range of decision support tools. The initial business drive was the need for improved oestrus detection to optimise pregnancy rates. As the field matured, manufacturers offered enhanced derivatives of the initial technology to yield additional information on animal welfare. The enhanced information not only brought further value to the farmer by enabling early intervention to prevent the onset of critical illness conditions and hence cost-saving, the resultant improvement in animal welfare was an evidenced indicator of quality indicator not only beneficial across the supply chain but in managing the citizen’s perceptions of the sector. Discerning consumers are reassured by industry-led quality markers, that the produce has been produced with consideration of the welfare of animals.

Furthermore, an additional benefit of a reduced carbon footprint is also derived from the fact that production is more efficient and hence less CO_2 generated for a given volume of milk or kilogram of beef produced. Production efficiency is further enhanced through the integration of multiple sensor streams that offer a tighter diagnosis of illness/welfare events as well as providing a pathway to optimise feeding. While the latter is difficult due to the individual feeding behaviour of animals, initial evidence has shown that the performance of cattle can in principle, be identified albeit at the low granularity ('top', 'middle' and 'bottom'), providing farm operatives with an additional tool in the route to optimal productivity.

While many of the core technologies is now accepted and widely adopted, challenges for the integration of data from multiple sources owing largely due to vendors' reluctance to share data with other commercial organisations. The prevailing perception that there is no benefit from reaching commercial agreements to share data can be attributed to a lack of operational standards within the industry that in turn necessitates effort to customise solutions on a case-by-case basis, an overhead that is currently viewed as delivering little commercial return at the outset with an ongoing obligation to support. Nonetheless, the opportunity to enhance operational efficiency through integration is compelling with a high potential to bring significant future value to the industry.

Many challenges remain at the technical, commercial and policy levels:
- extensible, standardised on-farm data network: 'plug n' play';
- scalable, integrated database supporting multiple data streams with a standardised data format that enables cleansing, mining and processing of combined data;
- ease of deployment and maintenance; reduction in the required infrastructure;
- robust, low-cost internet access e.g. 5G evolution – shared spectrum access?;
- data ownership/monetization agreements across the supply chain – 'shared value';
- user interface(s) that provide the most fulfilling experience for different stakeholders within the supply chain;
- location information per individual animal; any solution must not compromise the lifetime of battery-operated technologies;
- evidence-based value proposition for the migration to a recurring monthly charge viz. service provision.

The lack of standards – for both the infrastructure technologies and data formats – are hindering the migration to future solutions that in turn are limiting the potential benefits to the farming sector. Standards promote inter-operability, lowering the costs of acquiring solutions and empowering an overall optimisation of the supply chain. Furthermore, the Herdsman+ principles foster the option to offer a mix of services.

The traditional business model entrenched within the livestock farming sector is outright/ direct-purchase based on a return-on-investment (ROI) assessment. The evolution accelerates the migration to services dominated business models:
- 'hybrid' model where the infrastructure enabling the service is, for example at cost price and the service is provisioned at a reduced price per month;
- a fully priced per month per animal cost.

The move to services-based provision is revolutionary, a move that the dairy and beef sectors to date remains to be convinced of. However, the business model represents a potentially effective route to increasing adoption through offering a 'service bundle' comprising traditional communications/ Internet with agri-centric services. A number of service threads can be envisaged:

- fertility: improving milk yields per individual animal through increasing the likelihood of a successful pregnancy;
- integrated herd management: to maximise the farmers use of online data storage, the implementation and provision of a complete herd management system;
- pedigree: optimisation of the pedigree of particular herds for yield or quality;
- health: a record of diseases and treatments;
- feed/nutrition: optimising feed mixes for (say) improved health or quality;
- veterinary: on line veterinary service which aids the scheduling of farm visits and promotes preventative health practices;
- drug: pro-active identification of appropriate drugs and optimisation of drugs for particular health conditions on per animal or per herd basis.

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