The Use of ICT Tools to Capture Grass Data and Optimise Grazing Management

Diarmuid McSweeney (No. W20064801)

Department of Computing and Mathematics
Waterford Institute of Technology

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Supervisors: Dr. Bernadette O'Brien & Dr. Stepan Ivanov

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Declaration

I hereby declare that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy, is entirely my own work and has not been taken from the work of others save to the extent that such work has been cited and acknowledged within the text of my work.

Diarmuid McSweeney

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McSweeney, D., Foley, C., Halton, P. & O'Brien, B.(2015). Calibration of an automated grass measurement tool to enhance the precision of grass utilization and allocation in pasture based farming systems. In: Proceedings of the 18th Symposium of the European Grassland Federation. 'Grassland and forages in high output dairy farming systems'. Grassland Science in Europe, The Netherlands, 15-17 June. Volume 20: pp. 265-267.

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McSweeney, D., Ferard, A., Halton, P., Delaby, L. & O'Brien, B. (2016) Calibration of grass height data capture tool to convert compressed grass height to dry matter yield. Proceedings of the European Grassland Federation General Meeting, Grassland Science in Europe, Sustainable meat and milk production from grasslands, September 2016, Trondheim, Norway, pp. xxx–xxx.

McSweeney, D., Coughlan, N.E., Cuthbert, R.N., Halton, P. & Ivanov S. (2018). Micro-sonic sensor technology enables enhanced grass height measurement by a Rising Plate Meter In Proceedings of the European Grassland Federation General Meeting, Grassland Science in Europe, Sustainable meat and milk production from grasslands, 17–21 June 2018, Cork, Ireland, pp. 879.

McSweeney, D., Foley, C., Halton, P., Umstatter, C. & O'Brien, B. (2015) Proof of concept for the feasibility of the "Virtual fence" technology for application in intensive grazing systems. In: Precision Livestock farming Milan, Italy. pp 437-443.

Umstätter, C., McSweeney, D., Foley, C., Halton, P., Heitkämper, K., Schick, M. & O'Brien, B. (2016) Können virtuelle Zäune Arbeitszeit einsparen? In: Böttinger, S., Zick, M., Wörner, E., Schempp, T. (eds.), VDI-MEG Kolloquium Landtechnik 41 – Arbeitswissenschaften. Hohenheim, Germany, pp 51-58.

Umstatter, C., McSweeney, D., Foley, C., Halton, P., Heitkaemper, K., Schick, M. & O'Brien, B. (2015) Labour requirements of fencing in grazing systems and a potential technological solution. In: Guarino, M. and Berckmans, D. (eds.), Precision Livestock Farming `15. Milan, Italy, pp 84-92.

McSweeney, D., Foley, C., Halton P. & B. O'Brien (2015). Calibration of an automated grass measurement tool to enhance the precision of grass measurement in pasture based farming systems. In: Proceedings of Agricultural Research Forum, Tullamore, Ireland , 4-5-Mar-2015

O'Brien, B, Foley, C & McSweeney, D (2015). Technologies to enhance data precision for and automation of grazing management. Proceedings of Conference on Advances

in Knowledge and Technologies for Agriculture. Held at Tullamore Court Hotel, Tullamore, Ireland. June 10, 2015.

McSweeney, D., Ferard, A., Werner, J., Leso, L. & O'Brien, B. (2016). Preliminary study of cow activity in a pasture based automated milking system. Abstract no.: 22233. Presented at Precision Dairy Conference held in Leeuwarden, The Netherlands, 21-23 June, 2016.

Conference proceedings:

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O’Brien, B., Foley, C. & McSweeney, D. (2015). Automated grass measurement and animal control on dairy farms, In Butler S., Horan B., Mee J. and Dillon P. (eds), Open Day Proceedings. “Sustainable Expansion” 24 July 2017, Teagasc, Moorepark, Ireland pp. 48-49

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Contents

Glossary

Artificial intelligence (AI)

Automatic milking system (AMS)

Bit error rate (BER)

Compressed sward height (CSH)

Decision support tools (DST)

Differential Global Positioning System (DGPS)

Dry matter digestibility (DMD)

Geographic information systems (GIS)

Global Positioning System (GPS)

Grey steel wire (GSW)

Herbage allocation (HALC)

Herbage allowance (HA)

Herbage mass (HM)

Hours/cow/year (H/C/Y)

Information communication technology (ICT)

Internet of Things (IoT)

Knowledge Transfer (KT)

PastureBase Ireland (PBI)

Personal computer (PC)

Post grazing sward height (PGSH)

Precision livestock farming (PLF)

Radio Technical Commission for Maritime Services (RTCM)

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Satellite-based Augmentation System (SBAS)

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White nylon fencing tape (WNFT)

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ABSTRACT

In temperate regions, where pasture-based milk production systems predominate, the strategic allocation of pasture grazing area to dairy cows is essential for optimal management and increased milk outputs. Rising plate meters (RPM) are frequently used to estimate pasture herbage mass (HM; i.e. dry matter yield per hectare), through the use of simple regression equations that relate compressed sward height (CSH) to HM. Measurement must be accurate and efficient. Despite improved farm management practices aided by a variety of technological advances, the standard design of a RPM has remained relatively unchanged. As part of this thesis, a RPM utilising a micro-sonic sensor and digital data capture capability linked to a smart device application was developed. Further, the ability of the micro-sonic sensor RPM, to accurately and precisely measure fixed heights was examined. As correct allocation of grazing area requires accurate geolocation positioning, the associated GPS technology was assessed. In order to improve the accuracy and precision of these equations, so that inherent variation of grasslands is captured, there is a need to incorporate differences in grass types and seasonal growth As good bassline data are required for the development of effective conversion of CSH to HM, the variation of growth for both perennial ryegrass and hybrid ryegrass was recorded over the seven month growing season, using a total of 308 grass plots. Once the correct HM is established it must be allocated to the herd in an accurate and efficient manner. As intensive pasture-based farming systems rely on precise and frequent allocations of grass to animals, a Virtual Fence (VF) system to enhance automated allocation of correct forage areas to animals was developed and assessed, as was an associated cow training protocol. The micro-sonic sensor

RPM was found to be significantly more accurate for height capture than a traditional ratchet counter RPM. The ratchet counter RPM underestimated height by 7.68 ± 0.06 mm (mean ± SE), while the micro-sonic sensor RPM overestimated height by 0.18 ± 0.08 mm. These discrepancies can result in an under- and overestimation of HM by 13.71 % and 0.32 % per Ha^{-1}, respectively. The performance of the on-board GPS did not significantly differ from that of a tertiary device. Subsequently, three dynamic equations were derived for the effective conversion algorithms form CSH to HM incorporating different grass types, time of the year and dry matter percentage, one of algorithms is now in everyday commercial use. Although the operating capacity of the VF system was found to be robust, with dairy cows rapidly associating visual cues with VF boundary lines, and a cue-consequence association with the audio warning and corrective stimulus, the number of boundary challenges made by cows increased upon removal of all visual cues. Overall, although further research will be required, the results presented within this thesis allow for the further development of decision support tools to improve on-farm grassland management.

Chapter 1: General Introduction

1.1 Introduction

Precision livestock farming (PLF) has the ability to improve management strategies by increasing the data available to the farmer for decision making. The increased use of PLF can enable further growth in production by implementing data-driven decision making on farm. (Eastwood *et al*., 2004). These efficiencies and increases are required, as demand for dairy products is anticipated to increase by 2.3 % year on year until 2025 (IFCN, 2016). Furthermore, since the removal of the European Union dairy quota system in 2015, European dairy farmers have the opportunity to expand production for the first time in a generation. However, it is critical that this expansion is done in an efficient and sustainable manner, both economically and environmentally, to ensure the continued sustainable growth of the industry.

Grazed grass is the natural food source for bovines, and can fulfil the majority of dietary requirements of dairy cows. Nevertheless, in the last century, intensive confinement systems, with silage feeding and concentrate supplementation, have replaced many extensive pasture-based milk production systems. However, grazed grass is now acknowledged as the cheapest and most sustainable feed available, as a consequence of rising machinery, labour and feeding costs (O'Mara, 2008). Thus, in temperate regions of the world, grass-based ruminant production systems are undergoing a rejuvenation, and are increasingly being implemented (Dillon *et al*., 2005). Notably, the lower production costs associated with grass-based grazing systems aid farmers' ability to overcome the challenge of increased market price volatility, for inputs such as fertiliser and concentrates, and final milk outputs. In addition, policy objectives, societal expectations and environmental concerns have all supported an increased up-take of pasture-based milk production. The ability of Irish farms to grow and utilise grass in an efficient and profitable manner is widely considered to be a major competitive advantage over other ruminant producing countries, in terms of low cost animal production (Hurtado-Uria *et al.,* 2013). Research has shown that each 10% increase in the percentage grazed grass as a proportion of the overall diet of a dairy cow reduces the cost of milk production by 2.5 cents/litre^{-1} (Dillon *et al.,* 2005). This is further emphasized by Finneran *et al*. (2010), who reporting that grazed grass is the most cost effective feed available to all ruminant livestock production systems

Nationally, it is estimated that the average dairy farm utilises 7.1 tonnes of grass DM/ha^{-1} (Creighton *et al*., 2011), while more efficient farms are growing and utilising in excess of 12–14t of grass DM/ha^{-1} over a 280 day grazing season with stocking rates of over 3 cows/ha (Shalloo *et al*., 2011). A wide range of factors effect pasture growth at farm level which are outside of a farmer's control including soil type, region, altitude and meteorological conditions. However, Shalloo *et al.,* (2011) highlighted other factors within the farmers control such as, grassland management, soil fertility and national reseeding levels as having a strong influence on overall pasture production in Ireland. These are areas of grassland farming that could be vastly improved with the aid of data informed decision making on farm. In addition, there are a variety of further benefits to be realised from regular pasture measuring and budgeting, such as greater spring grass supply through improved autumn management, optimum utilisation of spring grass, early identification of pasture surpluses and deficits and the achievement of higher performances from pasture based systems (O'Donovan and Dillon, 1999). Research states that in Ireland, only approximately 10% of dairy farms carry out weekly grass measurements (Creighton *et al.,* 2011). The advancement in and accessibility to modern information technology and information science has supplied researchers with possibilities to provide farmers with improved decision support tools for management of grazing dairy systems not only for herbage mass (HM, i.e. dry matter yield) estimation but also for pasture allocation. The ability to objectively quantify HM will enhance the precision of pasture allocation and grass management decisions by farmers.

Profitability of grazing systems is driven by the degree of grass utilisation, which in turn is a function of both increased grass growth and optimum utilisation of that growth. The accurate and timely measurement of pasture is integral to effective grazing management practice (Creighton *et al*., 2011). The accurate estimation of HM and subsequently, the correct allocation of grass for the herd are crucial elements in maximising utilisation. In order for the farmer to allocate the grazing area correctly, they will need accurate, timely data on the herbage biomass availability on the farm. This can only be achieved by regular measurement of HM in each paddock. The HM of the paddock together with the herbage allowance (HA) (the amount of herbage the manager wants to give the herd) are used to calculate the herbage allocation (HALC) or area required for grazing, which is subsequently measured, fenced and offered to the herd. Inaccurate or subjective assessment of HM can result in the under or over allocation of grass to the herd.

The development of information communication technology (ICT) tools to capture data, such as smart device connected tools that measure herbage mass, automatically grant the ability to collect vast amounts of data with minimal operator effort, which was not previously possible through visual assessment.

Alternatively, measurements are conducted by a standardised ICT tool it allows consistent and repeatable values to be acquired. This objectivity of measurement offers the possibility for multiple users to operate the same piece of technology and obtain consistent results. With minimal training, an operator can expedite data collection, the reliability of these measurements ensures the correct quantity of grass DM is allocated, to provide for the high energy demands of the lactating cow, and establishes the correct post-grazing grass residual to increase the herbage quality of the paddock for subsequent rotations (Lee *et al.,* 2008). Previous studies have indicated that optimal daily HALC for lactating cows can increase milk production by 10% (Fulkerson *et al.,* 2005). It is not sufficient to know the correct HA for the herd, care must be taken to ensure that the appropriate HM and HACL is provided. This not only affects cow production, but also future HM and herbage quality. For example, grazing pastures with HM of 1,700 kg DM^{-1} ha^{-1} rather than 2,200 kg DM^{-1} ha^{-1}, significantly increased future sward quality and milk solids output per ha^{-1} (McEvoy *et al.,* 2009). Without the availability of accurate and relevant data, it is difficult to ensure this is archived.

Research investigating grass quality has concluded that the highest milk output per ha and per cow, with low post-grazing residuals and enhanced sward quality, was achieved using the management strategy of grazing a low HM (1,600 - 1,700 kg DM^{-1} ha^{-1}) at a high HA (20 kg DM^{-1} cow^{-1} day^{-1}) (McEvoy *et al*., 2009; Roca-Fernandez *et al*., 2012). However, under-estimating HM could potentially reduce milk solids per ha^{-1}, while inadvertently increasing the HA (or HALC) would increase the quantity of residual grass left behind, thus reducing the herbage quality in subsequent grazing rotations. A key factor in the success of

ICT tool adoption by farmers is the accurate and reliable performance of the ICT tool, which must be achieved through rigorous validation procedures.

The labour demand of grassland management in terms of grass measurement and allocation and fencing is considerable. Research on the labour requirement of grassland management was investigated by Demming *et al.* (2018). They found that some farmers were expending approximately 0.35 hours/cow/year for grass measurement and 0.43 hours/cow/year at allocation/fencing/setting up of strip wires. Lyons *et al.* (2016) suggested that progress on the usefulness of animal technologies is dependent on their integration in decision support software and combining data from different sources and processing information with powerful data analytics tools. That study also revealed, that to-date, automation technologies which are labour saving are more popular with farmers than those designed to collect data for decision making, especially for physically demanding tasks, such as for milking.

New technologies to assist in the measuring and managing of grassland have the potential to facilitate increased profitability of the farm enterprise. However, the implementation of sensor technology on commercial dairy farms remains slow, especially on pasture-based dairy systems. Consequently, the current management of grazing cows is largely not supported by technology. Until recently, the main application of sensor technology within the dairy sector was aimed at confinement systems, where cows are housed year round. However, high adoption rates of smart devices, such as smartphones has allowed the average farmer (within both indoor and outdoor production systems) to potentially have access to a platform with large computing capabilities, whilst also having a connection to the wealth of knowledge of the internet. These recent advances have made ICT in agriculture capable of performing complex tasks remotely. These smart devices (smartphones) may be ideally suited to pasture based production, as it allows for data collection and transmission in the absence of a designated technology hub (Shalloo *et al.,* 2018). These smart devices may represent vital tools for a dairy farmer implementing an efficient pasture based system of farming in the future. With increasing herd sizes and skilled labour shortages, sensor technology will likely play a significant role in overcoming the challenges associated with the expansion of dairy herds (Werner *et al.,* 2018). Sensor technology that can aid the measurement of pasture and enable data driven grassland management, for real-time decision support poses a considerable advantage to grass based farmers (Hanrahan *et al*., 2017)

Dolecheck *et al.* (2013) suggested that in an ideal precision operated farm, the technology should be low cost, reliable, robust, flexible, and easy to maintain and update, and should provide information that immediately can be turned into management action. This is the goal with regard to ICT within pasture management.

The potential impact of using ICT tools for grass measurement is considerable. The focus of this thesis has centred on the development of two ICT tools, (1) A smart-device linked, micro-sonic sensor enabled Rising Plate Meter (RPM), and (2) a prototype Virtual Fence (VF) system the potential for linking herbage measurement with a spatial dimension, thus allowing precise allocation of feed using GPS technology. This is accomplished through developing an ICT tool for automated data capture of grass data, a smart phone application and the integration with an online grassland management DST. This approach has resulted in an increase in farmer confidence in their ability to grass measure, as well as resulting in an increase in volume of information obtained, while sampling. Additionally, research work has been conducted with an objective to develop a protocol for the effective operation of the VF for dairy cows within an intensive pasture-based production system.

Equipped now with the tools to collect large volumes of data regarding HM and also the facility to autonomously allocate, and guide cows to, the necessary HA for the herd, the necessity of data management and decision support systems is critical for the uptake of sensor technology. Pasture management systems such as PastureBase Ireland furnish users with support around grassland management decisions, through the provision of decision support tools (DST), and also has the potential to contribute to new research pertaining to grassland management. Grass biomass estimates entered into the database are used to produce a grass wedge, giving a visual representation of the grass available on farm at a particular point in time. The grass wedge can identify the presence of potential surpluses or deficits in herbage availability expected to occur. If a surplus is identified, paddocks should be harvested as soon as possible, subject to weather conditions, thus allowing the paddock back into the grazing rotation. The PBI decision support tool/database also contains spring and autumn rotation planners to aid farmers' grazing management in the early and late periods of the season. The spring rotation planner assists farmers to plan the first grazing rotation which is critical to maximise subsequent sward quality and production of further rotations.

A micro-sonic sensor enabled RPM with global positioning system (GPS) technology and mapping capabilities, i.e. a reliable, precise, consistent and easy to use tool to estimate HM has been commercially launched. Also, the development of “smart” biomass prediction algorithms that can be implemented via a smart device application with the ability to autonomously apply detailed calculations that include parameters not previously practically implementable using traditional measurement techniques. Following on from this a VF system prototype to create boundaries that can (i) maintain cows in a space defined by a farm operative, dependent on grass availability; (ii) be respondent to grassland measures, such as height and density, so that the boundary advances as the herd residency time in a grazing area increases; (iii) be respondent to individual cow intake requirements so that the boundary advances for the individual cow were also designed and implemented within this thesis. Eastwood *et al*. (2009) states that more detailed information on pasture resources and utilisation are the ‘missing link’ for whole farm precision systems. However, it is important to remember such tools must improve whole farm pasture utilisation while at the same time reduce labour demand associated with grassland management tasks.

Chapter 2 Literature Review

2.1 The Global Dairy Industry

Since prehistoric times, humankind has comprehended that food security can be sustained through the domestication of animals, to be used as an easily accessible, reliable and nutritional food source. The primary focus in early domestication practices were ruminants, as they have the advantageous ability to convert high fibrous feedstuff into milk or meat, while not competing against humans for shared food sources (van Wieren, 1996). However, in the last century, with the intensification of agricultural production the resulting dairy husbandry practices have also radically changed. Previously, dairying was comprised of extensive small-scale production systems, which almost exclusively relied on small local pasture-based dairy herds. These were used for the provision of dairy products for a single household or a small number of neighbouring households. However, from approximately the mid-20th century, the mechanisation of agricultural production and the introduction modern agricultural practices has significantly advanced, resulting in the replacement of human labour, and the reduction of time and cost required for many aspects of herd management (Knaus, 2016; Thornton, 2010).

Increasing global demand, for animal-based protein, to be readily available throughout the year, has resulted in the increased and sustained production of dairy livestock. Consequently, for optimal and profitable production, and to guarantee consistent production in many regions of the world, it has become necessary to confine herds within housed systems (Pinxterhuis *et al.,* 2015). In particular, to ensure consistent and sustained milk production, many dairy producers in the European Union (EU) and the United States of America (US) have transitioned from low-cost, grazing-based systems into high-cost and intensive housed systems. In general, these intensive systems rely on the consumption of feed produced off farm, in the form of concentrates (Knaus, 2016). These concentrates are low-fibre, high-energy feeds, which may have a low, medium, or high protein content. Most often, concentrates are fed to raise the energy levels of dairy cows that are in negative energy balance and to compensate for any deficiencies in their diet. However, high production and transport costs make concentrates far more expensive per unit of feed value, than grass based forage. For the majority of grass-based systems, the majority of the herd dietary requirements are serviced by feed produced on the resident farm, allowing for more control over cost of production and quality of the feed produced. To maximise profit, cows should achieve as much of their maintenance, growth and production requirements from forage, preferably grazed grass produced on the resident farm. Nonetheless, concentrates are essential at key times in the production cycle of dairy cows, e.g. when grass growth is less than herd demand resulting in a grass deficit situation or in extreme weather periods.

Grass-based production systems have many benefits other than those directly related to the efficiency of production. As highlighted by Dillon *et al.* (2005), there are many environmental and societal benefits to the implementation of grass-based production systems. Furthermore, milk produced from a grass-based diet has been found to have significant human health benefits, attributed to increased levels of monounsaturated fatty acids and higher concentrations of conjugated linoleic acid relative to those found in milk produced from confinement systems (Dillon *et al.*, 2005). In Ireland, for example, grass-based production systems have a lower carbon footprint per unit of milk compared to confinement dairy systems in the UK and US (O'Brien *et al.*, 2014).

Historically, grass-based production systems were typical in many areas of Europe, particularly in regions such as the lowlands of north-western Europe. However, in recent times, grazing has been out-competed with maize production and biofuel crops for renewable energy systems (Taube *et al*., 2014). Since the beginning of the 1960s, the cost per unit of net energy for corn has been less than that for grass-based forage in regions of the EU and the US, including grazing, freshly harvested or grass preserved as hay or silage, where climate allows for the production of corn. Undoubtedly, this has encouraged farmers to include large amounts of concentrates in dairy cow diet, which has promoted the gradual transition towards intensive confinement within dairy production systems, particularly where land availability is a significant constraint (O'Brien *et al*., 2012c; Van Soest, 1994). For many European regions it is simply more cost-effective to increase production through concentrate feeding rather than pasture-based grazing (Macdonald *et al*., 2017). Despite grazing's potentially substantial economic and environmental benefits, the advancement of this sector is constrained by a lack of expertise in grassland management, compounded by farmers efforts to stabilise farm cash-flow and avoid underutilising capital investments, most European dairy farms now operate confinement and year-round calving systems (Knaus, 2016; Thomet, 2011).

In particular, with the abolition of the EU milk quota regime (EEC 3950/92) in March 2015, European dairy farmers were allowed to increase milk production without restrictions for the first time since April 1984. Access to the world market without quota constraints has allowed farmers to produce as much milk as the resources available on farm will allow for example, land availability for the production of herbage, access to skilled labour and capital infrastructure. Along with this, generations of selective breeding programs have led to the successful development of high-yielding dairy cows that return higher milk yields when fed a highly nutritious diet. This has resulted in a requirement to provide a consistently high nutritional diet to the cows, to prevent hunger and loss of body condition, and maintain high milk yields (Kolver & Muller, 1998).

Furthermore, the shortage of skilled and affordable labour has accelerated the development and uptake of robotic milking systems. Due to the robotic milking systems ability to decrease milking interval thus increasing milkings/cow/day, farmers are opting for a genetically superior cow with increased milk production capability, causing the energy demand of the herd to increase, further supporting the trend for continuous housing of dairy cows in recent years to ensure the increased energy demand is met (Arnott *et al.,* 2017). Currently as this trend continues, and research indicates that the use of pasture-based systems for dairy production is rapidly decreasing across Europe (Reijs *et al.,* 2013). For example, based on economic model calculations, it is expected that by 2025 the number of dairy cows in the Netherlands with access to pasture will be reduced by half (Wageningen, 2013). In fact in 2017, only 10% of global milk production originates from grazing systems (Dillon, 2017).

Nevertheless, in temperate regions of the world, intensive grass-based ruminant dairy production systems have experienced a rejuvenation, due to their improved environmental and financial sustainability when compared with intensive confinement systems (Van den Pol-van Dasselaar *et al.,* 2018; Dillon *et al*., 2005). The lower production costs associated with grass-based systems helps overcome the challenges of uncertainty regarding weather and the increased market volatility for outputs such as milk and meat.

2.2 The Dairy Industry Within Ireland

The dairy industry is a crucial component of the Irish economy, processing approximately seven billion litres of milk per annum, supplied by 18,000 family farms, many of whom are owners of the primary business. This results in over €4 billion worth of international exports in dairy products, ingredients and nutritional products per annum (DAFM 2017). The production system to be deployed on farms are primarily determined by weather patterns and the resources available to farmers (O'Brien & Hennessy, 2017). Ireland has a competitive advantage over many countries due to the ability to grow large quantities of pasture over a long growing season (Dillon *et al.,* 2008). This extended growing season is facilitated by a temperate humid maritime climate (Keane & Sheridan, 2004). The rate of grass growth is highly variable and is sensitive to many meteorological factors, such as soil moisture, soil temperature and solar radiation levels. Ireland's climate experiences steady air temperatures throughout the year, with cool summers (14 - 16°C) and mild damp winters (5 - 7°C) (Keane & Sheridan, 2004). Unlike many other countries at similar latitudes, Ireland does not experience the same seasonal climatic extremes because of its proximity to the Atlantic Ocean and the Gulf Stream. Soil moisture is generally sufficient with average rainfall levels of between 750 mm in the east and north-east and over 1200 mm in the west, north-west and south-west (Drennan *et al*., 2005), generally exceeding evapotranspiration rates. Air temperatures are important as they directly influence soil temperature which determines the start and end of the grass growing season. Soil temperature is measured at a depth of 100 mm, representing the soil profile available to the grass plant's root system. The threshold soil temperature for grass growth is 6°C, below which there is minimal growth (Keane & Sheridan, 2004). When soil temperature exceeds 5°C it is defined as a growing day. In Ireland the growing season ranges from 330 days in the south-west, to 240 days in the north-east. (O'Donovan *et al*., 2011).

Pasture growth typically commences in February and increases rapidly to peak pasture growth of up to 100 kg DM/ha per day in May/June and subsequently decreases on a gradual basis during the summer and autumn, until growth almost ceases in December (Hurtado-Uria *et al.,* 2013) (Figure 1). Irish farmers operate seasonal production systems, similar to systems in New Zealand and Australia and are established in such a manner as to maximise the utilisation potential of grazed pasture, through aligning the start of calving with onset of pasture growth (Dillon *et al.,* 2005). This is immensely beneficial as grass, particularly grazed grass, is of high nutritive value (O'Neill *et al.,* 2011), and has been found to be the cheapest source of feed available to Irish ruminant production systems (Finneran *et al*., 2012)

Ireland remains uniquely positioned to capitalise on the EU policy changes which have resulted in the removal of milk quotas. Early predictions by Lips & Rieder (2005) had suggested that Irish milk production could increase by 39%, while the Food Harvest 2020 report had set a target of 50% increased milk production by 2020, in relation to a pre-quota baseline. Interestingly, Ireland has already accomplished this target, with a record-breaking production of 7.5 billion litres in 2018. Thus, Ireland is now two years ahead of the Food Harvest 2020 target (DAFM 2010, 2019). However current, international food markets for agricultural produce are extraordinarily dynamic, and subject to the constant fluctuation of price, policy changes, higher societal expectations, and environmental constraints (Hanrahan *et al.,* 2018). In order to maintain and develop agriculture production within Ireland it is essential that robust and sustainable production systems are employed whilst continuously reducing the environmental impact. For dairy production systems, this may be achieved with increasing the proportion of grazed grass fed to dairy cows, as the cost of feeding the cow can contribute about 50% of the total cost of milk production. Also by increasing the proportion of grazed grass in the cow's diet it will result in having the lowest environmental impact (Hemme *et al.,* 2014; O'Brien *et al.,* 2014). French *et al.* (2015) illustrated that every extra ton of grass DM/ha utilized increased farm profit by €267/ha. Ramsbottom *et al*. (2015) also commented that it is not the system with the greatest milk production that is most profitable, but the system with the lowest total costs. Thus, with low cost grass production capability, the most appropriate system in the Irish scenario is the grass based system of milk production.

The seasonal production system that is operated in Ireland has been designed to match herd nutritional intake demands with the growth profile of perennial ryegrass swards (see Figure 2.1; Holmes *et al.,* 2002). The relative cost of pasture as a feed source for livestock production, when compared to grass silage (1.8 euro) and concentrate (2.4 euro) is very good at 1 euro (Finneran *et al.,* 2010). Moreover, in comparison to mechanically harvested or purchased feeds, grazed grass provides a relatively inexpensive and uniquely nutritious feed source for milk production (Finneran *et al.,* 2012). Additionally, maximising the amount of grass used improves farm profit with each additional tonne of grazed grass utilised per hectare, by increasing net profit/ha by €161 on Irish farms (Dillon, 2011). Increasing the proportion of grazed grass in the diet of the dairy cows by 10% has been shown to reduce costs of production by 2.5 cents per litre of milk produced (Dillon *et al.,* 2005). This has a significant impact on dairy farm profitability, as various farm economic analyses have demonstrated a lack of association between milk produced and operating profit (Silva-Villacorta *et al.,* 2005; Ramsbottom *et al.,* 2015). Furthermore, systems dependant on high inputs of concentrates tends to have reduced profitability relative to systems that rely on high quality grazed grass, particularly in periods of low milk price (McCarthy *et al.,* 2007b; Patton *et al.,* 2012; Ramsbottom *et al.,* 2015).

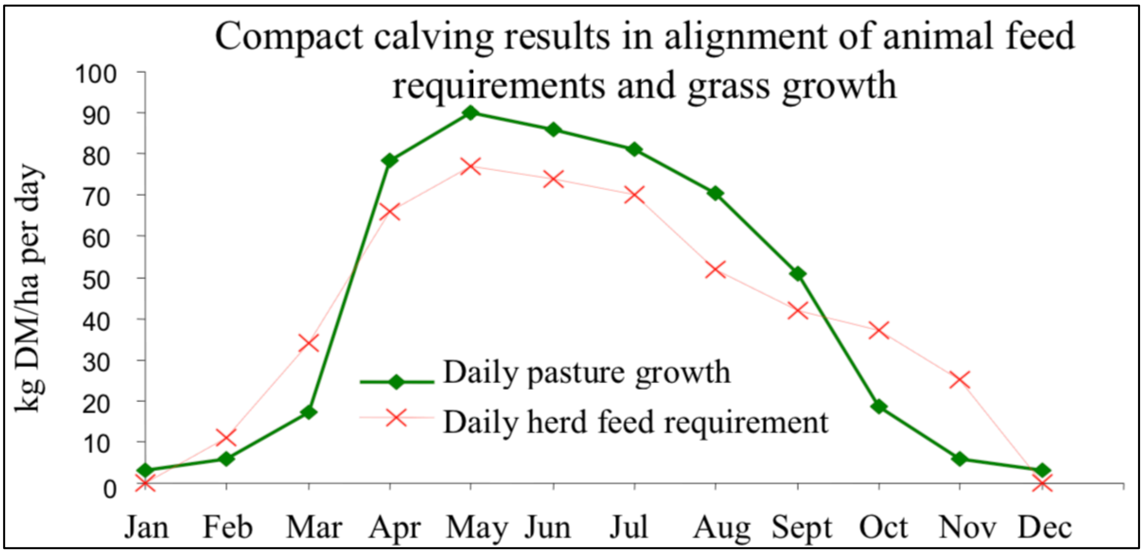

Figure 2.1 The Irish seasonal grazing system; cows are calved and dried off to ensure synchrony between herd demand and feed supply.

2.3 Challenges Facing Irish Dairy Farms

Since the removal of the EU milk quota, the predicted expansion of the Irish dairy industry has been met and surpassed (Läpple & Hennessy, 2012; DAFM, 2019). However, the rapid expansion coupled with volatile global milk-markets, requires that farmers develop sustainable milk production systems, focused on technical and financial efficiencies (Kelly *et al.,* 2012). Key to the success of the Irish dairy industry both nationally and internationally is the increased consumer interest in high quality food production, with consumers now displaying an increased preference for milk products produced from pasturing cows, particularly in the US and Asian markets (Weinrich *et al.,* 2014).

However, various challenges are associated with pasture-based systems. In particular, there is a shortage of skilled labour (Deming *et al.,* 2015), and suitable land availability (Thorne *et al.,* 2016). Teagasc (2017) estimated that by 2025 average herd size will increase to 104 cows from 75 cows in 2013, and this presents the challenge given the shortage of suitably skilled labour. Sourcing skilled labour is difficult as there are significant differences in the level of labour required during each season of the year in Irish dairy farming, with the spring time (February-April) having the highest demand for labour due to calving, calf rearing, and milking (O'Donovan, 2011; Deming *et al.,* 2015). The calving period is becoming more compact on Irish dairy farms with increasing numbers of farmers achieving a 90 % calving rate within six weeks (Teagasc, 2017). This intense seasonality poses an issue for employers as they require employees during a short period of high labour demand during the busy months. As a result employers often do not require full-time employees as it may be difficult to justify a full-time position during the low labour demand of the farm during the winter months. Given that second to feed costs, labour has been identified as one of the highest costs on dairy farms, farm employers find it difficult to retain trained skilled labour as many employees opt to move to a different industry for more consistent employment (Hemme *et al*., 2014).

Although there is the potential to increase the productivity of dairy farms given the current under-utilisation of land resources (O'Donnell *et al.,* 2008), a proportional increase in the amount of grazing land available to farmers is required to facilitate increased herd sizes (van den Pol *et al.,* 2008). Pastures also need to be easily accessible from the milking parlour, as increased distances between grazing pastures and milking-parlours could potentially have a negative impact on cow hoof health (Laven & Lawrence, 2006). Additionally, there is also an increased labour demand associated with herding the cows to and from the pasture (Ofner-Schröck *et al*., 2009). Local abiotic factors, such as regional weather conditions and geographical location of individual farms can also represent challenges for a high output pasture-based milk production system. For example, approx. 1000 mm of rainfall, being evenly distributed throughout the year, is ideally required for optimal grass growth but this does not always happen (Dillon *et al.,* 2005).

2.4 Herbage Production In Ireland

Many studies have highlighted the potential for increased milk yield from grazed grass through a focus on critical components of grass-based systems, particularly high grass utilisation (Creighton *et al.,* 2011; Dillon *et al.,* 2005; McCarthy *et al.,* 2013). Due to Ireland's favourable climatic conditions, there is potential to consistently produce between 13 and 15.5 t DM/ha annually under optimum grassland management (O'Donovan *et al.,* 2011), over a 300 day grazing season with stocking rates of over three cows/ha (Shalloo *et al.,* 2011). However, a wide range of factors affect pasture growth, many of which are outside of a farmer's control. These include soil type, region, altitude and meteorological conditions. Nevertheless, Shalloo *et al*. (2011) have highlighted that directly manageable factors, such as grassland management, soil fertility and reseeding levels, have a strong influence on overall pasture production. Further, these factors represent areas of grassland management that can be improved with the use of informed decision-making by farmers. At present, Irish dairy farmers are growing 9.1 t DM/ha (McEvoy *et al*., 2011). Records through Ireland's national grassland database, PastureBase Ireland (PBI), indicate that the bottom 20 % of farms measuring and managing grass are only growing 11.0 t DM/ha, with the average farm is growing 13.8 t DM/ha, while the topmost 20 % of recorded farms are growing 16.7 t DM/ha. The variation in seasonal herbage production on these PBI farms is as follows: 816 – 1,199 kg DM/ha in spring, 4,462 – 4,932 kg DM/ha in mid-season and 5,937 – 6,442 kg DM/ha in autumn. The farms producing the greatest quantity of herbage, achieve an extra grazing per year compared to the farms producing the least (7.7 and 6.8 grazings/paddock/year).

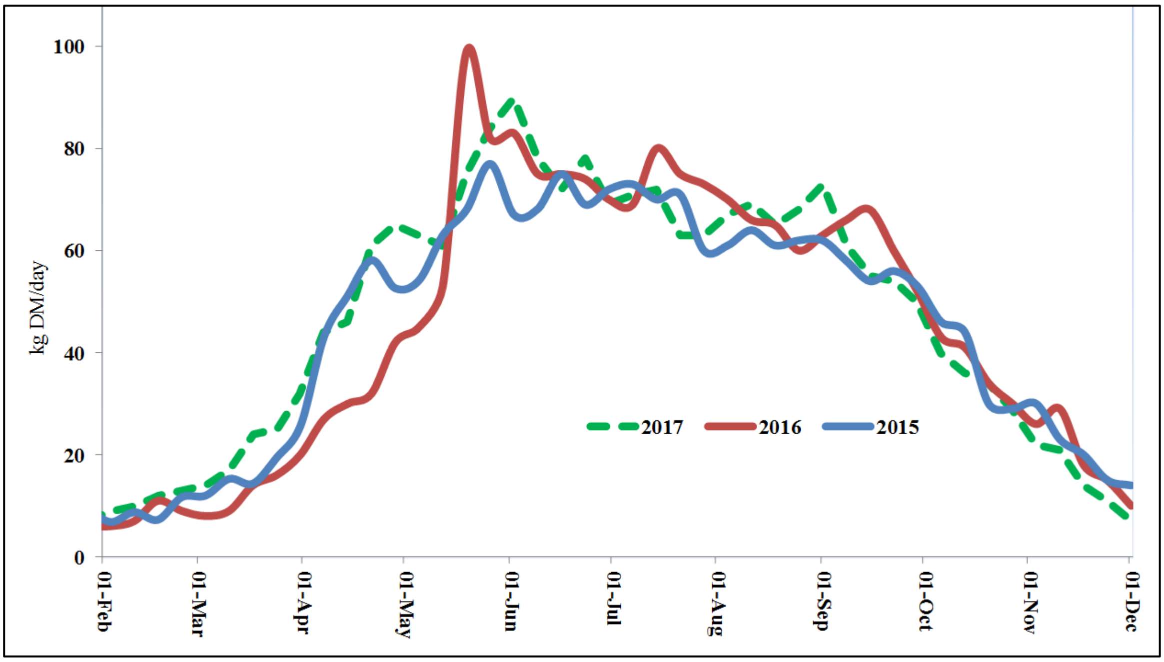

Figure 2.2. Grass growth curve for commercial grassland farms throughout Ireland 2015- 2017, from PastureBase Ireland

The value of grass within grazing production systems varies throughout the year because of seasonal differences in the nutritional value of grass and its availability. Due to low growth rates in the spring and autumn (Figure 2.2) and high animal intake demand, herbage grown during these periods cannot satisfy demand. Thus, this grass is of a higher economic value per tonne than pasture grown in the mid-season when supply exceeds demand (O'Donovan & Kennedy, 2007; McEvoy *et al.,* 2011), as herbage grown in beginning and end of the growing season can displace the use of expensive concentrates in the cows diets.

2.4.1 Perennial Ryegrass

Perennial ryegrass (Lolium perenne L.), Italian ryegrass (Lolium multiflorum Lam.) and hybrid ryegrass (Lolium × Boucheanum Kunth) are the predominantly sown forage grasses in north-western Europe (Wilkins and Humphreys, 2003). Perennial ryegrass is one of the most dominant forage grass species grown in temperate regions of the world (Wilkins and Humphreys, 2003). It is ideally suited to Irish conditions and as a result accounts for 95 % of Irish grass seed sales (Culleton *et al.,* 1992). Italian ryegrass is a bi-annual species, which offers a short-term yield advantage over perennial ryegrass. Hybrid ryegrass is a cross between perennial and Italian ryegrass, combining the persistence, density and quality of perennial ryegrass with the high yield potential of Italian ryegrass. Typically Italian and hybrid ryegrass are more suited to intensive conservation systems rather than animal grazing, hence, the dominant market share of perennial ryegrass in Ireland.

2.4.2 Herbage Utilisation

The key objective of grazing systems in Ireland is to achieve high levels of herbage utilisation (O'Donovan *et al*., 2011). Figure 2.3 shows the relationship between herbage utilisation and profit per hectare on dairy farms in 2015. Herbage utilisation explains much of the variation in net profit per hectare, with each additional tonne utilised increasing net profit by an estimated €173 per hectare on dairy farms (Hanrahan *et al*., 2018) and €105 per hectare on dry-stock farms (Crosson *et al.,* 2016). Management of stocking rate, rotation length and pre-grazing herbage mass influence sward utilisation levels (McCarthy *et al*., 2013). Sward structure can influence utilisation levels (O'Donovan *et al.,* 2011) as tetraploid varieties can achieve higher levels of herbage utilisation (Gowen *et al.,* 2003). On average, specialist Irish dairy farms utilise 7.8 t DM/ha (Hanrahan *et al.,* 2018).

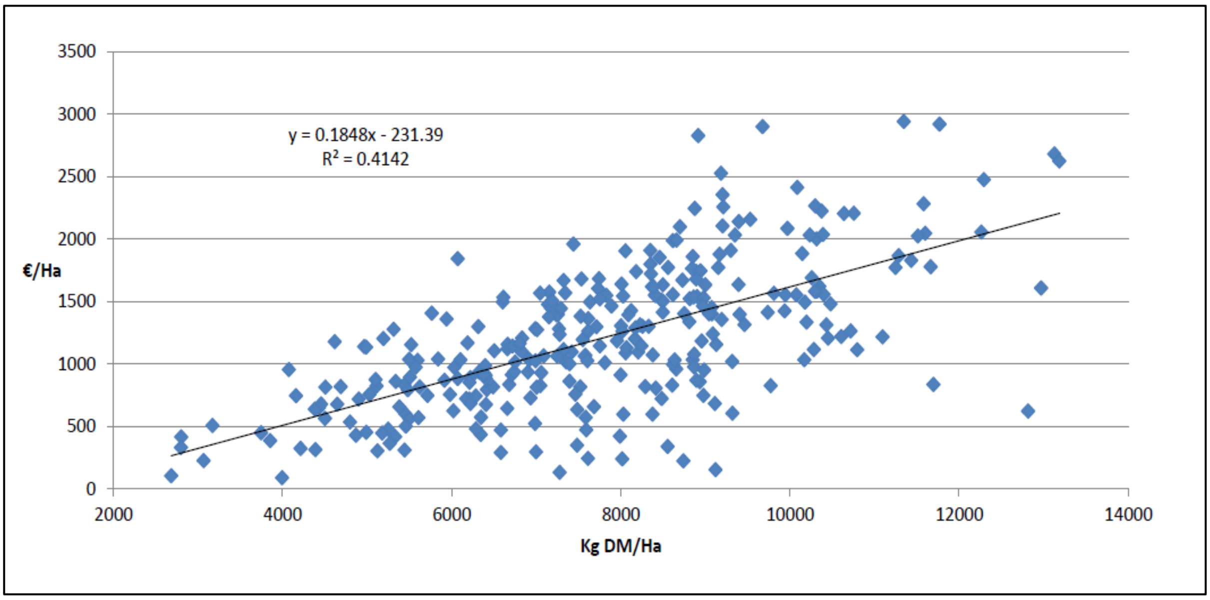

Figure 2.3. Association between herbage utilisation (kg DM/ha) and net profit (€/ha) on Irish dairy farms in 2015 (Hanrahan et al., 2018)

2.4.3 Grass Measurement

Appropriate pasture measurement and forage budgeting are important mechanisms to enable increased farm profitability through the effective use of available pasture (Creighton *et al.,* 2011). Measuring herbage availability regularly enables farmers to make better informed and more effective grassland management decisions. However, the correct estimation of available grass and subsequent allocation of pasture to grazing cows can be challenging. It can depend on grass growth rates, grass quality, and grass utilisation by cows, as well as identifying the herbage intake requirement of the cow at her stage of lactation (McEvoy *et al.,* 2011). McCarthy *et al*. (2011) also mentioned that the balance between feed 'supply and demand' is critical, as an imbalance will result in either underfeeding of the herd or waste of excess feed resulting in reduced regrowth or reduced grass quality. A range of methods, both destructive and non-destructive have been shown to be effective in the measurement of grass. In a comparison of four grass measurement methods by O'Donovan *et al.* (2002a), four methods of herbage mass estimation were accessed, visual assessment, Rising Plate Meter (RPM), sward stick and pasture probe capacitance meter with coefficient of variation results of 9, 10, 12, 21 % respectively. In that study, swards which were visually assessed were under-estimated for herbage mass. It is essential to combine visual non-destructive measurement with destructive measurement for assessor calibration. This can also be done by farmers who wish to calibrate themselves for visual estimation by cutting a series of small quadrats (0.25 m^2) to the target animal grazing residual height (3.5 - 4 cm). The cut herbage can then be placed in a bag to be weighed using pocket scales and the herbage mass calculated using an appropriate dry matter content for the prevailing conditions, as recommended by Kennedy *et al.* (2016). Following this, the herbage yield per hectare is estimated as: Kg Dry Matter(DM)/ha = Fresh weight (kg) x (DM % ÷ 100) × 40,000

An alternative non-destructive method for the collection of biomass data is the use of a rising plate meter (RPM). Formulas developed by applying the regression relationship of a standing grass crop to predictive values, such as plant height, leaf area, vegetation density, canopy, cover and age (Vermeire & Gillen, 2001). The RPM has been widely investigated as a predictor of Herbage

Mass (HM) (Castle,1976; Earle & McGowan, 1979; Mitchell, 1982; Stockdale, 1984; Stockdale & Kelly, 1984; Douglas & Crawford, 1994; Karl & Nicholson, 1987). Commercial instruments often come with standard equations, and the precision of the instrument depends on the adjustment of these calibration equations. Many studies have shown that the use of indirect methods to obtain a measure of HM, using the standardised equations are not repeatable in different conditions and situations, because of variations in pastures, management and climate (Frame, 1993). Dowdeswell (1998) reported a poor relationship between yields estimated with a RPM using New Zealand equations and actual measured yield calculated from the cut and weigh method. These authors suggested that a coefficient of variation larger than 10% could be considered statistically acceptable, but economically inaccurate. Given the inherent spatial and temporal variability of pastures, it may be difficult for a producer to achieve an error lower than the proposed 10%, however, some authors found that local calibrations can reduce error to about 10% (Rayburn & Rayburn, 1998). From the total height of the sward, the target Post Grazing Sward Height (PGSH) is subtracted to determine the amount of herbage available to grazing animals.

Grassland measurement plays a major role in the level of herbage utilisation achieved. Pre-grazing HM directly influences sward utilisation, with lower herbage masses achieving higher utilisation (Holmes *et al.,* 1992). Curran *et al.* (2010) reported increased levels of herbage utilisation when HM was reduced from 2,400 kg DM/ha to 1,600 kg DM/ha, where the daily allocation of herbage was 20 kg DM. Swards that have a low pre- grazing herbage mass contain higher proportions of green leaf and lower proportions of stem and dead material, resulting in higher dry matter digestibility (DMD) values and higher cow milk production (Hoogendoorn *et al.,* 1992). Improved utilisation is further enhanced by the farmer offering lower HM to cows as they preferentially select green leaf material from the sward (Gilliland *et al.,* 2002, Tuñon *et al.,* 2014).

The optimum pre-grazing HM ranges between 1,400 – 1,600 kg DM/ha (Wims *et al.,* 2014). This range maintains herbage growth and utilisation levels, with no negative impact on sward quality and animal performance (Wims *et al.,* 2014). Maintaining pre-grazing HM below 1,250 kg DM/ha for prolonged periods is shown to cause a reduction in herbage production (O'Donovan, 2000). Low herbage masses are maintained by using a short regrowth interval, however, this can deplete water soluble carbohydrate (WSC) reserves used to fuel the regrowth of defoliated plants (Fulkerson & Slack, 1995, Fulkerson & Donaghy, 2001). Inaccuracies in HM assessments can result in the incorrect herbage allowances being allocated to the herd giving rise to suppressed milk production and poor herbage utilisation. Consequently the measurement of herbage needs to be as accurate as possible.

2.4.4 Grassland Time and Labour Requirement

Grassland measurement is a demanding task on a farmer's time. Regardless of the method of measurement the task is laborious and complex with multiple opportunities for error to occur. Kolver *et al.* (1996) highlights that farmers' need extensive practical experience of grassland management and the computer skills necessary to apply model calculations from systems such as PastureBase Ireland (PBI) to handle the various changes and fluctuations during the pasture season. Research on the labour requirement of grassland measurement was investigated by Demming *et al.* (2018). The efficiency of the operators was accessed on the time assigned to grass measurement on a hours/cow/year (H/C/Y) basis. For herds with less than 150 cows, the operator spent a mean (±SD) 0.35 ±0.2 H/C/Y on grass measurement, while herds of between 150-249 cows expended 0.30 ±0.19 H/C/Y and herds of >250 cows, expended 0.23 ± 0.26 H/C/Y. The most efficient 25% of farmers were found to spend 0.28 ± 0.23 H/C/Y on grassland measurement, while the least efficient farms devoted 0.41 ± 0.23 H/C/Y. It needs to be noted that the farmers involved in this study were already "known to be efficient" Farmers.

2.4.5 Decision Support Tools

Several pasture management software systems exist worldwide, e.g. Agrinet (UK), Pasturemate & FarmIQ (NZ), PasturePlan (France) and PastureBase (Ireland) (PBI). PBI is a web-based, grassland database which has a dual function of providing real time decision support for practitioners while functioning as a national grassland database, capturing information for benchmarking and research purposes (Hanrahan *et al.,* 2017). This allows the quantification of grass growth and herbage production (total and seasonal) across different enterprises, grassland management systems, regions and soil types using a common measurement protocol and methodology. The system operates with the individual farm paddock as the basic measurement unit. All measurements on PBI are described and calculated on a per hectare basis for individual paddocks. All grassland data is recorded by the farmer through the web or smartphone interface.

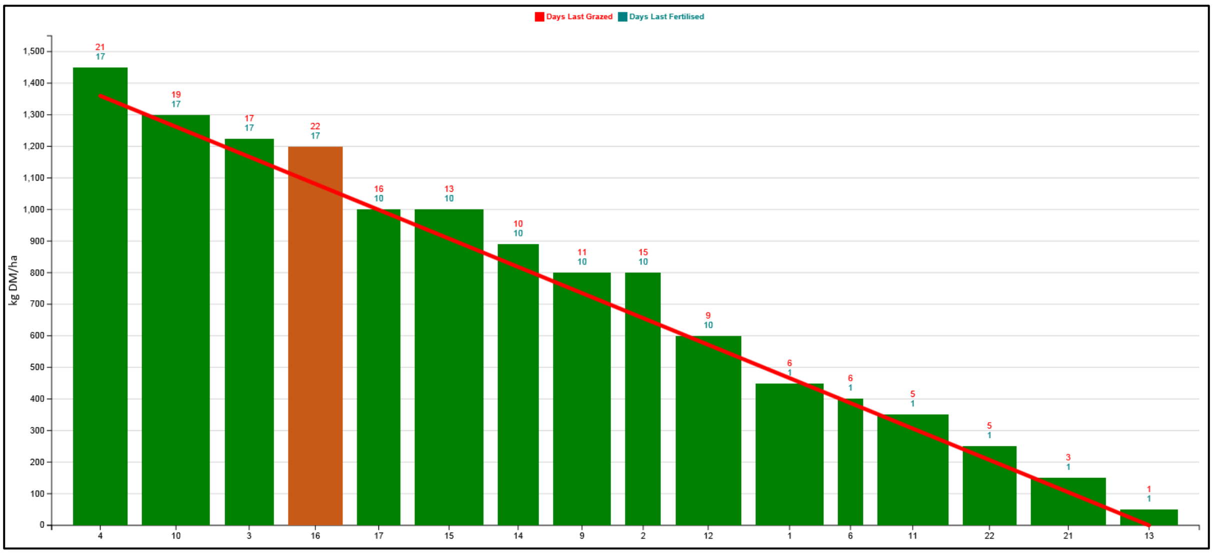

Figure 2.4: Grass wedge generated from PastureBase Ireland.

Grass biomass estimates entered into the database are used to produce a grass wedge, giving a visual representation of the grass available on farm at a point in time. The grass wedge can identify the presence or potential surpluses or deficits in herbage availability to occur (Figure 2.4). A line from the target pre-grazing cover (eg. 1,600 kg DM/ha) to the target residual cover (eg. 100 kg DM/ha) is plotted on the wedge graph. A perfect wedge is one where each paddock is meeting the wedge line, indicating an adequate grass supply. If a surplus is indicated (paddock above the wedge line), paddocks should be removed as silage as soon as possible depending on weather conditions, allowing the paddock back into the grazing rotation. Generally, the paddocks selected for surplus silage are those where covers exceed the targeted pre grazing cover of 1,600 kg DM/ha. When a deficit in herbage availability occurs, the surplus silage can be supplemented back into animals' diets, filling the gap on the wedge or additional concentrate can be supplemented to correct the drop in herbage availability. The use of PBI allows operators more foresight and to make timely decisions regarding grassland management.

The PBI decision support tool/database also contains spring and autumn rotation planners to aid farmers' grazing management in the early and late periods of the season. The spring rotation planner assists farmers to plan the first grazing rotation which is critical to maximise subsequent sward quality and production of further rotations. This planner is not a feed budgeting tool. It divides the grazing platform into weekly proportions ensuring sufficient grass is grazed early enough to allow for adequate regrowth in the second grazing rotation, this helps to form an evenly shaped grass wedge in the second rotation. The aim is to have 30% of the grazing platform grazed by the 1st of March, 60% by the 17th of March and the first rotation completed by the 1st of April.

The autumn rotation planner facilitates extending the grazing season late into the year and allows grass covers to build sufficiently to allow for early spring grazing to coincide with the calving period. Depending on the seasonal growth profile of the regional farm, the planner commences the close-off of paddocks after grazing from early October, with 60% of the land area being unused from the 1st of November, and the remaining 40% closed by the 1st of December. The actual area versus the target is plotted in the respective reports generated by PBI.

2.4.6 Technical Support for Grass Management

A study by Hanrahan *et al.* (2017) has shown that automated sensor systems capable of measuring and managing pasture production have provided measurable benefits on farm. Eastwood *et al*. (2009) noted that more detailed information on pasture resources and their efficient utilisation are the 'missing link' for the improvement of whole farm production systems. However, Hanrahan *et al.* (2017) highlights that farmers' need practical experience of grassland management and the computer skills to apply model calculations from systems such as PBI to handle the various changes and fluctuations during the pasture season.

2.4.7 Allocation of Grass

Allocation refers to the appropriate area being assigned to the herd based on demand (quantity of cows X targeted daily intake X residency time) and the HM available in the paddock. The correct allocation is critical to achieving the targeted PGSH. The accuracy of the allocation is dependent on the data on which it is based. Inaccurate data in terms of demand or HM availability will lead to the under or over allocation of herbage to the herd, resulting in poor utilisation of grass as well as a negative effect on subsequent rotations.

Originally, all the ancestors of modern domesticated livestock roamed freely. With domestication by mankind, livestock were fenced in using primitive materials such as wood and stone, these were slow and expensive to establish and weren't completely effective. Animal containment with modern fences as we know it today can trace it origins back to the mid-18th century with the development of barbed wire in France (McCallum & McCallum, 1972). In the last 50 years due to the risk of injury to both livestock and human, electrified fencing has become the standard for livestock containment.

The profitability of intensive pasture-based systems is reliant upon precise, accurate and timely grazing management strategies. Therefore, there is a clear need to meet, but not exceed, daily nutritional demands of grazing animals

(Kennedy *et al.,* 2009). In particular, the practice of strip-grazing, whereby animals are moved once or more on a daily basis between predefined grazing areas of known grass height and quality, is considered to be a best practice protocol for optimal grass utilisation and improved farm productivity (Abrahamse *et al.,* 2008; Umstatter, 2011; Koene *et al*., 2016).

Therefore, the effective control of grazing animal movements is imperative to any intensive pasture-based system. Consequently, the implementation of Precision Livestock Farming (PLF) techniques in relation to grassland management represents a considerable opportunity to enhance farm productivity and profitability (Dillon 2011). Accordingly, interest in flexible fencing technology to improve pasture allocation has greatly increased (Umstatter *et al.,* 2015a,b). Such technology can facilitate rapid and less-labour intensive manipulation of stocking densities, improved use of seasonal growth, protection of vulnerable areas, and reduce human-wildlife conflict caused by conventional fencing (Umstatter, 2011; Umstatter *et al.,* 2013). Although some improvement to flexibility was made possible by the invention of single-strand electric fencing, further developments are urgently required to optimise management protocols, improve ease of allocation, and reduce labour.

Electric fencing relies on each individual animal forming a cue-consequence association between the visual cue of the fence structure (fence posts and wire) with the negative stimulus of a mild electric shock. Although this method is effective, erecting and maintaining fencing is both time and labour intensive (Umstatter *et al.,* 2015a). Yet, a number of studies have demonstrated that domesticated cattle can respond to a variety of visual and auditory sensory cues (Howery *et al*., 2000; Lee *et al*., 2007; Umstatter, 2011; Umstatter *et al.,* 2013). Accordingly, virtual fence (VF) systems have sought to utilise novel sensory cues in the formation of cue-consequence learning (Bishop-Hurley *et al.,* 2007).

Virtual fencing can be defined as a structure or system which acts as a boundary or enclosure, in the absence of any physical barrier (Umstatter, 2011). Various types of VF system have been developed and examined, utilising wearable technology upon a variety of livestock across a range of agricultural settings (Butler *et al.,* 2004; Bishop-Hurley *et al*., 2007; Jouven *et al.,* 2012; Umstatter *et al.,* 2013; Brunberg *et al.,* 2015; Monod *et al.,* 2009). However, the overwhelming majority of these studies have focused on rangelands, where animals can freely roam over large areas. Currently, while a small-scale VF system approach has been effectively utilised to contain domestic pets, few trials have been put in place to examine if a VF system is a feasible and welfare friendly means of controlling livestock movement in a small-scale intensive farm (Umstatter, 2014). The successful implementation of a VF system into a working farm can potentially be complex and fraught with technical challenges, such as network communications, differential system interfaces, farm topography, precision confinement energy supply, animal welfare and training (Umstatter, 2011). In addition, although the installation of an induction cable fence line is less labour intensive than erecting and moving electric fences on a frequent basis, global positioning system (GPS) based systems could potentially eliminate the need for such cabling entirely. As systems which rely on buried cables can also be labour intensive to establish and reorganise. Accordingly, VF systems which do not require perimeter cabling could provide a beneficial solution for farmers needing to move fences on a frequent basis, such as in strip grazing (Umstatter *et al.,* 2015a).

Within intensive pasture-based systems, VF requires a management system to dynamically deploy and move boundaries, depending on herd size and available grazing resources. The system should allow managers to increase, decrease, or provide completely new areas of pasture by redeploying the VF boundary. Moreover, the system could be used to incrementally herd cows from one area to another by slowly redeploying the VF boundary in small stages, e.g. 1 m min^{-1}, which would force the animals to shift their position along the pasture, while retaining or decreasing the overall grazing area allocation. Additionally, to be truly successful, the VF system must be applicable to the full herd, a subset of the herd, or even an individual animal as dependent upon grazing requirements. It could be envisaged that some herd members may have larger or separate grazing areas than other animals, such as in-calf cows or bulls. Moreover, to be truly dynamic a VF system should not need to rely on perimeter cabling, which can be expensive and labour intensive to establish and redeploy. Equally, it is imperative that the VF system is understood by the animals, as ambiguity in relation to boundary areas can cause a significant negative impact in terms of stress, which has been shown to reduce milk yield and weight gain in dairy cows (Hedlund & Løvlie, 2015; Adamczyk, 2018). Therefore, the location of the boundaries of a VF system, within which cows are contained, must be effectively communicated to each individual animal.

Although electric fences are routinely used for controlling livestock, the use of electric stimuli has become less ethically acceptable for many stakeholders, scientists and a larger proportion of the general public (Umstatter, 2011). As VF systems require wearable technology, systems should aim to utilise warning-cues that reduce the need for aversive electric stimuli. Key is to establish a cue-consequence association to ensure animal welfare (Spitzer, 2017). Therefore, the development of a suitable training programme, which can be easily implemented by the farmer to quickly familiarise livestock with the VF system is required (Umstatter, 2011; Koene *et al*., 2016).

2.4.8 Role of Technology in Grassland Production

The growing population coupled with diminishing arable land and unpredictable weather conditions raise concerns of food security in the near future, thus, making it imperative to utilise the available natural resources efficiently. The use of Information Communication Technology (ICT) in agriculture has been proposed to allow precise monitoring and automation of farm processes under the umbrella of Precision Farming. This is expected to improve control over the farm processes and, in turn, increase the productivity and sustainability of farming. Originally, Remote Sensing along with Geographic Information Systems (GIS) and GPS was used for monitoring the farms (Seelan *et al*., 2003).

However, these systems are expensive and offer a limited spatial-temporal resolution. Today, sensor devices facilitate collection of a wide variety of farm data such as soil composition and dynamics, crop growth, climate changes and animal health and mobility. Timely analysis of the sensor data allows prediction of the onset of diseases, adverse weather conditions and fodder availability in early warning systems to help farmers make informed decisions (Rehman *et al*., 2003). Individual agricultural sensor systems exist already. Taylor *et al.* (2013)

for instance, described a wireless sensor network (WSN) system deployed at the Kirby farm near Armidale, New South Wales. The system incorporates various sensors to monitor soil moisture, temperature, humidity and pressure, rainfall, and hail. Monitoring data from sensors is transmitted to a centralised entity, where it is formatted and analysed to be sent to farmers. A survey conducted in the Netherlands (Steeneveld & Hogeveen, 2015) shows that almost two-fifths of the farms surveyed have adopted some sensor-based farm monitoring. Another study, Auat-Cheein & Carelli (2013), discusses the use of unmanned robotic systems for farming applications. These systems aim at the automation of specific farm monitoring and mapping tasks, e.g. yield mapping, to reduce manual labour. Several systems have also been developed for monitoring animal health and mobility, with the aim of early detection of diseases to promote animal welfare. A review of various sensor systems for animal health management in dairy farming has been presented in Rutten *et al.* (2013). These systems are primarily designed to monitor animal fertility, metabolism, and mastitis. A few systems have also been developed for mobility monitoring of animals. Mobility patterns give an understanding of animal behaviour and can be used to detect health issues such as lameness (Alsaaod *et al.,* 2012). Additionally, mobility tracking facilitates the implementation of the VF technology that uses acoustic and electric stimuli to control the movement of animals within a farm. Current VF solutions make use of either electromagnetic coupling between animal wearable sensor devices, and an insulated wire unrolled on the farm (Monod *et al.,* 2018) or GPS receivers fitted to the wearable devices to estimate the position of animals concerning the VF (Swain *et al*., 2009).

Despite the numerous advantages, very few sensor systems have been deployed into use for pasture-based production systems. This is primarily due to the limited capability of sensor devices in pasture conditions coupled with the lack of confidence on a typical farm. Conventionally, the tasks assigned to these devices are limited to data collection and transmission while the analysis takes place on a smart device or the cloud. A study conducted by Rutten *et al*. (2013) describes such a system for animal health management and highlights the lack of analytics and intelligence in sensor devices. This introduces latency in analysis and poses a significant constraint in sensor technology implementation in large-scale, rural farm environments that suffer from intermittent or no Internet connectivity. While additional infrastructure may resolve specific issues, it would increase the deployment and maintenance costs of the system causing reluctance among farmers to embrace the use of technology systems. Consequently, there is a need to improve the operation of communication network systems to allow on-site analysis and prediction, especially, for latency-sensitive data to develop cost-effective and autonomous farming solutions.

Furthermore, while different sensor technology systems have been designed to cater to various aspects of a farm - crops, soil, yield and animals performance, these systems work independently of each other. This causes difficulty and delay in correlating data from different systems to expedite the decision-making process. Cooperation between these systems is, thus, desirable for the design of effective decision-support systems that aim at integrated farm management. Real-time actionable data needs to be made available to the farmer to aid in instantiations data-informed decision making. For instance, a system capable of capturing real-time pasture biomass data and autonomously assigning the livestock to the correct grazing area via a VF system. We consider and address these gaps in the existing design of grass-based technology solutions through the research presented in this thesis.

Technologies that support grass utilisation and cow reproductive fertility will likely facilitate positive economic returns for farmers, through the intensification of pasture-based production resulting in increased milk yield and reduced costs (Shalloo *et al.,* 2018; Yahya, 2018).

2.5 Thesis Objectives

This thesis was undertaken to design and develop ICT tools to assist grassland famers to improve the accuracy and precision of pasture management, to thereby increase the efficiency of their farming system. The primary objective of this thesis was to facilitate the development of a micro-sonic enabled RPM to allow automatic and precise grass measurement and thus improve real time allocation of grass and subsequently the integration of this data with an online DST to allow the enhanced dataset produced by the RPM to be automatically uploaded for detailed decision support on farm.

A further objective of this thesis was to develop and test the principle of virtual fence technology for control of cow movement and confinement within an intensive grazing system, i.e. strip-grazing. A detailed examination of the livestock training and behaviour was deemed to be a focal point of this work as it was not previously investigated in the context of intensive strip-grazing, and was identified as a significant challenge to overcome.

The combination of these two ICT tools could bring grazing into the domain of precision livestock farming. The combination of herbage mass data and live animal parameters such as grazing behaviour and accelerometer data is essential in understand and achieving grazing efficiency (Werner *et al.,* 2018). By studying the production of the sward as well as the demand of the herd and having strategies developed to direct and retain livestock in a prescribed grazing area will be a great benefit to the farmer.

2.6 Research Questions

1. *Can a grass measurement system be developed that would incorporate high accuracy micro sonic measurement technology as well as having a geospatial dimension associated with the data?*

2. *Can site-specific algorithms be developed to predict grass quantity using a smart-device application?*

3. *Is the integration of virtual fence technology into an intensive grazing production system possible?*

2.7 Reference List

Abrahamse, P.A., Dijkstra, J., Vlaeminck, B. & Tamminga, S. (2008). Frequent allocation of rotationally grazed dairy cows changes grazing behaviour and improves productivity. Journal of Dairy Science 91:2033–2045.

Adamczyk, K. (2018). Dairy cattle welfare as a result of human-animal relationship – a review, *Annals of Animal Science*, *18*(3):601-622. doi: https://doi.org/10.2478/aoas-2018-0013

Alsaaod, M., Römer, C., Kleinmanns, J., Hendriksen, K., Rose-Meierhöfer, S., Plümer, L., & Büscher, W., (2012) Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behaviour. Applied Animal Behaviour Science, 142(3):134 – 141.

Arnott, G., Ferris, C.P. & O'Connell, N.E. (2017) Review: welfare of dairy cows in continuously housed and pasture-based production systems. Animal 11(2):261-273.

Bishop-Hurley, G.J., Swain, D.L., Anderson, D.M., Sikka, P., Crossman, C. & Corke, P. (2007). Virtual fencing applications: Implementing and testing an automated cattle control system. Computers and Electronics in Agriculture, 56:14-22.

Brunberg, E.I., Bøe, K.E. & Sørheim, K.M. (2015). Testing a new virtual fencing system on sheep. Acta Agriculturae Scandinavica, Section A - Animal Science, 65:168-175.

Butler, Z., Corke, P., Peterson, R. & Rus, D. (2004). Virtual fences for controlling cows. In: Proceedings of the IEEE International Conference Robotics and Automation. 5:4429-4436. New Orleans, LA.

Castle, M.E. (1976) A simple disc instrument for estimate herbage yield, Journal of the British Grassland Society 1:89-100.

Combellas, J. & Hodgson, J. (1979), Herbage intake and milk production by grazing dairy cows 1. The effects of variation in herbage mass and daily herbage allowance in a short-term trial. Grass and Forage Science, 34:209-214. doi:10.1111/j.1365-2494.1979.tb01469.x

Creighton, P., Kennedy, E., Shalloo, L., Boland, T.M. & O' Donovan, M. (2011) A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. Grass Forage Sci. 66:251–264.

Crosson, P., Woods, A. & Keane, J. (2016) Suckler beef systems–assessing steps to improve profitability. In: MCGEE, M., ed. Beef 2016 'Profitable Technologies', July 5th, Teagasc, 14-19.

Culleton, N., Cullen, T. & McCarthy, V. (1992) The decline of the herbage seed production industry in Ireland. Irish Geography, 25:98-101.

Curran, J., Delaby, L., Kennedy, E., Murphy, J., Boland, T. & O'Donovan, M. (2010) Sward characteristics, grass dry matter intake and milk production performance are affected by pre-grazing herbage mass and pasture allowance. Livestock Science, 127:144-154.

DAFM (Department of Agriculture, Food and the Marine). 2017. Available online: http://www.agriculture.gov.ie/media/migration/custom-erservice/careers/currentcompetitions/2017/FactsheetIrishAgricultureSept17210917.pdf[accessed 20 June 2017].

DAFM. 2010. Food harvest 2020 - A vision for Irish agri-food and fisheries. Department of Agriculture Food and the Marine. Dublin, Ireland. Accessed Jun01,i2016.ihttps://www.agriculture.gov.ie/media/migration/foodindustrydevopmenttrademarkets/agrifoodandtheeconomy/foodharvest2020/2020FoodHarvestE xeSummary240810.pdf

DAFM. 2019. Fact Sheet on Irish Agriculture 2018. Department of Agriculture Food and the Marine. Dublin, Ireland. Accessed Jun https://www.agriculture.gov.ie/media/migration/publications/2019/IrishAgricultureFactsheetFullYear2018010519.pdf

Deming, J., Gleeson, D., O'Dwyer, T., Kinsella, J. & O'Brien, B. (2018) Measuring labour input on pasture-based dairy farms using a smartphone, Journal of DairyScience,101(10):95279543,ISSN00220302,https://doi.org/10.3168/jds.2017-14288.

Dillon P (2011) The Dairy Industry - Planning for 2020. In: Proceedings of the Teagasc National Dairy Conference. Held at Rochestown Park Hotel, Cork and Hodson Bay Hotel, Athlone, 15-16 November, 2011. pp 1-25.

Dillon, P. (2017) Irish dairying - Challenges and opportunities, pp 7-9 in Open Day Proceedings. “Irish Dairying - Resilient Technologies” 4 July 2017, Teagasc, Moorepark, Ireland.

Dillon, P., Hennessy, T., Shalloo, L., Thorne, F. & Horan, B., (2008) Future outlook for the Irish dairy industry: a study of international competitiveness, influence of international trade reform and requirement for change. Int. J. Dairy Technol. 61:16-29.

Dillon, P., Roche, J.R., Shalloo, L. & Horan, B. (2005) Optimising financial return from grazing in temperate pastures. Pages 131-147 in Proc. Satellite Workshop Xxth Int.Grassland Congr., Cork, Ireland. J. J. Murphy ed. Wageningen Pers., Wageningen, The Netherlands.

Dolecheck, K.A., Heersche, G J.R. & Bewley JM (2013) Investment analysis of automated estrus detection technologies. In: Proceedings of the Precision Dairy Conference and Expo. University of Minnesota. Held at Mayo Civic Center, Rochester, Minnesota. June 26-27, 2013. pp 103-104.

Douglas, J.T. & Crawford, C. E. (1994) An evaluation of the drop-disc technique for measurements of herbage production in ryegrass for silage. Grass and Forage Science, 49:252-255. doi:10.1111/j.1365-2494.1994.tb01998.x

Dowdeswell, A. (1998), Grass 99 Monitor Farms Project, DRC Dairylink, May-April.

Drennan, M., Carson, A. & Crosse, S. (2005) Overview of animal production from pastures in Ireland. Utilisation of grazed grass in temperate animal systems: proceedings of a satellite workshop of the XXth International Grassland Congress, Cork, Ireland, pp 19-35.

Earle, D.F. & McGowan, A.A., (1979) Evaluation and calibration of an automated rising plate meter for estimating dry matter yield of pasture, Australian Journal of Experimental Agriculture and Animal Husbandry 19:337.

Eastwood, C., Chapman, D., Paine, M. (2004) Precision dairy farming-taking the microscope to dairy farm management.

Eastwood, C.R., Mata, G., Handcock, R.N., Kenny, S., (2009) Evaluating satellite-based pasture measurement for Australian dairy farmers. In: Precision Livestock Farming. C. Lokhorst and P.W.G. Groot Koerkamp (eds.), pp.183-190.

F. A. Auat Cheein & R. Carelli. Agricultural robotics: Unmanned robotic service units in agricultural tasks. IEEE Industrial Electronics Magazine, 7(3):48–58, Sep 2013.

Finneran, E., Crosson, P., O'Kiely, P., Shalloo, L., Forristal, D. & Wallace, M. (2010) Simulation modelling of the cost of producing and utilising feeds for ruminants on Irish farms. Journal of Farm Management, 14:95-116.

Finneran, E., Crosson, P., O'Kiely, P., Shalloo, L., Forristal, D., & Wallace, M., (2012) Stochastic simulation of the cost of home-produced feeds for ruminant livestock systems. J. Agric. Sci. 150:123-139.

Frame, J., (1993) Herbage mass, in: A. Davies, R.D. Baker, S.A. Grant, S. Laidlaw (Eds.), Sward Measurement Handbook, The British Grassland Society, Reading, UK, , pp. 59-63.

French, P., O'Brien, B., & Shalloo, L., (2015) Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. Animal Production Science 55(7):931-935.

Fulkerson, W. & Donaghy, D. (2001) Plant-soluble carbohydrate reserves and senescence-key criteria for developing an effective grazing management system for ryegrass-based pastures: a review. Animal Production Science, 41, 261-275.

Fulkerson, W. & Slack, K. (1995) Leaf number as a criterion for determining defoliation time for Lolium perenne: 2. Effect of defoliation frequency and height. Grass and forage Science, 50:16-20.

Fulkerson, W. J., K. McKean, K. S. Nandra, & I. M. Barchia. (2005) Benefits of accurately allocating feed on a daily basis to dairy cows grazing pasture. Australian Journal of Experimental Agriculture 45:331-336.

Gilliland, T., Barrett, P., Mann, R., Agnew, R. & Fearon, A. (2002) Canopy morphology and nutritional quality traits as potential grazing value indicators for Lolium perenne varieties. The Journal of Agricultural Science, 139, 257-273.

Gowen, N., O'Donovan, M., Casey, I., Rath, M., Delaby, L. & Stakelum, G. (2003) The effect of grass cultivars differing in heading date and ploidy on the performance and dry matter intake of spring calving dairy cows at pasture. Animal Research, 52:321-336.

Hanrahan, L., McHugh, N., Hennessy, T., Moran, B., Kearney, R., Wallace, M. & Shalloo, L., (2018) Factors associated with profitability in pasture based systems of milk production. Journal of Dairy Science 101, 1–12.

Hedlund, L. & Løvlie, H. (2015). Personality and production: nervous cows produce less milk. J. Dairy Sci., 98:5819–5828

Hemme, T., Uddin, M.M. & Ndambi, O.A. (2014) Benchmarking cost of milk production in 46 countries. Journal of Reviews on Global Economics 3:254-270.

Holmes, C. W., Wilson, G.F., Mackenzie, D.D.S., Flux, D.S., Brookes, I.M. & Davey, A.W.F. (2002) Feeding the herd. Pages 33–89 in Milk Production from Pasture. Butterworths, Wellington, New Zealand.

Holmes, C., Hoogendoorn, C., Ryan, M. & Chu, A. (1992) Some effects of herbage composition, as influenced by previous grazing management, on milk production by cows grazing on ryegrass/white clover pastures. 1. Milk production in early spring: effects of different regrowth intervals during the preceding winter period. Grass and Forage Science, 47:309-315.

Hoogendoorn, C., Holmes, C. & Chu, A. (1992) Some effects of herbage composition, as influenced by previous grazing management, on milk production by cows grazing on ryegrass/white clover pastures. 2. Milk production in late spring/summer: effects of grazing intensity during the preceding spring period. Grass and Forage Science, 47:316-325.

Hostiou, N., Fagon, J., Chauvat, S., Turlot, A., Kling-Eveillard, F., Boivin, X. & Allain, C. (2017) Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. Biotechnologie, Agronomie, Société et Environnement 21(4):268-275.

Howery, L.D., Bailey, D.W., Ruyle, G.B. & Renken, W.J. (2000) Cattle use visual cues to track food locations. Applied Animal Behaviour Science, 67:1-14.

Hurtado-Uria, C. (2013) Adaption, Evaluation and Validation of a Mechanistic Grass Growth Simulation Model for Temperate Grass Based Systems J. Dairy Sci. 100:6400–6413 https://doi.org/10.3168/jds.2016-12068

Hurtado-Uria, C., Hennessy, D., Shalloo, L., Schulte, R. P. O., Delaby, L. & O'Connor, D. (2013) Evaluation of three grass growth models to predict grass growth in Ireland. The Journal of Agricultural Science, 151:91-104.

IFCN (International Farm Comparison Network). 2016. Dairy Report. 2016. International Farm Comparison Network.

Jouven, M., Leroy, H., Ickowicz, A. & Lapeyronie, P. (2012). Can virtual fences be used to control grazing sheep? The Rangeland Journal, 34:111-123.

Karl, M.G., & Nicholson, R.A. (1987) Evaluation of the Forage-Disk Method in Mixed-Grass Rangelands of Kansas, Journal of Range Management 40(5):467-471. doi:10.2307/3899613.

Keane, T. & Sheridan, T. (2004) Climate of Ireland. Climate, weather and irish agriculture. AGMET, Dublin, 27-62.

Kelly, E., Shalloo, L., Geary, U., Kinsella, A. & Wallace, M., (2012) Application of data envelopment analysis to measure technical efficiency on a sample of Irish dairy farms. Irish J. Agric. Food Res. 51:63–77.

Kennedy E., O'Donovan, M., McEvoy, M. & Murphy, J.P. (2009). Effect of restricted access time to pasture on dairy cow milk production, grazing behaviour and DM intake. Journal of Dairy Science, 92:168–176.

Kennedy, J., Carty, D., McCarty, J., Kennedy, E. & O'Donovan, M. (2016) Grazing Guide 2. In: Teagasc, M., Fermoy, Co. Cork (ed.). Irish Farm Centre, Bluebell, Dublin 12: Irish Farmers Journal.

Knaus, W. (2016) Perspectives on pasture versus indoor feeding of dairy cows. Journal of the Science of Food and Agriculture 96(1):9-17.

Koene, P., Hogewerf, P. & Ipema, B. (2016) Dairy cow welfare: effects of a virtual fence on social behavior. Proceedings of Precision Dairy Farming conference.

Leuwarden, the Netherlands. 21-23 June, 2016. 337-341. Eds C. Kamphuis and W. Steeneveld. Wageningen Academic Publishers.

Kolver, E. & L. Muller. (1998) Performance and nutrient intake of high producing holstein cows consuming pasture or a total mixed ration1. Journal of Dairy Science 81(5):1403-1411.

Kolver, E.S., Barry, M.C., Penno, J.W. & Muller, L.D. (1996) Evaluation of the Cornell net carbohydrate and protein system for dairy cows fed pasture-based diets. Proc N Zealand Soc Anim Prod 56:251–254.

Läpple, D. and Hennessy, T. (2012) The capacity to expand milk production in Ireland following the removal of milk quotas. Irish Journal of Agricultural and Food Research, 51:1–11.

Laven, R. and Lawrence, K. (2006) An evaluation of the seasonality of veterinary treatments for lameness in UK dairy cattle. Journal of Dairy Science 89(10):3858-3865.

Lee, C., Prayaga, K., Reed, M. & Henshall, J. (2007). Methods of training cattle to avoid a location using electrical cues. Applied Animal Behaviour Science, 108, 229-238.

Lee, J. M., Donaghy, D.J., & Roche J.R., (2008) Effect of Defoliation Severity on Regrowth and Nutritive Value of Perennial Ryegrass Dominant Swards. Agronomy Journal 100: 308-314.

Lips, M. & Rieder. P. (2005) Abolition of raw milk quota in the European Union: A CGE analysis at the member country level. J. Agr. Econ. 56:1-17.

Lyons, N., Eastwood, C., Rueb, B.D., & Kerrisk, K. (2016) Current and future adoption of milking related technologies on Australian and New Zealand dairy farms. Pages 445-450 in Proc. Int. Precision Dairy Farming Conf., Leeuwarden, the Netherlands.

Macdonald, K.A., Penno, J.W., Lancaster, J.A.S., Bryant, A.M., Kidd, J.M. & Roche, J.R. (2017) Production and economic responses to intensification of pasture-based dairy production systems. J Dairy Sci. 2017 Aug;100(8):6602-6619. doi: 10.3168/jds.2016-12497.

McCallum, H.D. & McCallum, F.T. (1972) The Wire that Fenced the West, vol. 4. University of Oklahoma Press, Norman, USA, pp 285.

McCarthy, B., Pierce, K.M., Delaby, L., Brennan, A., Fleming, C. & Horan, B., (2013) The effect of stocking rate and calving date on grass production, utilization and nutritive value of the sward during the grazing season. Grass Forage Sci. 68:364–377.

McCarthy, S., Horan, B., Dillon, P., O'Connor, P., Rath, M., & Shalloo, L., (2007) Economic comparison of divergent strains of Holstein-Friesian cows in various pasture-based production systems. J. Dairy Sci. 90:1493-1505.

McEvoy, M., O'Donovan, M., Kennedy, E., Murphy, J. P., Delaby, L., & Boland, T. M. (2009). Effect of pregrazing herbage mass and pasture allowance on the lactation performance of Holstein-Friesian dairy cows. *Journal of Dairy Science*,*92*(1), 414–422. https://doi.org/10.3168/jds.2008-1313

McEvoy, M., O'Donovan, M. & Shalloo, L. (2011) Development and application of an economic ranking index for perennial ryegrass cultivars, J. Dairy Sci., 94:1627-1639

Mitchell, P. (1982) Value of a rising-plate meter for estimating herbage mass of grazed perennial ryegrass-white clover swards, Grass and Forage Science 37:81-87.

Monod, M.O., Faure, P., Moiroux, L. & Rameau, P. (2009) Stakeless fencing for mountain pastures. In: Lockhorst, C., Groot Koerkamp, P.W.G. (Eds.), Precision Livestock Farming '09. Wageningen Academic Publishers, Wageningen, NL, pp. 175–181.

Monod, M.O., Faure, P., Moiroux, L., & Rameau, P. (2008) A virtual fence for animals management in rangelands. In MELECON 2008 - The 14th IEEE Mediterranean Electrotechnical Conference, pp 337–342, May.

O'Brien, B. & Hennessy, D. (2017) Scientific appraisal of the Irish grass-based milk production system as a sustainable source of premium quality milk and dairy products, Irish Journal of Agricultural and Food Research, 56(1):120-129. doi: https://doi.org/10.1515/ijafr-2017-0011

O'Brien, D., Capper, J.L., Garnsworthy, P.C., Grainger, C. & Shalloo, L., (2014) A case study of the carbon footprint of milk from high-performing confinement and grass-based dairy farms, Journal of Dairy Science, Volume 97,Issue3,Pages18351851,ISSN00220302,https://doi.org/10.3168/jds.2013-7174.

O'Brien, D., Shalloo, L., Patton, J., Buckley, F., Grainger, C. & Wallace, M. (2012) Evaluation of the effect of accounting method, IPCC v. LCA, on grass-based and confinement dairy systems' green- house gas emissions. Animal 6:1512–1527.

O'Donovan, M., Lewis, E. & O'Kiely, P. (2011) Requirements of future grass-based ruminant production systems in Ireland. Irish Journal of Agricultural and Food Research 50:1–21.

O'Mara, F. (2008) Country pasture/forage resource profile/Ireland [Online]. Available: http://www.fao.org/ag/AGP/AGPC/doc/pasture/forage.htm. 2011. A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. Grass and Forage Science, 66:251-264.

O'Donnell, S., Shalloo, L., Butler, A.M. & Horan, B., (2008) A survey analysis of opportunities and limitations of Irish dairy farmers. J. Farm Man. 13:419-434.

O'Donovan, M. & Kennedy, E. (2007) Using grass to reduce feed costs. Exploiting the Freedom to Milk", Teagasc National Dairy Conference, 63-80.

O'Donovan, M. (2000) The relationship between the performance of dairy cows and grassland management on intensive dairy farms in Ireland. University College Dublin.

O'Donovan, M., Connolly, J., Dillon, P., Rath, M. & Stakelum, G. (2002) Visual Assessment of Herbage Mass. Irish Journal of Agricultural and Food Research, 41:201-211.

O'Donovan, M., Dillon, P. (1999) Measurement of Grassland Management Practice on Commercial Dairy Farms, End of Project Reports, Teagasc.

O'Donovan, M., Lewis, E. & O'Kiely, P. (2011) Requirements of future grass-based ruminant production systems in Ireland. Irish Journal of Agricultural and Food Research, 50:1-21.

Ofner-Schröck, E., A. Preinerstorfer, A. Leithold, T. Guggenberger, G. Huber, B. Krimberger, S. Suchanek, D. Vockenhuber, B. Rudorfer & I. Zainer. (2009) Bericht über die Fragebogenerhebung zur Evaluierung der Wirkung und

Akzeptanz der Tierschutzmaßnahme im österreichischen Programm für die Ländliche Entwicklung 07–13. Bundesministerium für Land- und Forstwirtschaft, Umwelt und Wasserwirtschaft, Vienna.

Patton, D., Shalloo, L., Pierce, K.M. & Horan, B. (2012) A biological and economic comparison of 2 pasture-based production systems on a wetland drumlin soil in the northern region of Ireland. J. Dairy Sci. 95:484-495.

Peyraud, J.L., Comeron, E.A., Wade, M.H., & Lemaire, G., (1996) The effect of daily herbage allowance, herbage mass and animal factors upon herbage intake by grazing dairy cows. Annales de zootechnie, INRA/EDP Sciences, 45(3), pp.201-217. ffhal-00889554f

Pinxterhuis, J., Beare, M., Edwards, G., Collins, R., Dillon, P. & Oenema, J. (2015) Eco-efficient pasture based dairy farm systems: a comparison of New Zealand, The Netherlands and Ireland. Grassland Science in Europe 20:349-366.

Ramsbottom, G., Horan, B., Berry, D.P. & Roche, J.R. (2015) Factors associated with the financial performance of spring-calving, pasture-based dairy farms. J. Dairy Sci. 98:3526-3540.

Rayburn, B., Rayburn, S.B. (1998) A standardised plate meter for estimating pasture mass in on-farm research trials, Agronomy Journal 90 238-241.

Rehman, A., Abbasi, A.Z., Islam, N., & Shaikh, Z.A., (2014) A review of wireless sensors and networks' applications in agriculture. Computer Standards & Interfaces, 36(2):263 – 270.

Reijs J.W., Daatselaar, C.H.G., Helming, J.F.M., Jager, J. & Beldman, A.C.G. (2013) Grazing dairy cows in North-West Europe. Economic farm performance and future developments with emphasis on the Dutch situation, in LEI Report 2013 – 001. LEI Wageningen UR, The Hague.

Roca-Fernández, A. I., González-Rodríguez, A. & Vázquez-Yáñez, O.P. (2012) Effect of pasture allowance and cows' lactation stage on perennial ryegrass sward quality, pasture dry matter intake and milk performance of Holstein-Friesian cows, 10: 16.

Rutten, C.J., Velthuis, A.G.J., Steeneveld, W. & Hogeveen, H. (2013) Invited review: Sensors to support health management on dairy farms. Journal of Dairy Science, 96(4):1928– 1952.

Seelan, S.K., Laguette, S., Casady,G.M. & Seielstad, G.A., (2003) Remote sensing applications for precision agriculture: A learning community approach, Remote Sensing of Environment, 88(1–2):157-169, ISSN 0034-4257, https://doi.org/10.1016/j.rse.2003.04.007.

Shalloo L, Creighton, P. & O'Donovan, M. (2011) The economics of reseeding on a dairy farm. Irish Journal of Agricultural and Food Research 50:113–122.

Shalloo, L., O' Donovan, M., Leso, L., Werner, J., E. Ruelle, Geoghegan, A., Delaby, L., & O'Leary, N. (2018) Animal 12(S2):262–272 Review: Grass-based dairy systems, data and precision technologies

Silva-Villacorta, D., Holmes, C., Shadbolt, N., Lopez-Villalobos, N., Prewer, W., Glassey, C., & Blackwell, M. (2005) The productivity of pasture-based dairy farms in New Zealand with different levels of extra feed input. Proc. N.Z. Soc. Anim. Prod. 65:63-67.

Spitzer, M. (2017) Cyberkrank! Wie das digitalisierte Leben unsere Gesundheit ruiniert. Droemer Verlag, München, Taschenbuchausgabe, 432

Steeneveld, W. and Hogeveen, H. (2015) Characterization of Dutch dairy farms using sensor systems for cow management. Journal of Dairy Science, 98(1):709 – 717.

Steeneveld, W., Rutten, C.J., Oude Lansink, A. and Hogeveen, H. (2017) Why not investing in sensors is logical for dairy farmers. In Proceedings of the European Conference on Precision Livestock Farming'17, Nantes, France, pp. 55–64.

Stockdale, C.R. & Kelly, K.B. (1984) A Comparison of a rising-plate meter and an electronic capacitance meter for estimating the yield of pastures of dairy cows, Grass and Forage Science 39:391-394.

Swain, T.B.D., Crossman, C., Valencia, P., Bishop-Hurley, G. & Handcock, R., (2009) Sensor and actuator networks: Protecting environmentally sensitive areas. IEEE Pervasive Computing, 8(1):30–36, Jan.

Taube, F., Gierus, M., Hermann, A., Loges, R. & Schönbach, P. (2014) Grassland and globalization – challenges for north-west European grass and forage research. Grass Forage Science 69:2–16.

Taylor, K., Griffith, C., Lefort, L., Gaire, R., Compton, M., Wark, T., Lamb, D., Falzon, G. and Trotter, M. (2013) Farming the web of things. IEEE Intelligent Systems, 28(6):12–19, Nov.

Teagasc (2017) The people in dairy project: A report on the future people requirements of Irish dairy farming to support sustainable and profitable dairy expansion. Teagasc Moorepark, Fermoy, Co. Cork. Accessed Jun 02. https://www.teagasc.ie/media/website/publications/2017/The-People-in-Dairy- Project.pdf

Thomet, P. & Piccand, V. (2011) Ressourceneffiziente Milchproduktion – Welcher Kuhtyp ist geeignet? in Proc Cattle Conference, Agricultural Research and Education Centre (AREC), Raumberg-Gumpenstein, Irdning, Austria, 13–14 April, pp. 11–18.

Thorne, F., Donnellan, T., Hennessy, T. & Shalloo, L. (2016) Competitiveness of the Irish dairy sector at farm level in 2015. Proceedings of Positive Farmers' Conference, Cork, pages 2–16.

Thornton, P.K. (2010) "Livestock production: recent trends, future prospects." Philosophical transactions of the Royal Society of London. Series B, Biological sciences vol. 365,1554: 2853-67. doi:10.1098/rstb.2010.0134

Tunon, G., Kennedy, E., Horan, B., Hennessy, D., Lopez-Villalobos, N., Kemp, P., Brennan, A. & O'Donovan, M. (2014) Effect of grazing severity on perennial ryegrass herbage production and sward structural characteristics throughout an entire grazing season. Grass and Forage Science, 69:104-118.

Umstatter C., Bhatti S., Michie C. & Thomson S. (2014) Overview of Ultra-High Frequency technology in livestock farming and stakeholder opinions. In: International Conference of Agricultural Engineering, 6-10 July 2014, Zurich, Switzerland.

Umstatter, C. (2011) The evolution of virtual fences: A review. Computers and Electronics in Agriculture, 75:10–22.

Umstatter, C., Brocklehurst, S., Ross, D.W. & Haskell, M.J. (2013) Can the location of cattle be managed using broadcast audio cues? Applied Animal Behaviour Science, 147:34-42.

Umstatter, C., McSweeney, D., Foley, C., Halton, P., Heitkaemper, K., Schick, M. & O'Brien, B. (2015a) Labour costs of fencing in grazing systems and virtual fencing as a potential technological solution. In: Precision Livestock Farming '15, Milan, Italy, 80-92.

Umstatter, C., Morgan-Davies, J. and Waterhouse, T. (2015b). Cattle responses to a type of virtual fence. Rangeland Ecology and Management, 68:100-107.

Van den Pol, A., Vellinga, T.V., Johansen, A. and Kennedy, E. (2008) To graze or not to graze, that's the question. Pages 706-716 in Proc. Proceedings of the 22nd. General Meeting of the European Grassland Federation, Uppsala, Sweden, 9-12 June.

Van den Pol-van Dasselaar, A., Becker T, Botana Fernández, A., Hennessy, T. and Peratoner, G. (2018) Social and economic impacts of grass based ruminant production. In Proceedings of the European Grassland Federation General Meeting, Grassland Science in Europe, Sustainable meat and milk production from grasslands, 17–21 June, Cork, Ireland, pp. 697–708.

Van Soest, P.J. (1994) Nutritional Ecology of the Ruminant, 2nd edition. Cornell University Press, Ithaca, NY.

Van Wieren, S. E. (1996) Digestive strategies in ruminants and non-ruminants. Van Wieren. ISBN 90-5485-611-4

Vermeire, L.T. & Gillen, L.R. (2001) Estimating herbage standing crop with visual obstruction in tallgrass prairie, Journal of Range Management 54:57-60.

Weinrich, R., Kühl, S., Zühlsdorf, A. & Spiller, A. (2014) Consumer attitudes in Germany towards different dairy housing systems and their implications for the marketing of pasture raised milk. International Food and Agribusiness Management Review 17(4):205-222

Werner, J., Leso, L., Umstatter, C., Niederhauser, J., Kennedy,E., Geoghegan, A., Shalloo, L., Schick, M., O'Brien, B. (2018) Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows, Journal of Neuroscience Methods, 300:138-146, ISSN 0165-0270, https://doi.org/10.1016/j.jneumeth.2017.08.022.

Wilkins, P.W. & Humphreys, M. O. (2003) Progress in breeding perennial forage grasses for temperate agriculture. Journal of Agricultural Science, 140:129-150.

Wims, C., Delaby, L., Boland, T. & O'Donovan, M. (2014) Effect of pre-grazing herbage mass on dairy cow performance, grass dry matter production and output from perennial ryegrass (Lolium perenne L.) pastures. Animal, 8:141-151.

Yahya, N. (2018) Agricultural 4.0: It's Implementation Toward Future Sustainability. pp 125-145 in Green Urea. Springer. ISBN 978-981-10-7578-0.

Chapter 3: Micro-Sonic Sensor Technology enables enhanced grass height measurement by a Rising Plate Meter

Information Processing in Agriculture(2019) 6 279–284

Abstract

Globally, the Rising Plate Meter (RPM) is a device used to measure compressed sward height, to estimate herbage mass. Despite improved farm management practices aided by a variety of technological advances, the standard design of a RPM has remained relatively unchanged. Recently, a RPM utilising a micro-sonic sensor and digital data capture capability *via* a Bluetooth communications link to a smart device application has been developed. Here we assess the comparable ability of both the cumulative ratchet counter RPM, and the micro-sonic sensor RPM, to accurately and precisely measure fixed heights. Moreover, as correct allocation of grazing area requires accurate geolocation positioning, we assess the associated GPS technology. The micro-sonic sensor RPM was significantly more accurate for height capture than the cumulative ratchet counter RPM. Overall, across all heights, the cumulative ratchet counter RPM underestimated height by 7.68 ± 0.06 mm (mean ± SE). Alternatively, the micro-sonic sensor RPM overestimate height by 0.18 ± 0.08 mm. In relation to a practical applications, these discrepancies can result in an under- and overestimation of kilograms of dry matter yield by 13.71% and 0.32% per hectare, respectively. The performance of the on-board GPS did not significantly differ from that of a tertiary device. The wireless technology, integrated mapping, and decision support tools offered by this innovative micro-sonic sensor RPM provides for a highly efficacious grassland management tool.

3.1 Introduction

The development of electronic and data transmission systems continues to enable radical changes in agricultural practices worldwide (Pivoto *et al.,* 2018). Enhanced data capture, information and communication technologies have facilitated considerable improvements to the efficiency, effectiveness and productivity of various agricultural sectors (Pivoto *et al.,* 2018; Zhang *et al.,* 2018). However, these technologies remain substantially underutilised in modern agricultural production systems (O'Grady & O'Hare, 2017). Although smart farming systems may utilise these technological advancements to feed into automated management systems, incorporation of information and communication technologies into machinery, equipment, and sensors can also facilitate real-time decision support tools within non-automated systems.

The profitability of intensive pasture-based systems is reliant upon precise, accurate and timely grazing management strategies. Consequently, the implementation of precision data capture and communication technologies in relation to grassland management represents a considerable opportunity to enhance farm productivity and profitability (Zhang *et al*., 2018; Wathes *et al*., 2008; Dillion, 2011). Sward herbage mass (HM) can be utilised to inform efficient daily grassland management, *via* allocation of a sufficient grazing area to meet (but not exceed) the daily nutritional demands of grazing animals (Hanrahan *et al*., 2017; Kennedy *et al*., 2011). Moreover, regular estimation of paddock HM can be utilised to inform long term grassland management, to achieve optimal pasture utilisation and animal performance (Hanrahan *et al*., 2017). Currently, in Ireland, for example, farmers' use of grass measurement remains low; only *circa* 10% of dairy farmers conduct weekly grass measurements. Therefore, there exists considerable potential to increase grass measurement frequency and farmland productivity (Dillion, 2011; Creighton *et al*., 2011).

Traditionally, HM is determined by observer visual estimation. However, this method is highly subjective and prone to considerable inter-observer variability (Tucker, 1980). Although more accurate estimates of HM can be obtained from the sward weights obtained from clipped sample quadrats, this process is destructive and time intensive (Brummer *et al*., 1994; Adesogan *et al*., 2000). The Rising Plate Meter (RPM) is a grassland management tool utilised worldwide as a method of measuring compressed sward height (CSH). This technology is considered to be an accurate, precise, time efficient, and less labour intensive method for sampling HM (Sanderson *et al*., 2001;Soder *et al*., 2006), from which dry matter yield (DMY; i.e. the grass nutritional value) can be calculated. However, device accuracy can be affected by numerous factors, such as growth state of plants (Mosquera-Losada & Gonzalez-Rodriguez, 1998), season (Bransby, 1977), species composition (Castle, 1976) and grassland management regime (Powell, 1974).

Despite many recent advances in various precision agriculture, data capture and communication technologies (O'Grady & O'Hare, 2017; Pivoto *et al*., 2018), the design and application process of RPMs has remained similar to that of earlier devices (Sanderson *et al*., 2001; Castle, 1976). Most RPMs consist of an aluminium steel plate through which a one metre vertical shaft freely passes. When this shaft is lowered to ground level within a grass sward, the plate will rise (depending on grass height) relative to the shaft, and this distance is recorded on a cumulative ratchet counter mounted upon the device. The average CSH can then be calculated across multiple samples. The RPM is calibrated by relating the CSH readings of a number of sample quadrats to the DMY of these quadrats, cut to ground level.

In recent years, technological advances such as various plant sensitive sensors, Global Positioning Systems (GPS), Bluetooth connectivity, and low-power portable user interfaces (smart phones and tablets), have been used to improve farm management practices (Pivoto *et al*., 2018; O'Grady & O'Hare, 2017; Dillion, 2011). These data capture and communication technologies can likely be utilised to improve grass measurement and facilitate real-time decision support in relation to grassland management, e.g. grazing allocations. Recently, a RPM utilising a micro-sonic sensor and digital data capture *via* a Bluetooth communications link to a smart device application has been developed (Figure 3.1).

In essence, the time of flight- taken from transmission of a micro-sonic beam to return of the reflected echo signal is used to calculate the distance between the sensor and the sampling plate. The higher the upwards displacement of the sampling plate, the shorter the time between transmission and return of the reflected signal. The height of the object underneath the rising plate is then calculated. This measured height is then transmitted *via* Bluetooth to a smart device. This smart device also utilises GPS technology for paddock mapping and advisory (decision-support) grazing-area allocation based on animal in-take requirements. Although the cumulative ratchet counter RPM does not facilitate on-board GPS, users can use tertiary GPS enabled devices to manually map paddock areas.

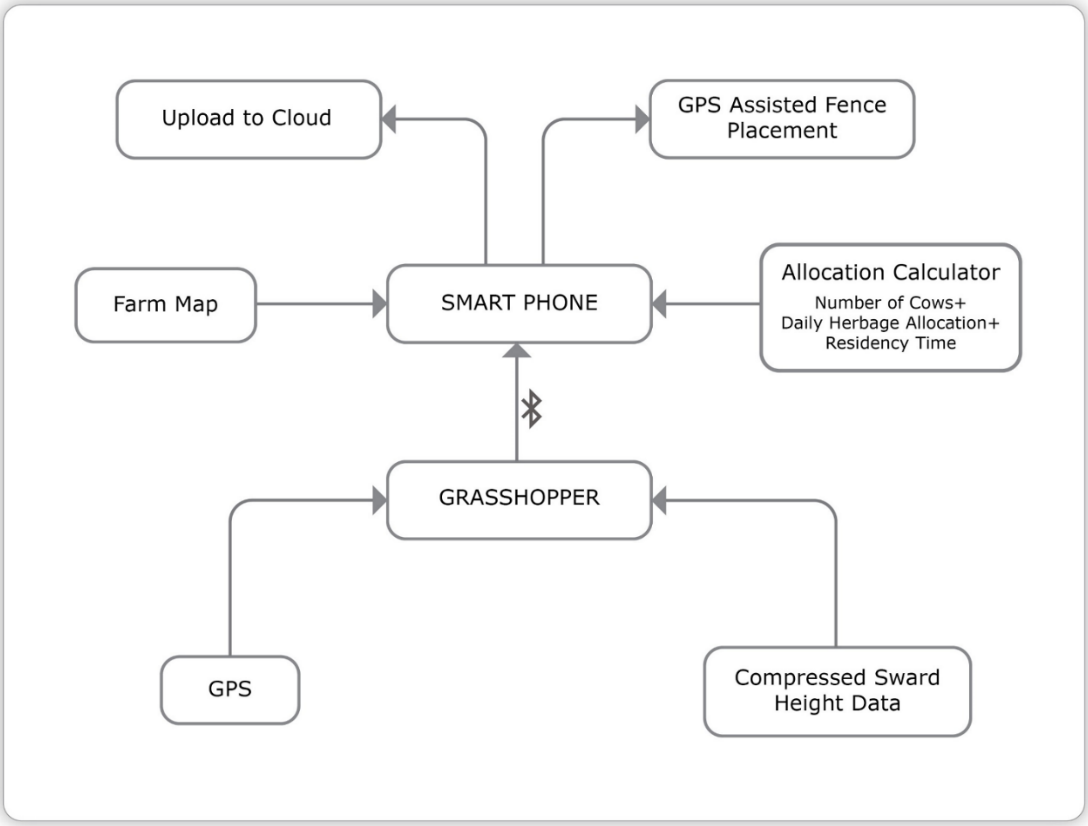

Figure 3.1: Infographic depicting the wireless communication process between the Grasshopper micro-sonic sensor Rising Plate Metre, global positioning system, and accompanying smart device application: 1) GPS and compressed sward height data are captured by the device; 2) this data is wirelessly transmitted to the associated smart device application; 3) a designated farm paddock area can be created, stored, or selected; 4) grazing intensity parameters can be inputted; 4) the Allocation Calculator can provide real-time decision support; 5) GPS assisted fence placement is provided; and 6), all data is consolidated within the smart device application, and can be wirelessly uploaded to Cloud computing and integrated smart farm databases.

Here we assess the accuracy and precision of RPM height measurements by both the standard cumulative ratchet counter, and the newly developed micro-sonic sensor unit. Given that correct allocation of grazing area requires accurate geolocation positioning, the on-board GPS technology of the newly developed RPM was compared to the GPS functionality of a representative and commonly used device, i.e. a smartphone.

3.2 Methods

Experiment 1: repeated accuracy of height data capture by two Rising Plate Meters (RPMs)

A cumulative ratchet counter RPM (Jenquip; Filip's Manual Folding Plate Meter, New Zealand) and the micro-sonic sensor RPM (Grasshopper II; True North Technologies, Ireland) were used to measure standing PVC pipes (110 mm diameter; n = 31) of known heights, 25–178 mm (McSweeney *et al*., 2015). The pipes were accurately cut to the specified length by a professional engineering company. All pipe sections were placed on a level surface, and each pipe was randomly chosen to be measured by the RPMs. A total of 30 height measures were recorded per pipe by each RPMs. The micro-sonic sensor RPM sample measurements were obtained first, immediately followed by the cumulative ratchet counter RPM.

Although the micro-sonic sensor RPM facilitated instantaneous digital capture and storage (.csv format) of measurement data, via a Bluetooth communications link between the sensor unit and an accompanying smart device application (Android operating system), the ratchet counter RPM data was recorded by hand, and height measurement calculated. Prior to data capture, the micro-sonic sensor was normalised to ensure a baseline of height zero was established. The cumulative ratchet counter does not require normalisation.

Experiment 2: geolocation performance of a Rising Plate Meter (RPM) utilising on-board and external GPS technology.

To assess device geolocation performance, latitude and longitude output was sampled directly upon a known georectified point that consisted of a brass rivet set in concrete footpath (IRENET control station D130, Ordnance Survey Ireland). Both the on-board GPS and GPS functionality of a representative smartphone device (Samsung S7 Edge SM-G935F OS 7.0), were simultaneously assessed (both n = 30). The smartphone was held directly over the handle of the RPM, which was positioned centrally and precisely upon the georectified point. To force the devices to continually recalculate their geolocation positioning, between each georectified sampling event, the experimental operators walked (≥ 20m) in a random direction away from the sampling point and recorded an additional non-test measurement with both devices. Although, mobile network accessibly may improve geolocation accuracy, in situ signal connection opportunities can vary greatly. Therefore, the smartphone mobile network connection was disabled during sampling. This required the smartphone to rely on satellite connections only when triangulating its geolocation, as does the RPM device.

Statistical analysis

All statistical analyses were performed using R v3.4.3 (R Core Development Team., 2017). The difference between actual and recorded pipe heights was converted to proportional error and analysed using beta regression with the 'betareg' package in R (Cribari & Zeileis, 2010). This model incorporated both the effects of 'device' and 'pipe height', and their interaction. We transformed data to reduce extremes (0s) prior to analysis (Smithson & Verkuilen, 2006):

$$y_t = (y(n-1) + 0.5)/n$$

eqn. (1)

where y_t is the transformed output and n is the sample size.

As the captured geolocation data did not meet the assumptions of parametric tests, latitudinal and longitudinal error, relative to the georectified baseline point, were analysed between devices using paired Wilcoxon tests.

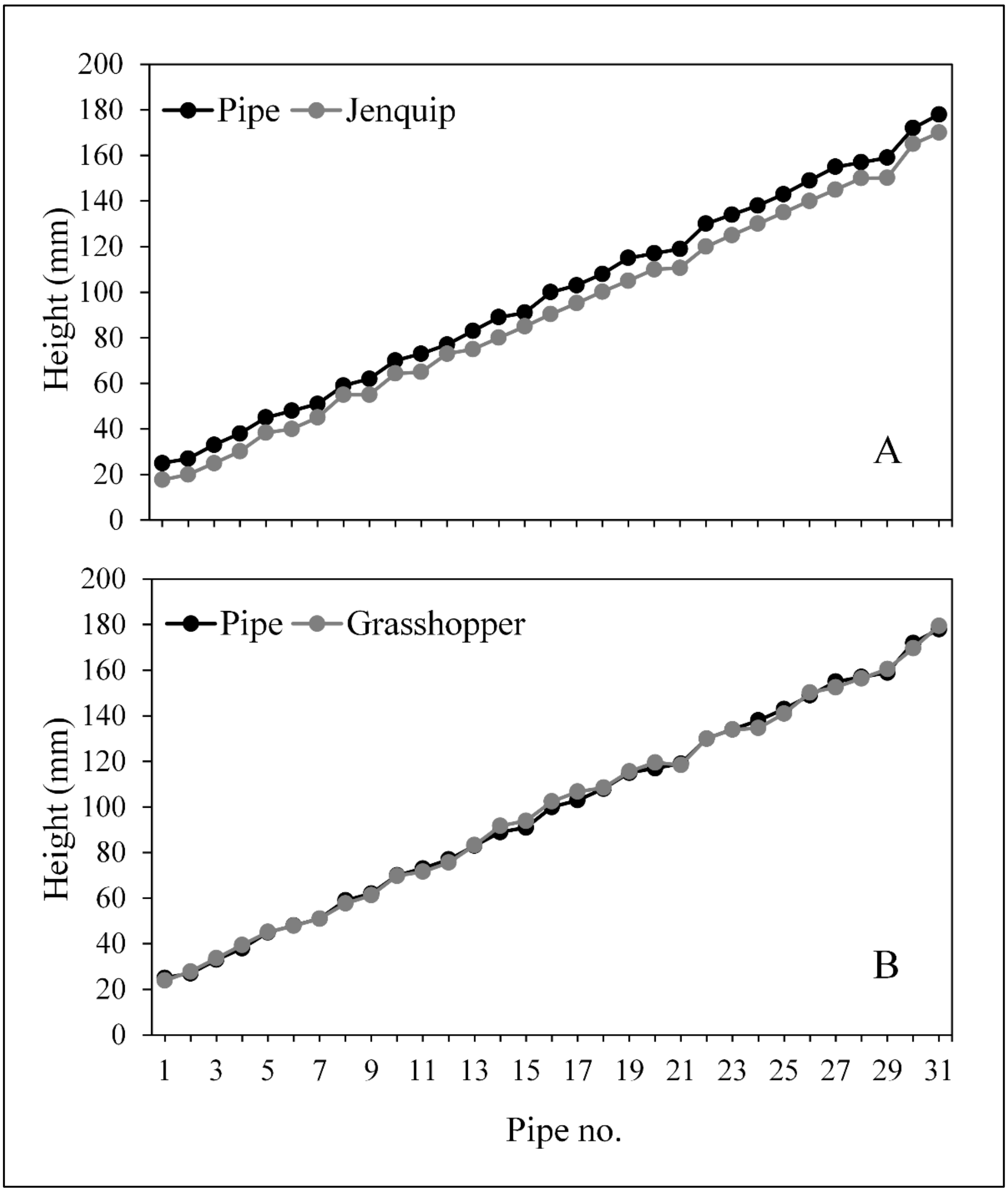

Figure 3.2: Comparable ability of the cumulative ratchet counter Rising Plate Metre (A: Jenquip), and micro-sonic sensor Rising Plate Metre (B: Grasshopper), to accurately measure fixed heights (n = 31). Standard error ≤ 1 in all cases.

Table 3.1: Mean latitude and longitude recorded by each device in relation to the known georectified sampling point (IRENET control station D130, Ordnance Survey Ireland).

Device	Mean latitude (± 1SD)	Georectified latitude	Mean longitude (± 1SD)	Georectified longitude
Grasshopper	52.16265970 (± 5.145×10^{-5})	52.16264111	8.27727091 (± 1.327×10^{-4})	8.27729278
Smartphone	52.16265204 (± 6.827×10^{-5})	52.16264111	8.27726680 (± 1.121×10^{-4})	8.27729278

3.3 Results

Across all pipe heights, the cumulative ratchet counter RPM underestimated height (mean ± SE) by 7.68 ± 0.06 mm, with a maximum underestimate of 11 mm (Figure 3.2A). Alternatively, the micro-sonic sensor RPM overestimated height by 0.18 ± 0.08 mm, with a maximum overestimate of 6 mm (Figure 3.2B). Overall, the micro-sonic sensor RPM more accurately measured the pipe heights than the cumulative ratchet counter RPM (z = 40.42, P < 0.001; Figure 3.3). Proportional recording errors were reduced significantly as pipe heights increased overall (z = -9.08, P < 0.001). The 'RPM × pipe height' effect was significant (z = -16.60, P < 0.001), reflecting greater differences in accuracy between the RPMs at lower pipe heights. Neither of the devices differed significantly in their accuracy relative to a georeferenced point, across either latitudinal (V = 346.00, P = 0.25) or longitudinal readings (V = 344.00, P = 0.26. Both of these devices were consistently precise (Table 3.1).

3.4 Discussion and Conclusion

Accurate, precise and timely measurement of pasture HM is integral to effective implementation of optimal grazing management practices, particularly for farmers who rely on pasture as a primary feed source. This examination of a recently developed micro-sonic sensor, has shown that such technological advancements can enhance the accuracy and precision of grass measurement and data capture. Until recently, the traditional cumulative ratchet counter design only facilitated measurement in increments of five millimetre (0, 5, 10 …), however, the micro-sonic sensor RPM has accomplished one millimetre increments. Although the average underestimation of height by the cumulative ratchet counter RPM (7.68 ± 0.06 mm) is low, small errors in measurement can lead to larger errors over large pasture areas. At an average overestimate of 0.18 ± 0.08 mm, the micro-sonic sensor has been shown to be highly accurate.

As a brief practical example, in the case of the cumulative ratchet counter, if we assume height of 1 cm = 250 kg dry matter yield per hectare, then 250 kg × 0.768 cm = 192 kg of DMY. In a simplified gazing allocation regime of ten grazing assignments per year, an underestimation of 192 kg DMY ha^{-1} is multiplied by ten, giving an error of 1920 kg DMY ha^{-1}. Scaling upwards, across a 50 ha farm, annual underestimation is 50 × 1920 = 96,000 kg DMY ha^{-1}. If we assume the farm (50 ha) will grow 14,000 kg DMY ha^{-1}, then annual dry matter production is 700,000 kg ha^{-1}. The annual underestimation of DMY would be 13.71 % (i.e. 96, 0000 ÷ 700, 000). Contrastingly, inflation of grass height by 0.18 mm on the same hypothetical farm and grazing regime, results in an annual overestimated DMY of 0.32 % when using the micro-sonic sensor RPM.

Underestimation of available DMY results in poor allocation of forage to animal requirements. In essence, the stocking rate could be increased to better utilise the available grassland and increase overall farm production and profitability. In Ireland, for example, one metric tonne of grass has a monetary feed resource value of €162 – 267 to dairy farmers (Dillion, 2011; French *et al*., 2015), depending on milk market prices. Underestimation of available DMY essentially results in a loss of this forage value to the overall farm profitability.

The micro-sonic sensor RPM, by utilising on-board GPS technology, can facilitate digital data capture features not currently associated with other RPMs, which utilise a cumulative ratchet counter design. Use of the micro-sonic sensor RPM would enable the real-time paddock mapping, give fence plotting directions, and direct appropriate grass allocation for the herd. The integration of the smart device application would allow for real-time assessment of the palatability of grass swards by consideration of pre- and post-grazing residuals.

The micro-sonic sensor RPM incorporates GPS technology to aid decision support of grazing area allocation in relation to animal in-take requirements and available sward HM. Although the cumulative ratchet counter RPM does not facilitate on-board GPS, basic GPS enabled smartphones can be used to map paddock areas within an integrated Geographic Information System (GIS) environment. However, while the GPS enabled RPM did not perform better than the smartphone, manual recording of GPS data and the associated cumulative ratchet scores is a time consuming process. Automatic capture of geolocation data by the micro-sonic sensor RPM, communicated through a Bluetooth communications link to a smart device application, and further presented in a single data file, represents a highly efficient method for real-time decision support.

Further automated geo-tagging of ground reference points can facilitate calibration of herbage evaluation from satellite aerial imagery, and integrated with within a communication network for the transmission of data from other in field sensor technology.

The application of any grass height measurement technique requires the operator to collect a sample size within a pasture that is sufficient to ensure that the variation in grass height and HM is accurately captured. The smart device application associated with the micro-sonic sensor RPM, coupled with the available GPS technology, can facilitate assessment of intra paddock variations in grass growth and grazing pressure, while inter and intra paddock DMY can be mapped and assessed to inform future fertiliser applications. Captured data can subsequently be uploaded to on-line decision support tools, which can advise on the allocation of grazing areas. Although manual placement of fences is necessary at present, there is considerable potential to link the recommended grazing area allocation to fenceless farming (i.e. virtual fencing; (Umstatter, 2011). Therefore, while the cumulative ratchet counter RPM has been a valuable tool for researchers and practitioners since its conception, the recently developed micro-sonic sensor RPM represent a significant advancement for grassland management. As the micro-sonic sensor device relies on algorithms to calculate DMY, rather than an operator performed manual calculation, the associated smart application can be directed to make formula corrections for seasonal and regional HM variation (Nakagami, 2016). However, despite the substantial benefits, further research and development is required to improve application of this device (e.g. incorporation of grass quality measurement), and integrate the device into smart farming systems.

3.5 References

Adesogan, A.T., Givens, D.I., Owen, E. (2000) Chemical composition and Nutritive Value of Forages. Chapter 11. In: Field and Laboratory Methods for Grassland and Animal Production Research. T'Mannetje, L., Jones, R.M., (Eds.), pp. 263-278. CABI Publishing. Wallingford UK.

Bransby, D.I., Matches, A.G., Krause, G.F. (1977) Disk meter for rapid estimation of herbage yield in grazing trials. Agron J. 69:393–396.

Brummer, J.E., Nichols, J.T., Engel, R.K., Eskridge, K.M. (1994) Efficiency of different quadrat sizes and shapes for sampling standing crop. J Range Manage. 47:84-89.

Castle, M.E. (1976) A simple disc instrument for estimating herbage yield. Grass Forage Sci. 31:37–40.

Creighton, P., Kennedy, E., Shalloo, L., Boland, T.M., O' Donovan, M. (2011) A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. Grass Forage Sci. 66:251–264.

Cribari-Neto, F., Zeileis, A. (2010) Beta regression in R. J Stat Softw. 34:1–24.

Dillon, P., (2011) The Irish dairy industry-Planning for 2020. In: National Dairy Conference ′11, The Irish Dairy Industry: To 2015 and Beyond. Cork, Ireland. p.1-24.

French, P., Hanrahan, L., Shalloo, L. (2015) Principles of sustainable dairy expansion. In: Moorepark′15 Irish Dairying – Sustainable Expansion. Cork, Ireland. pp.9 -14.

Hanrahan, L., Geoghegan, A., O’Donovan, M., Griffith, V., Ruelle, E., Wallace, M., Shalloo, L. (2017) PastureBase Ireland: A grassland decision support system and national database. Comp Electron Agric. 1:193–201.

Kennedy, E., McEvoy, M., Murphy, J.P., O’Donovan, M. (2009) Effect of restricted access time to pasture on dairy cow milk production, grazing behaviour, and dry matter intake. J Dairy Sci. 292:168–176.

McSweeney, D., Foley, C., Halton, P., O’Brien, B. (2015) Calibration of an automated grass height measurement tool equipped with global positioning system to enhance the precision of grass measurement in pasture-based farming systems. In: Grassland Science in Europe ′15, Grassland and forages in high output dairy farming systems. The Netherlands pp.265-67.

Mosquera-Losada, R., Gonzalez-Rodriguez, A. (1998) Effect of annual stocking rates in grass and maize + rye system on production by dairy cows. Grass Forage Sci. 53:95–108.

Nakagami, K. (2016) Effects of sites and years on the coefficients of rising plate meter calibration under varying coefficient models. Grass forage Sci. 62:128-132.

O'Grady, MJ., O'Hare, G.M.P. (2017) Modelling the smart farm. Inform Process Agric. 4:179–187.

Pivoto, D., Waquil, P.D., Talamini, E., Finocchio C.P.S., Dalla Corte, VF,. de Vargas Mores, G. (2018) Scientific development of smart farming technologies and their application in Brazil. Inform Process Agric . 5:21–32.

Powell, T.L. (1974) Evaluation of weighted disc meter for pasture yield estimation in intensively stocked dairy pasture. New Zeal J Exp Agr. 2:237–241.

R Core Development Team. (2017) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria pp.108-124.

Sanderson, M.A., Rotz, A.C., Fultz, S.W., Rayburn, E.B. (2001) Estimating Forage Mass with a Commercial Capacitance Meter, Rising Plate Meter, and Pasture Ruler. Agron J. 93:1281–1286.

Smithson, M., Verkuilen, J. (2006) A Better Lemon Squeezer? Maximum-Likelihood Regression with Beta-Distributed Dependent Variables. Psychol Methods. 11:54–71.

Soder, K.J., Sanderson, M.A., Stack, J.L., Muller, L.D. (2006) Intake and performance of lactating cows grazing diverse forage mixtures. J Dairy Sci. 89:2158–2167.

Tucker, C.J. (1980) A critical review of remote sensing and other methods for non-destructive estimation of standing crop biomass. Grass Forage Sci. 35:177–182.

Umstatter, C. (2011) The evolution of virtual fences: A review. Comp Electron Agric. 75:10–22.

Wathes, C.M., Kristensen, H.H., Aerts, J.M., Berckmans, D. (2008) Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Comp Electron Agric. 64:2-10.

Zhang, Y., Chen, D., Wang, S., Tian, L. A. (2018) Promising trend for field information collection: An air-ground multi-sensor monitoring system. Inform Process Agric. 5:224–233.

Chapter 4 Dynamic Algorithmic Conversion of compressed sward height to dry matter yield by a Rising Plate Meter

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Abstract

The strategic allocation of pasture grazing area to dairy cows is essential for optimal management and increased outputs. Rising plate meters are frequently used to estimate pasture herbage mass, i.e. dry matter yield per hectare) through the use of simple regression equations that relate compressed sward height to herbage mass. However, to improve the accuracy and precision of these equations, so that inherent variation of grasslands is captured, there is a need to incorporate differences in grass types and seasonal growth. Yet, good bassline data is required for the development of effective algorithms. Using a total of 308 grass plots, the variation of growth for both perennial ryegrass and hybrid ryegrass was recorded over the seven month growing season, i.e. March – September. From these data, three dynamic equations were derived. Overall, although all equations were found to be highly accurate and precise, Eq. 2 was considered the most effective (R^2 =0.7; RMSE = 248.05), allowing herbage mass to be predicted reliably from compressed sward height data. Accordingly, smart-device linked rising plate meters, programmed with dynamic algorithms, can be used to reliably calculate herbage mass, whilst improving time and labour efficiency on-farm. Although further research will be required, the results presented allow for the further development of decision support tools to improve on-farm grassland management, particularly at the paddock rather than national level.

4.1 Introduction

Currently, there exists a growing demand for dairy products worldwide (Godfray *et al*., 2010). In temperate climates, pasture-based ruminant production offers a competitive and sustainable alternative to intensive, high-input systems (Dillon *et al*., 2008; Lawrence *et al*., 2016). In particular, the utilisation of grazed grass provides for a highly efficient, nutritious and inexpensive source of energy for ruminant production (Dillon *et al*., 2005; Finneran *et al*., 2012). Importantly, the quantity and quality of herbage offered to grazing animals has a substantial impact on their performance e.g. milk production (Patton *et al*., 2016). Accordingly, to meet the daily nutritional demands of animals, the strategic allocation of grazing area is an essential management practice (O'Donovan, 2000; O'Donovan & Delaby, 2008; Kennedy *et al*., 2009; Curran *et al*., 2010). However, determination of the appropriate allocation of grazing area can only be achieved when using reliably accurate and precise estimates of herbage mass (HM; kg DM/ha), i.e. dry matter yield per hectare).

Accurate measurement of HM can also be used to budget available forage in grazing systems, particularly as grass is an unstable resource (Sanderson *et al*., 2001; López-Díaz *et al*., 2011). For example, regular estimation can help ensure an adequate supply of herbage to meet demand throughout the grazing season, and inform decisions on the removal of surplus herbage to balance its supply and demand, whist maintaining herbage quality. In addition, regular measurement of herbage can be used to identify poor performing grass swards, allowing the farmer to take corrective action such as reseeding, addressing soil fertility issues, and drainage (O'Donovan, 2000; Hakl *et al*., 2012; Shalloo *et al*., 2011). Considerable potential exists to increase the accuracy and precision of pasture allocation, and subsequent farm productivity (Creighton *et al*., 2011; Dillon, 2011). In essence, greater use of reliably collected on-farm data can improve management practices, through the provision of knowledge-based real-time decision support tools.

While accurate estimation of HM can be achieved through assessment of sward heights obtained from clipped quadrants, this is laborious and time intensive endeavour (Asdogen *et al*., 2000; Sanderson *et al*., 2001; López-Díaz *et al*., 2011). Although HM is most often estimated by visual observation, this method is highly subjective and prone to considerable inter-observer variability (Tucker, 1980; O'Donovan *et al*., 2002; López-Díaz *et al*., 2011). For optimal and informed management, grass needs to be measured quickly and reliably in relation to both accuracy and precision. The rising plate meter (RPM) can be used to estimate the HM of grasslands based on the compressed sward height (CSH) (Sanderson *et al*., 2001; Hakl *et al.,* 2012). Overall, this device is considered to be an accurate, precise and labour efficient method for sampling HM (Sanderson *et al*., 2001; Soder *et al*., 2006). However, device reliability can be affected by the naturally large variation of dry matter (DM) within CSH, which is governed by numerous factors, such as plant growth state (Mosquera-Losada & Gonzalez-Rodriguez, 1998), season (Bransby *et al*., 1977), species composition (Castle, 1976), and grassland management regime (Powell, 1974).

In recent years, technological advances such as accurate sensors, Global Positioning Systems (GPS), Bluetooth connectivity, and low-power portable user interfaces (i.e. smart-devices), have been used to improve farm management practices (Dillon, 2011). Accordingly, these technologies can be used to improve in-field measurement and facilitate real-time decision support in relation to grassland management. In particular, a RPM utilising a micro-sonic sensor and digital data capture *via* a Bluetooth communications link to a smart-device application has been developed (i.e. Grasshopper) (McSweeney *et al*., 2019). This RPM device and its associated micro-sonic sensor were found to measure sward height correctly (McSweeney *et al*., 2019). Although the device can be programmed to calculate HM within its associated smart-device application using various formulas, a good reference population to act as baseline data that has realistically captured inherent variations of grassland is required for the development of effective, reliable and dynamic algorithms.

To optimize reliability, equations need to be developed across the growing season and for different grass species, ploidies and varieties. Previously, for example, a dynamic formula was developed for North West France on perennial ryegrass (*Lolium perenne L.*) monoculture swards and mixed swards of perennial ryegrass and white clover (Defrance *et al*., 2004). However, a significant effect of season was observed within this formula, i.e. calculated HM based upon CSH varied by month. Accordingly, optimal grassland management requires the use of a formula altered on a monthly basis. Here, therefore, we develop a dynamic formula to accurately determine HM for Irish grasslands throughout the grass growing season, for both perennial and hybrid ryegrass.

4.2 Methods

4.2.1 Study site

The study was conducted upon perennial ryegrass and hybrid ryegrass plots (n = 308) sown on a free-draining acid brown earth soil of sandy loam texture at Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland (52°09'50"N, 08°15'50"W). Plots were managed under simulated (n = 120: 5 × 1.5 m) or actual grazing (n = 188: 10 × 1.5 m) regimes. Plots managed under simulated grazing conditions were mechanically harvested on eight to nine occasions annually. While animal grazed plots were managed equally on a 21-30 day grazing rotation resulting in eight to nine sampling occasions annually.

Prior to sowing, glyphosate was used to kill the previous sward, the entire area was then ploughed and tilled to provide a fine and firm seed bed which received 37 kg N ha^{-1}, 37 kg P ha^{-1} and 74 kg K ha^{-1}. All plots were sown using a plot seeder (WINTERSTEIGER Plotseed S; WINTERSTEIGER AG., Austria) in August. Once the newly sown plots had reached the two leaf growth stage they were sprayed with a post-emergence herbicide to control the establishment of broad-leaved weeds.

With an equal number of diploids and tetraploids, simulated grazing plots were comprised of perennial ryegrass or hybrid ryegrass. Both ryegrass types were established as monocultures at a sowing rate of 37 kg ha^{-1}, and as polycultures totalling 37 kg ha^{-1}, for all possible combinations for sowing rates of: 9.25; 18.5; and 27.75 kg ha^{-1}. For example, sowing rates were combined for perennial ryegrass (9.25 kg ha^{-1}) and hybrid ryegrass (27.5 kg ha^{-1}), and again for the corresponding mix of perennial ryegrass (27.5 kg ha^{-1}) and hybrid ryegrass (9.25 kg ha^{-1}). Plots designated for actual grazing were likewise constructed using an equal number of diploid and tetraploid perennial ryegrass types, with sowing rates of 34 and 37 kg ha^{-1}, respectively. All actual grazing plots were sown as ryegrass monocultures.

All plots were constructed in a randomised complete block design, consisting of four replicates. For a simulated grazing protocol, plots were harvested using a rotary blade mower to a cutting height of 4 cm (Etesia Hydro 124D; Etesia Ltd., UK), when HM was visually estimated as ~1500 kg DM ha^{-1}. Animal grazed plots were likewise allowed to reach a visually estimated pre-grazing HM of ~1500 kg DM ha^{-1}. The grazed area was offered on a replicate basis to dairy cows for 24-36 hours, dependant on animal intake, to reach a target grass height of ~4 cm.

4.2.2 Dry Matter Yield

Dry matter (DM) yield was determined by weighing all herbage cut from simulated grazing plots. Similarly, a 1 m^2 sub-sample was cut from actual grazing plots, this material was then returned to the source plot to allow consumption by grazing cows. In all cases, a 0.1 kg subsample was retained and dried at 60°C for 48 hours to determine percentage DM content (% DM m^2) in relation to original wet weight. The HM was then derived with respect to the area cut, the wet weight and the percentage DM content.

4.2.3 Grass Height Measurement

Ten CSH measurements were collected from each plot both immediately prior to and post herbage removal. These measurements were captured with a micro-sonic sensor unit (Grasshopper II; True North Technologies, Ireland), mounted perpendicular to the shaft of a handheld, commercially available RPM (Jenquip; Filip's Manual Folding Plate Meter, New Zealand). The Grasshopper micro-sonic sensor is designed to measure the distance between the sensor and the top of the rising plate, to determine height displacement of an object underneath the plate. Instantaneous digital data capture of measurement data, together with a geo-tag describing the location, was facilitated via a Bluetooth communications link between the sensor unit and an accompanying smart-device application (Android operating system). All captured data was saved to the smart-device in a Microsoft Excel File (.CSV Format). Prior to data capture, the micro-sonic sensor could be normalised to ensure a baseline of height zero is established while the plate was at its resting position.

4.2.4 Algorithm Establishment

To establish an algorithm for the conversion of CSH to predicted HM, a variety of variables were examined, including: type of ryegrass (TRG; 2 levels: perennial ryegrass and hybrid ryegrass); Month (7 levels: March – September, inclusive); the percentage DM content (% DM); actual HM (kg DM^{-1} ha^{-1}); pre-cut CSH of grass (cm); height cut (cm), i.e. pre-cut CSH minus the post-cut CSH; and DM per centimetre of grass cut, i.e. HM divided by height cut (kg DM^{-1} cm^{-1}). Pre-cut CSH of < 5 cm were discarded, as were unrealistic values of > 550 kg

DM^{-1} cm^{-1}. Correlation coefficients were calculated for the examined variables to determine effect statistics (see Table 1). These coefficients were used to derive and validate values for the prediction of HM, in relation to actual values recorded for each plot. Pearson's R^2 and associated Root Mean Square Error (RMSE) values were calculated for each equation.

4.3 Results

In total, the constructed dataset was comprised of 1640 usable plot assessments, with each of these including values for all the required variables. Firstly, a value for predicted HM was derived in relation to actual pre-cut CSH (h) values, and the pre-cut CSH square expression (h^2). Within the equation, the corresponding coefficients for the statistical effect statistics were each multiplied by these selected parameters (Eq. 1: R^2 =0.59; $P < 0.001$). All coefficients were highly significant at $P < 0.001$ (Table 4.1). RMSE of 291.21 was calculated for Eq.1:

$$\text{Predicted herbage mass} = (-227.6 + (233.3 \times h) + (-5.35 \times h^2)) \qquad \text{(Eq. 1)}$$

Secondly, building on this approach, a predicted value for HM was derived using coefficients for TRG (t) and month (m), with inclusion of the actual pre-cut CSH (h) and the pre-cut CSH square expression (h^2). Once again, the correlation coefficients for the statistical effect of both pre-cut CSH and the pre-cut CSH square expression were each multiplied by these model parameters (Eq. 2; R^2 =0.7; $P < 0.001$). All coefficients were highly significant at $P < 0.001$ (Table 4.1). RMSE of 248.05 was calculated for Eq. 2:

Predicted herbage mass = (-446.5 + t + m + (263.9 × h) + (-6.6 × h^2))   (Eq. 2)

Further, a third model for predicted HM was then developed using coefficients for TRG (t) and month (m), with inclusion of the percentage DM content (d) and the corresponding value for pre-cutting CSH (h). As before, the correlation coefficients for statistical effect were each multiplied by their dependent model parameter (Eq. 3; R^2 =0.68; P < 0.001). All coefficients were significant at P < 0.001, other than calculated percentage DM at P < 0.05 (Table 4.1). RMSE of 256.56 was calculated for Eq. 3:

Predicted herbage mass = (111.8 + t + m + (8.9 × d) + (118.7 × h))   (Eq. 3)

Table 4.1: Derived correlation coefficients, and associated F values (n = 1640). All P < 0.001, excepting the effect of percentage dry matter content (% DM) at P < 0.05.

	Equation 1	*F*	Equation 2	*F*	Equation 3	*F*
Origin	-227.6		-446.5		111.8	
TRG		--		83.58		86.89
PRG	--		72.3		78.2	
HRG	--		-72.3		-78.2	
Month		--		76.2		64.11
March			90		-0.3	
April	--		22.5		5.4	
May	--		75.1		75.1	
June	--		64.3		33.6	
July	--		-275.9		-209.7	
August	--		-160		-154.2	
September	--		184		250.1	
Pre-cut CSH	233.3	279.34	263.9	388.9	118.7	2133.01
Sq. Pre-cut CSH	-5.35	70.49	-6.6	120.67	--	--
% DM	--	--	--	--	8.9	6.48
R^2	0.59	1170.54	0.7	428.09	0.68	388.35
Root Mean Square Error	291.21		248.05		256.56	

4.4 Discussion

This study confirms the relationship between CSH and HM. In essence, the height of grass can be used as a reliable indicator of HM. Although Eq. 1 provides a simple straightforward estimate based on pre-cut CSH values alone, this equation cannot facilitate a dynamic assessment for type of ryegrass measured and time of year. Eq. 1 is also the least accurate or precise given the associated Pearson's R^2 and RMSE values, respectively. However, both Eq. 2 and 3 are especially beneficial as both can account for perennial ryegrass type and variation in relation to time of year. These equations will allow for the construction of dynamic formula within the smart-device application and associated novel micro-sonic RPM linked technology. In essence, the most applicable formula can be selected by an on-farm operator, based on the readily available information concerning the type of ryegrass and sampling month, to reliably predict HM. However, Eq. 2 is marginally more accurate and precise than Eq. 3, with respect to Pearson's R^2 and RMSE values. Importantly, Eq. 2 is also a more advantageous formula, as it is derived from pre-cut CSH values rather than actual percentage DM content, which is not necessarily readily measurable on-farm due to impracticalities.

As demonstrated by many previous studies, it has been difficult to achieve RMSE values of below 250 kg DM^{-1} ha^{-1}, with most studies achieving values closer to 300 kg DM^{-1} ha^{-1} (López-Díaz *et al*., 2011). Although the relationship is still imprecise, a RMSE ranging from 250-300 kg DM^{-1} ha^{-1} has been the limit of predictive equations for HM assessment based on measurements obtained from RPMs. Accordingly, the RMSE values obtained for all equations in this study are within an acceptable range, while both Eq. 2 and 3 have especially favourable

RMSE statistics. To date, most regression formulas used to calculate HM from CSH have been linear in nature, as this allows for easier calculations. However, smart polynomial regression formula, such as the equations derived by this study, are a far more accurate estimation of HM. For example, Mitchell and Large (1983) achieved strong correlations between CSH and HM ($R^2 = 0.98$) for specific time points across the grass growing season. However, when Sanderson *et al*. (2001) applied one of these time specific formulas consistently over a full grazing season, the correlation was significantly reduced ($R^2 = 0.31$). The additional model parameters required by Eq. 2, i.e. type of ryegrass and month, will be known to farm operators in the field.

Despite statistical indications of high accuracy and precision, further research will be required to better understand elements of formula inaccuracy and imprecision. As such, an improved knowledge of on-farm variability is needed. To achieve this, additional model parameters could be included and validated, with a view to produce regional if not paddock specific formula, rather than national level equations. These equations could then be used to produce dynamic algorithms capable of calculating reliable HM estimates, based on operator selected criteria. With the advent of automated grass height data capture tools, such as micro-sonic RPMs and associated smart-device web-applications, dynamic and reliable calculation of HM can be achieved in a practical user-friendly manner. In addition, these tools can potentially be linked to other grassland technologies, to provide ‘smart-farm’ solutions through highly automated systems. For example, upon collection of CSH data with a smart-device linked to a RPM with an on-board GPS, using a web based geolocation application can define the optimal grazing area for the herd within a pasture.

Here, we have produced a series of formula that can be used within smart-device linked RPMs, for reliable algorithmic conversion of CSH to HM. Although further research is required to develop the equations to encompass more site-specific effects, our results represent a promising starting-point for the further advancement of decisions support tools, to improve on-farm grassland management.

4.5 References

Castle, M.E. (1976) A simple disc instrument for estimating herbage yield. Journal of the British Grassland Society, 31: 37–40

Creighton, P., Kennedy, E., Shalloo, L., Boland, T.M. and O' Donovan, M. (2011) A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. Grass and Forage Science, 66: 251-264

Defrance, P., Delaby, L. and Seure, J.M. (2004) Mieux connaître la densité de l'herbe pour calculer la croissance, la biomasse d'une parcelle et le stock d'herbe disponible d'une exploitation, Renc Rech Ruminants, 11: 291-294

Dillon, P., (2011) The Irish dairy industry-Planning for 2020. In: Proceedings of the Teagasc National Dairy Conference Athlone, Ireland, pp. 1–8

Dillon, P., Hennessy, T., Shalloo, L., Thorne, F. and Horan, B. (2008). Future outlook for the Irish dairy industry: A study of international competitiveness, influence of international trade reform and requirement for change. Int. J. Dairy Technol. 61:16–29

Dillon, P., Roche, J.R., Shalloo, L. and Horan, B. (2005) Optimising financial return from grazing in temperate pastures. In: Murphy J.J. (ed) Utilisation of grazed grass in temperate animal systems: Proceedings of a satellite meeting of the XXth International Grassland Congress; Cork, Ireland, September 2005, pp. 131–147. Wageningen, the Netherlands: Wageningen Academic Publishers.

Finneran, E., Crosson, P., O'Kiely, P., Shalloo, L., Forristal, D. and Wallace, M. (2012) Stochastic simulation of the cost of home-produced feeds for ruminant livestock systems. The Journal of Agricultural Science, 150:123–139

Godfray, H.C., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., Pretty, J., Robinson, S., Thomas, S.M., and Toulmin, C. (2010) Food security: The challenge of feeding 9 billion people. Science 327:812–818

Hakl, J., Hrevusova, Z., Hejcman, M. and Fuksa, P. (2012) The use of a rising plate meter to evaluate Lucerne (*Medicago sativa L.*) height as an important agronomic trait enabling yield estimation. Grass and Forage Science, 67: 589–596

Jewiss, O.R. (1993) Shoot development and number. In: Davies, A., B.R.D., Grant, S.A. and Laidlaw, A.S. (ed.) Sward measurement handbook 2nd edition. Reading, UK: The British Grassland Society.

Kennedy, E., McEvoy, M., Murphy, J. P. and O'Donovan, M. (2009). Effect of restricted access time to pasture on dairy cow milk production, grazing behaviour, and dry matter intake. J. Dairy Sci. 92:168–176

Lawrence, D.C., O'Donovan, M., Boland, T.M. and Kennedy, E. (2016) Effects of autumn and spring defoliation management on the dry-matter yield and herbage quality of perennial ryegrass swards throughout the year. Grass and Forage Science, 72: 38–49

Lopez-Diaz, J., Roca-Fernandez, A. and Gonzalez-Rodriguez, A. (2011) Measuring herbage mass by non-destructive methods: A review. Journal of Agricultural Science and Technology, 1: 303-314

McSweeney, D., Coughlan, N.E., Cuthbert, R.N., Halton, P., Ivanov, S. (2019) Micro-sonic sensor technology enables enhanced grass height measurement by a Rising Plate Meter. Information Processing in Agriculture. 6: 279-284

Mitchell, P. and Large, R.V. (1983) The estimation of herbage mass of perennial ryegrass swards: A comparative evaluation of a rising-plate meter and a single-probe capacitance meter calibrated at and above ground level. Grass and Forage Science, 38: 295-299

O’Donovan, M., Dillon, P., Stakelum, G. and Rath, M., (2000) The grazing management practise, feed budgets and herd performance of six spring calving herds over a three year period. Grassland Science in Europe, 5: 306

O'Donovan, M., Connolly, J., Dillon, P., Rath, M. and Stakelum, G. (2002) Visual Assessment of Herbage Mass. Irish Journal of Agricultural and Food Research, 41: 201-211

Patton, D., Pierce, K.M. and Horan, B. (2016) Effect of stocking rate on milk and pasture productivity and supplementary feed use for spring calving pasture fed dairy systems. Journal of Dairy Science, 99:5904 – 5915

Sanderson, M.A., Rotz, A.C., Fultz, S.W. and Rayburn, E.B., (2001). Estimating Forage Mass with a Commercial Capacitance Meter, Rising Plate Meter, and Pasture Ruler. Agronomy journal 93: 1281–1286

Shalloo, L., Creighton, P. and O’Donovan, M. (2011) The economics of reseeding on a dairy farm The economics of reseeding on a dairy farm. Irish Journal of Agricultural and Food Research, 50: 113–122

Soder, K.J., Sanderson, M.A., Stack, J.L. and Muller, L.D. (2006) Intake and performance of lactating cows grazing diverse forage mixtures. Journal of Dairy Science 89: 2158–2167.

Chapter 5: Virtual Fencing without Visual Cues: Design, Difficulties of Implementation, and Associated Dairy Cow Behaviour.

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Abstract

Intensive pasture-based farming systems rely on precise and frequent allocations of grass to animals. Virtual fence (VF) systems have been successfully used to contain animals within predefined boundaries. Accordingly, utilisation of a VF system to enhance automated allocation of correct forage areas to animals would represent a major advancement for grazing management strategies. Traditional VF systems rely on a perimeter cable to establish the boundary line, and this then needs to be deployed and physically moved to alter the parameters of the boundary. In our study, wearable GPS technology was used to implement a VF system without the need for such cabling. To accomplish this, we designed and developed a VF system comprised of a wearable collar with associated on-farm communication infrastructure. Moreover, we attempted to train dairy cows to associate an audio warning stimulus with boundary encroachment. Overall, the operating capacity of the cow-collar and the communications network were found to be robust. However, although dairy cows rapidly associated visual cues with VF boundary lines, and quickly developed a cue-consequence association between the audio warning and corrective stimulus, the number of boundary challenges made by cows increased upon removal of all visual cues. In addition, we observed a reduction in time spent grazing and ruminating during the training period, which suggested cows had become stressed within the designated inclusion zone. Nevertheless, our results are preliminary and further experimental work is required to truly assess best implementation protocols for virtual fencing without visual cues.

5.1 Introduction

The profitability of intensive pasture-based systems is reliant upon precise, accurate and timely grazing management strategies. Therefore, there is a clear need to meet, but not exceed, daily nutritional demands of grazing animals (Kennedy *et al.,* 2009). In particular, the practice of strip-grazing, whereby animals are moved once or more on a daily basis between predefined grazing areas of known grass height and quality, is considered to be a best practice protocol for optimal grass utilisation and improved farm productivity (Abrahamse *et al.,* 2008; Umstatter, 2011; Koene *et al*., 2016). Research suggests that Irish dairy farms can increase profit per grazed hectare by *circa* €267 for each additional tonne of grass utilised (French, 2015). Therefore, the effective control of grazing animal movements is imperative to any intensive pasture-based system. Consequently, the implementation of Precision Livestock Farming (PLF) techniques in relation to grassland management represents a considerable opportunity to enhance farm productivity and profitability (Dillon, 2011). Accordingly, interest in flexible fencing technology to improve pasture allocation has greatly increased (Umstatter *et al.,* 2015a,b). Such technology can facilitate rapid and less-labour intensive manipulation of stocking densities, improved use of seasonal growth, protection of vulnerable areas, and reduce human-wildlife conflict caused by conventional fencing (Umstatter, 2011; Umstatter *et al*., 2013). Although some improvement to flexibility was made possible by the invention of single-strand electric fencing, further developments are urgently required to optimise management protocols, improve ease of allocation, and reduce labour.

Electric fencing relies on each individual animal forming a cue-consequence association between the visual cue of the fence structure (fence posts and wire) with the negative stimulus of a mild electric shock. Although this method is effective, erecting and maintaining fencing is both time and labour intensive (Umstatter *et al.,* 2015a). Yet, a number of studies have demonstrated that domesticated cattle can respond to a variety of visual and auditory sensory cues (Howery *et al*., 2000; Lee *et al*., 2007; Umstatter, 2011; Umstatter *et al*., 2013). Accordingly, virtual fence (VF) systems have sought to utilise novel sensory cues in the formation of cue-consequence learning (Bishop-Hurley *et al*., 2007; Campbell, 2019). Virtual fencing can be defined as a structure or system which acts as a boundary or enclosure, in the absence of any physical barrier (Umstatter, 2011). Various types of VF system have been developed and examined, utilising wearable technology upon a variety of livestock across a range of agricultural settings (Butler *et al*., 2004; Bishop-Hurley *et al*., 2007; Jouven *et al*., 2012; Umstatter *et al*., 2013; Brunberg *et al*., 2015; Monod *et al*., 2009). However, the overwhelming majority of these studies have focused on rangelands, where can freely roam over large areas. Currently, while a small-scale VF system approach has been effectively utilised to contain domestic pets, few have been put in place to prove if a VF system is a feasible and welfare friendly means of controlling animal movement in a small-scale intensive farm (Umstatter, 2014). However, recently there has been two commercially VF systems that have become available to the general farming public (Nofence AS, Batnfjordsøra, Norway & Agersens, Victoria, Australia)

The successful implementation of a VF system into a working farm can potentially be complex and fraught with technical challenges, such as network communications, differential system interfaces, farm topography, precision confinement, energy supply, animal welfare and training (Umstatter, 2011). In addition, although the installation of an induction cable fence line is less labour intensive than erecting and moving electric fences on a frequent basis, labour is associated with burying of cables and GPS based systems could potentially eliminate the need for such cabling entirely. Particularly as systems which rely on buried cables can also be labour intensive to establish and reorganise. Accordingly, VF systems which do not require perimeter cabling could provide a beneficial solution for farmers needing to move fences on a frequent basis, such as in strip grazing (Umstatter *et al*., 2015a).

Within intensive pasture-based systems, VF requires a management system to dynamically deploy and move boundaries, depending on herd size and available grazing resources. The system should allow managers to increase, decrease, or provide completely new areas of pasture by redeploying the VF boundary. Additionally, to be truly successful, the VF system must be applicable to the full herd, a subset of the herd, or even an individual animal as dependent upon grazing requirements. It could be envisaged that e.g some herd members may have larger or separate grazing areas to other animals, such as in-calf cows or bulls. To be truly dynamic a VF system should not need to rely on perimeter cabling, which can be expensive and labour intensive to establish and redeploy. But it is imperative that the VF system is understood by the animals, as ambiguity in relation to boundary areas can cause a significant negative impact in terms of stress, which has been shown to reduce milk yield and weight gain in dairy cows (Hedlund & Løvlie 2015; Adamczyk, 2018). Therefore, the location of the boundaries of a VF system, within which cows are contained, must be effectively communicated to each individual animal.

Although electric fences are routinely used for controlling livestock, the use of electric stimuli has become less ethically acceptable for many stakeholders, scientists and a larger proportion of the general public (Umstatter, 2011). As VF systems require wearable technology, systems should aim to utilise warning-cues that reduce the need for aversive electric stimuli. Key is to establish a cue-consequence association to ensure animal welfare (Spitzer, 2017). Therefore, the development of a suitable training programme, which can be easily implemented by the farmer to quickly familiarise livestock with the VF system is required (Umstatter, 2011 Koene *et al.,* 2016).

In our study, we aimed to: (a) develop and deploy a user-friendly VF system, which did not rely on perimeter cabling, to retain small groups of grazing dairy cows within a pre-defined grazing allocation; and (b) evaluate the concept of VF without visual cues in terms of (i) the retention of dairy cows by a VF with the use of warning stimuli alone; and (ii) animal behaviour as an expression of welfare.

5.2. Materials And Methods

All experimentation was completed at the Animal and Grassland, Research and Innovation centre, Teagasc Moorepark, Ireland (50°7N; 8°16W), and approved by the Teagasc Animal Ethics Committee under the European Union (Protection of Animals used for Scientific Purposes) (Amendment) Regulation 2013.

5.2.1 Technical Description Of The Virtual Fencing System

The cow-collar

Many animal management systems employ wearable technologies, which are most often deployed in the form of a collar. Accordingly, the VF prototype designed and developed in this study utilised a collar based system. The collar consisted of a housing-unit (HU) and a 75 mm wide nylon based laminated strap to facilitate attachment to the animal. The HU (174 mm L × 131 mm W × 105 mm H; 1132 g) was constructed from a high density polymer and contained the system electronics, microprocessor and a four pin block connector, which acted as a combined re-charge port and a firmware upgrade port. The electrodes (stainless steel braids; 100 mm L × 10 mm W) for delivery of the electric stimulus were located at two points on the collar strap. Both the collar strap and HU were treated with waterproofing spray and targeted silicon barrier use, to minimise moisture ingress to the components. Equally, the collar strap incorporated a cabling pocket to facilitate cabling for communication between the HU, the electrodes and a GPS with a DGPS (Differential Global Positioning System) receiver. The GPS and DGPS receivers were located at the highest point on the collar to permit best view of available GPS satellites (i.e. both receivers sat on the dorsal side of a collared cow’s neck, with the HU located 180º below, at the ventral). The GPS receiver chosen for the project was a MediaTek MT 3711 (MediaTek USA Inc., Woburn, Massachusetts, USA) with a DGPS custom firmware option loaded for both SBAS (satellite-based augmentation system) and RTCM 104 protocol (Radio Technical Commission for Maritime Services). The receiver was controlled by the unit microprocessor.

A light-weight LiPo power solution was selected for storage capacity (4400 mAh; achieving a design life with average consumption of 3 - 4 days) and short re-charge times. In order to enhance precision and accuracy of the VF system, a permanent reference point, utilising a DGPS reference station, was established on-site at Moorepark using a Trimble 4000 series GPS receiver.

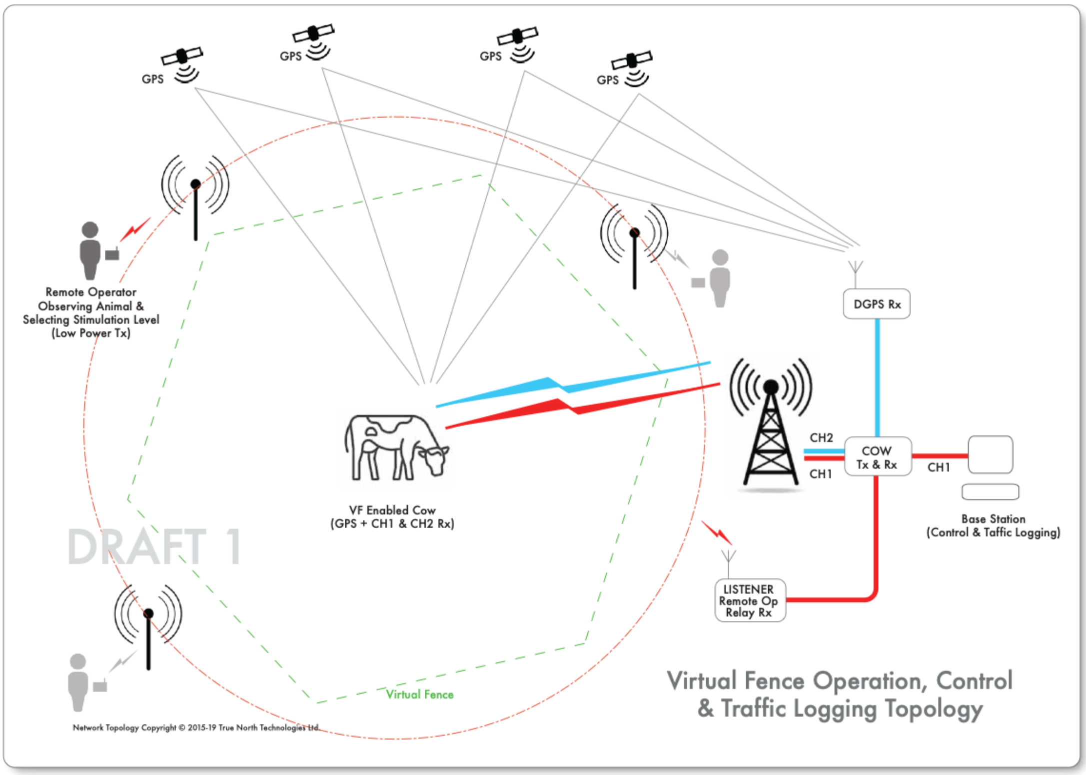

Figure 5.1: Topology design for the communion infrastructure of the virtual fence VF system.. The communication methodology linking the operator, base station and the VF collar on the cow using channel 1. Channel 2 describes the implementation of the DGPS correction via the DGPS receiver system and the VF collar on the cow.

5.2.2 The Radio Data Network

The Ultra High Frequency (UHF) 433 MHz radio band (designated as Channel 1 for this study) represented the cow based network over which all traffic data (except DGPS data, which was sent over at the UHF 900 MHz band, i.e. Channel 2) was passed to and from the cow. These bands were operated within the ISM (i.e. the industrial, scientific, and medical radio bands). However, given the limitation of the ISM bands, a robust methodology was used at an on-air rate of 9600 Bits s^{-1}. The typical usage may be described as follows: a command message was passed to the cow, to which the cow responded (i.e. once an individual command was received, the collar acknowledged receipt), and a notice of command completion was then sent to the control station, where an operator used a Personal Computer (PC) and keyboard to issue commands or access the system logs. Base station power requirements were supplied by the national electric system and an Uninterruptible Power Supply (UPS) backup system was provided for the control station equipment and the reference DGPS station (figure 5.1).

Command messages could be addressed to the herd as a whole or to each individual separately. Initially, however, when the command message was addressed to the herd as a whole, an acknowledgement was not returned, as data collisions occurred when responses were transmitted almost simultaneously. To address this, a unique transmission delay (*circa* 5 – 20 ms) was included on each collar, and this permitted acknowledgements to be received. Typical examples of commands sent in real-time by an operator included: (a) activation or deactivation of the VF as required; (b) arm/disarm a single or combination of selected stimulus options (audio, tactile, electrical shock); or (c), a housekeeping command requesting position, battery life and other data. All traffic on Channel 1 was logged by the system, and this provided a record of the number and type of stimulus a cow received and the cow position when the stimulus was delivered.

The confinement of DGPS data to the 900 MHz band (Channel 2) allowed for a separate receiver (carried by each animal) to receive satellite corrections. The rationale for this approach was primarily a data traffic consideration. DGPS data was transmitted every second in approximately 400 ms bursts. This occupied a significant proportion of the available airtime on the channel, and given the requirement to have command messages sent from both the control station and an in-paddock, mobile command interface asynchronously (i.e. on independent timelines), a separate data channel for DGPS was considered appropriate.

5.2.3 Mobile Command Interface

In addition to the use of a PC, it was also considered necessary that an operator should have remote in-paddock control of the VF system for experimental purposes. A smart-device application (i.e. phone or tablet App) was developed to send commands to a mobile control station. Both the UHF radio band and DGPS networks successfully transmitted data up to 1 km. Moreover, to facilitate greater levels of mobile connectivity, secondary relay points could also be deployed to suit local topography and increase the network communication range. A smart protocol was used so that data collisions between an operator at the control station and an in-paddock operator did not occur. The App developed to achieve this used an android operating version 4.3 or later. Both the field based radio network elements and the cow-borne hardware were designed to meet IP67 standards.

5.2.4 Data Logging

Raw GPS data was processed using a standard firmware library. Selected outputs of latitude, longitude, altitude, SBAS status, DGPS status, satellites, date, time, individual cow identification, and alert stimulus options, were produced. These data were then sent to the operator *via* Channel 1 when requested, together with other metrics such as battery status. All items of data traffic to and from each cow was logged (utilising TeraTerm© open source data management software, Tera Term Project, Japan) at the base station by a dedicated receiver and PC, time stamped with sub-second precision. All data were saved to a dedicated drive as self-generating log files in .csv format. Equally, this time-stamped record of all data traffic ensured ethical and animal welfare procedures were adhered to. Equally, each time the VF system was revised, an acknowledgement that the new coordinates had been successfully implement was received from all active collars.

5.2.5 Deployment Of Virtual Fencing Without Visual Cues; Proof Of Concept

The operating capability of the VF system was examined on a daily basis (prior to proceeding with experimental trials) for robustness of the communication infrastructure, by monitoring the Bit Error Rate (BER); once this was below the acceptable threshold the system was deemed robust. Any identified shortcomings of the VF system (e.g. electronics, battery longevity, GPS accuracy, and suitability of the collar strap) were subsequently corrected. All collar stimuli were delivered manually by an operator *via* remote control to ensure that the behaviours shown by the cows were a direct result of the cue applied. Upon delivery, the exact time was noted and this was then later checked against the time-stamped record held within the collar.

5.2.6 Assessment Of Audio And Tactile Warning Stimuli

Initially, cow response to both the audio and tactile warning stimuli, and the adverse stimulus (electric shock) during a boundary challenge event, i.e. an attempt by an animal to cross an active VF boundary line, was assessed. A small experimental paddock was enclosed on three sides with electrified, single-strand wire fencing. The remaining fourth side utilised the VF system as a boundary. The area within these boundaries was considered the ‘inclusion zone’ (52 m L × 21 m W), while the larger paddock area directly beyond the VF was the ‘exclusion zone’. The inclusion and exclusion zones combined had an area of *circa* 0.51 hectares.

Twelve non-lactating, multiparous Holstein Friesian dairy cows were selected from the Teagasc, Moorepark dairy herd. All twelve cows were fitted with a VF collar and randomly divided into two groups of six cows each: Group A and Group B. Only one cow was placed within the inclusion zone at any one time, entering at the furthest point from the VF boundary. When an individual cow from

Group A challenged the VF boundary, it was exposed to an audio warning (120 dB for three seconds) followed by a single electric shock (0.8 kV). In contrast, individuals from Group B were exposed to a tactile warning (vibration for three seconds) followed by a single electric shock. Animals within the experimental paddock were observed at all times by two operators from a concealed location.

A boundary challenge was defined as a cow moving to within 0.5 m of the central VF boundary line. The reactive behaviour of each animal on receiving the warning and/or adverse stimuli were classified into five categories: (1) no response; (2) halted; (3) halted, then moved quickly forward almost immediately; (4) halted, then moved quickly backwards almost immediately; and (5) halted, then slowly turned back. If a cow did not voluntarily approach the VF boundary within 15 minutes post commencement of the trial, the animal would be slowly herded at walking pace towards the VF boundary, but was not herded across it. Each animal was given two opportunities to challenge the VF boundary.

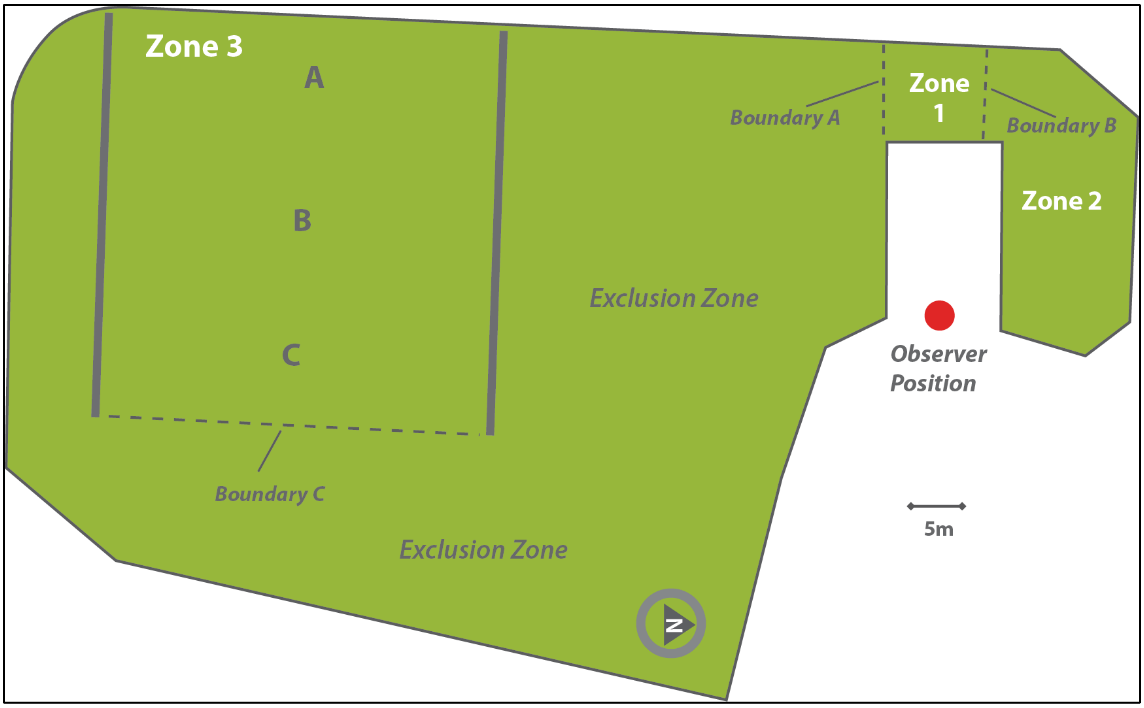

Figure 5.2: Map of experimental arena. The virtual fence (VF) boundary line 'Boundary A' was deployed for Experiment 1, and redeployed as 'Boundary B' for Experiment 2. Equally, 'Boundary C' was deployed for Experiment 3. The area beyond these boundary lines was considered to be the exclusion zone.

Table 5.1: Description of the utilisation of visual cues, combined audio warning cues and adverse stimulus, and audio warning cues alone, or lack thereof, for Experiment 1: Implementation of a basic cow training protocol; Experiment 2: Relocation of the virtual fence boundary line; and Experiment 3: Learning evaluation. Where a double dose (i.e. × 2 doses) was given, these were separated by a two second interval. See Methods text for greater experimental detail.

Exposure Day	Visual Cue	Stimulus Received *
Experiment 1		
1(a & b)	No boundary	None given
2a	Boundary A: visual cue = WNFT	Audio cue + Adverse stimulus ×2 (1,2) Subsequently Audio cue only
2b	Boundary A: visual cue = WNFT	Audio cue + Adverse stimulus ×2 (1,2) Subsequently Audio cue only
3a	Boundary A: visual cue = WNFT	Audio cue + Adverse stimulus ×1 (1,2) Subsequently Audio cue only
3b	Boundary A: visual cue = GSW	Audio cue + Adverse stimulus ×1 (1,2) Subsequently Audio cue only
4a	Boundary A: visual cue = GSW	Audio cue + Adverse stimulus ×1 (1,2) Subsequently Audio cue only
4b	Boundary A: visual cue = none	Audio cue + Adverse stimulus ×1 (1,2) Subsequently Audio cue only
5 (a & b)	Boundary A: visual cue = none	Audio cue only
Experiment 2		
6a	Boundary B: visual cue = GSW	Audio cue + Adverse stimulus ×1 (1) Subsequently Audio cue only
6b	Boundary B: visual cue = none	Audio cue + Adverse stimulus ×1 (1) Subsequently Audio cue only
7 (a & b)	Boundary B: visual cue = none	Audio cue only
Experiment 3		
8 (a & b)	Boundary C: visual cue = none	Audio cue only
9 (a & b)	Boundary C: visual cue = none	Audio cue only

* ×1 = 1 dose; ×2 = 2 doses; (1) = 1st Boundary Challenge; (2) = 2nd Boundary Challenge; WNFT = white nylon fencing tape; GSW = grey steel wire

Table 5.2: Descriptions of behavioural characteristics displayed by the cows in accordance with Schirmann et al. (2012). In this study, due to low observation counts, associated behaviours were combined to produce three main behaviour categories.

Behaviour Type	Abbrev.	Combined Behaviours	Description
Stand + Ruminate	SR	Stand	Stands on four extended legs + chewing food boluses
Stand + Inactive	SI		Stands on four extended legs + all behaviour except ruminating, e.g. sleeping or vigilance
Lying + Ruminate	LR	Lying	Any position lying down + chewing food boluses
Lying + Inactive	LI		Any position lying down + all behaviour except ruminating, e.g. sleeping or vigilance
Grazing	G	GWD	Head held close to the ground + continuously grazing while either standing stationary or moving slowly
Walking	W		Pacing too fast to graze, with head held in a raised position
Drinking	D		Drinking water at water trough + time taken between gulps

5.2.7 Test Of The Efficiency Of A Cow Training Protocol For Use With A Virtual Fence System And Evaluation Of The Concept Of VF Without Visual Cues

The introduction of a training protocol was informed by the results of the first deployment. Therefore, only the audio warning stimulus was retained for further experimental work. This was deployed in conjunction with the adverse stimulus. The experimental paddock, utilised during the training study, was subdivided into two inclusion zones: Zone 1 (191 m^2) and 2 (374 m^2). The remainder of the paddock was considered to be the exclusion zone (Figure 2). The external boundaries of Zones 1 and 2 and the exclusion area consisted of electrified, single-strand wire fencing and/or wooden fencing. The training protocol involved two experiments over seven days: Experiment 1 (Days 1–5) and Experiment 2 (Days 6–7). Evaluation of the VF was conducted in Experiment 3 (Days 8-9), which utilized Zone 3 (975m^2; see Figure 2).

A first test of a training protocol was conducted on a small number of cows due to availability of experimental animals and the time pressure of being close to the end of the vegetation period. Nine non-lactating multiparous Holstein Friesian cows, which had not been previously exposed to the VF system, were used. The nine cows were randomly divided into three groups of three individuals: Groups 1, 2 and 3. Each group was trialled successively and independently of the other groups. Cows proceeded directly from Experiment 1 to Experiment 2 to Experiment 3. All animals were allowed to acclimatise to wearing the VF collars for a seven-day period prior to experimental commencement. Collars were fitted and removed daily for both the seven-day acclimatisation period and the subsequent seven-day experimental period. All animals were also examined for signs of lesions or rubbing caused by the collars.

To incentivise the cows to challenge the VF boundary, all zones were managed such that grass availability was always greater in the exclusion zone relative to all inclusion zones. The grass heights were recorded daily using a Jenquip rising-plate meter (Agriworks LTD, Feilding, New Zealand) pre and post the experimental period. To ensure cows achieved their nutritional requirements within every 24 h period, cows were placed in holding paddocks outside of the experimental period. To prevent the cows from gorging during non-experimental periods, grass allocation within the holding paddocks was based on dry matter (DM) availability, such that the combined DM of the experimental and holding paddocks would not exceed the animals' daily DM hr^{-1} grazing requirements.

5.2.7.1 Experiment 1: Implementation of a basic cow training protocol

Experiment 1 was conducted for a five day period (Day 1 – 5) from 11:00 – 16:00, daily. Each experimental day was further split into two half-days of an equal 2.5 h duration (e.g. Day 1a = 11:00 – 13:30; Day 1b = 13:30 – 16:00; see Table 5.1). On Day 1, Group 1 cows were allowed to move freely across the entire experimental paddock, i.e. combined inclusion and exclusion zones. Cows were then restricted to the combined area of Zones 1 and 2 on Day 2a, 2b and 3a. This was achieved by using a visual reference for the active VF boundary, a strip of white nylon fencing tape (WNFT; 710 cm L × 30 mm W) was placed on the ground to enable animals to identify the centre line of the active VF (Boundary A; Figure 2). Subsequently, on Day 3b and 4a, the WNFT was replaced with a strip of grey steel wire (GSW; 710 cm L × 2.5 mm W). Following this, on Day 4b, 5a and 5b, the GSW was removed and no visual reference depicting the centre line of the VF was supplied to the cows.

To develop an association between the audio warning stimulus and the adverse electric shock stimulus, when a cow approached Boundary A on Day 2a and 2b the animal received an audio warning followed by the adverse stimulus. This delivery of the audio and aversive stimuli was repeated twice (within 2 s) on both the first and second boundary challenge made by an animal (Table 5.1). This was done to rapidly enforce the cue-consequence associate from commencement. Following this, for any subsequent boundary challenges made by cows on Day 2a and 2b, the animal only received the audio warning stimulus. On Day 3a, the animal received the combined warning and aversive stimuli once for both its first and second boundary challenge, and only the audio warning cue for any subsequent boundary challenges. This protocol was repeated on Day 3b and 4a during the utilisation of GSW as a visual cue, and again on Day 4b when the GSW was removed (Table 5.1). This was done to reinforce the cue-consequence association for the cows on a daily basis. On day 5a and 5b the cows only received an audio warning if they challenged the VF boundary, and did not receive an adverse stimulus.

5.2.7.2 Experiment 2: Relocation of the virtual fence boundary line

On Day 6a cow response to the redeployment of the VF boundary was examined. Cows were restricted to Zone 2 *via* activation of Boundary B (Figure 2). Once again, the GSW was provided as a visual reference point for the animals. However, the GSW was removed on Day 6b, 7a and 7b, with no visual reference provided. On Day 6a and 6b the animals received the combined warning and adverse stimuli for their first Boundary B) challenge event, and an audio warning only for any subsequent boundary challenge. On Day 7a and 7b, animals only received an audio warning if Boundary B was challenged (Table 5.1).

5.2.7.3 Experiment 3: Learning evaluation

To evaluate the extent to which the animals retained an awareness of the cue-consequence association between the audio warning and the aversive stimulus, Group 3 animals were subsequently placed together in an additional inclusion Zone 3, on two consecutive days (Days 8 and 9) (6 h: 11:00 – 17:00). The animals were not supplied with a visual reference depicting the centre line of the VF boundary. Animals only received an audio warning if they challenged the boundary (Table 5.1).

5.2.7.4 Data collection

The total number of boundary challenges and the subsequent animal response was recorded on each half-day. Change in behavioural characteristics displayed by the cows on each half-day was used to assess the success of the training protocol and its impact on animal stress levels. All behaviour characteristics displayed by all cows were recorded in accordance with behavioural traits described by Schirmann *et al*. (2012; Table 5.2). Due to very few counts, the behaviours of 'grazing', 'drinking' and 'walking' were combined to create a single category 'GWD', while 'stand + ruminate' and 'stand + inactive' became 'Stand'. Equally, 'lying + ruminate' and 'lying + inactive' were combined as 'Lying'. Cow behaviour was observed for the duration of every experimental period (5 h) by two trained operators. Instantaneous scan sampling at 10 minute intervals was utilised to collect 30 scans for each individual cow per day during Experiments 1 and 2, while 36 day behavioural scans/day were collected for each individual cow in Experiment 3. The location of each cow within Zone 3 was recorded with each scan sample. This was achieved by dividing Zone 3 into three equal sections (A, B and C; each of 0.03 ha), the boundaries of which were denoted by a red mark on timber posts, visible to the experimental operators (Figure 5.2). To encourage cows to graze the entire Zone 3 area and challenge the VF boundary, DM availability across Zone 3 was kept exceptionally low. Operators were able to differentiate between individual animals by the differently coloured VF system collars when recording behaviours displayed and boundary challenges made.

In all instances, for all experiments, cows were manually and immediately reintroduced to the inclusion zone by an operator when they moved beyond the bounds of the VF. On days with extreme weather conditions and particularly wet days (n = 2), no experimental work was carried out in order to avoid behavioural bias due to environmental influences.

5.3 Results

Proof of Concept

The operating capacity of the wearable cow-collar and the communications infrastructure proved to be robust over the duration of the experimental work. The cow-collars and on-farm infrastructure remained impervious to environmental conditions and functioned as desired. Moreover, no lesions or rubbing from the collars were observed on cows. Cow-collars were charged nightly and performed as required. The main power requirements for the cow-collar included the combined GPS/DGPS receiver (*circa* 60%), the microprocessor control unit (*circa* 20%), and the stimulus unit (*circa* 5 - 20%).

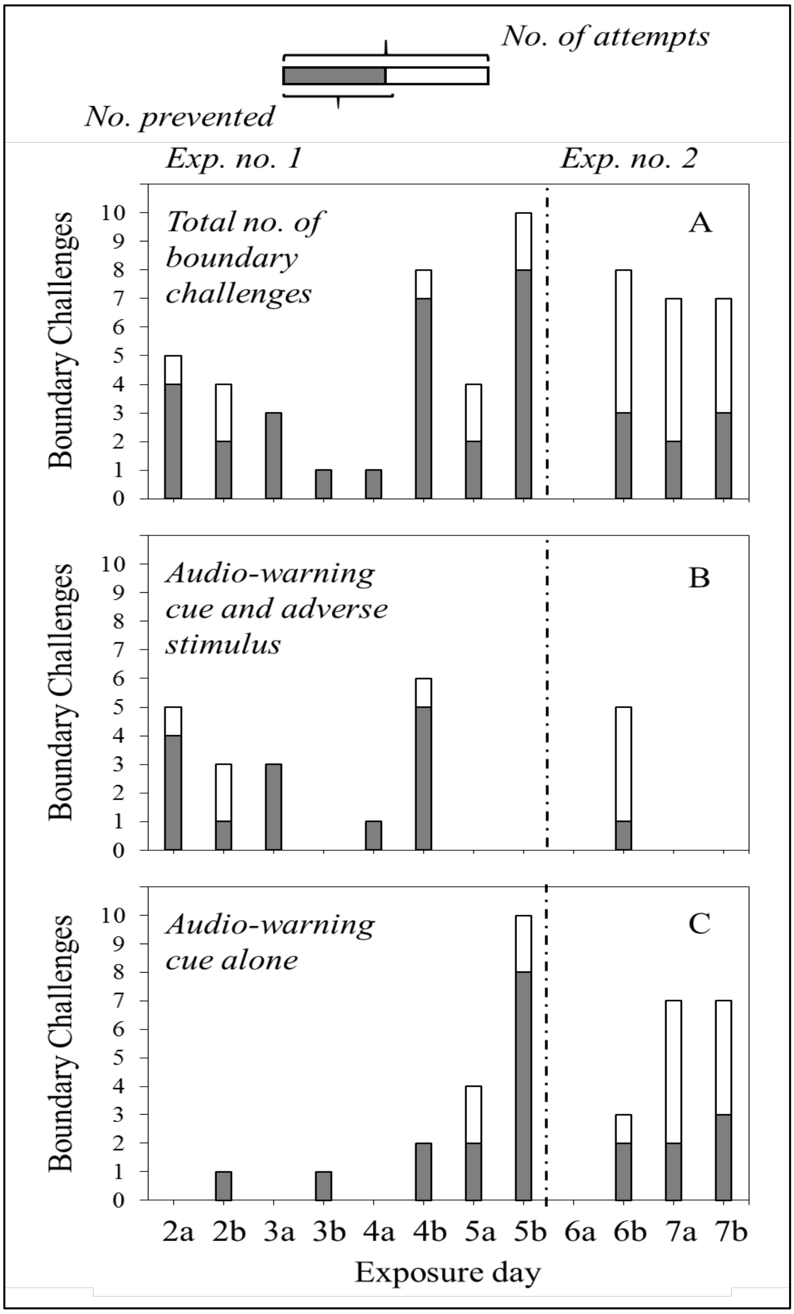

Figure 5.3: Total number of virtual fence (VF) boundary challenges made by dairy cows during Experiment 1, Day 2 – 5, and Experiment 2, Day 6 – 7 (A). Total number of boundary challenges made resulting in the combined cue-consequence stimuli (i.e. audio warning and adverse stimulus; B). Total number boundary challenges resulting in delivery of the audio-warning only cue alone (C). See also Table 5.1.

These power requirements varied between a 15 - 150 mA drain on the battery. The collars were observed to be accurate at *circa* 10 – 50 cm. In all cases, the stimuli recorded manually by the experimental operators was similar to the record stored within the cow-collar.

5.3.1 Warning Cue Assessment

It was established by observing cow reactions, that all animals responded to both of the combined stimuli options (i.e. audio warning and the adverse electric shock; tactile warning and the adverse electric shock), as the behaviour of all 12 cows noticeably changed on receipt of the stimuli. In most instances, cows initially halted and then ran forward across the VF boundary in response to both treatments. Upon the second boundary challenge event, when Group B animals received only a tactile warning stimulus, five (83.3%) animals displayed no alteration in behaviour. These animals did not halt, turn back, or move forward at a faster pace. However, five cows from Group A displayed a clear alteration of behaviour upon receipt of the audio stimulus. Therefore, it was considered that the audio warning was more effective than the tactile stimulus for inducing a behavioural change. Accordingly, only audio warnings were used in the subsequent experiments.

5.3.2 Experiment 1: The Training Protocol

The total number of VF boundary challenges made by the dairy cows decreased with each half-day of exposure during utilisation of visual cues (Days 2a–4a; Figure 5.3 A). Equally, few cows subsequently re-challenged the VF after receiving the audio warning-cue coupled with the adverse stimulus, while visual cues were present (Days 2a–4a; Figure 5.3 B, C). However, those which did were successfully retained by the audio warning cue (Days 2a–4a; Figure 5.3 C). Post Day 2a and 2b, the audio warning cue combined with the adverse consequence, and the audio warning cue alone, prevented all cows from crossing the VF boundary (Days 3a–4a; Figure 5.3). However, the number of boundary challenges made by cows increased upon removal of the visual cues (Days 4b–5b; Figure 5.3), while successful detention of cows within the VF decreased by up to 50% (Day 4b–5b; Figure 5.3).

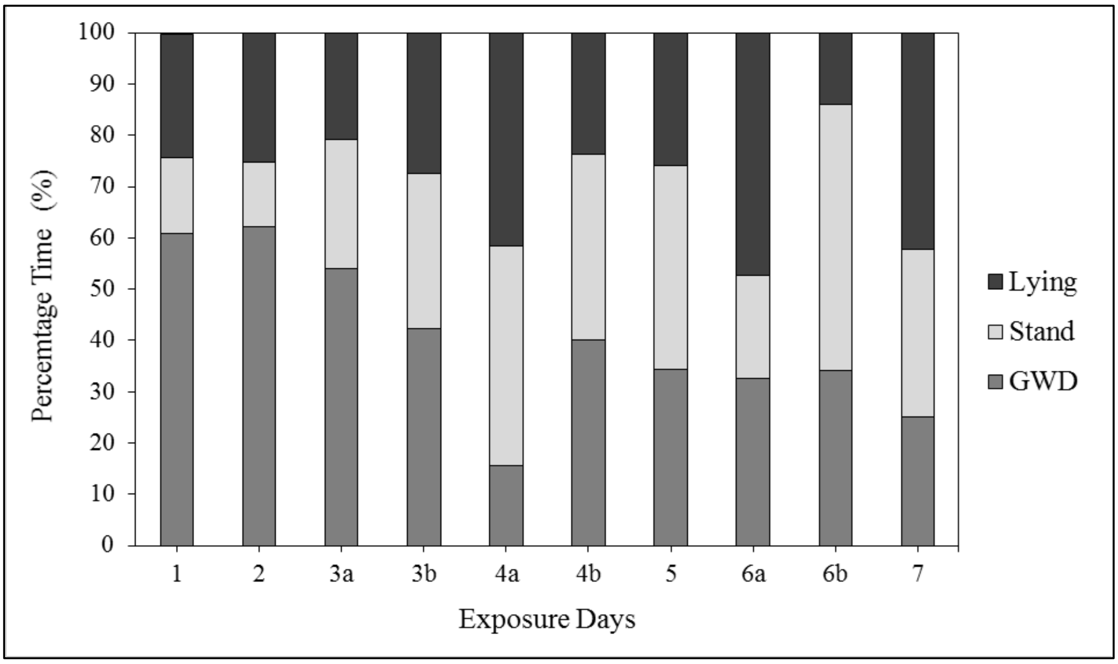

Figure 5.4: Observed dairy cow percentage time allocated to behaviours of 'GWD' (i.e. grazing, walking and drinking), Lying and Standing (see Table 5.2), throughout the duration of acclimation day (Day 1), Experiment 1 (Day 2 – 5), and Experiment 2 (Day 6 – 7). See also Table 5.1.

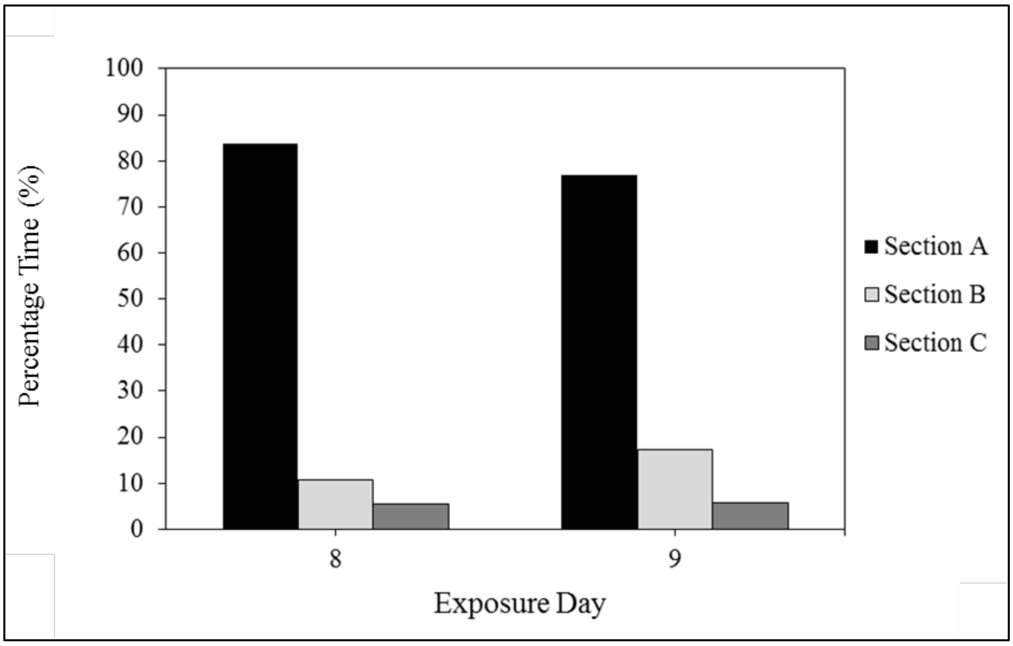

Figure 5.5: Observed dairy cow percentage time allocated to Sections A, B and C within Zone 3 over the six-hour experimental period (11:00 – 17:00) on Days 8 and 9, based upon 36 instantaneous scan samples per day.

While the number of boundary challenges decreased with each half-day of exposure during utilisation of visual cue, scan samples indicated that time spent GWD by the dairy cows also decreased, from *circa* 62% to 16% over this period (Day 2–4a; Figure 5.4). In particular, time spent standing increased between Days 2–4a, from *circa* 13% to 43%. However, time allocated to GWD increased to *circa* 40% of the observed dairy cow time budget, upon removal of the visual cues (Days 4b–5; Figure 5.4). Time spent standing remained high, *circa* 40%, when compared to 'Stand' times observed at the beginning of this experiment (Days 1–5; Figure 5.4).

5.3.3 Experiment 2: Boundary Relocation

Upon initial redeployment of the VF from Boundary A (Experiment 1) to Boundary B, highlighted to animals *via* utilisation of GSW as a visual cue, no boundary challenges were made (Day 6a; Figure 5.3A). However, the complete removal of visual cues resulted in an increased number of boundary challenges (Days 6b–7b; Figure 5.3A).

Scan samples indicate that cow GWD behaviour remained at moderately low levels upon redeployment of the VF boundary (Days 6a–7), while 'Lying' behaviour increased up to *circa* 47%, and time spent standing decreased to *circa* 20% (Days 6a; Figure 5.4). However, upon removal of the visual cue, observed 'Lying' behaviour greatly decreased to *circa* 14% of the cows' time budget, while time spent at 'Stand' greatly increased to *circa* 52% (Day 6b; Figure 5.4). On the last day of the experiment, time spent 'Lying' and at 'Stand' equated to 75% of dairy cow time budgets.

5.3.4 Experiment 3: Learning evaluation: Redeployment and Recollection of Cue-Consequence – Zone 3

To evaluate the extent to which dairy cows retained an awareness of the cue-consequence association when moved to a novel area, Group 3 cows were moved to Zone 3 for two days immediately post cessation of Experiment 2 (i.e. Days 8 and 9; Figure 2). In total, nine VF boundary challenges were made on Day 8, and ten challenges on Day 9. The audio warning cue successfully prevented cows crossing the VF boundary on only 22% and 20% of VF these challenges, respectively.

Overall, the cows spent *circa* 84% and 77% of their collective time budget within Section A of Zone 3 on Days 8 and 9, respectively (Figure 5). Cows displayed a similar behavioural budget of *circa* 33.5% GWD, 44% Lying; 22.5% Standing on both Days 8 and 9.

5.4 Discussion

Virtual fence technology can be a useful tool for those who need to restrict livestock movements. Here, our prototype VF system of a wearable cow-collar, linked to a server for the purpose of processing changeable user commands and redeployment of VF boundary lines in a user-friendly manner, was effectively utilised in a non-automated trial, upon a realistic intensive dairy farming scenario. Although only three cows were used per experimental unit, with animals incentivised to move beyond the VF boundary for improved foraging opportunities, the allocated spatial areas in Experiment 1 and Experiment 2 were in excess of normal stocking densities, e.g. *circa* 100 m^2 cow^{-1} at a DM availability of 1500 kg hectare^{-1}. This equates to approximately 2.6 cows/ha. However, provision of larger grazing areas is typical of low DM availability.

The VF system deployed in this study fully auto-saved all data with a time-stamped record and animal ID. This can be used to ensure all ethical and animal welfare procedures are adhered to, and represents an opportunity for greater *in situ* farm animal welfare monitoring. However, to ensure precise timing of stimuli application, further development of our VF system to prevent data collisions when multiple cow-collars simultaneously transmit data is required. Additionally, our data transmission infrastructure, communication network and wearable cow-collar, could be further developed and deployed for animal location tracking, motion sensing, health and welfare monitoring, and automated ID logging at milking parlour stalls. Equally, the communication network developed during this experiment could possibly allow for the deployment of a range of on-farm sensors.

VF systems rely on animals quickly associating a warning cue with boundary encroachment, and a subsequent adverse stimulus. While the VF system was successfully deployed, the response of the dairy cows to the proposed VF training regime was less than optimal. As reported by a number of studies (e.g. Umstatter *et al*., 2013; Koene *et al*., 2016, Campbell *et al*., 2019), we observed that an audio warning combined with a corrective stimulus can rapidly facilitate a cue-consequence association. The cows appeared to quickly associate visual cues with the boundary line of the VF. In particular, boundary challenges decreased over the duration of Experiment 1, when visual cues were present. However, upon complete removal of the visual cues, the number of boundary challenges greatly increased. In addition, at the beginning of

Experiment 2, with the reinstatement of a visual cue, no boundary challenges were made. Once again, however, upon removal of visual cues the number of boundary challenges increased. Similar rapidly learnt associations of visual cues and an adverse stimulus have previously been recorded in cattle (Umstatter *et al*., 2015b; Koene *et al*., 2016). In particular, Umstatter *et al*. (2015b) observed that once cows became familiar with the VF system, the animals appeared to use the visual cue of the perimeter cable for boundary orientation, rather than the audio warning cue. Accordingly, visual cues may provide for a stronger reinforcement than the audio warning. Notably, to facilitate cow familiarisation with a VF system, Koene *et al*. (2016) used an electric wire as a visual cue over a six-day training period. However, although Koene *et al*. (2016) discussed cow behavioural changes in relation to the VF system, no data concerning success of cow containment by the VF system was presented. Interestingly, in our study, the vibrating tactile warning stimulus did not induce a behavioural change for almost all of the examined cows. Overall, this may reflect an innate reliance of herd animals upon visual and audio cues for predator avoidance, and spatial orientation in relation to foraging opportunities and the location of the herd.

Despite the rapid pace at which the 'steps' of the training protocol progressed (e.g. visual cues, boundary redeployment, combined cue-consequence, or audio warning cue alone), the success of dairy cow containment within the designated zones, whereby animals were deterred from crossing the VF boundary, remained reasonably high during Experiments 1 and 2. Equally, the response of cows in Experiment 2 would suggest that redeployment of boundaries utilising visual cues is an effective method to convey boundary changes to cows. However, removal of the GSW resulted in several instances of cows crossing the VF boundary despite receiving full cue-consequence stimuli. Moreover, the boundary challenge behaviour of cows assessed in Experiment 3 suggest that the audio warning cue-consequence association will break-down within a novel area without some form of continual corrective reinforcement. Accordingly, the development and deployment of more robust experimental protocols are required to truly assess learning evaluation in dairy cows post training exposure. In addition, as is suggested by Koene *et al*. (2016), a simpler training protocol enacted over a longer duration may enhance cow cue-consequence formation. Also, the inclusion of a trained cow to a group of novice individuals may facilitate peer-to-peer learning. Smaller training zones, which would force cows to challenge the VF boundary in a more consistent and systemic way, may also be beneficial for improved cue-consequence association.

Individual cows are likely to learn at different speeds. Similarly, each cow will likely be exposed to the cue-consequence at different rates, as individuals will likely vary in their motivation to leave the inclusion zone (i.e. challenge the VF boundary). For example, greater grass availability within the inclusion zone may further reduce the number of boundary challenge attempts. Accordingly, strip grazing may place excessive pressure on the animals due to the limited grass availability in that system. Audio warning cues emitted from the cow-collar may be problematic for animals to associate with an exact VF boundary, due to their possible inability to pinpoint the locational direction to which the cue pertains. Equally, as the audio originated from the ventral of the animals neck, this may not support the learning process to avoid an area in front of the animal. This may explain some instances of VF boundary crossing documented by this study, whereby cows quickly moved forward rather than backward. Such a response has also been noted in other studies in which audio cues were used (Lee *et al*., 2007; 2009). Interestingly, as described by Lee *et al.* (2007), application of stimuli based the animal's directional movement rather than their exact location may allow cattle to learn the association between its behaviour of crossing a VF boundary rather than merely challenging the line due to spatial proximity. However, despite this, other mechanisms for the delivery of warning cues need to be examined. Further in-depth experimental work is required to evaluate if dairy cows truly learn the principle of the VF system, rather than simply display avoidance behaviour of a perceived threat. In more detail, Campbell *et al*. (2019) found that animals learned to respond to the audio cue, however, "this may have been socially-facilitated avoidance learning in addition to associative avoidance learning". The concentrated use of Section A within Zone 3 in our study, despite limited grass availably (240kg/DM/ha), suggested that the cows were uncomfortable grazing near or approaching the VF boundary. Although, as mentioned, the majority of boundary challenges during Experiment 3 failed to be deterred by the audio warning alone.

In addition, the audio warning cue was observed to have a contamination effect across the groups, whereby animals responded to audio cues broadcast from other individual's collars. Experimental operators recorded that in > 80% of cases, the audio cue emitted from one cow-collar noticeably affected at least one other individual within the groups, *via*, *inter alia*, head movement, cessation of rumination or grazing, and even flight response (i.e. running away). Incidentally, several instances of abnormal behaviour were observed. In particular, a number of individuals repeatedly pushed others in the direction of the VF. This may have been a display of dominance or an attempt to force other individuals to 'discover' a safe route of passage through the VF boundary line. A general decrease in grazing activity was observed across all three experiments following deployment of the VF system, a similar cow behavioural change was documented by Koene *et al.* (2016).

5.5 Conclusion

We effectively utilised wearable GPS technology to implement an instantaneously deployable and changeable VF system without the need for a perimeter cable. While our developed communications infrastructure was found to be robust, the response of cows to our VF system was less than optimal. Nevertheless, our results suggest that dairy cows kept within intensive strip-grazing systems can be quickly and successfully trained to recognise VF boundary encroachment *via* the cue-consequence association of an audio warning and adverse stimulus. However, it appears that without continued reinforcement this cue-consequence association can deteriorate. Furthermore, the negative behavioural effects experienced by the cows in the experiment are of paramount importance, as any future work will need to develop protocols to minimise these negative effects on animal welfare. Overall, our results are preliminary and further experimental work is required to truly assess best implementation protocols for VF system without visual cues. In particular, further evaluation of the time needed by dairy cows to learn to negotiate complex VF systems is required. The use of visual cues may be counterproductive, leading to competition in saliency of visual and audio stimuli. Equally, audio warning cues broadcasted from the cow-collar may be problematic for animals to associate with an exact VF boundary, due to their possible inability to pinpoint the locational direction to which the cue pertains. Therefore, other mechanisms for the delivery of warning cues need to be examined.

5.6 References

Abrahamse, P.A., Dijkstra, J., Vlaeminck, B. & Tamminga, S. (2008). Frequent allocation of rotationally grazed dairy cows changes grazing behaviour and improves productivity. *Journal of Dairy Science* 91, 2033–2045.

Adamczyk, K. (2018). Dairy cattle welfare as a result of human-animal relationship - A review. *Annals of Animal Science*, 18, 601-622.

Bishop-Hurley, G.J., Swain, D.L., Anderson, D.M., Sikka, P., Crossman, C. & Corke, P. (2007). Virtual fencing applications: Implementing and testing an automated cattle control system. *Computers and Electronics in Agriculture*, 56, 14-22.

Brunberg, E.I., Bøe, K.E. & Sørheim, K.M. (2015). Testing a new virtual fencing system on sheep. *Acta Agriculturae Scandinavica, Section A - Animal Science*, 65, 168-175.

Butler, Z., Corke, P., Peterson, R. & Rus, D. (2004). Virtual fences for controlling cows. In: Proceedings of the IEEE International Conference Robotics and Automation. 5, 4429-4436. New Orleans, LA.

Campbell D.L.M., Haynes S.J., Lea J.M., Farrer W.J. & Lee C. (2019) Temporary Exclusion of Cattle from a Riparian Zone Using Virtual Fencing Technology. Animals 9, 5, doi:10.3390/ani9010005.

Dillon, P. (2011). The Irish dairy industry-Planning for 2020. In: Proceedings of the Teagasc National Dairy Conference, Athlone, Ireland.

French, P., O'Brien B. & Shalloo L. (2015). Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. *Animal Production Science*, 55, 931-935.

Hedlund L., Løvlie H. (2015). Personality and production: nervous cows produce less milk. J. Dairy Sci., 98: 5819–5828

Howery, L.D., Bailey, D.W., Ruyle, G.B. & Renken, W.J. (2000). Cattle use visual cues to track food locations. *Applied Animal Behaviour Science*, 67, 1-14.

Jouven, M., Leroy, H., Ickowicz, A. & Lapeyronie, P. (2012). Can virtual fences be used to control grazing sheep? *The Rangeland Journal*, 34, 111-123.

Kennedy E., O'Donovan, M., McEvoy, M. & Murphy, J.P. (2009). Effect of restricted access time to pasture on dairy cow milk production, grazing behaviour and DM intake. *Journal of Dairy Science*, 92, 168–176.

Koene, P., Hogewerf, P. & Ipema, B. (2016). Dairy cow welfare: effects of a virtual fence on social behavior. Proceedings of Precision Dairy Farming conference. Leuwarden, the Netherlands. 21-23 June, 2016. 337-341. Eds C. Kamphuis and W. Steeneveld. Wageningen Academic Publishers.

Lee, C., Henshall, J.M., Wark, T.J. Crossman, C.C., Reed, M.T., Brewer, H.G., O'Grady, J. & Fisher, A.D., (2009). Associative learning by cattle to enable effective and ethical virtual fences. *Applied Animal Behaviour Science*, 119, 15–22.

Lee, C., Prayaga, K., Reed, M. & Henshall, J. (2007). Methods of training cattle to avoid a location using electrical cues. *Applied Animal Behaviour Science*, 108, 229-238.

Monod, M.O., Faure, P., Moiroux, L. & Rameau, P., (2009). Stakeless fencing for mountain pastures. In: Lockhorst, C., Groot Koerkamp, P.W.G. (Eds.), Precision Livestock Farming '09. Wageningen Academic Publishers, Wageningen, NL, 175–181.

Spitzer, M. (2017). Cyberkrank! Wie das digitalisierte Leben unsere Gesundheit ruiniert. Droemer Verlag, München, Taschenbuchausgabe, 432

Umstatter, C. (2011). The evolution of virtual fences: A review. *Computers and Electronics in Agriculture*, 75, 10–22.

Umstatter, C., Brocklehurst, S., Ross, D.W. & Haskell, M.J. (2013). Can the location of cattle be managed using broadcast audio cues? *Applied Animal Behaviour Science*, 147, 34-42.

Umstatter C., Bhatti S., Michie C. & Thomson S. (2014). Overview of Ultra-High Frequency technology in livestock farming and stakeholder opinions. In: International Conference of Agricultural Engineering, 6-10 July 2014, Zurich, Switzerland.

Umstatter, C., McSweeney, D., Foley, C., Halton, P., Heitkaemper, K., Schick, M. & O'Brien, B. (2015a). Labour costs of fencing in grazing systems and virtual fencing as a potential technological solution. In: Precision Livestock Farming ‘15, Milan, Italy, 80-92.

Umstatter, C., Morgan-Davies, J. & Waterhouse, T. (2015b). Cattle responses to a type of virtual fence. *Rangeland Ecology and Management*, 68, 100-107.

Wathes, C.M., Kristensen, H.H., Aerts, J.M. & Berckmans, D. (2008). In precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? *Computers and Electronics in Agriculture*, 64, 2-10.

Chapter 6: General Discussion

6.1 Overview

The research presented in this thesis has examined the potential for capturing reliable herbage mass (HM) measurement (i.e. Dry Matter Yield) in relation to compressed sward height (CSH), using an innovative, smart-device linked micro-sonic sensor enabled RPM. Conversion equations were also developed to support improved assessment, based on time of year and grass type were also developed. Further, the RPM was designed to link captured measurements with a geo-spatial dimension, thus allowing for improved real-time decision making and optimised allocation of the grazing area needed to fulfil daily herd requirements. In addition, grazing allocations can potentially be made through a GPS enabled Virtual Fence (VF) system, for which this study developed a working-porotype. Both of these devices confirm the rational of implementing ICT enabled tools for optimisation of pasture based farming.

Initially, an automated data capture tool for the collection of HM was developed. This device was based on the concept of the classic RPM, but was innovated through the application of micro-sonic sensor and on-board geo-locational technology. Moreover, the information captured by the RPM can be successfully transmitted to a smart-device, through a wireless Bluetooth connection, and displayed via an application interface. Communication and integration of the data within an online grassland management DST, e.g. PBI, was also successfully achieved.

Validation of the micro-sonic sensor enabled RPM was conducted to assess the accuracy and precision of the device for the measurement of CSH and geo-location positioning. The experimental results contained within this thesis, have shown this ICT based tool to be a substantial improvement, in respect to device accuracy and precision, in comparison to the existing state of the art technology, i.e. the ratchet counter RPM (Chapter 3). In addition, this thesis has further advanced the availability of dynamic algorithms for the conversion of CSH measurements to available HM, which incorporate significant grass growth variables, such as month effect, DM and grass type. These algorithms were integrated with the micro-sonic sensor enabled RPM, which is now commercially available to farmers, researchers and stake-holder organisations. It is envisaged that this device will further facilitate improved data collection and aid informed grassland management decision making, i.e. data driven decisions.

The second ICT grazing tool developed, as a result of this thesis, was a functioning prototype for a VF system. Here, the aim was to design a system that could be used to govern cow movement and grazing allocation through a containment boundary line, without the utilisation of conventional fencing systems. By integrating herd HM, captured with the micro-sonic sensor enabled RPM and with online DST's, it was envisioned that the VF system would guide and contain the herd within an allocated area with the correct herbage allocation (HALC), while also collecting geo-spatial information of individual cow movement. The development and validation of the communications network, hardware and firmware for the VF system was a considerable undertaking, though, the implementation of different proof of concept designs. Initially, a working-prototype of a VF system was assembled and installed. A detailed study of an animal training protocol was then conducted. However, it was not deemed to be successful as there were considerable issues regarding the cue-consequence association for the cows involved in the experiment (Chapter 5). Correspondingly, however, a significant change in cow behaviour was observed, altering from a large proportion of time grazing and/or ruminating to standing/lying inactive when the fence was turned on. This indicated that there was a negative effect on cow behaviour as a result of the VF being turned on.

Overall, however, the outcome of this thesis indicates that ICT has a significant role to play in the future of grazing production systems. The approach used in this study has allowed for the development of an ICT tool to aid farmers in their capability to manage grass effectively through improved management practices, through the provision of a real-time decision support tool. An important factor identified for technology adoption by pasture-based farmers, is the technology's ability to provide a financial return on investment, be it in terms of increased efficiency in relation to production, promotion of sustainability or direct financial benefit. Yet, the development of systems that return meaningful decision support to farmers will play a major role in grass-based milk production in the future and are predicted to improve financial return (Hostiou *et al*., 2017; French *et al.,* 2015).

This chapter will summarise the contributions and in particular discuss the insights from the results of the multi-disciplinary research of this thesis.

6.2 Thesis Findings

6.2.1 Micro-Sonic Sensor Enabled RPM

Until recently, grassland management was a 'best guess' scenario, with farmers quantifying the available herbage intuitively, predominantly through visual observation, and allocating grazing area to the herd accordingly (O'Donovan *et al.,* 2002a). This resulted in an underutilisation of grass, and often failed to capture the production performance of individual paddocks. Further, the lack of data-driven decision-making has resulted in significant losses to the farming enterprise in terms of efficiency, production and profitability (Hanrahan *et al.,* 2018). While this may not have created issues previously, with the modern expansion of herd size, the application of visual observation may now be insufficient for the enterprise to increase or even sustain profitability. Visual observation is a time-consuming and laborious task and can only be conducted by experienced operators (O'Donovan *et al*., 2002b). However, as the development of sensor technologies and ICT have progressed, the availability of pasture-suitable sensors have improved. Currently, farmers have a variety of technologies available for incorporation into ICT systems, such as grassland DST, grazing behaviour monitoring systems and cow-borne accelerometer for individual cow health monitoring, allowing for automated measurement of cow performance in a grazing system (French *et al.,* 2015). The missing link, to have a holistic approach to smart-grazing, is the automated data capture of herbage mass and subsequent allocation of grazing area. The development of ICT tools for intensive grass-based production systems could potentially be a major advancement for pasture-based farming practices (Eastwood *et al*., 2009). Increasing, data available to farmers in relation to the performances of key parameter, such as grass growth, soil quality, weather conditions, to aid increased production and improved on-farm decision making can have a positive effect for efficiency, and consequently, profitability.

Advisory services to farmer may also wish to consider developing knowledge and expertise on the data generated by sensor systems so that independent sources of advice and resources are available to farmers to improve the returns farmers make from investments into technology, and so drive the adoption of beneficial technology. In addition to DST's these could include centralised information sources on technology efficacy, standard operating procedures for using the technology and budgeting tools designed with technology investment appraisal in mind (O'Leary *et al*., 2018).

During the research, development and validation stages of the micro-sonic sensor enabled RPM product lifecycle, an assessment into the primary end users (grassland farmers) requirements was conducted. This assessment was completed through a comprehensive discussion with focus groups via the Knowledge Transfer (KT) networks throughout Ireland. The objective of the KT Programme is to inform and up-skill Irish farmers on best practice, to encourage efficiency and effectiveness of work and ensure they engage in a process of continuous improvement which will not only develop their enterprise but also contribute the overall development of the agri-food sector. As part of their commitment to the programme farmers attend regular meetings with their KT Group (Bohan *et al*., 2017). After discussion with the participants at these meetings the optimal product offering was derived. The primary requirement of the micro-sonic sensor enabled RPM was to allow novice and inexperienced grassland farmers a solution that could expedite the training and acquisition of technical knowledge required to make informed grassland decisions.

An initial proof of concept was conducted where each element including; the micro-sonic sensor, Bluetooth, GPS, microprocessor and the ease of mechanical assembly were assessed through feed-back groups. After design testing was deemed to be successful, the development cycle continued with the laying out of technical specification, and feature set requirements, incorporating the findings of the research from pasture producer focus groups. During the development process several prototypes were developed and thoroughly tested for inadequate performance, such as sensor malfunction. A performance report documenting “bugs” with the smart device application, device firmware and RPM mechanical assembly was produced for each protype and used to improve subsequent models. When a minimal viable product was produced, i.e. a product with enough features to satisfy early adopters, a selection of receptive farmers were selected to conduct an assessment on a working farm and provide feedback. Upon receiving their comments, further improvements were made. Before commercial release each element of the design was critically evaluated by a team, expert in the operation of similar devices, any recommendations deemed valid were implemented. Special attention was paid to the user experience and ensuring that the operational process was as practical and intuitive as possible. Ergonomics is the science that aims to learn about human abilities and limitations, and then apply this learning to improve people's interaction with products, systems and environments (Kadefors *et al*., 1993). Ergonomics were also evaluated in relation to the product weight, ease of operation and minimisation of operator fatigue. To facilitate this, alterations were made to the design, e.g. the grip, and build materials that reduced weight but maintained durability were selected.

6.2.2 Development of a Dynamic Algorithm for the Conversion of CSH

The study in chapter 4 confirms that a relationship between CSH and HM can be measured using an RPM, and that CSH can be used an indication of HM. However, from the literature, the relationship between CSH and HM can be described as variable, with RMSE values varying significantly (López-Díaz *et al*., 2011). In order to determine the relationship between CSH and HM, three equations were developed in this study. All equations were acceptable for use with RPM's, although Eq. 1 provided the simplest formula to implement as it is based on pre-cut CSH values alone. Yet, Eq. 1 was limited in its inability to incorporate the type of ryegrass measured and time of year into its assessment. Therefore, Eq. 1 was the least accurate or precise of the equations presented. Yet, Eq. 1 would still be acceptable for on-farm herbage assessment. However, both Eq. 2 and 3 incorporated ryegrass type and variation, in relation to time of year, allowing both equations more accuracy. Eq. 3 had the added advantage of including DM as a parameter. However, as the exact DM is not always available to the operator in the paddock at the time of measurement, Eq. 3 is less practical for most end-users.

From the literature, it had been difficult to achieve RMSE below 250 kg DM^{-1} ha^{-1}, with most equations generated accomplishing values closer to 300 kg DM^{-1} ha^{-1} (López-Díaz *et al.,* 2011). However, from the work completed in this study, equations have been generated that have been below 300 kg DM^{-1} ha^{-1}. The major development from the work of this thesis was the proof of concept that the smart device application which receives data from the micro-sonic sensor enabled RPM, can perform more advanced calculations in the conversion of CSH to HM that previously was not practically achievable. After further assessment, the most implementable equation developed from the study was Eq. 2 as the parameters necessary for its application were type of ryegrass and month, both of which are known to the operator in the field. Consequently, Eq. 2 has been combined with the micro-sonic sensor enabled RPM and is now being used commercially.

6.2.3 Design, Implementation, and Associated Dairy Cow Behaviour within a Virtual Fence System

One of the research aims of the thesis was the development of a working prototype of a VF system that could be evaluated within an intensive grazing system (Chapter 5). While existing VF systems can be deployed in rangeland environments, a wire free VF system does not currently exist for intensive grazing systems (Umstatter, 2011) However, VF technology for intensive strip-grazing would be a useful tool for farmers that need to control livestock movements remotely. This could also include the automated fetching of cows that are overdue for milking within an automatic milking system (AMS). Further applications of VF within AMS could facilitate the dynamic control of residency time of the cows in a block to ensure that distribution of milking's is optimised to minimise cow waiting for access to the AMS, thus, fully utilising the performance potential of AMS by maximising cow flow while minimising cow waiting times. In Chapter 5, our prototype VF system of a wearable cow-collar, linked to a wireless network communication system, for the purpose of transmitting and receiving user commands and redeployment of VF boundaries was developed and tested.

The development of the VF working protype system was a considerable task. In order to ensure cow comfort and welfare, several methods of attaching the VF collar to the cow were investigated. Central to this was the selection of the textile from which the collar strap was composed from. The material had to be durable, IP 67 rated, and allow for the protected transfer of cabling from the electronic housing unit to the probes which delivered of the electric stimuli. Cabling was also run from the DGPS receiver, which was placed at the top of the collar, to enhance the device localisation. An essential welfare element for consideration was to avoid abrasion between the textile and the cow's skin. Ultimately, a high-grade nylon strapping was selected, two pieces were stitched together to allow for the transport of cabling and the fabric was treated with water repellent solution. The textile did not compromise the integrity of the cow's skin, however, water ingress was still an issue in conditions of heavy and prolonged precipitation.

During the experiments conducted to test the efficacy of the training protocol design, every effort was made to minimise the stress caused to the cows and to minimise any adverse effect. During the experiment detailed data was collected by the VF system, such as stimulus delivery, cow location, device status was saved with a time-stamped record and animal ID to ensure no negative effects were experienced by the cows. The training protocol used can act as a starting point for the further development of training protocols for effective VF systems (Hedlund & Lovlee, 2015; Adamczyk, 2018).

6.3 Farmer Implications

The micro-sonic sensor enabled RPM has been commercialised and is now available for purchase by farmers, researchers and research organisations. Currently over 700 units have been sold across Ireland, UK, France, Germany, Belgium, Switzerland and other EU countries, as well as NZ, Australia and South Africa. This ICT tool allows an inexperienced grassland farmer, with minimal training, to capture high quality data in relation to the HM availability on farm, thus enabling informed real-time decision making on grassland management. The tool will capture pasture performance at farm and paddock level, allowing the user to make informed grassland decisions, both long-term and immediate real-time, such as identification of paddocks requiring reseeding, immediate assignment of HA to a herd, respectively. An important innovation of the micro-sonic sensor enabled RPM, is its ability to accurately map each paddocks' productive areas for grass growth, i.e. removing unproductive areas immediately adjacent to paddock entrances and excluding areas around water troughs. It is critical for a grassland manager to know the accurate area of productive grassland on the farm, as this will dictate stocking rate, HA allocation, and fertiliser use. A further feature within the smart-device application is the ability to virtually plot the fence position for deployment of new fencing lines, e.g. strip-grazing, with the appropriate allocation of grass required by herd. The associated smart-device application can then be used to navigate the operator to set-up the fence in the correct position, further minimising any guesswork by the farmer.

The development of equations for the prediction of HM from CSH (Chapter 4) in conjunction with the smart device application, affords farmers the ability to use a site specific formula for on-farm calculations of HM for a range of different conditions and periods of the year. This will increase the reliability of predicted HM for the farm, thus improving the grassland decision making process. Further, the integration of the micro-sonic sensor enabled RPM dataset with online DST's (e.g. PBI) is a significant first step in the creation of a whole farm smart grazing technology system. The amalgamation of datasets from several on farm sensor systems such as soil, weather, grass and cow performance allows farmers a deeper understanding of the interaction of the different parameters of production on the farm (French *et al.,* 2015). This collective data displayed via an easy-to-use interface would make for a major advancement of the decision support and performance reporting available to the farmer (Shalloo *et al*., 2018).

Although VF systems have recently become commercially available in both Norway and NZ, the primary focus of these systems is still rangeland management, and therefore, do not need the same resolution that an application within intensive grazing production systems would need. However, the use of VF would offer considerable advantages to intensive grassland farmers. For example, the potential flexibility offered would allow farmers to implement more dynamic grazing strategies(as it can be conducted remotely), particularly in the spring, as the VF system could be used to further allocate or restrict pasture as weather and ground conditions would dictate facilitating the use of a spring rotation planner (Hanrahan *et al.,* 2017).

The research conducted in this thesis has contributed to a recent trend of deploying sensor technology in the form of DST linked RPMs. In general, while it is expected that sensor technology will play a vital part in the sustainable future growth of the agricultural industry there are a few obstacles to first overcome (Shalloo *et al*., 2018). For the successful adoption of agricultural technology within the farming population, farmers must be made aware of the benefits that this technology can offer to their enterprise. To ensure the equipment is accurate and independently validated, it should come from an independent research organisation where the information disseminated to farmers is unbiased. Furthermore, while many sensor systems are intuitive to operate, farmers do need an appropriate level of understanding, but this is no more complicated than the operation of an average off-the-shelf smart device. From personal experience, during the set-up process of a new micro-sonic sensor enabled RPM with a farmer, the farmer had a good working knowledge of the system in under one hour. This level of training guarantees that the sensor was operated correctly, ensuring the accuracy of the data. Also, knowledge transfer in the interpretation of the results and the use of DST's to induce data driven decision making on the farm is imperative to the successful use of sensor technology. Another important element is farmer confidence in the accuracy of the technology. If there is skepticism about accuracy of the sensor results, then the farmer will not trust the data and most likely discard it. It is crucial that data is accurate and repeatable to ensure high levels of adoption. The high accuracy reported in chapter 3 of the data captured by the tool, combined with the real-time user feedback via the smart device application allows operators to ensure that the device is operating correctly, this encourages trust from the farmer.

6.4 Industry Implications

The ability of the micro-sonic sensor enabled RPM to capture an enhanced dataset (CSH, time, date, latitude, longitude and ambient temperature) offers commercial companies an opportunity to amalgamate this data with other sensor data being collected on farm. The consolidation of all these data streams will enhance DST outputs to framers. For companies that offer holistic farm management packages, it will greatly influence their market share and additionally, it provides them with valuable information on the utility of technology deployed, determining if on-farm sensors can add additional value to the product offering.

Although VF technology would have considerable advantages to an intensive grazing system and has the possibility to become a very successful product offering for a commercial agricultural industry, considerable development is necessary before a product solution can be commercially offered to the farming public.

6.5 Research Implications

The ability of the micro-sonic sensor enabled RPM to record each measure point with millimetre resolution while also including a geo-tag offers researchers invaluable insights into sward dynamics. Furthermore, the capacity to upload a .CSV file directly from the smart device significantly reduces the time and the possibility of error that was previously necessary for the transcription of the hand written record into a software package such as Microsoft Excel. Currently the micro-sonic sensor RPM system is being used by agricultural research organisations across Europe and NZ.

Further, automated geo-tagging of ground reference points can facilitate calibration of herbage evaluation from satellite aerial imagery. Integration with the communication network for the transmission of data from other in field sensor technology e.g. grass quality sensors. The application of any grass height measurement technique requires the operator to collect a sample size, within a pasture, that is sufficient to ensure that the variation in grass height and HM is accurately captured (Murphy *et al*., 2018). The smart device application associated with the micro-sonic sensor RPM, coupled with the available GPS technology, can facilitate assessment of intra paddock variations in HM therefore informing the operator when the necessary number of samples have been achieved. Inter and intra paddock DMY can be mapped and assessed to inform future fertiliser applications. Captured data can subsequently be uploaded to online DST's, which can allow for accurate pasture analysis and reporting of pasture performance.

In addition, these ICT tools can potentially be linked to other grassland technologies, to provide 'smart-farm' solutions through highly automated systems. For example, based on Yahya (2018) employing technologies such as drones, robotics, Internet of Things (IoT), vertical farms, artificial intelligence (AI), and solar energy, systems could use machine learning to automation decision making on farm and enact the decision. However is it important that care should be taken that fail safes are built in not to cause major issue due to an incorrect action being taken. Although the VF prototype developed and tested in this thesis does not have immediate commercial potential, the data transmission infrastructure developed during the experiment is now robust. This network can be used to facilitate communication between wearable cow-collars to monitor location tracking, motion sensing, health and welfare monitoring, and automated ID logging at milking parlour stalls (Bhargava *et al.,* 2018). The system can easily be adapted to integrate sensor systems that can transmit real time data to the base station and influence the actioning of parameters within an experiment. The VF system deployed in this study fully auto-saved all data with a time-stamped record and animal ID, ensuring all animal welfare standards were adhered too.

6.6 Future Work

Optimising the operation of the Micro-sonic sensor RPM

Currently, there is no definitive sampling protocol for the use of RPMs. Increased accuracy of the micro-sonic enable sensor RPM system could be achieved by development of a more robust sampling protocol. The development of a smart protocol that notifies the operator in real-time via the smart device application about the correct resolution and distribution of samples to be taken in the paddock would be of high utility to the operator as it could achieve labour saving, which is currently the key limitation to grass measurement. Consequently, this will result in a greater uptake in grass measurement, as well as ensuring that data collected is of high accuracy. The optimum sampling rate would be dependent on the heterogenicity and grass height variation within the sward.

The communications network and infrastructure developed as part of the micro-sonic sensor enabled RPM has the capacity to be used for ‘add-on’ sensors. An example may be represented by a sensor that can utilise infrared waves to analyse the quality and dry matter of sward and translate it to a smart device, with data being further transmitted to an online DST where it could be added to the parameters to allow for more data driven decision support. However, there is a considerable body of work in the development of the algorithms necessary for the conversion of these results to an actionable value that can be interpreted by the farmer.

Heterogeneity of HM within grass swards due to grass species, fertilizer application, period of the growing season, prevailing weather condition and clover content is recognised as a significant variable within literature but effects on the application of RPM operation are relatively unknown. A detailed investigation into the factors that influence heterogeneity would offer an insight to the development of the most advantageous sampling methodology. The ability of the micro-sonic sensor enabled RPM allows for the automatic acquisition of GPS data and compilation of all CSH data in a single .CSV file will allow for detailed statistical analysis of the data. An economic analysis, on the number of sampling strategies, to determine financial feasibility will be further advance our knowledge of grassland measurement.

Investigation Into Sward Parameters To Identify Useful Relationships

An extension of the study conducted in chapter 4 to explore if more sward parameters are available to measure that may influence the prediction of HM from CSH. Identifying new parameters may further strengthen the accuracy and precision of conversion algorithms.

Following on from the above, future development of the dynamic biomass prediction algorithms will be required. The extension of the experimental protocol to incorporate different experimental sites both in Ireland and internationally will be required to enhance the robustness of the algorithms produced. An experiment investigating the effect of sampling during the entirety of the grass growing season, various enterprises (i.e. dairy, beef and sheep production systems), and a broad range of cultivars will be necessary to further develop site specific algorithms. To accomplish this close collaboration with both domestic and international stakeholders and research institutes will be required for development and validation of new algorithms. Furthermore, localised algorithms can be produced and made readily available to the micro-sonic sensor enabled RPM smart device application.

In order to fully utilise the capabilities of the dataset generated by the micro-sonic sensor enabled RPM, CSH and geo-locational measurement should be integrated with a machine learning system and better statistical models capable of accounting for more variance created by farm environments. This should allow for detailed yield maps of the farm to be generated over time to assess the performance of specific areas of the farm, increasing the granularity of the data from paddock data to site specific data, i.e. 50cm^2 plots.

Future Research Necessary for the Successful Implementation of a Virtual Fence System

A significant challenge for VF technologies revolves around the efficient use of electrical power. This subject should be investigated in a multifaceted approach. The challenge would be to investigate high capacity power cells that could prolong operation, followed by fast charging technology allowing the VF collar to be charged via electrical induction transfer, (wireless charging) during milking or at a feed barrier. Furthermore, the opportunity to charge the collars by some means of renewable rower, kinetic, solar or heat transfer from the cow's own body heat. Finally, research into alternative communication networks that have a low power demand (i.e. Lora, Sigfox or Zigbee) and other power saving strategies on board the collar.

Currently US and EU government policy have allowed for the roll out of the 5G network. One of the features of a 5 GHz network is their ability to accurately pinpoint location and transmit high data volumes in a relatively low-energy fashion. A study investigating the feasibility of its application within VF technology could be very beneficial to the further progression of VF systems.

Given the sub optimal response of the cows to the VF training protocol developed in this study, it is important that future protocols are developed and tested based on research conducted in this thesis. The most important conclusion that is highlighted by the VF study in Chapter 5 is the adverse effect the VF has on cow behaviour, it is of paramount importance that future VF systems address the increase in cow stress levels associated with the VF system. In the study presented in this thesis, the effect of the VF system on dairy cow milk production was not investigated. It would be important that further studies investigate the effects of VF on milk yield.

Interfacing of Different on Farm Data Streams

Low utility of on-farm data in relation to analyses is an issue that needs to be addressed. Lyons *et al.* (2016) noted that progress on the usefulness of animal technologies is centred on their integration into decision support software, and combining data from different sources and processing information with powerful data analytics tools is difficult due to mutable data format standards. This highlights the need for the introduction of a common open-source and standardised data collecting procedure for on-farm sensor technology. This would allow for the seamless transfer of data between different DST systems instead of the current proprietary nature of device data.

6.7 Conclusion

The results of this thesis have demonstrated that ICT support tools can be can be highly useful for applications within dairy farming, particularly pasture-based farming. The precise and accurate estimation of HM and HA, combined with the fine resolution control of each cow with a VF system have the potential to reduce labour associated with fencing, optimise pasture utilisation, and subsequent cow milk production. Integration of DST systems and VF network infrastructure have been developed and further work will combine these technologies to advance the precision of grazing management in pasture based dairy systems.

This thesis has facilitated the development of a micro-sonic sensor RPM, and has shown that such technological advancements can enhance the accuracy and precision of grass measurement and data capture. Traditional methods of HM assessment only facilitated low resolution measurement. However the micro-sonic sensor RPM has accomplished millimetre accuracy and precision.

However, a major consideration to any future VF experimentation has to carefully investigate strategies to minimise cow stress. The level of stress needs to at a minimum be on par with conventional fencing systems.

6.8 References

Adamczyk, K. (2018). Dairy cattle welfare as a result of human-animal relationship – a review, Annals of Animal Science, 18(3):601-622.doi: https://doi.org/10.2478/aoas 2018-0013

Bhargava, K., Ivanov, S., McSweeney, D. & Donnelly W. (2018) “Leveraging Fog Analytics for Context-Aware Sensing in Cooperative Wireless Sensor Networks,”. Journal ACM Transactions on Sensor Networks 15(2):1-32.

Eastwood, C.R., Mata, G., Handcock, R.N. & Kenny, S. (2009) Evaluating satellite based pasture measurement for Australian dairy farmers. In: Precision Livestock Farming. C. Lokhorst and P.W.G. Groot Koerkamp (eds.), pp.183-190.

French, P., B. O'Brien & Shalloo, L. (2015) Development and adoption of new technologies to increase the efficiency and sustainability of pasture-based systems. Animal Production Science 55(7):931-935.

Hanrahan, L., McHugh, N., Hennessy, T., Moran, B., Kearney, R., Wallace M & Shalloo, L. (2018) Factors associated with profitability in pasture based systems of milk production. Journal of Dairy Science 101:1–12.

Hedlund, L. & Løvlie, H. (2015) Personality and production: nervous cows produce less milk. J. Dairy Sci., 98:5819–5828

Hostiou, N., J. Fagon, S., Chauvat, A., Turlot, F., Kling-Eveillard, X., Boivin, & Allain, C. (2017) Impact of precision livestock farming on work and human-animal interactions on dairy farms. A review. Biotechnologie, Agronomie, Société et Environnement 21(4):268-275

Kilbom, Å., Mäkäräinen, M., Sperling, L., Kadefors, R. & Liedberg, L. (1993) Tool design, user characteristics and performance: a case study on plate-shears. Applied Ergonomics. 24(3):221-230. ISSN 0003-6870, https://doi.org/10.1016/0003-6870(93)90010-7.

López-Díaz, J., A. Roca-Fernández, and A. González-Rodríguez. (2011). Measuring Herbage Mass by Non-Destructive Methods: A Review. Journal of Agricultural Science and Technology. 1:303-314.

Lyons, N., Eastwood, C., Rueb, B. D. & Kerrisk, K. (2016) Current and future adoption of milking related technologies on Australian and New Zealand dairy farms. pp. 445-450 in Proc. Int. Precision Dairy Farming Conf., Leeuwarden, the Netherlands.

Murphy, D.J., O'Brien, B. & Murphy, M.D. (2018) Development of an optimum grass measurement strategy for precision grassland management, In Proceedings of the European Grassland Federation General Meeting, Grassland Science in Europe, Sustainable Meat and Milk Production from Grasslands, 17– 21 June, Cork, Ireland, pp. 883–885.

O'Donovan, M., Connolly, J., Dillon, P., Rath, M. & Stakelum, G. (2002a) Visual Assessment of Herbage Mass. Irish Journal of Agricultural and Food Research, 41:201-211.

O'Donovan, M., Dillon, P., Rath, M. & Stakelum, G. (2002b) A Comparison of Four Methods of Herbage Mass Estimation. Irish Journal of Agricultural and Food Research, 41:17-27.

O'Leary, N., Ahrend, A., McDonagh, A., O'Brien, B. & Shalloo, L. (2018) A partial budgeting tool to assess investments in precision dairy technologies. In

Proceedings of the European Grassland Federation General Meeting, Grassland Science in Europe, Sustainable Meat and Milk Production from Grasslands, 17– 21 June 2018, Cork, Ireland, pp. 810–812.

Shalloo, L., O' Donovan, M., Leso, L., Werner, J., Ruelle, E., Geoghegan, A., Delaby, L. & O'Leary, N. (2018) Review: Grass-based dairy systems, data and precision technologies. Animal. 12(2):262–271

Umstatter, C. (2011) Review: The evolution of virtual fences: A review. Comput. Electron. Agric. 75:10-22.

Yahya, N. (2018) Agricultural 4.0: Its Implementation Toward Future Sustainability. Pages 125-145 in Green Urea. Springer. ISBN 978-981-10-7578-0

Appendix

Appendix A:

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Micro-sonic sensor technology enables enhanced grass height measurement by a Rising Plate Meter

D. McSweeney [a,b,*], N.E. Coughlan [c], R.N. Cuthbert [c], P. Halton [d], S. Ivanov [b]

[a] Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland
[b] Telecommunications Software & Systems Group, Waterford Institute of Technology, Waterford, Ireland
[c] Institute for Global Food Security, School of Biological Sciences, Queen's University Belfast, Medical Biology Centre, 97 Lisburn Road, Belfast BT9 7BL, Northern Ireland, United Kingdom
[d] True North Technologies, Unit 14, Shannon Business Centre, Shannon, County Clare, Ireland

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ABSTRACT

Globally, the Rising Plate Meter (RPM) is a device used to measure compressed sward height, to enable estimation of herbage mass. Despite improved farm management practices aided by a variety of technological advances, the standard design of a RPM has remained relatively unchanged. Recently, however, a RPM utilising a micro-sonic sensor, with digital data capture capability *via* a Bluetooth communications link to a smart device application, has been developed. Here, we assess the comparable ability of both a standard cumulative ratchet counter RPM and the micro-sonic sensor RPM, to accurately and precisely measure fixed heights. Moreover, as correct allocation of grazing area requires accurate geolocation positioning, we assess the associated GPS technology. The micro-sonic sensor RPM was significantly more accurate for height capture than the cumulative ratchet counter RPM. Overall, across all heights, the cumulative ratchet counter RPM underestimated height by 7.68 ± 0.06 mm (mean ± SE). Alternatively, the micro-sonic sensor RPM overestimated height by 0.18 ± 0.08 mm. In relation to a practical applications, these discrepancies can result in an under- and overestimation of dry matter yield by 13.71% and 0.32% kilograms per hectare, respectively. The performance of the on-board GPS did not significantly differ from that of a tertiary device. Overall, the wireless technology, integrated mapping, and decision support tools offered by the innovative micro-sonic sensor RPM provides for a highly efficacious grassland management tool.

1. Introduction

The development of electronic and data transmission systems continues to enable radical changes in agricultural practices worldwide [1]. Enhanced data capture, information and communication technologies have facilitated considerable improvements to the efficiency, effectiveness and productivity of various agricultural sectors [1,2]. However, these technologies remain substantially underutilised in modern

* Corresponding author at: Teagasc, Animal & Grassland Research and Innovation Centre, Moorepark, Fermoy, Co. Cork, Ireland.
E-mail address: diarmuidmcsweeney90@gmail.com (D. McSweeney).
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agricultural production systems [3]. Although smart farming systems may utilise these technological advancements to feed into automated management systems, incorporation of information and communication technologies into machinery, equipment, and sensors can also facilitate real-time decision support tools within non-automated systems.

The profitability of intensive pasture-based systems is reliant upon precise, accurate and timely grazing management strategies. Consequently, the implementation of precision data capture and communication technologies in relation to grassland management represents a considerable opportunity to enhance farm productivity and profitability [2,4,5]. Sward herbage mass (HM) can be utilised to inform efficient daily grassland management, *via* allocation of a sufficient grazing area to meet (but not exceed) the daily nutritional demands of grazing animals [6,7]. Moreover, regular estimation of paddock HM can be utilised to inform long term grassland management, to achieve optimal pasture utilisation and animal performance [6]. Currently, in Ireland, for example, farmers' use of grass measurement remains low; only *circa* 10% of dairy farmers conduct weekly grass measurements. Therefore, there exists considerable potential to increase grass measurement frequency and farmland productivity [5,8].

Traditionally, HM is determined by observer visual estimation. However, this method is highly subjective and prone to considerable inter-observer variability [9]. Although more accurate estimates of HM can be obtained from the sward weights obtained from clipped sample quadrats, this process is destructive and time intensive [10,11]. The Rising Plate Meter (RPM) is a grassland management tool utilised worldwide as a method of measuring compressed sward height (CSH). This technology is considered to be an accurate, precise, time efficient, and less labour intensive method for sampling HM [12,13], from which dry matter yield (DMY; i.e. the grass nutritional value) can be calculated. However, device accuracy can be affected by numerous factors, such as growth state of plants [14], season [15], species composition [16] and grassland management regime [17].

Despite many recent advances in various precision agriculture, data capture and communication technologies [3,1], the design and application process of RPMs has remained similar to that of earlier devices [12,16]. Most RPMs consist of an aluminium steel plate through which a one metre vertical shaft freely passes. When this shaft is lowered to ground level within a grass sward, the plate will rise (depending on grass height) relative to the shaft, and this distance is recorded on a cumulative ratchet counter mounted upon the device. The average CSH can then be calculated across multiple samples. The RPM is calibrated by relating the CSH readings of a number of sample quadrats to the DMY of these quadrats, cut to ground level.

In recent years, technological advances such as various plant sensitive sensors, Global Positioning Systems (GPS), Bluetooth connectivity, and low-power portable user interfaces (smart phones and tablets), have been used to improve farm management practices [1,3,5]. These data capture and communication technologies can likely be utilised to improve grass measurement and facilitate real-time decision support

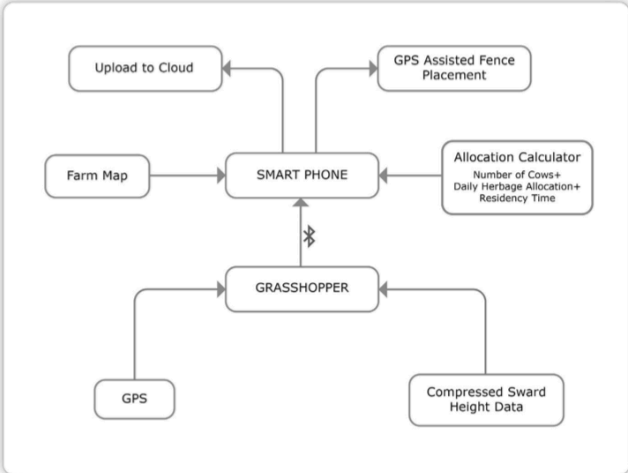

Fig. 1 – Infographic depicting the wireless communication process between the Grasshopper micro-sonic sensor Rising Plate Metre, global positioning system, and accompanying smart device application: (1) GPS and compressed sward height data are captured by the device; (2) this data is wirelessly transmitted to the associated smart device application; (3) a designated farm paddock area can be created, stored, or selected; (4) grazing intensity parameters can be inputted; (4) the Allocation Calculator can provide real-time decision support; (5) GPS assisted fence placement is provided; and (6), all data is consolidated within the smart device application, and can be wirelessly uploaded to Cloud computing and integrated smart farm databases.

in relation to grassland management, e.g. grazing allocations. Recently, a RPM utilising a micro-sonic sensor and digital data capture *via* a Bluetooth communications link to a smart device application has been developed (Fig. 1).

In essence, the time of flight- taken from transmission of a micro-sonic beam to return of the reflected echo signal is used to calculate the distance between the sensor and the sampling plate. The higher the upwards displacement of the sampling plate, the shorter the time between transmission and return of the reflected signal. The height of the object underneath the rising plate is then calculated. This measured height is then transmitted *via* Bluetooth to a smart device. This smart device also utilises GPS technology for paddock mapping and advisory (decision-support) grazing-area allocation based on animal in-take requirements. Although the cumulative ratchet counter RPM does not facilitate on-board GPS, users can use tertiary GPS enabled devices to manually map paddock areas.

Here we assess the accuracy and precision of RPM height measurements by both the standard cumulative ratchet counter, and the newly developed micro-sonic sensor unit. Given that correct allocation of grazing area requires accurate geolocation positioning, the on-board GPS technology of the newly developed RPM was compared to the GPS functionality of a representative and commonly used device, i.e. a smartphone.

2. Methods

2.1. *Experiment 1: Repeated accuracy of height data capture by two Rising Plate Meters (RPMs)*

A cumulative ratchet counter RPM (Jenquip; Filip's Manual Folding Plate Meter, New Zealand) and the micro-sonic sensor RPM (Grasshopper II; True North Technologies, Ireland) were used to measure standing PVC pipes (110 mm diameter; $n = 31$) of known heights, 25–178 mm [18]. The pipes were accurately cut to the specified length by a professional engineering company. All pipe sections were placed on a level surface, and each pipe was randomly chosen to be measured by the RPMs. A total of 30 height measures were recorded per pipe by each RPMs. The micro-sonic sensor RPM sample measurements were obtained first, immediately followed by the cumulative ratchet counter RPM.

Although the micro-sonic sensor RPM facilitated instantaneous digital capture and storage (.csv format) of measurement data, via a Bluetooth communications link between the sensor unit and an accompanying smart device application (Android operating system), the ratchet counter RPM data was recorded by hand, and height measurement calculated. Prior to data capture, the micro-sonic sensor was normalised to ensure a baseline of height zero was established. The cumulative ratchet counter does not require normalisation.

2.2. *Experiment 2: Geolocation performance of a Rising Plate Meter (RPM) utilising on-board and external GPS technology*

To assess device geolocation performance, latitude and longitude output was sampled directly upon a known georectified point that consisted of a brass rivet set in concrete footpath (IRENET control station D130, Ordnance Survey Ireland). Both the on-board GPS and GPS functionality of a representative smartphone device (Samsung S7 Edge SM-G935F OS 7.0), were simultaneously assessed (both $n = 30$). The smartphone was held directly over the handle of the RPM, which was positioned centrally and precisely upon the georectified point. To force the devices to continually recalculate their geolocation positioning, between each georectified sampling event, the experimental operators walked ($\geq$20 m) in a random direction away from the sampling point and recorded an additional non-test measurement with both devices. Although, mobile network accessibly may improve geolocation accuracy, in situ signal connection opportunities can vary greatly. Therefore, the smartphone mobile network connection was disabled during sampling. This required the smartphone to rely on satellite connections only when triangulating its geolocation, as does the RPM device.

2.3. *Statistical analysis*

All statistical analyses were performed using R v3.4.3 [19]. The difference between actual and recorded pipe heights was converted to proportional error and analysed using beta regression with the 'betareg' package in R [20]. This model incorporated both the effects of 'device' and 'pipe height', and their interaction. We transformed data to reduce extremes (0 s) prior to analysis [21]:

$$y_t = (y(n-1) + 0.5)/n \tag{1}$$

where y_t is the transformed output and n is the sample size.

As the captured geolocation data did not meet the assumptions of parametric tests, latitudinal and longitudinal error, relative to the georectified baseline point, were analysed between devices using paired Wilcoxon tests.

3. Results

Across all pipe heights, the cumulative ratchet counter RPM underestimated height (mean ± SE) by 7.68 ± 0.06 mm, with a maximum underestimate of 11 mm (Fig. 2A). Alternatively, the micro-sonic sensor RPM overestimated height by 0.18 ± 0.08 mm, with a maximum overestimate of 6 mm (Fig. 2B). Overall, the micro-sonic sensor RPM more accurately measured the pipe heights than the cumulative ratchet counter RPM ($z = 40.42$, $P < 0.001$; Fig. 2). Proportional recording errors were reduced significantly as pipe heights increased overall ($z = -9.08$, $P < 0.001$). The 'RPM × pipe height' effect was significant ($z = -16.60$, $P < 0.001$), reflecting greater differences in accuracy between the RPMs at lower pipe heights.

Neither of the devices differed significantly in their accuracy relative to a georectified point, across either latitudinal ($V = 346.00$, $P = 0.25$) or longitudinal readings ($V = 344.00$, $P = 0.26$. Both devices were consistently precise (Table 1).

4. Discussion

Accurate, precise and timely measurement of pasture HM is integral to effective implementation of optimal grazing management practices, particularly for farmers who rely on pasture as a primary feed source. This examination of a

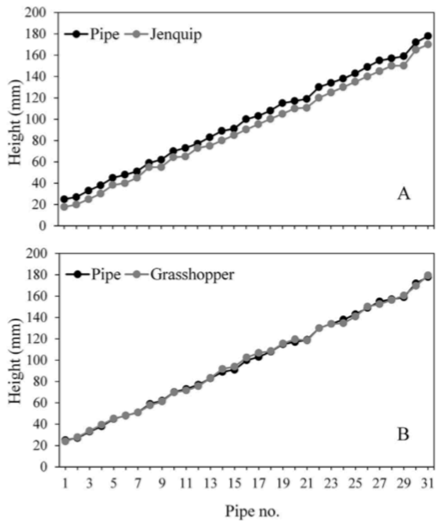

Fig. 2 – Comparable ability of the cumulative ratchet counter Rising Plate Metre (A: Jenquip), and micro-sonic sensor Rising Plate Metre (B: Grasshopper), to accurately measure fixed heights ($n = 31$). Standard error ≤ 1 in all cases.

recently developed micro-sonic sensor, has shown that such technological advancements can enhance the accuracy and precision of grass measurement and data capture. Until recently, the traditional cumulative ratchet counter design only facilitated measurement in increments of five millimetre (0, 5, 10 ...), however, the micro-sonic sensor RPM has accomplished one millimetre increments. Although the average underestimation of height by the cumulative ratchet counter RPM (7.68 ± 0.06 mm) is low, small errors in measurement can lead to larger errors over large pasture areas. At an average overestimate of 0.18 ± 0.08 mm, the micro-sonic sensor has been shown to be highly accurate.

As a brief practical example, in the case of the cumulative ratchet counter, if we assume height of 1 cm = 250 kg dry matter yield per hectare, then 250 kg × 0.768 cm = 192 kg of DMY. In a simplified gazing allocation regime of ten grazing assignments per year, an underestimation of 192 kg DMY ha^{-1} is multiplied by ten, giving an error of 1920 kg DMY ha^{-1}. Scaling upwards, across a 50 ha farm, annual underestimation is 50 × 1920 = 96,000 kg DMY ha^{-1}. If we assume the farm (50 ha) will grow 14,000 kg DMY ha^{-1}, then annual dry matter production is 700,000 kg ha^{-1}. The annual underestimation of DMY would be 13.71% (i.e. 960,000 ÷ 700,000). Contrastingly, inflation of grass height by 0.18 mm on the same hypothetical farm and grazing regime, results in an annual overestimated DMY of 0.32% when using the micro-sonic sensor RPM.

Underestimation of available DMY results in poor allocation of forage to animal requirements. In essence, the stocking rate could be increased to better utilise the available grassland and increase overall farm production and profitability. In Ireland, for example, one metric tonne of grass has a monetary feed resource value of €162–267 to dairy farmers [5,22], depending on milk market prices. Underestimation of available DMY essentially results in a loss of this forage value to the overall farm profitability.

The micro-sonic sensor RPM, by utilising on-board GPS technology, can facilitate digital data capture features not currently associated with other RPMs, which utilise a cumulative ratchet counter design. Use of the micro-sonic sensor RPM would enable the real-time paddock mapping, give fence plotting directions, and direct appropriate grass allocation for the herd. The integration of the smart device application would allow for real-time assessment of the palatability of grass swards by consideration of pre- and post-grazing residuals.

The micro-sonic senor RPM incorporates GPS technology to aid decision support of grazing area allocation in relation to animal in-take requirements and available sward HM. Although the cumulative ratchet counter RPM does not facilitate on-board GPS, basic GPS enabled smartphones can be used to map paddock areas within an integrated Geographic Information System (GIS) environment. However, while the GPS enabled RPM did not perform better than the smartphone, manual recording of GPS data and the associated cumulative ratchet scores is a time consuming process. Automatic capture of geolocation data by the micro-sonic sensor RPM, communicated through a Bluetooth communications link to a smart device application, and further presented in a single data file, represents a highly efficient method for real-time decision support. Further automated geo-tagging of ground reference points can facilitate calibration of herbage evaluation from satellite aerial imagery, and integrated with within a communication network for the transmission of data from other in field sensor technology.

The application of any grass height measurement technique requires the operator to collect a sample size within a pasture that is sufficient to ensure that the variation in grass height and HM is accurately captured. The smart device appli-

Table 1 – Mean latitude and longitude recorded by each device in relation to the known georectified sampling point (IRENET control station D130, Ordnance Survey Ireland).

Device	Mean latitude (±1SD)	Georectified latitude	Mean longitude (±1SD)	Georectified longitude
Grasshopper	52.16265970 (±5.145 × 10^{-5})	52.16264111	8.27727091 (±1.327 × 10^{-4})	8.27729278
Smartphone	52.16265204 (±6.827 × 10^{-5})	52.16264111	8.27726680 (±1.121 × 10^{-4})	8.27729278

cation associated with the micro-sonic sensor RPM, coupled with the available GPS technology, can facilitate assessment of intra paddock variations in grass growth and grazing pressure, while inter and intra paddock DMY can be mapped and assessed to inform future fertiliser applications. Captured data can subsequently be uploaded to on-line decision support tools, which can advise on the allocation of grazing areas. Although manual placement of fences is necessary at present, there is considerable potential to link the recommended grazing area allocation to fenceless farming (i.e. virtual fencing; [23]). Therefore, while the cumulative ratchet counter RPM has been a valuable tool for researchers and practitioners since its conception, the recently developed micro-sonic sensor RPM represent a significant advancement for grassland management. As the micro-sonic sensor device relies on algorithms to calculate DMY, rather than an operator performed manual calculation, the associated smart application can be directed to make formula corrections for seasonal and regional HM variation [24]. However, despite the substantial benefits, further research and development is required to improve application of this device (e.g. incorporation of grass quality measurement), and integrate the device into smart farming systems.

Conflict of interest

Paddy Halton is employed by True North Technologies Ltd., but this did not inappropriately influence the interpretation of the data or the reporting of the research results. True North Technologies Ltd. had no role in the collection, analyses, or interpretation of data, and in the decision to publish the results.

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Author contributions

DMS and NEC preformed the experiment, RNC analysed the data. PH advised on experimental design. All authors contributed to the writing the manuscript.

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REFERENCES

[1] Pivoto D, Waquil PD, Talamini E, Finocchio CPS, Dalla Corte VF, de Vargas Mores G. Scientific development of smart farming technologies and their application in Brazil. Inform Process Agric 2018;5:21–32.

[2] Zhang Y, Chen D, Wang S, Tian L. A promising trend for field information collection: An air-ground multi-sensor monitoring system. Inform Process Agric 2018;5:224–33.

[3] O'Grady MJ, O'Hare GMP. Modelling the smart farm. Inform Process Agric 2017;4:179–87.

[4] Wathes CM, Kristensen HH, Aerts JM, Berckmans D. Is precision livestock farming an engineer's daydream or nightmare, an animal's friend or foe, and a farmer's panacea or pitfall? Comp Electron Agric 2008;64:2–10.

[5] Dillon P. The Irish dairy industry-Planning for 2020. In: National Dairy Conference '11, The Irish Dairy Industry: To 2015 and Beyond. Cork, Ireland; 2011. p. 1–24.

[6] Hanrahan L, Geoghegan A, O'Donovan M, Griffith V, Ruelle E, Wallace M, Shalloo L. PastureBase Ireland: A grassland decision support system and national database. Comp Electron Agric 2017;1:193–201.

[7] Kennedy E, McEvoy M, Murphy JP, O'Donovan M. Effect of restricted access time to pasture on dairy cow milk production, grazing behaviour, and dry matter intake. J Dairy Sci 2009;292:168–76.

[8] Creighton P, Kennedy E, Shalloo L, Boland TM, O' Donovan M. A survey analysis of grassland dairy farming in Ireland, investigating grassland management, technology adoption and sward renewal. Grass Forage Sci 2011;66: 251–64.

[9] Tucker CJ. A critical review of remote sensing and other methods for non-destructive estimation of standing crop biomass. Grass Forage Sci 1980;35:177–82.

[10] Brummer JE, Nichols JT, Engel RK, Eskridge KM. Efficiency of different quadrat sizes and shapes for sampling standing crop. J Range Manage 1994;47:84–9.

[11] Adesogan AT, Givens DI, Owen E. Chemical composition and nutritive value of forages Chapter 11. In: T'Mannetje L, Jones RM, editors. Field and laboratory methods for grassland and animal production research. Wallingford UK: CABI Publishing; 2000. p. 263–78.

[12] Sanderson MA, Rotz AC, Fultz SW, Rayburn EB. Estimating forage mass with a commercial capacitance meter, rising plate meter, and pasture ruler. Agron J 2001;93: 1281–6.

[13] Soder KJ, Sanderson MA, Stack JL, Muller LD. Intake and performance of lactating cows grazing diverse forage mixtures. J Dairy Sci 2006;89:2158–67.

[14] Mosquera-Losada R, Gonzalez-Rodriguez A. Effect of annual stocking rates in grass and maize + rye system on production by dairy cows. Grass Forage Sci 1998;53:95–108.

[15] Bransby DI, Matches AG, Krause GF. Disk meter for rapid estimation of herbage yield in grazing trials. Agron J 1977;69:393–6.

[16] Castle ME. A simple disc instrument for estimating herbage yield. Grass Forage Sci 1976;31:37–40.

[17] Powell TL. Evaluation of weighted disc meter for pasture yield estimation in intensively stocked dairy pasture. New Zeal J Exp Agric 1974;2:237–41.

[18] McSweeney D, Foley C, Halton P, O'Brien B. Calibration of an automated grass height measurement tool equipped with global positioning system to enhance the precision of grass measurement in pasture-based farming systems. In: Grassland Science in Europe '15, Grassland and forages in high output dairy farming systems. The Netherlands; 2015. p. 265–67.

[19] R Core Development Team. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing; 2017.

[20] Cribari-Neto F, Zeileis A. Beta regression in R. J Stat Softw 2010;34:1–24.

[21] Smithson M, Verkuilen J. A Better Lemon Squeezer? Maximum-likelihood regression with beta-distributed dependent variables. Psychol Methods 2006;11:54–71.
[22] French P, Hanrahan L, Shalloo L. Principles of sustainable dairy expansion. In: Moorepark'15 Irish Dairying – Sustainable Expansion. Cork, Ireland; 2015. p. 9–14.
[23] Umstatter C. The evolution of virtual fences: A review. Comp Electron Agric 2011;75:10–22.
[24] Nakagami K. Effects of sites and years on the coefficients of rising plate meter calibration under varying coefficient models. Grassl Sci 2016;62:128–32.

Appendix B

Leveraging Fog Analytics for Context-Aware Sensing in Cooperative Wireless Sensor Networks

KRITI BHARGAVA and STEPAN IVANOV, Telecommunications Software & Systems Group, Waterford Institute of Technology, Ireland
DIARMUID MCSWEENEY and WILLIAM DONNELLY,
Waterford Institute of Technology, Ireland

In this article, we present a fog computing technique for real-time activity recognition and localization onboard wearable Internet of Things(IoT) devices. Our technique makes joint use of two light-weight analytic methods—Iterative Edge Mining(IEM) and Cooperative Activity Sequence-based Map Matching(CASMM). IEM is a decision-tree classifier that uses acceleration data to estimate the activity state. The sequence of activities generated by IEM is analyzed by the CASMM method for identifying the location. The CASMM method uses cooperation between devices to improve accuracy of classification and then performs map matching to identify the location. We evaluate the performance of our approach for activity recognition and localization of animals. The evaluation is performed using real-world acceleration data of cows collected during a pilot study at a Dairygold-sponsored farm in Kilworth, Ireland. The analysis shows that our approach can achieve a localization accuracy of up to 99%. In addition, we exploit the location-awareness of devices and present an event-driven communication approach to transmit data from the IoT devices to the cloud. The delay-tolerant communication facilitates context-aware sensing and significantly improves energy profile of the devices. Furthermore, an array-based implementation of IEM is discussed, and resource assessment is performed to verify its suitability for device-based implementation.

CCS Concepts: • **Networks** → **In-network processing**; *Location based services*; • **Computer systems organization** → **Sensor networks**; *Embedded systems*; • **Information systems** → *Location based services*;

Additional Key Words and Phrases: Fog computing, edge mining, cooperative wireless sensor network, localization, precision farming, testbeds

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Authors' addresses: K. Bhargava (corresponding author) and S. Ivanov, Telecommunications Software & Systems Group, Waterford Institute of Technology, WIT West Campus, Carriganore, Waterford, Waterford, X91P20H, Ireland; emails: {kbhargava, sivanov}@tssg.org; D. McSweeney and W. Donnelly, Waterford Institute of Technology, Waterford, Ireland; emails: diarmuid.mcsweeney@teagasc.ie, wdonnelly@wit.ie.

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1 INTRODUCTION

With increase in the number of Internet of Things (IoT) applications, localization of IoT devices—such as routers, smartphones, and various wearable technology—has gained significant importance for improving context-awareness and providing Location Based Services (LBS), such as navigation and target tracking [1]. Traditionally, use of Global Positioning Systems (GPS) has been proposed for realization of outdoor LBS. GPS-enabled Ceres tags [2], for instance, have been designed for livestock and farmland management in pursuit of Precision Farming. Besides detecting feeding rates and rumination for individual cows, these ear tags are used for mobility tracking to detect boundary breakouts and alert farmers in case of theft or an ambitious animal. Location awareness can, in turn, be used to control navigation of animals within farms for implementation of virtual fence [3]. While GPS technology is preferred due to ease of integration with IoT devices, majority of modern-day IoT solutions are replacing its use, owing to poor accuracy in bad weather conditions and crowded environments, as well as the energy-hungry nature of GPS receivers that negatively affects the battery-life of the IoT devices. Alternatively, use of Wireless Sensor Networks (WSN) has been proposed for localization [4]. The WSN-based techniques perform triangulation using range-based measures, such as Received Signal Strength (RSS) [5], to estimate the relative distance of mobile nodes from static, anchor nodes for localization. SmartBow [6], for instance, is an ear tag that has been designed to monitor mobility and rumination of dairy cows. The system uses a triangulation algorithm to calculate the x/y/z coordinates of cows with respect to a fixed access point (wallpoint). Although WSN-based techniques are low power when compared to GPS, they require the use of either additional infrastructure deployed on the farm or external cloud resources for data analysis. While the former increases the cost of system deployment and maintenance, the latter requires accessibility to cloud resources, which is typically limited in remote applications, such as in dairy farms. Furthermore, the performance and efficiency of these approaches is often affected by outdoor noise and the need for frequent time synchronization between devices.

Meanwhile, with advances in the design and computational capabilities of IoT edge devices (e.g., smartphones and sensors), localization on-board these devices (using data from built-in inertial sensors) has been suggested under the umbrella of Fog Computing [7]. Fog Computing is a novel paradigm that extends Cloud Computing to the edge of the network and proposes the use of existing compute and networking resources available at the IoT edge devices for real-time data analytics. In doing so, it aims at optimizing resource efficiency of the system while improving responsiveness to alerts through reduced cloud dependency. As such, fog-enabled localization on edge devices can potentially overcome limitations of the WSN-based approaches discussed above. Indoor localization on-board user smartphones, for instance, has been discussed in Reference [8]. The proposed technique detects activity states using inertial data obtained from user smartphones and performs activity-sequence-based map matching (ASMM) using Hidden Markov Model (HMM) to identify special points on the map as the user walks around the given topology. While quite a few smartphone-based localization techniques have been proposed to date (discussed in detail in Section 2), certain IoT applications designed using the WSN technology lack such relatively powerful edge devices. Current animal health monitoring systems in dairy farms, for instance, consist only of low-power animal-wearable sensor devices, such as Moomonitor [9] and HerdInsights [10]. These devices borrow principles of Fog Computing and operate autonomously (without continuous interaction with third-party components, such as gateways/PC or the cloud) to detect small-scale health or behaviour anomalies. These events are stored locally on the collar devices and transmitted to end-users in a delay-tolerant manner. Such devices, however, lack location awareness, owing to inadequate infrastructure in remote farms. To ensure real-time contextualization of sensor data in similar mobility tracking WSN that are deployed in remote applications, there is a need to design novel light-weight localization algorithms suitable for implementation on-board the low-power, resource-constrained sensor devices.

Edge Mining [11] is a Fog Computing approach that proposes implementation of light-weight data mining tasks on sensor devices. The approach aims at improving real-time responsiveness of these devices through on-board detection of application-related events. Furthermore, it improves the energy efficiency of devices through reduced packet transmissions to the cloud. ClassAct, an instance of Edge Mining, has been proposed for sensor-based activity classification. It is a decision-tree-based technique that uses acceleration data from wearable inertial sensors to estimate the user activity state. The activity states can, in turn, be analyzed to determine the location. However, ClassAct bases its prediction on low-order moments, such as windowed mean and variance at fixed time intervals. This limits its use in applications where the acceleration signal comprises of activity states with significant overlap in measurements. As such, while the values may come from different distributions, they exhibit the same feature values and cannot be distinguished from each other. To address this limitation, the authors have previously proposed Iterative Edge Mining (IEM) in Reference [12]. Unlike ClassAct, IEM classifies the activity states based on the histograms of acceleration measurements across multiple bins. It, thus, captures the distribution of signal and is particularly useful in scenarios where the overlap in states is significant and the mixture is imbalanced, i.e., the likelihood of occurrence for a certain activity is significantly higher, compared to the others. The histogram approach, however, incurs additional costs in calculating and maintaining the bins and may affect resource efficiency of the approach.

To overcome this limitation, in this article, we present an extension of the IEM approach, namely IEM2.0. The IEM2.0 algorithm replaces the histograms with Moving Windowed Minimum and Maximum features for analyzing the signal distribution and classification. The adaptation aims at reducing the program size and number of computations for activity classification, while capturing changes in the distribution. In addition, we propose a novel localization technique based on IEM2.0 that is suitable for execution on low-power wearable sensor devices. The technique makes joint use of two light-weight analytic methods—IEM2.0 and Cooperative Activity Sequence-based Map Matching (CASMM). First, the approach performs acceleration-based activity recognition using IEM2.0. The sequence of activities generated by IEM2.0 is then analyzed by the CASMM method to detect the location. CASMM exploits the spatial-temporal coherence of neighboring sensor devices for Cooperative activity-state detection by facilitating exchange of location updates between devices and extends the ASMM approach proposed in Reference [8] to map the resultant sequence of activities to a given topology and determine the location. Furthermore, we exploit the location information of devices and present a context-aware, event-driven communication framework for data transmission to the cloud. The framework is proposed to improve the energy efficiency of the devices by reducing unnecessary periodic transmissions. We illustrate the use of our IEM2.0-CASMM approach for activity recognition and localization of animals in a pasture-based dairy farm. While IEM2.0 is used for classification of high-level activity states of animals, CASMM is used to map the sequence of activities to an outdoor road network and estimate the location. The main contributions of the article can be summarized in the following:

- Adaptation of the IEM approach proposed in Reference [12], namely IEM2.0, for activity classification. IEM2.0 is proposed to reduce the number of on-board computations and improve resource efficiency of devices. It replaces the histogram-based approach with windowed feature analysis to capture the signal distribution while removing unnecessary calculations. The mathematical formulation of IEM2.0 is discussed, and its suitability over ClassAct is demonstrated for naturally occurring mixed Gaussian signals with different mixture proportions.
- Design of an end-to-end WSN system for IEM2.0-CASMM-based context-aware sensing and communication. The system performs activity recognition using IEM2.0 and adapts the existing ASMM technique for cooperative activity sequence-based map matching to allow on-board localization in outdoor environments. We also present theoretical models for calculating communication energy cost incurred by the devices and discuss an event-driven communication framework for optimizing energy consumption of the network.
- An application of our IEM2.0-CASMM approach for high-level activity recognition and localization of animals in a pasture-based dairy farm. An extensive evaluation has been carried out to analyze the accuracy and energy efficiency of our localization approach using real-world animal-mobility data collected during a pilot study in Kilworth, Co. Cork, Ireland. Moreover, a dedicated memory analysis has been carried out to assess the resource requirements of IEM-2.0 to verify its suitability for sensor-based execution.

The remainder of this article is structured as follows: In Section 2, we present the related work. In Section 3, we present our system architecture and discuss the IEM2.0-CASMM-based localization approach. We also describe our context-aware communication framework. In Section 4, we present our case study and the implementation of IEM2.0-CASMM in the context of dairy farming. We also discuss our experimental setup and field study. In Section 5, we present an extensive evaluation of our approach using real animal-mobility data, followed by a resource assessment of IEM-2.0 in Section 6. In Section 7, we conclude the article.

2 RELATED WORK

In this section, we review state-of-the-art IoT-based localization and discuss the recent advances in sensor-based analytics.

2.1 Localization Techniques

Several localization techniques have been proposed, to date, for IoT applications. Traditional IoT-based systems make use of GPS for outdoor localization due to their high accuracy as well as ease of integration of GPS receivers with IoT devices. For instance, GPS units have been used for localization of the elderly for assisted living in Reference [13]. While the approach achieves high accuracy, the system relies on a remote reasoning system for data analysis and may incur delay in getting insights due to the intermittent Internet connectivity. Moreover, the use of GPS receivers coupled with the frequent data transmissions may negatively impact the lifetime of the devices. Alternatively, the use of cellular systems has been proposed for trajectory tracking. In Reference [14], for instance, the system uses cellular technology to estimate the coarse location of mobile devices through signal trilateration. This information is combined with stationary state detection and HMM-based algorithms to decipher the most probable path. The performance of such a system, however, is affected by low sampling frequency and may result in errors ranging to a few kilometers. A digital map-matching system called SnapNet [15] has been proposed to improve the location accuracy of cellular-based systems. The system implements an incremental HMM algorithm to account for the noise in the input data and uses digital map hints to enhance the accuracy of the estimated road segments. The use of such systems, however, is limited to scenarios with reliable cellular networks. In Reference [16], a Wi-Fi-based localization approach has been discussed. The approach uses commodity Wi-Fi (Intel 5300) to estimate the doppler velocity and angle of arrival measures for localization purposes and incurs an error as low as 35cm. The performance of Wi-Fi-based localization systems, however, is usually affected by radio signal noise, making it unsuitable for outdoor environments.

Alternatively, the use of WSN for localization has also been proposed. In Reference [17], for instance, the authors present a light intensity-based indoor positioning system that performs predictions using RSS measures within WSN. Another study in Reference [5] investigates the feasibility of RSS-based sensor node localization in well-defined outdoor topology. Such range-based measures, however, often exhibit a low signal-to-noise ratio, thus affecting the quality of prediction. An experimental evaluation of WSN-based localization has been carried out in Reference [4]. Alternatively, with advances in embedded sensor technology, the use of Pedestrian Dead Reckoning (PDR) systems has been proposed for localization purposes. PDR systems use mobility data (e.g., acceleration,velocity) from built-in inertial sensors in user wearables/smartphones and calculate displacement to get the current location. The authors in Reference [18] present a PDR system that uses 8 Inertial Motion Units (IMU) worn on the body and a force sensor worn under the feet to capture joint movements for user localization. Another instance of a PDR system has been discussed in Reference [19]. The system presents a blind localization algorithm that combines data from built-in inertial and acoustic sensors in user smartphones using a maximum likelihood estimator to gauge the location of the smartphone. Standalone PDR systems, however, often accumulate errors due to drift with walking distance over time. To overcome this issue, assisted-PDR approaches have been proposed. In Reference [20], a PDR system is accompanied by iBeacons and the Kalman-Filter-based calibration algorithm is used to correct the drift. A PDR-based ASMM technique has been proposed for indoor localization in Reference [8]. The system performs low-level activity recognition, such as turning or walking up and down different floors, using built-in inertial sensors in user smartphones as a user walks to special points, such as corners, elevators, escalators, and stairs. The sequence of activities is then used to establish the user's trajectory and, in turn, mapped to an indoor road network for accurate positioning. The ASMM approach presents a cost-effective solution for indoor localization, as it requires minimum interaction with external third-party components.

In this work, we present our IEM2.0-CASMM-based PDR system for real-time localization. The approach takes as input acceleration data from built-in inertial sensors in wearable devices and performs decision-tree-based activity recognition using the IEM2.0 algorithm. As compared to the existing techniques, IEM2.0 is light-weight and suitable for implementation on-board low-cost sensor devices. The sequence of activities generated using IEM2.0 is then analyzed by the CASMM module for localization. CASMM is a cooperative extension of the ASMM approach discussed in Reference [8]. At first, the approach implements cooperative computing via collective participation between co-located devices to improve accuracy of classification on individual devices. Next, if a change in activity state is observed for any device, then ASMM is performed to map the sequence of activities to a given outdoor topology for localization. While HMM is used to implement ASMM in Reference [8], we replace this approach with a light-weight window analysis using a threshold $\mathcal{T}$ to ensure suitability for sensor-based execution. The two techniques are discussed in detail in Section 3.

2.2 Sensor Analytics

With increase in the number of IoT devices, huge amounts of data is periodically created and uploaded on the cloud for analysis. Such data abundance (typically referred to as "big data"), however, burdens the existing cloud resources and causes latency in getting insights into the data. Subsequently, the Fog Computing paradigm has been proposed to shift certain intelligence from the cloud towards the data sources, i.e., the network edge devices [21]. The use of compute and network capabilities available at these devices would allow localized reduction of data within the network to not only optimize the use of existing resources but also improve the responsiveness of the IoT system by reducing dependency on the cloud [22]. As mentioned earlier, while the use of IoT edge devices (e.g., network switches, smartphones) as fog agents has widely been proposed, recent studies have further brought down the computations to sensor devices. Owing to improvements in the computational capabilities of sensor devices conventionally limited to sense and send, the tasks designed for these devices today incorporate certain sophisticated data analytics. For instance, Data Fusion within WSN has been proposed in Reference [23] to reduce redundancy in overlapping data and improve coverage. Another study in Reference [24] suggests the mapping of an Artificial Neural Network (ANN) onto WSN for the design of "Smart Furniture." The authors in Reference [11] propose Edge Mining techniques to perform data mining on-board sensor devices. Edge Mining forms the basis of our activity classification approach, IEM2.0, and is discussed in greater detail below.

Edge Mining [11] is a Fog Computing technique that suggests the implementation of lightweight data mining tasks on sensor devices. It adopts the principles of the *Spanish Inquisition Protocol* (SIP) [25] that proposes transmission of only the unexpected information from the network to a sink (gateway). SIP converts the raw data from sensors into an application relevant state that is considered significant and reported by the sensor only if it cannot be predicted using the past estimates. Three instances of Edge Mining have been discussed based on generalized SIP—Linear SIP (L-SIP), Bare Necessities (BN), and ClassAct. L-SIP defines the application state as the point-in-time value and the rate of change. BN represents the state as a distribution of data across non-overlapping bins where each bin defines a possible outcome [26]. ClassAct is a decision-tree-based classifier. It takes as input raw sensor data and encodes the application state as a probability distribution over a given set of states. The use of ClassAct has been shown for identification of low-level activities, such as sitting, standing, and walking, in Reference [27]. While the system achieves a high classification accuracy, the classification is performed using low-order moments, such as windowed mean and variance at fixed points in time. This approach inevitably leads to classification errors while separating signals (time-variant data reflecting a particular behaviour, such as acceleration while walking and standing) for which measurements have similar mean and variance though come from different distributions. While the use of higher moments (e.g., skewness and kurtosis) may help in identifying the different states, their calculation is computationally complex for the sensor devices.

IEM has been previously proposed by the authors in Reference [12] to overcome the limitation of ClassAct approach. IEM is a decision-tree classifier that is designed as the superimposition of two Edge Mining algorithms—BN and ClassAct. First, IEM runs the BN algorithm to convert raw sensor measurements into a distribution across a set of non-overlapping and exhaustive bins, where each bin represents a range of values that the variable can take. The distribution is smoothed over the past readings using a decay factor γ on account that no sudden changes occur in the activity state. Next, the percentage change in distribution is estimated. If the change exceeds a threshold ε, where $0 < \varepsilon < 1$, the distribution for all bins is fed as input to the ClassAct algorithm for activity-state recognition. By considering the signal distribution as input to the classifier (as opposed to windowed mean and variance), IEM captures the nature of the signal over time and thereby addresses the limitation of ClassAct. The performance of IEM has been evaluated for classifying low-level activities, such as walk and stand in Reference [12]. While IEM is shown to achieve an accuracy of 95% with very low frequency of computations, the histogram-based implementation (inspired

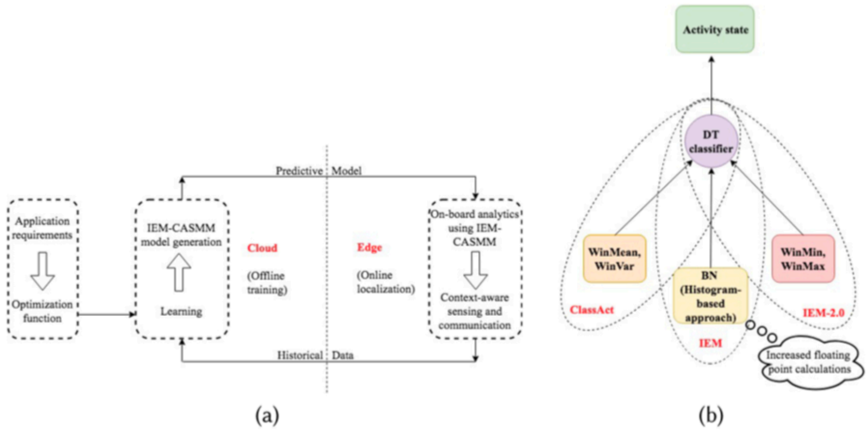


Fig. 1. (a) System architecture (b) ClassAct-, IEM-, and IEM-2.0-based classification.

by the BN algorithm) requires multiple floating-point operations to maintain the bin counts and distribution. Based on the selection of bins, this may negatively affect the resource efficiency of the algorithm for sensor-based execution. In this work, we discuss an adaptation of IEM that is more suited for implementation on sensor devices (Section 3.1) and evaluate its performance for high-level activity recognition for dairy cows. An array-based implementation of the algorithm is also discussed in Section 6 to evaluate the resource requirements.

3 IEM2.0-CASMM FOR ON-BOARD LOCALIZATION

Figure 1(a) illustrates the architecture of our IEM2.0-CASMM-based localization system. As can be seen, the system operates in two phases—offline training phase on the cloud and online localization phase at the edge. While the IEM2.0-CASMM model is light-weight and suitable for sensor-based localization, training the model is a compute-intensive task and is, therefore, carried out offline on the cloud. In the training phase, at first, historical data is collected from in-built inertial sensors in wearable devices and analyzed to extract suitable feature(s) for classification. Then, (un)supervised learning is performed to train and test the IEM2.0 and CASMM models for the given application scenario. IEM-based classifier (*DT*) is generated for different values of input parameters. The *DT* is used to analyze the acceleration data and identify the activity state. The sequence of activities generated by IEM is then analyzed by the CASMM method for map-matching-based localization. CASMM performs cooperative analysis between neighboring devices (considered as a coalition) by allowing exchange of location updates to improve accuracy of individual predictions and maps the updated sequence of activities to a given topology for identifying the location. The performance of CASMM is evaluated for different coalition sizes. Based on the performance evaluation and a given optimization function (e.g., maximizing location accuracy or minimizing energy consumption) that is derived from application requirements, the values for input parameters for IEM2.0-CASMM are fixed (i.e., *windowSize*, ε, and coalition size). The optimal performing model is then transferred onto the sensor devices for on-board analysis. In the online phase, IEM2.0-CASMM is executed to analyze the periodically sensed acceleration data for real-time activity recognition and localization. The estimated location is combined with data from other sensors (such as temperature, humidity) to facilitate context-aware sensing and communication. An instance of this architecture is discussed for localization of dairy cows in Section 4 (depicted in Figure 6). The IEM2.0-CASMM model is suitable for implementation on-board animal-wearable devices and allows for real-time context-aware sensing as the cows move around the farm. We assume prior knowledge of the farm topology for the CASMM module. Furthermore, as CASMM assumes presence of co-located or coherently moving devices for coalition-based cooperation, we consider conventionally milked dairy cows that move together in a herd between parlour and paddocks. Note, however, the CASMM approach extends easily to scenarios where devices move independently: for instance, in case of automatic milking wherein dairy cows may follow different milking cycles, by forming dynamic coalitions on the move (as discussed in Section 3.2). The calculation of overhead while setting up coalitions is beyond the scope of this work. In the remainder of this section, we present a detailed description of the two analytic approaches and our context-aware, event-driven communication framework.

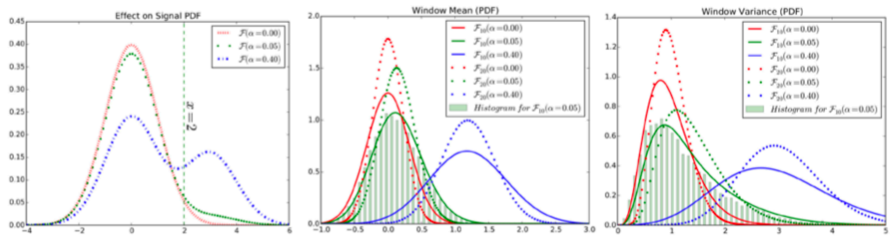
3.1 Iterative Edge Mining (IEM)

IEM2.0 is an adaptation of the IEM approach, which replaces the histogram-based analysis with Windowed Minimum and Maximum ($winMin$, $winMax$) features for activity-state classification. The moving window analysis examines the temporal patterns present within the signal and captures the variability in distribution of values over time. The use of these features ensures sensitivity to minute changes in distribution of sensor measurements while reducing the unnecessary floating-point operations. This, in turn, improves the efficiency of the algorithm, making it suitable for increased range of IoT devices and applications. Here, the window size is an input parameter that accounts for smoothing over the historical data similar to the decay factor γ used in histogram-based IEM (discussed in Section 2.2). Classification is performed only if the percentage change in either of the feature values exceeds the threshold ε, where $0 < \varepsilon < 1$. When it comes to floating-point operations, IEM-2.0 requires only $\geq$ and $<$, as opposed to the floating-point division and multiplication (e.g., histogram estimation, smoothing) that are additional requirements of the previously proposed IEM technique. The difference between ClassAct-, IEM-, and IEM-2.0-based classification is depicted in Figure 1(b). We present the mathematical formulation of IEM2.0 and illustrate its suitability over ClassAct for normal and mixed Gaussian distributions in the next section. We consider these signals owing to the nature of real-world acceleration data collected for different activity states as seen in this study (see Figure 15).

3.1.1 Gaussian Mixtures and Their Impact on ClassAct Classification. Consider signals S_{norm} and S_{mix} for which values are i.i.d. and come from a normal Gaussian distribution $p_{norm}(x) = \mathcal{N}(x, \mu_1, \sigma^2)$ and a two-component Mixed Gaussian distribution, respectively, where x represents sensor measurements. The first component of the mixture follows the same normal distribution as S_{norm}, while the second component follows a normal distribution with the same variance σ^2 but larger expectation $\mu_2 > \mu_1$. The samples x are drawn from the first and second components with probabilities $1 - \alpha$ and α, respectively, where $\alpha < 0.5$ (i.e., dominance of the first component). Accordingly, the distribution of S_{mix} values has the probability density function (PDF) expressed here:

$$p_{mix}(x, \alpha) = (1 - \alpha) \cdot \mathcal{N}(x, \mu_1, \sigma^2) + \alpha \cdot \mathcal{N}(x, \mu_2, \sigma^2). \tag{1}$$

Naturally, both S_{norm} and S_{mix} can be treated as representatives of the same parametric family $\mathcal{F}$ of signals, where values come from distributions with PDF specified by the Equation (1) for different α-values. In a way, α describes the impact of minor component on the overall value distribution. Figure 2(a) illustrates the effect of α on the signal values and their distribution (generated using Equation (1)) for $\mu_1 = 0$, $\mu_2 = 3$, and $\sigma = 1$. As expected, $\mathcal{F}(0.00)$ produces the normal signal S_{norm}. As α increases, the impact becomes more apparent (e.g., $\mathcal{F}(0.05)$) and eventually makes the signal



(a) (b) (c)

Fig. 2. Gaussian Mixture Effect and its impact on (a) Signal distribution (b) Win mean (c) Win variance.

bi-modal (e.g., $\mathcal{F}(0.40)$).[1] This directly impacts the precision with which samples of $\mathcal{F}(0.00)$ (i.e., normal distribution) can be separated (e.g., using windowed mean and variance as in ClassAct) from samples of other, truly Mixed Gaussian elements of $\mathcal{F}$ (i.e., $\alpha > 0.00$). For a fixed $\alpha \in (0, 0.5)$, an arbitrary window $\mathcal{F}_n(\alpha)$ of n consecutive samples from $\mathcal{F}(\alpha)$ will include exactly $n - i$ and i values from the major and minor components with probability

$$P(\mathcal{I}(\mathcal{F}_n(\alpha)) = i) \quad = \quad C_n^i \cdot \alpha^i \cdot (1-\alpha)^{n-i}, \tag{2}$$

where $\mathcal{I}$ is an indicator function that shows the number of values from the minor component of $\mathcal{F}_n(\alpha)$ window. Under the condition $\mathcal{I}(\mathcal{F}_n(\alpha)) = i$, the window can be analyzed as if it consisted of n independent normal variables. Therefore, conditional PDFs for windowed mean and variance of these variables equates to

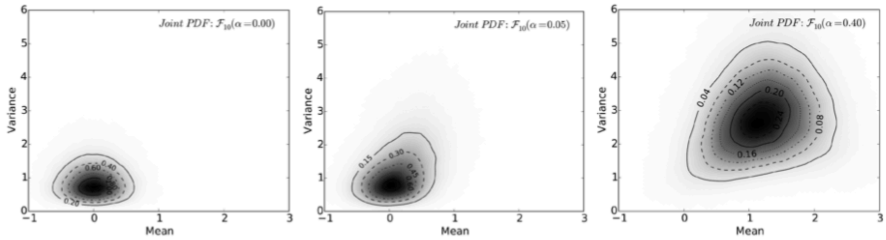
$$\begin{aligned} P(E(\mathcal{F}_n(\alpha)) = x |\, \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \quad &= \quad n \cdot N(n \cdot x,\ (n-i) \cdot \mu_1 + i \cdot \mu_2,\ n \cdot \sigma^2), \\ P(Var(\mathcal{F}_n(\alpha)) = x |\, \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \quad &= \quad n \cdot \mathcal{X}^2(n \cdot x, n, (n-i) \cdot \mu_1^2 + i \cdot \mu_2^2), \end{aligned} \tag{3}$$

where $\mathcal{X}^2$ is a non-central chi-squared distribution. Here, to simplify the formulae, we deliberately make use of the fact that all of the normal variables are uni-variate with $\sigma^2 = 1$ (see Figure 2). Subsequently, using Equations (2) and (3), the overall probability function of windowed mean and variance can be calculated as

$$\begin{aligned} P(E(\mathcal{F}_n(\alpha)) = x) \quad &= \quad \sum_{i=0}^{i=n} P(E(\mathcal{F}_n(\alpha)) = x |\, \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \cdot P(\mathcal{I}(\mathcal{F}_n(\alpha)) = i), \\ P(Var(\mathcal{F}_n(\alpha)) = x) \quad &= \quad \sum_{i=0}^{i=n} P(Var(\mathcal{F}_n(\alpha)) = x |\, \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \cdot P(\mathcal{I}(\mathcal{F}_n(\alpha)) = i). \end{aligned} \tag{4}$$

Note, the above equations (Equation (4)) also hold for windowed mean and variance of normal signals represented by the α-value equal 0.00. These equations particularly help us evaluate the impact of α on the distributions of windowed mean and variance of various signals from $\mathcal{F}$ family. Figures 2(b) and 2(c) show exemplar distributions (generated using Equation (4)) for various window sizes (i.e., 10 and 20) and α-values (i.e., 0.00, 0.05, 0.40). The histograms for mean and variance are generated using simulated data. As shown, signals with $\alpha = 0.00$ and $\alpha = 0.05$ share majority of their windowed mean and variance values, which significantly affects separability of the two cases using traditional ClassAct method. As $alpha$ increases, typical windowed mean and variance values move further away from those of $\alpha = 0.00$ and, hence, increase separability. An increase

[1]Figure 2(a) demonstrates that a mixture of multiple components that follow normal distributions may not always follow a normal distribution. The distribution is, in fact, governed by the α factor.



(a) (b) (c)

Fig. 3. Gaussian Mixture Effect on joint windowed mean and variance distribution. (a) No effect ($\alpha = 0.0$) (b) Low effect ($\alpha = 0.05$) (c) Medium effect ($\alpha = 0.4$).

in window size compresses the distributions along the value axis and also aids the separation. A similar behaviour is observed if the windowed mean and variance are used jointly, as shown in Figure 3.

As seen in Figure 2, while $\alpha = 0.05$ increases the ratio of higher values (i.e., above $x = 2$), the increase is not sufficient to warrant a noticeable impact on windowed mean and variance and, therefore, classification of signals. To overcome this, Iterative Edge Mining [12] is based on histogram representation of signal and, therefore, has higher sensitivity to minute changes of signal distributions. Subject to bin selection, the increase in ratio of higher values will be reflected by the histograms, thereby improving the classification. This method, however, comes at a cost where multiple bins need to be continuously maintained and analyzed on-board IoT devices. Accordingly, we discuss an adaptation of IEM that is more suitable for IoT-based execution.

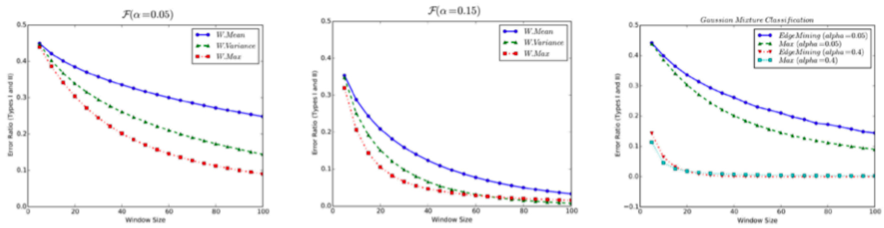
3.1.2 IEM-2.0 for Classification of Mixed-Gaussian Signals. To analyze the predictive capabilities of IEM-2.0, we first evaluate distribution of values for the $winMax$ feature for $\mathcal{F}(\alpha)$ Mixed-Gaussian Signals. For brevity, we omit the $winMin$ feature, since the analysis for it is a mere adaptation of the analysis presented here. Consider the maximum of an arbitrary window $\mathcal{F}_n(\alpha)$. Similar to Equation (3), under conditions $\mathcal{I}(\mathcal{F}_n(\alpha)) = i$, the Cumulative Distribution Function (CDF) for $winMax$ equals to:

$$P(Max(\mathcal{F}_n(\alpha)) <= x | \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \quad = \quad N^*(x, \mu_1, \sigma^2)^{n-i} \cdot N^*(x, \mu_2, \sigma^2)^i, \qquad (5)$$

where N^* denotes a CDF of normal distribution. Accordingly, the overall CDF of $\mathcal{F}_n(\alpha)$ is:

$$P(Max(\mathcal{F}_n(\alpha)) \leq x) \quad = \quad \sum_{i=0}^{i=n} P(Max(\mathcal{F}_n(\alpha)) \leq x | \mathcal{I}(\mathcal{F}_n(\alpha)) = i) \cdot P(\mathcal{I}(\mathcal{F}_n(\alpha)) = i). \qquad (6)$$

Now, let us assume that for a particular $n \geq 1$ and $\alpha > 0$, a decision tree is used to separate sequences $\mathcal{F}_n(\alpha)$ from $\mathcal{F}_n(0.00)$, based on a particular m-dimensional feature f that is a function from $\mathbb{R}^n$ onto $\mathbb{R}^m$. While $m = 1$ implies Window Mean, Variance, Maximum, and Minimum are used independently, $m = 2$ implies they are used jointly. Assume that CDF for the possible feature values of $\mathcal{F}_n(0.00)$ and $\mathcal{F}_n(\alpha)$ sequences are known and denoted as $P_{\mathcal{F}_n(0.00)}$ and $P_{\mathcal{F}_n(\alpha)}$, respectively. During the decision-tree analysis, feature values are first derived from the given n signal values and then subjected to a number of threshold assessments, as specified by the decision tree. Going back to the example considered in Figure 2, it is fair to assume that the optimal decision tree will consist of only one node. Sequences for which features exceed the threshold will be classified as $\mathcal{F}_n(\alpha)$, whereas the sequences for which the features are below the threshold will be classed as $\mathcal{F}_n(0.00)$. Subsequently, for a threshold x_{tr}, probabilities of type I and II errors (P_I, P_{II})



(a) (b) (c)

Fig. 4. Gaussian Mixture Effect on single-feature classification for low ($\alpha = 0.05$ (a)) and low-to-medium mixture effects ($\alpha = 0.15$ (b)); Joint windowed mean & variance classification for low and medium mixture effects ($\alpha \in \{0.05, 0.4\}$ (c)).

are equal to:

$$\begin{aligned} P_I(x_{tr}) &= P_{\mathcal{F}_n(\alpha)}(x_{tr}), \\ P_{II}(x_{tr}) &= 1 - P_{\mathcal{F}_n(0.00)}(x_{tr}). \end{aligned} \tag{7}$$

Therefore, the optimal threshold minimizing the error of both types can be calculated as:

$$X_{OPT} = Argmin_{x \in \mathbb{R}^n} \left(Max(P_{\mathcal{F}_n(\alpha)}(x),\ 1 - P_{\mathcal{F}_n(0.00)}(x)) \right). \tag{8}$$

As all CDF are continuous, monotonously increasing functions with range between [0,1], it can be shown that X_{OPT} always exists and that $P_I(X_{OPT}) = P_{II}(X_{OPT})$. Thus, where 1-dimensional features (m=1) are concerned, the solution for the problem in Equation (8) can be calculated thusly:

$$P_{\mathcal{F}_n(\alpha)}(x) = 1 - P_{\mathcal{F}_n(0.00)}(x)). \tag{9}$$

For $m \geq 2$, solving Equation (9) will generate a subset $\widetilde{X}$ of the original feature space $\mathbb{R}^m$. Subsequently, the optimization problem can be re-formulated as:

$$X_{OPT} = Argmin_{\widetilde{X}}\ P_{\mathcal{F}_n(\alpha)}(x). \tag{10}$$

Knowing X_{OPT} allows us to further numerically evaluate probabilities of P_I and P_{II} errors for selected features. Figures 4(a) and 4(b) demonstrate results of such evaluation that have been performed using CDF functions for windowed mean, variance, and maximum obtained above (note that for the first two metrics, we derive PDFs that can be easily transformed into CDFs). The evaluation was made for the same set of μ and σ^2 parameters and shows that for windows of low and moderate sizes *winMax* and, therefore, IEM-2.0 has a lower error rate (i.e., better prediction capability) than ClassAct. The advantage of the IEM-2.0 is more apparent for lower α-values (Figure 4(a)) and diminishes as α and/or window-size increase (Figure 4(b)). And, finally, Figure 4(c) demonstrates this effect when Window Mean and Variance are used jointly. While in this work, we do not present analytic formulae for joint CDF for Window Mean and Variance; during the analysis, we interpolate these functions based on results of numeric simulations. As evident, it is particularly beneficial to use IEM-2.0 for classification of signals whose behaviour closely resembles that of $\mathcal{F}_\alpha$ with lower α values. Note that while the *winMax* feature of IEM-2.0 has been deliberately used in this example due to the positive nature of histogram shift (as demonstrated in Section 3.1.1), the shift in histogram is typically non-stationary and may be positive or negative in nature. Therefore, in IEM-2.0, we perform classification based on the joint use of (*winMin*, *winMax*) features.

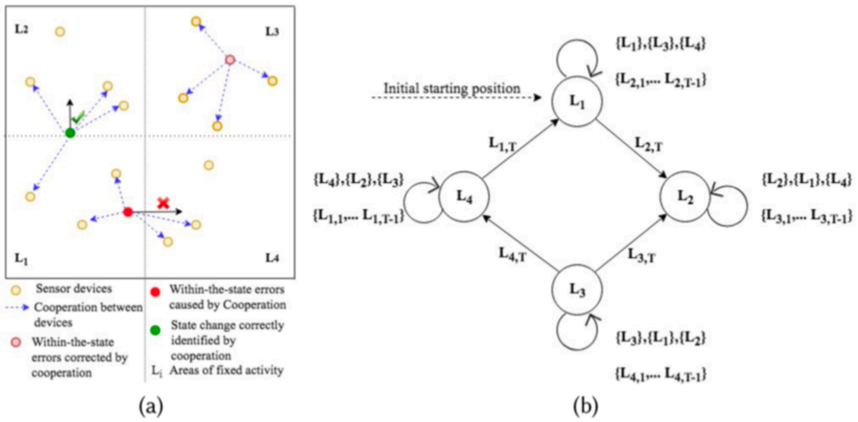


Fig. 5. (a) Effect of cooperation (b) Implementation of ASMM.

3.2 Cooperative Activity Sequence-Based Map Matching (CASMM)

Once the activity state is identified, the sequence of activities generated by IEM[2] is analyzed by the CASMM method for localization. The CASMM method consists of two light-weight computational tasks—Cooperative activity-state detection and ASMM.

Despite the improved classification accuracy of IEM over ClassAct, certain (P_I, P_{II}) errors may persist, owing to strong overlap between signals, especially, for lower α values. These errors may further increase in the presence of >2 signals (i.e., more than two activity states). Now, let us assume that at any given time t, a set of devices N ($|N|$), where each device $n \in N$ runs the IEM algorithm for on-board localization, are located within the same physical area denoted by L_i (Figure 5(a)). The area L_i is defined such that all IoT devices within this area exhibit a common high-level activity state. Therefore, while each node n analyzes individual activity state, it can be argued that analysis on a single node (referred to as the initializing node (IN)) would suffice the activity recognition for all N in L_i. However, we suggest analysis on all $n \in N$ or a subset of N devices as well as cooperation between the neighboring participating devices for exchange of activity-state updates to improve accuracy of individual predictions.

We envisage a set of participating devices N' ($|N'| \leq |N|$) nearest to node n (at any given time) as a coalition that exhibits a common activity state based on the location. Besides the individual predictions, we propose that each participating device maintains a local copy of the shared network state. If a change in activity is predicted by any device $n \in N'$ such that the predicted state differs from the shared network state, then it initiates cooperation with the remaining nodes in N'. We use an equal-weight majority-voting scheme wherein the shared network state is calculated as the mode of the predicted state at each device $n \in N'$. If the majority of devices in N' agree with change in state, then it implies that device has departed from L_i and moved to another area L_j, $i \neq j$ and, therefore, exhibits a different activity state. Otherwise, it is assumed that the device has predicted an untimely change in activity state, and the last updated activity state is maintained. Such cooperation between devices would not only allow detection of misclassified states but also facilitate the timely detection of state transitions. For instance, as shown in Figure 5(a), cooperation between devices facilitates correction of within-the-state errors (in L_3) and timely detection of

[2]All mentions of IEM hereafter refer to IEM-2.0 unless specified otherwise.

change in state as a node moves from $L1 \rightarrow L2$. Depending on the vicinity of the node, however, cooperation may lead to certain errors. As shown in Figure 5(a), a node in L_1 may assume the activity state in L_4, owing to its closeness to the sensor devices. The ASMM module is used to identify such errors and improve accuracy of state detection and, thereby, localization.

Once the cooperation is performed, the sequence of activity states is interpreted by the ASMM module. As mentioned earlier, ASMM is primarily proposed for indoor pedestrian localization [8]. The approach uses activity-related locations (e.g., staircase and corners) within a building as virtual landmarks to determine user trajectory and location. While a large outdoor environment may lack such characteristic landmarks, the ASMM approach can be extended to outdoor IoT-based localization, since the high-level activity and mobility of a user are essentially bounded by the outdoor topology. We, therefore, propose to determine the location of a node by mapping the sequence of activities along with their corresponding duration to a given outdoor map. Such mapping is light-weight and suitable for sensor-based implementation. If a change in state is recorded after cooperation, then the sequence of previously stored activities along with the corresponding duration is fed as input to the ASMM module. The ASMM module accepts the change in state only if it is consistent with the topology (i.e., physically feasible) and has been predicted for a continuous period higher than a given threshold $\mathcal{T}$. The trajectory of motion and location is then determined. Otherwise, the change in state is regarded as a classification error, and the user activity state and location is considered unchanged. For instance, consider that a user (sensor device) in Figure 5(a) can only move in a clockwise direction from $L_1 \rightarrow L_2 \rightarrow L_3 \rightarrow L_4 \rightarrow L_1$, as shown in Figure 5(b). Given the initial reference point (L_1), a node can either remain in the same activity state (and location) or move to L_2. Therefore, any changes in state corresponding to locations L_3 and L_4 are discarded by the ASMM module. Moreover, location is updated to L_2 only if the corresponding state is predicted for a duration of $\mathcal{T}$. Similar behavior is implemented for all state transitions. While such an approach may increase the delay in detecting state transitions (depending on the value of $\mathcal{T}$), it reduces the incoherent and untimely changes in activity that may be predicted after cooperation (e.g., error in L_1 in Figure 5(a)).

Our IEM2.0-CASMM-based localization approach is summarized in Algorithm 1. The algorithm takes as input acceleration data at time t (acc_t), parameters $windowSize, \varepsilon$, and decision-tree DT for IEM-based classification, set of nodes N, coalition N_t' at time t, threshold $\mathcal{T}$ and $roadMap$ for CASMM, and returns two vectors containing the sequence of activities ($actVector$) and locations ($locVector$). First off, the distribution of acc values is estimated using `DIST` function that calculates the $winMin, winMax$ features. If the percentage change in either of the features exceeds the threshold ε, then DT is used to classify the activity state ($state$). If the predicted state differs from the last updated device state ($lastUpdatedState$) as well as the last stored network state ($lastNetworkState$), then the change in activity may suggest a change in the device location. Subsequently, cooperation between N_t' neighboring devices is performed to obtain the majority voted activity state. If the $networkState$ is not in harmony with the $state$ value, then the change in activity is considered as a classification error and discarded. Otherwise, if the change in state persists for a period $\mathcal{T}$, then ASMM is performed to validate the change in activity and estimate location of the device. If the change in state is inconsistent with the given topology map ($roadMap$), then the prediction is discarded and a $NULL$ value is returned. Else, the location of the device is returned and the activity and location vectors are updated.

3.3 Context-Aware Event-Driven Communication

As mentioned above, the optimal IEM2.0-CASMM model is determined based on the localization accuracy as well as an optimization function. The function is designed to meet the application requirements of the WSN-system and sets the criterion for selecting values of the input

ALGORITHM 1: IEM2.0-CASMM-based localization

Input: acc_t, $windowSize, \varepsilon, DT, N, N'_t, \mathcal{T}, roadMap$
Output: $actVector, locVector$
repeat
  Read sensor for acc_t
  $accVector \leftarrow$ APPEND($accVector, acc_t$)
  $(winMin, winMax) \leftarrow$ DIST($accVector, windowSize$) **#Evaluating distribution**
  if $((|winMin - lastUpdatedMin| \geq \varepsilon * lastUpdatedMin) \vee (|winMax - lastUpdatedMax| \geq \varepsilon * lastUpdatedMax))$
  then
    $lastUpdatedMin \leftarrow winMin$
    $lastUpdatedMax \leftarrow winMax$
    $state \leftarrow$ PREDICT($DT, winMin, winMax$) **#Classification**
    if $((state \neq lastUpdatedState) \wedge (state \neq lastNetworkState))$
    then
      $networkState \leftarrow$ MODE($lastUpdatedState[1 : N'_t - 1]$) **#Cooperation**
      if $(networkState[\mathcal{T} - t + 1 : t] == state[\mathcal{T} - t + 1 : t])$
      then
        $location \leftarrow$ ASMM($roadMap, actVector, state$) **#ASMM**
        if $(location \neq NULL)$
        then
          $lastUpdatedState \leftarrow state$
          $lastNetworkState \leftarrow state$
          $actVector \leftarrow$ APPEND($actVector, state$)
          $locVector \leftarrow$ APPEND($locVector, location$)
        end
      end
    end
  end
until *Offload data to gateway*

Function DIST($accVector, windowSize$)
  return $(min(accVector[(t - windowSize + 1) : t]), max(accVector[(t - windowSize + 1) : t]))$

parameters. In this work, we consider minimization of the device energy consumption and determine the appropriate IEM2.0-CASMM model for sensor-based execution.

A vast majority of WSN-based systems are deployed to monitor remote areas that stretch over several kilometers. As such, communication of data packets from sensor devices to a cloud gateway is the most energy-intensive task performed by these devices. Continuous packet transmissions to the gateway can significantly reduce the operational time of these battery-operated devices. However, most sensor data is not time sensitive enough to maintain continuous real-time Internet connectivity. Accordingly, we propose a context-aware event-driven communication approach to transfer data from WSN to the gateway. We exploit the location information of devices obtained from IEM2.0-CASMM-based analysis and transmit data to the gateway only at the occurrence of a change in location. The delay-tolerant approach would not only improve energy efficiency of the devices through reduced packet transmissions but also reduce the operational cost of the system by eliminating the need for continuous Internet connectivity. As such, accuracy of localization has a direct impact on the energy consumption of the devices. The energy cost incurred in sending a data packet to the cloud can be calculated as shown below [28]:

$$E_{CL} = (e + \beta \cdot d^2) \cdot bits. \tag{11}$$

E_{CL} is the energy consumed by a node for sending a packet containing $bits$ number of bits to the gateway over a distance d. The variable e denotes the energy cost of transceiver for receiving and transmitting unit data (hardware dependent) and β is a constant $[J/bit.m^2]$.

As discussed previously, the CASMM method can help improve accuracy of classification of IEM (via cooperation between devices) and, in turn, the accuracy of localization. The cooperation itself, however, incurs a communication overhead in sending and receiving cooperation requests and location updates. These costs can be estimated using the following equations:

$$\begin{aligned} E_{CO} &= q_n \cdot ((2e + \beta \cdot d'^2) \cdot bits' \cdot (N' - 1) + E_{agg}) + (1 - q_n) \cdot ((2e + \beta \cdot d'^2) \cdot bits'), \\ E_{LO} &= p_n \cdot (e + \beta \cdot d'^2) \cdot bits' \cdot (N - 1) + (1 - p_n) \cdot (e \cdot bits'), \\ E_C &= \sum_{t=1}^{\tau}(r_t \cdot \sum_{n=1}^{N}(E_{CL} + E_{LO}) + s_t \cdot \sum_{n=1}^{N} E_{CO}). \end{aligned} \tag{12}$$

E_{CO} is the energy consumed by node n per cooperation between N' nodes, d' is the distance between the participating devices N', $bits'$ represents the number of bits per packet, and E_{agg} is the energy cost for aggregating the location data of N' nodes. The decision variable q_n takes a value of 1 if the cooperation is initiated by node n and 0 if it receives a request from another node. E_{LO} is the energy consumed by node n per distribution of location updates among N devices. The decision variable p_n assumes 1 if node n predicts the change in location and disseminates packets to other nodes and 0 if it receives a packet from another node. Note that the value of $bits' < bits$, as the packet sent to the gateway contains accumulated sensor data over time while the packet sent locally among devices contains just the state information. Moreover, $d' < d$, as the packet sent to gateway is over a longer distance than device-to-device communication. The overall communication energy consumed by N devices over a planning time horizon τ then equates to E_C. The variable r_t takes a value 1 if a change in location is predicted at time t and 0 otherwise. Similarly, the variable s_t takes a value of 1 if a cooperation is initiated at time t and 0 otherwise. We study the effect of $windowSize$, ε, and coalition size $|N'|$ on the energy consumption of the network in Section 5.

4 EXPERIMENTAL DESIGN

In this section, we present an application of our IEM2.0-CASMM system for animal localization in dairy farms. We describe our application scenario and discuss the implementation of IEM2.0-CASMM on-board animal-wearable sensor devices, followed by the design of our WSN-based prototype and the pilot study.

4.1 Animal Activity Monitoring and Localization

Real-time activity monitoring and localization of livestock is strongly advocated for on-farm LBS, such as behavior analysis, virtual fencing, and feed management under the umbrella of Precision Dairy Farming. Today, animal-wearable sensors are widely used to facilitate continuous monitoring of the physiological state of the cows for early diagnosis and treatment of diseases [29]. Enriching the results of health monitoring with animal-mobility data will allow for better understanding of animal behavior and well-being [30]. Combined analysis of both physiological and behavioral data with respect to location of the animal has been shown to provide vital insights into the farm processes and help improve their overall efficiency [31].

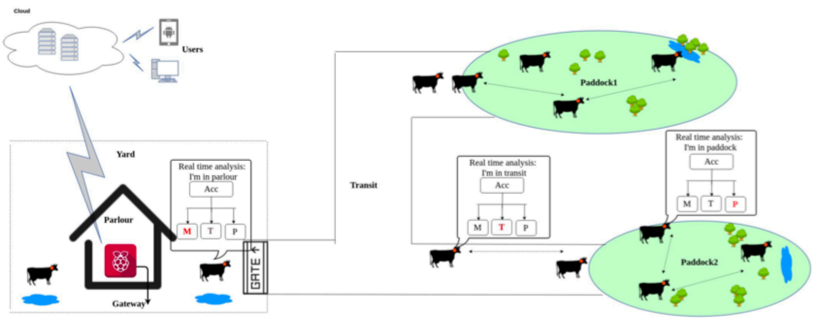


Fig. 6. IEM2.0-CASMM-based animal localization in dairy farms.

4.1.1 *Application Scenario.* Figure 6 depicts our application scenario. Our WSN system consists of animal-wearable sensor devices and a cloud gateway and allows for location-aware data collection for livestock management. The animal wearable is an extensible sensor device that consists of sensors to monitor the physiological state as well as the mobility of cows. We propose the implementation of IEM on-board the collar devices to predict the activity state of cows as they move around a farm. Furthermore, device-to-device communication is proposed to allow cooperation between the cows and perform ASMM to estimate the location as they predict changes in activity state. A gateway node is installed within the farm (hosted inside the parlour in Figure 6) to collect location-enriched data from sensor devices and upload it onto the cloud for future analysis. Since a typical farm spans across a large area and the majority of the data relating to the farm processes is delay-tolerant, we adopt the event-driven communication approach discussed in Section 3.3. Accordingly, sensor data combined with location information is stored locally on the collar devices as cows move around the farm, and the data is transmitted to the gateway once a change in location is predicted. This eliminates the need for continuous Internet connectivity within a farm, which is particularly important in rural deployments. Whereas the existing animal-wearable technologies such as RumiWatch [32] also follow a delay-tolerant communication approach, sensor data is transmitted to the cloud every 15 minutes, as the devices incorporate very little intelligence and rely on external (e.g., cloud-based) analysis for localization and behavior modelling. Implementation of IEM2.0-CASMM is expected to reduce the frequency of packet transmissions and improve the energy efficiency of the device operation. Moreover, real-time localization on-board collar devices could potentially allow timely detection of behavior anomalies in cows that may be indicative of stress and other health-related issues. Our WSN-based approach, thus, lays the foundation for future smart livestock farming.

4.1.2 *IEM2.0-CASMM Approach for Animal Localization.* In Reference [12], we evaluate the performance of IEM (histogram-based approach) for classification of low-level activities, such as standing and walking. Since the mobility of a cow is random, identification of such low-level activities is unnecessary and irrelevant for localization. Rather, we model our IEM (v. 2.0) classifier to predict the coarse location of cows—parlour (M), paddock (P), and transit between parlour and paddocks (T) within a farm, as shown in Figure 6. These locations span the entire farm topology and correspond to the three primary activities performed by a cow—milking, grazing, strolling around a farm, respectively.[3] The IEM-based classification, thus, helps identify the high-level activity state and location of cows.

[3]Note, we identify the entire yard as parlour, since the primary activity associated with cows within a yard is milking.

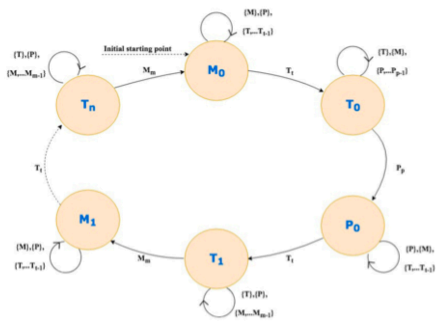


Fig. 7. Behavioural state transitions using ASMM.

Furthermore, as cows move in a herd, we exploit their spatial-temporal coherence for CASMM. Consider a herd of size N such that all cows $n \in N$ are equipped with a collar device and move together from one state to another. As such, a single cow or subset of N cows can suffice localization for the entire herd. We envisage the set of participating devices $N' \subseteq N$ within a herd to form a coalition that exhibits a common high-level activity based on location of the herd at any given time. If any device $n \in N'$ predicts a change in the activity state that differs from the network state, then it initiates cooperation between the participating devices to allow exchange of state information. Based on majority voting, the device updates its prediction and performs ASMM if required. Any change in location is disseminated to all N devices. The cooperation, thus, ensures a consistent activity state across the herd and is expected to reduce classification errors as cows replicate low-level mobility patterns from one activity state to another. For instance, CASMM may help fix errors in prediction when the classifier identifies a transit state while cows walk to a water trough within a paddock, owing to the similarity in behavior.

In Reference [8], while the route chosen by a user is unknown, the ASMM approach is used to establish the user's trajectory based on low-level activities, as the user follows a fixed mobility pattern on each route. On the contrary, in a dairy-farming scenario, the cows follow designated routes between the parlour and the paddocks due to the restricted topology of the farm. However, as mentioned above, they perform random low-level activities (e.g., walking, standing, and sitting) while moving along these routes and grazing within the paddocks. However, the cows follow a fixed sequence of the high-level activities (e.g., milking, transit, and grazing). The cows are brought into the parlour for milking. Once milked, they transit through the pathways to a paddock. After grazing, the cows leave the paddock and transit back through the same path to the parlour, and so on. Accordingly, we propose an adaptation of the ASMM approach to estimate the animal location based on the sequence of these high-level activities generated by IEM, as shown in Figure 7. The monitoring of cows commences at the milking parlour, location M_0, on day 1. At M_0, the cows can either remain within the parlour or enter into the pathways, i.e., transit state T_0. Therefore, any state changes to paddock predicted after cooperation can be ignored. If a change in state to transit is predicted for a continuous period of $\mathcal{T}$ (denoted as $T, ..T_t$ in Figure 7), then it is considered feasible and the location is changed to T_0. At T_0, the cows can either remain in transit state (i.e., stroll along the pathways) or enter into the paddocks. Any state changes to parlour can, therefore, be ignored. Moreover, continuous change in state to paddock denoted by $P, ..P_p$ is accepted and location is changed to P_0. Similar logic is followed to change location from P_0 to T_1 as cows return to the parlour (M_1) for milking and so on. Since the farmers follow a specific sequence of paddocks to

(a) (b) (c)

Fig. 8. (a) and (b) Animal-wearable collar devices (c) Cloud gateway.

Table 1. Implementation Details

Device type	Characteristic	
Collar device	Components	CM5000 mote [33], MPU9255 Inertial Motion Unit (IMU) [34]
	Memory	48KB program flash and 1MB non-volatile flash for data storage
	Battery	2xAA batteries
	Operating system	TinyOS [35]
Gateway device	Components	CM5000 mote, Raspberry Pi (v. 2B) [36], Wi-Fi dongle

be grazed, the state transitions along with the sequence numbers $1..n$ detected by IEM2.0-CASMM can be used to determine which paddock the cows must be headed to after milking. Based on the selection of paddock, the pathway can be determined and the time elapsed in transit state can be used to estimate the exact location along the pathway.

4.2 Field Experiment

As mentioned earlier, our WSN prototype consists of two types of devices—wearable collar devices and a cloud gateway, as shown in Figure 8. The design details of the two devices are given in Table 1. While collar devices are responsible for data collection and on-board analysis of animal health and mobility, the role of gateway is to collect sensor data from the collar devices (via mote-to-mote communication) and upload it onto the cloud for future analysis. We deployed our prototype in a Dairygold-sponsored farm located in Kilworth, Co. Cork, Ireland (Latitude: 52.168096, Longitude: -8.24206) (Figure 9(a)). The farm is operated by TEAGASC, the Agriculture and Food Development Authority of Ireland. The experiment was conducted on 5 Holstein Friesian cows (using five collar devices) selected randomly from a herd of 46 cows over a period of five days in June 2017. For the purpose of this study, we programmed the collar devices for collecting raw acceleration data of cows at a frequency of 1Hz for a 10h duration per day (in accordance with the daytime milking cycle). The data was used to examine the behaviour of cows within the milking parlour, transit, and paddock and build the IEM2.0-CASMM model to evaluate its performance in a real-life scenario.

A LELY collar is used to place the device around a cow's neck, as shown in Figure 8(b). An additional weight is attached to the collars to keep the device stable. The ideal orientation of the accelerometer axes is as follows: *y-axis towards the front of the cow, z-axis was out on the side, and x-axis was downwards.* The cows follow a fixed milking cycle, as shown in Figure 9(b). They are brought into the yard for milking in the morning. Once the milking is complete, cows exit the parlour and proceed to the waiting area, as shown in Figure 10(a). Once the entire herd is milked, the cows are released towards the paddocks (Figure 10(b)). Figure 10(c) shows two of the

(a) (b)

Fig. 9. (a) Map of the Dairygold farm in Kilworth, Co. Cork, Ireland (b) Milking cycle followed by the cows.

(a) (b) (c)

Fig. 10. Dairy cows during the pilot study (a) In yard (b) In transit (c) In paddock.

experimental cows inside a paddock. A single paddock is assigned to the herd per day. During the experiment, the herd was taken to paddock NA7 on days 1 and 2, NA5 on day 3, and NA3 on days 4 and 5 (earmarked in Figure 9(a)). In the evening, the cows are brought back into the yard for milking. For this study, the gateway node was hosted inside the milking parlour, and data from the devices was transmitted to the gateway once the cows enter the parlour in the evening. The time corresponding to changes in location (parlour → transit → paddock → transit → parlour) is recorded using manual observations for annotating the data with ground-truth locations, i.e., parlour, transit, and paddock. These observations are made by qualified TEAGASC technicians who handle the herd for ensuring animal safety. Since we study high-level localization of animals, the use of these timestamps along with start and end time of experiment suffice the labelling of raw acceleration data. In addition, the system time corresponding to the receipt of the first data packet from each node is maintained at the gateway. The recorded time is compared with clock on collar device to assess drift in clock speed, as discussed in Section 5.1. For the purpose of CASMM, a simple topology map is required that illustrates the relative position of parlour and different paddocks with respect to each other. In this study, we obtained an existing map of the Dairygold farm depicting the various paddocks (designed by Grasstec, as shown in Figure 9(a)) from TEAGASC.

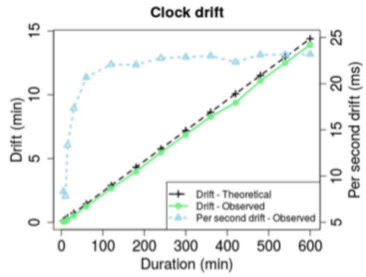


Fig. 11. Clock drift incurred by a collar device over time.

5 EVALUATION

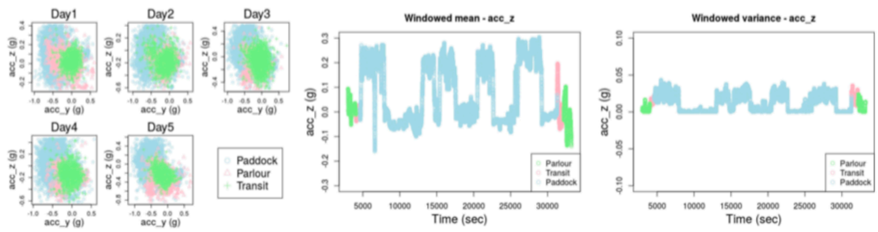
In this section, we evaluate the performance of our IEM2.0-CASMM approach using the animal-mobility data collected during our pilot study described in Section 4.2. We discuss our data exploration and feature selection approaches used for IEM-based classification, followed by the supervised learning and performance analysis of IEM2.0-CASMM for different values of input parameters. All analysis is performed using R programming.

5.1 Data Exploration and Feature Selection

Prior to training the IEM classifier, we analyze the acceleration data for necessary pre-processing and feature extraction. First off, we annotate the raw data with location (i.e., parlour, transit, and paddock) using the recorded timestamps. A positive clock skew is observed on comparing time of transmission of the first packet on the sensor devices with the corresponding system time (recorded by the Raspberry Pi). That is, the devices associate with the gateway node prior to expiration of the 10h duration. This is because a skew of 24ms per second has been noted for TelosB devices [37], owing to the software implementation of device clock in TinyOS. Furthermore, this value is affected by environmental factors, such as temperature, humidity, and vibration. The theoretical and observed drift is illustrated in Figure 11. As can be seen, the observed drift maps closely to the theory but is slightly less than the expected values. A skew of roughly 14min is incurred over the 10h period and must be accounted for to correctly annotate the acceleration readings. We also calculate the per-second drift for different time duration, as shown in Figure 11. Whereas the value increases initially, it stabilizes for longer duration. We model the linear dependency between the drift and the time duration using the *lm* function in R, as shown below. We then calculate the value of drift until each state transition and label the data accordingly:

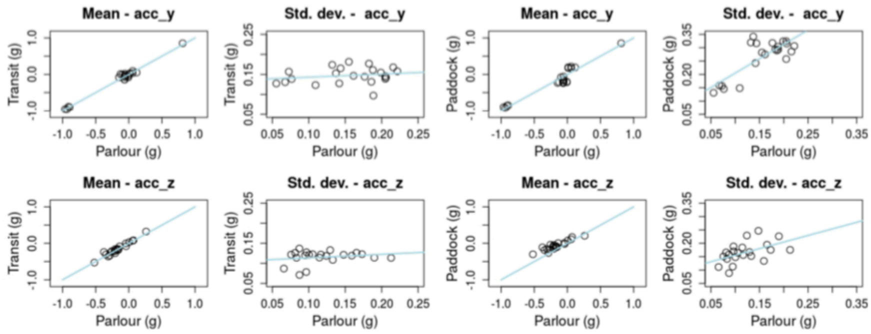
$$drift\ (min) = -0.158 + 0.023 * duration\ (min).$$

Next, we examine the raw data for outliers. Figure 12(a) shows the acceleration of a cow in the plane of movement after removal of the outliers. As can be seen, distribution of values in each state (i.e., parlour, paddock, and transit) varies across the five days. This is due to environmental factors, such as weather conditions and the quality of grass in the paddocks that affect behavior of the cow. We recalibrate the acceleration data to reduce the effect of the environment on the performance of the classifier. As evident from Figure 12(a), there is a significant overlap in the acceleration measurements of the three states. Figures 12(b) and 12(c) illustrate the windowed mean and variance of z-axis acceleration for all states. We use the Spearman's Correlation Coefficient to measure the correlation between the mean and standard deviation of parlour and transit, and parlour and paddock data along the y and z axis, i.e., plane of movement. The test suggests a



(a) (b) (c)

Fig. 12. (a) Acceleration of a cow during different activity states in the y-z plane (b) Windowed mean of acc_z (c) Windowed variance of acc_z at $windowSize = 60$.

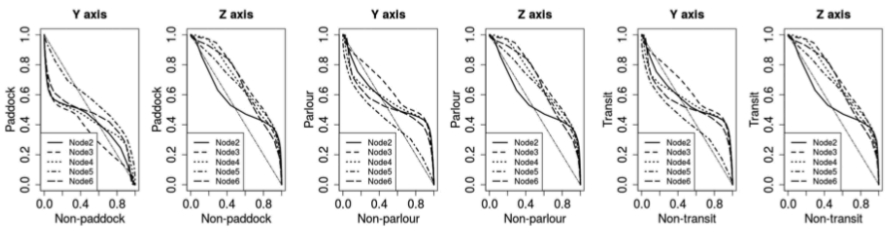


(a) (b)

Fig. 13. Linear dependence between mean & std dev. of (a) parlour & transit (b) parlour & paddock values.

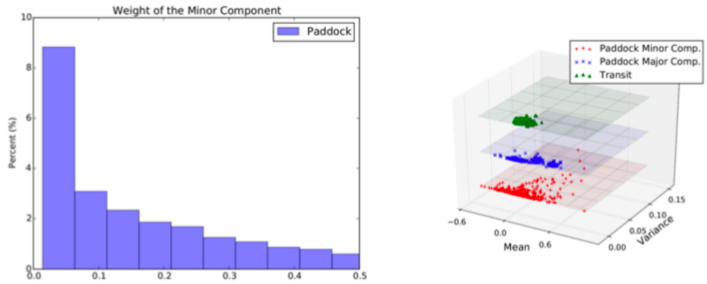
moderate correlation between the states. Accordingly, we derive the linear dependency between mean and standard deviation of y and z-axis acceleration in the parlour and transit and paddock data across the entire dataset, as shown in Figure 13. The mean of parlour is then set to zero, and the linear models are used to recalibrate the data for all three states.

Thereafter, we direct our attention to feature selection for classification. We use the Receiver Operating Characteristic (ROC) criterion to test the diagnostic ability of x-axis acceleration (acc_x), y-axis acceleration (acc_y), z-axis acceleration (acc_z), and net acceleration ($\sqrt{acc_x^2 + acc_y^2 + acc_z^2}$) for different cut-off values. Since we have a multiclass problem, we carry out a pairwise comparison (one state vs. all other states). While the acc_x and net acceleration do not capture clear distinction between the three states, acc_y and acc_z achieve a reasonable quality of separation for all nodes, as shown in Figure 14. The area under curve for the z-axis is greater than the y-axis for all nodes, thereby suggesting a better classification performance. Accordingly, we base our IEM implementation on feature values derived from acc_z measurements. The z-axis reflects horizontal movement of a cow's neck. The difference in behaviour between the states is potentially caused by the movement of cows as they graze within the paddocks and eat fodder during milking. Figure 15 provides further insights into the acceleration data from paddock and transit states across the entire dataset. While Figure 15(a) shows prevalence of two-component Gaussian mixtures with lower α values for windowed measurements in the paddock state, Figure 15(b) illustrates the similarity between



(a) (b) (c)

Fig. 14. ROC curves to evaluate the performance of acc_y and acc_z for classifying (a) Paddock (b) Parlour (c) Transit states.



(a) (b)

Fig. 15. Mixture effect in animal-mobility data at $windowSize = 60$ (a) Ratio of two-component mixtures within paddock state (b) Mixture fitting of transit and two-component paddock values.

parameters of major components of those two mixtures and one-component mixtures ($\alpha = 0.00$) prevalent during transit. The dominance of major component in the mixture and the significant overlap between the measurements highlights the need to use IEM-2.0 rather than ClassAct for animal-activity classification. Accordingly, we use *winMin*, *winMax* features for classification and study the performance of the IEM2.0-CASMM approach for different values of input parameters.

5.2 Supervised Learning

Once the classification features are selected, we train and test the IEM2.0-CASMM model for different sets of parameter values. We start by analyzing the effect of *windowSize* and ε on the performance of IEM, followed by the effect of coalition size on the performance of CASMM.

The accuracy of IEM is primarily governed by the input parameters *windowSize* and ε. The window size affects the calculation of min and max values and, thus, characterizes the signal distribution. While a small window may not capture the local min and max in close vicinity, a large window will increase the impact of historical data and may miss the small fluctuations that reflect actual state changes. As a result, increase in window size may cause a reduction in within-the-state classification errors at the expense of increasing cross-state errors around state transitions. To analyze the effect of *windowSize*, we train the IEM classifier *DT* for each device across three window sizes: 10s, 30s, 60s. First, we calculate the *winMin* and *winMax* pairs for each trace per window size. Next, we combine the data files from all five days per device and *windowSize*, and generate training sets using stratified sampling. Each training set consists of 10% of the total samples with an equal number of parlour, paddock, and transit measurements. This is done to ensure that the classifiers are fairly trained for all three states and the dominance of paddock data does not conceal the behavior in other states. Thus, we generate three training sets corresponding to the three window sizes for each of the five nodes. The sampled data is then fed to the $C5.0$ classifier to build the decision trees. We assign $\varepsilon = 0$ and study the effect of window size on the classification accuracy. The performance is evaluated per data trace (file) for all five days using appropriate DT (per device and $windowSize$). A value of 0 for ε allows us to evaluate the classifier for all possible distributions for a given $windowSize$. The training process is iterated ten times, i.e., 10 DT are generated for each node and window size, for performance validation.

Next, we introduce the ε parameter and study its effect on the performance of IEM. The value of ε controls the frequency of classification. Whereas a small ε will feed even the slightest changes in distribution to the classifier, a large ε value will accommodate significant changes in the distribution without presuming change in the activity state. Accordingly, while a large ε may improve the energy profile of the system through reduced classifications, it may increase the errors due to delay in detecting state transitions. Moreover, an error within the state persists longer due to infrequent classifications. We evaluate the impact of ε on the number of classifications as well as the classification accuracy across three values: 0.2, 0.4, 0.6, which correspond to 20%, 40%, and 60% change in distribution of the signal, using the DT trained above. While $winMin$ and $winMax$ are calculated per acc_z reading, classification is performed only if the difference between the updated values and the previous estimates exceeds ε. The cows are considered to be in the same activity state as the last identified state until the next classification. Furthermore, as we adopt an event-driven communication approach, we study the effect of $windowSize$ and ε on total number of packet transmissions to the cloud by the network (P_{CL}) and resultant E_C prior to applying the CASMM.

Finally, we evaluate the performance of CASMM for localization. As discussed in Section 3.2, we use an equal-weight majority voting scheme for cooperative activity-state detection. Accordingly, we estimate the shared activity state per day and per ε for window size 60s for different coalitions. The performance of cooperation varies with the coalition size, i.e., the number of participating devices. Since we have a total of five nodes, we analyze the effect of cooperation on accuracy of state detection for four different coalition sizes—$N' = 2/3/4/5$. Moreover, we study its impact on P_{CL}, total number of packet transmissions within the network for collaboration (P_{CO}) and dissemination of updates (P_{LO}), and the resultant communication energies (E_{CL}, E_{CO}, E_{LO}, and E_C). Once the appropriate coalition size is selected, we evaluate the performance of ASMM for localization. The effect of ASMM is governed by the threshold parameter $\mathcal{T}$. To set the value of $\mathcal{T}$, we evaluate the distribution of the errors within each state. We use the eighth decile value as the threshold for each state. We then implement ASMM (as shown in Figure 7) each time a change in state is observed after cooperation. We assess the effect of ASMM on accuracy of localization, P_{CL}, and E_C for different ε.

5.2.1 *Effect of Window Size.* To test the performance of IEM for different window sizes, we predict the activity state for each ($winMin$, $winMax$) pair across the entire dataset using the appropriate DT. The error in classification is calculated by comparing the predicted states against the observed states for each activity as well as net trace per data file for all days. This evaluation is repeated over ten iterations using the 10 DT models generated above. Figure 16 illustrates the classification errors for all traces over the ten iterations. The errors per activity state are shown in Figure 16(a). An overall reduction in error of each state is observed with an increase in the window size from 10s to 60s. While a median error of 11% is incurred for transit states at $windowSize = 10$, the value reduces to 3% and 1.5% at $windowSize = 30$ and $windowSize = 60$, respectively. Similarly,

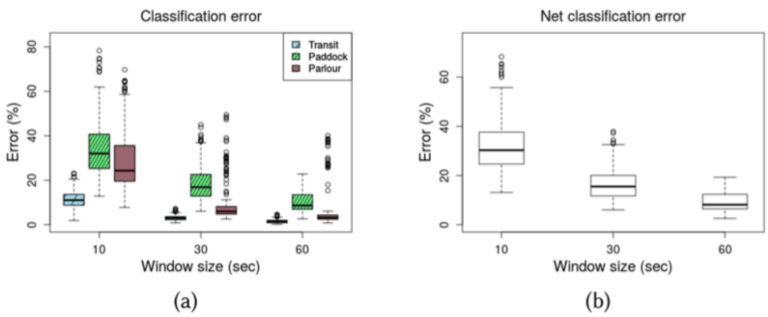


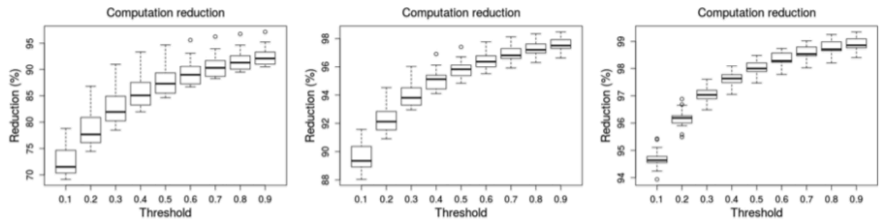
Fig. 16. Effect of *windowSize* on (a) Classification error per activity state (b) Net classification error.

the median errors for paddock and parlour states reduce from 32% and 24.3% at $windowSize = 10$ to 16.8% and 5.9% at $windowSize = 30$, and 8.6% and 3.1% at $windowSize = 60$, respectively. This is because a small time window is too narrow to correctly capture the local min and max values. As such, the calculated distribution of the signal misses the short-lived fluctuations in the vicinity and, in turn, affects the classification accuracy. While the median errors are low for transit and parlour at $windowSize = 60$, the median error for paddock states is slightly high with error for certain traces as high as 31.7%. On examining the traces, we observe that most of these errors are caused by misclassifications within an activity state, as opposed to misclassifications due to delay in detecting state transitions. This is because the classifier is unable to separate certain instances of stationary behavior and long walks within the paddocks (e.g., if a cow walks to and from a water trough located in one corner of the paddock) with the mobility patterns that are mainly observed in parlour and transit activity states, respectively. Figure 16(b) depicts the net error (all three states) for all traces. A median error of 30.2% is incurred at $windowSize = 10$, and the value decreases to 15.5% and 8.1% with increase in the window size to 30s and 60s, respectively. Furthermore, as is seen, the net error closely resembles the error in paddock as they constitute majority of the data points in any trace. The results suggest that while a $windowSize = 10$ is too narrow to capture the activity state of animals, a $windowSize = 60$ (i.e., 60 sensor readings) is capable of identifying the behavior with an accuracy over 90%. A window of 60s implies a set of 60 readings, as we collect data with a very low frequency of 1Hz. However, a window size of 10s presents the lower boundary of our analysis wherein classification is performed based on ten readings. It represents an extreme case and has been included in the analysis to illustrate the scope of our technique. The analysis shows that, despite a small set of readings, our technique can correctly classify 70% of the observations. However, the use of larger window sizes (i.e., 30s and 60s) is preferred for further analysis and CASMM-based localization. Since typical activity classifiers use high-frequency inertial data (usually 10Hz), we believe that our approach would work well with the commercially available activity trackers for the different window sizes.

5.2.2 Effect of Epsilon. As mentioned above, the value of ε controls the frequency of classification. It sets the threshold for change that is acceptable in the distribution of signal assuming the same activity state. We study the effect of ε on the frequency and accuracy of classification for all three window sizes. A summary of the analysis results is shown in Table 2. As expected, the number of classifications (computations) as percentage of the total number of readings per trace reduce with increase in the ε value for a constant window size. The median value of reduction percent increases from 77.5% at $\varepsilon = 0.2$ to 89% at $\varepsilon = 0.6$ for $windowSize = 10$; that is, only 11%

Table 2. Performance Summary of IEM (without Collaboration) for $\varepsilon \neq 0$

Metric		Window = 10s			Window = 30s			Window = 60s		
		$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$	$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$	$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$
Comp reduction (%)		77.5	85.0	89.0	92.1	95.0	96.2	96.2	97.5	98.2
Error (%)	T	11.9	12.0	12.0	4.4	6.1	7.0	2.5	3.4	7.5
	P	31.9	32.5	32.5	17.2	18.6	19.1	9.7	11.5	12.4
	M	27.1	27.6	28.9	9.0	12.6	13	7.6	11.3	14.1
P_{CL} - P1		8,438	6,350	4,963	2,693	1,835	1,355	998	643	450
Net E_{CL} (J) - P1		1.31	0.98	0.77	0.42	0.28	0.21	0.15	0.10	0.07
Net E_{LO} (J) - P1		$0.70e^{-3}$	$0.53e^{-3}$	$0.41e^{-3}$	$0.22e^{-3}$	$0.15e^{-3}$	$0.11e^{-3}$	$0.08e^{-3}$	$0.05e^{-3}$	$0.04e^{-3}$
P_{CL} - P5		7,577	5,715	4,503	2,451	1,701	1,244	957	619	432
Net E_C (J) - P5		1.17	0.89	0.70	0.38	0.26	0.19	0.15	0.09	0.07

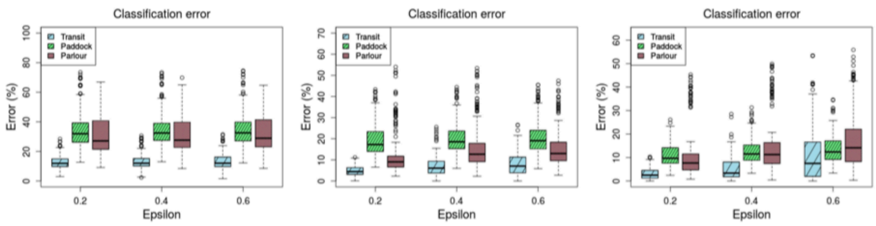


(a) (b) (c)

Fig. 17. Effect of ε on reduction of IEM classifications for *windowSize* (a) 10s (b) 30s (c) 60s.

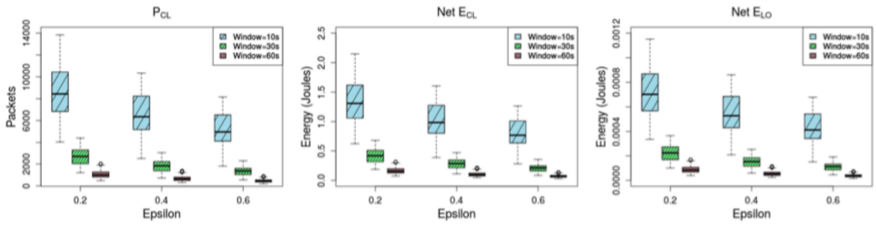
of the data traces are classified if a change in signal distribution ≥60% is considered significant for classification. A similar trend in reduction percentage is observed for window sizes 30s and 60s. Moreover, the value of reduction is higher for larger window sizes, as the smoothing in data is increased such that the small fluctuations in the signal are concealed, resulting in fewer changes in the distribution that exceed the threshold. Figure 17 illustrates the trend in computation reduction for different values of ε and *windowSize*. The reduction in classification not only improves the memory usage by storing fewer readings in the flash but can also improve energy profile of the devices. This could, in turn, result in an increase in the operational time of the wearable devices.

Next, we examine the effect of ε on the classification accuracy of the three activity states: transit (T), paddock (P), and parlour (M), for the three window sizes. We calculate error as the percentage of misclassified states per trace across all ten iterations, as shown in Figure 18. For a small window of 10s, the value of ε has very little impact on the classification accuracy. The median error of transit, for instance, increases from 11.9% at $\varepsilon = 0.2$ to 12% at $\varepsilon = 0.4$ and $\varepsilon = 0.6$, as shown in Figure 18(a); that is, an approximate increase of 1%, compared to the resultant error at $\varepsilon = 0$ (see Figure 16(a)). We associate the small changes in the median errors with the nature of smoothing in the data. For a small window, the smoothing is very low, such that the slightest change in the distribution exceeds the threshold value. As such, a small ε filters out the redundant data (see Figure 17) and maintains the quality of the results. The effect of ε is more prominent for larger window sizes (30s and 60s) due to increased smoothing, as shown in Figures 18(b) and 18(c). An increase in error is observed with increase in the value of ε. Moreover, the change in error with ε value is greater, compared to the change in errors for *windowSize* = 10. However, an overall



(a) (b) (c)

Fig. 18. Effect of ε on classification error of IEM for $windowSize$ (a) 10s (b) 30s (c) 60s.



(a) (b) (c)

Fig. 19. Effect of $windowSize$ and ε on (a) P_{CL} (b) Net E_{CL} (c) Net E_{LO} for scenario P1.

reduction in the error values is observed for all states with increase in the $windowSize$ as local min and max in the signals are accurately captured.

As mentioned earlier, the accuracy of IEM affects the frequency of packet transmissions to the cloud and, in turn, the communication cost incurred by the sensor nodes. We assume that each node sends a single packet to the cloud per state change. The energy cost incurred by each node in sending one packet to the cloud (E_{CL}) is calculated in Equation (11). For our analysis, we set the constants $e = 50x10^{-9}J$ and $\beta = 10^{-11}J/bit \cdot m^2$ [28], $d = 120m$ (maximum radio range of CM5000 motes for outdoor), and $bits = 800$ (maximum payload of 802.15.4 packets). Ideally, it suffices to run the IEM algorithm on one node (IN) to localize a given herd within the farm (denoted as scenario P1 in Table 2). Each time the IN predicts a change in its activity state, it assumes the same change in state across the entire herd and forwards the location update to the remaining nodes within the herd. All nodes then transmit their sensor data along with the location information to the cloud gateway. The energy cost incurred by each node due to the local communication between nodes (E_{LO}) is calculated in Equation (12). We set $d' = 20m$ (usual maximum distance between neighboring cows within a herd) and $bits' = 1$ (payload required for sending location update). We calculate the total number of packets sent by all nodes to the cloud (P_{CL}) per day and resultant net E_{CL} and E_{LO} values for the network by considering each node as IN for different values of $windowSize$ and ε. Since each node has a different prediction accuracy, the value of P_{CL}, and net energies also varies. The median values for all nodes over ten iterations are listed in Table 2.

Despite the increase in classification error, the value of P_{CL} reduces with increase in the value of ε for a fixed window size (Figure 19(a)). This is attributed to the significant drop in the number of classifications at higher ε values that results in fewer predictions and, in turn, a lesser number of state changes. Note, however, the error in classification is higher, owing to the prolonged effect of a misclassified state and delay in detecting state changes. The value of P_{CL} further reduces

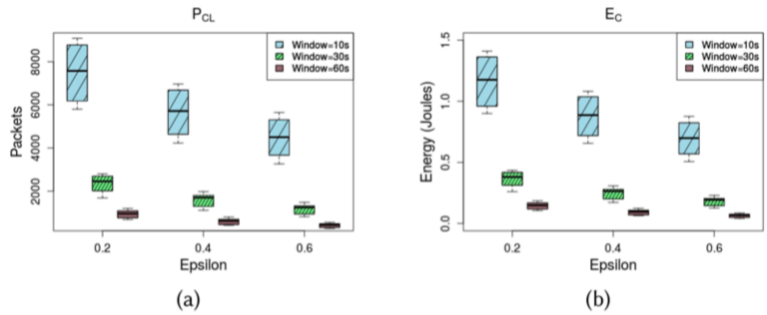


Fig. 20. Effect of $windowSize$ and ε on (a) P_{CL} (b) E_C for scenario P5.

with increase in $windowSize$, owing to better smoothing in the signal that reduces within-the-state misclassifications and thereby prevents untimely state-change predictions. A similar trend is observed in the values of resultant communication energies E_{CL} and E_{LO} with changes in the input parameters, as shown in Figures 19(b) and 19(c). Whereas $E_{CL} = 1.31J$ for $windowSize = 10$ and $\varepsilon = 0.2$, it reduces to 0.77J with increase in ε to 0.6, and further reduces to 0.07J with increase in the value of $windowSize$ to 60s. Similarly, $E_{LO} = 0.70e^{-3}$ for $windowSize = 10$ and $\varepsilon = 0.2$, and reduces to $0.41e^{-3}$ with increase in ε to 0.6, and further to $0.04e^{-3}$ for $windowSize = 60$ and $\varepsilon = 0.6$. As is evident, the energy cost incurred by the local communications is significantly lower, compared to energy spent in the long-range communication to the cloud gateway. The network communication energy, in this case, is calculated as the summation of net E_{CL} and E_{LO}. Furthermore, we consider the scenario where each node runs the IEM algorithm and predicts its activity state in isolation (denoted as scenario P5 in Table 2). That is, the nodes do not communicate locally with each other and directly send data packets to the cloud at the occurrence of individual state changes. We calculate the total packets sent by all five nodes to the cloud per day (P_{CL}) and resultant energy cost E_{CL} for different values of $windowSize$ and ε over ten iterations (as illustrated in Figure 20). The value of P_{CL} and, thereby, E_{CL}, follows the same trend with increasing $windowSize$ and ε values as P1. Moreover, the median values for P_{CL} and net E_{CL} in P5 are lower than the corresponding values in P1, as shown in Table 2. This is because, whereas in P5 the packet transmissions are governed by a node's own accuracy, transmissions in P1 are guided by the accuracy of one node. As a result, the number of packets increase across all nodes if the IN has poor accuracy.

5.2.3 Effect of Coalition Size. As discussed above, the performance of CASMM is primarily governed by the coalition size. Given that our pilot study includes five nodes, we consider four possible scenarios based on the coalition sizes 2,3,4, and 5 and evaluate the performance for each coalition group shown in Table 3 for a fixed $windowSize = 60$. $N' = 2$, for instance, represents the scenario where two of the five nodes form a coalition and participate in the analysis. We study the effect of coalition size on classification accuracy, net packet transmissions for cooperation (P_{CO}), local communication (P_{LO}) and cloud communication (P_{CL}), and the resultant energy E_C that comprises of E_{CL}, E_{LO}, and E_{CO}. The median values for the above metrics across traces for all ten iterations are summarized in Table 4.

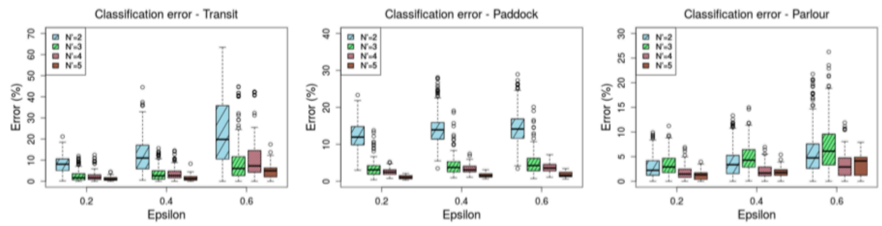
We calculate the classification error for each state, considering the network as a whole by comparing the shared network state with the observed states. The error values are affected by both coalition size and selection of nodes (as participating nodes have different accuracy), as depicted in Figure 21. As can be seen, the error varies for a particular value of N' (owing to the selection

Table 3. Coalition Groups

$N' = 2$	$N' = 3$	$N' = 4$	$N' = 5$
{N2,N3}	{N2,N3,N4}	{N2,N3,N4,N5}	{N2,N3,N4,N5,N6}
{N2,N4}	{N2,N3,N5}	{N2,N3,N4,N6}	
{N2,N5}	{N2,N3,N6}	{N2,N3,N5,N6}	
{N2,N6}	{N2,N4,N5}	{N2,N4,N5,N6}	
{N3,N4}	{N2,N4,N6}	{N3,N4,N5,N6}	
{N3,N5}	{N2,N5,N6}		
{N3,N6}	{N3,N4,N5}		
{N4,N5}	{N3,N4,N6}		
{N4,N6}	{N3,N5,N6}		
{N5,N6}	{N4,N5,N6}		

Table 4. Performance Summary of IEM (with Collaboration) for *windowSize* = 60

		$N' = 2$			$N' = 3$			$N' = 4$			$N' = 5$		
Metric		$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$	$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$	$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$	$\varepsilon = 0.2$	$\varepsilon = 0.4$	$\varepsilon = 0.6$
Error(%)	T	8.1	11.0	19.8	1.7	2.6	6.1	1.7	2.7	7.3	1.0	1.2	5.0
	P	12.0	13.9	14.1	3.1	3.8	4.3	2.4	3.1	3.6	1.0	1.5	1.6
	M	2.2	3.4	4.7	2.9	4.3	6.1	1.5	1.7	2.9	1.3	1.8	4.1
Packets	P_{CO}	325	211	149	728	486	342	1,361	900	636	2,118	1,386	974
	P_{LO}	966	620	432	392	288	212	364	276	196	176	164	118
	P_{CL}	1,240	795	553	510	385	280	463	350	255	235	220	150
Energy (J)	E_{LO}+E_{CO}	$0.17e^{-3}$	$0.11e^{-3}$	$0.08e^{-3}$	$0.19e^{-3}$	$0.13e^{-3}$	$0.10e^{-3}$	$0.33e^{-3}$	$0.22e^{-3}$	$0.15e^{-3}$	$0.46e^{-3}$	$0.31e^{-3}$	$0.21e^{-3}$
	E_{CL}	0.19	0.12	0.09	0.08	0.06	0.04	0.07	0.05	0.04	0.04	0.03	0.02
	E_C	0.19	0.12	0.09	0.08	0.06	0.04	0.07	0.05	0.04	0.04	0.03	0.02



(a) (b) (c)

Fig. 21. Effect of coalition size on classification error for (a) Transit (b) Paddock (c) Parlour states at *windowSize* = 60.

of nodes) and decreases with increase in N' from 2 to 5. This decrease in error is achieved, as classification errors of a node with low accuracy are masked by the accurate classification of other nodes via majority voting. Moreover, the error values are lower when compared to Table 2, with the exception of $N' = 2$, wherein majority implies the vote of one node against the other. As expected, the errors increase with increase in the ε value due to reduced frequency of classification. For $N' = 5$, the cooperation achieves an accuracy >98% for all three states at $\varepsilon = 0.2$ and ≥95%

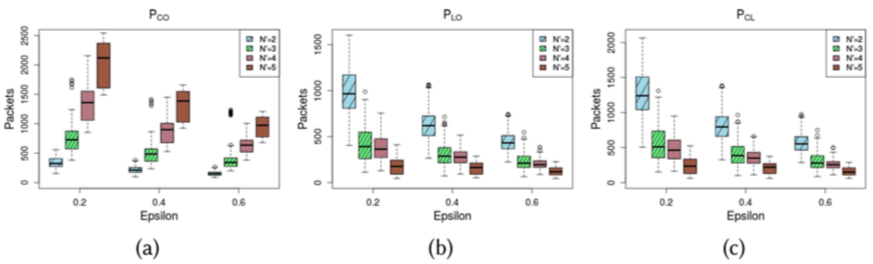


Fig. 22. Effect of coalition size on (a) P_{CO} (b) P_{LO} (c) P_{CL} at $windowSize = 60$.

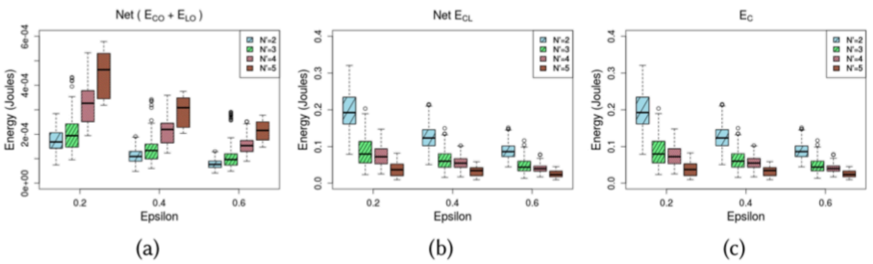
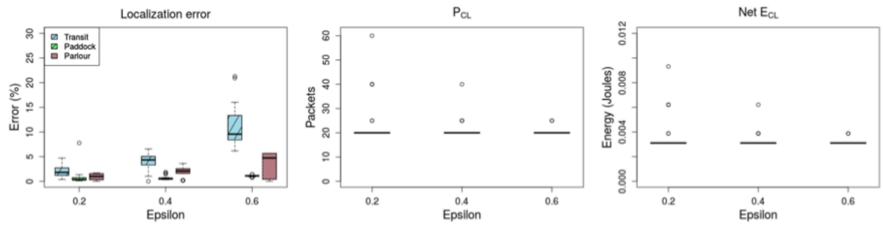


Fig. 23. Effect of coalition size on (a) Net local energy ($E_{CO} + E_{LO}$) (b) Net E_{CL} (c) E_C at $winsdowSize = 60$.

at $\varepsilon = 0.6$, with a corresponding reduction in classifications by 96.2% and 98.2%, respectively (see Table 2). Although it is feasible to further reduce the number of computations by increasing the ε value, it will adversely affect the system accuracy. The values of the input parameters should, therefore, be chosen such that they balance the trade-off between the number of classifications and accuracy to meet the application requirements.

Next, we consider the impact of N' on P_{CO}, P_{LO}, and P_{CL}. The values depict net packet transmissions for the network of five nodes, as shown in Figure 22. We observe an increase in the value of P_{CO} with an increase in the value of N' (Figure 22(a)). This is due to an increase in the number of participating nodes that are polled during cooperation. On the contrary, a decrease in the values of P_{LO} and P_{CL} is observed with increase in N' (Figures 22(b) and 22(c)), owing to the improved accuracy. For a fixed N', the values of P_{CO}, P_{LO}, and P_{CL} decrease with increase in the ε value, due to reduced number of classifications on each node. Moreover, the packet transmissions are lower, compared to P1 and P5 scenarios discussed earlier, with the exception of $N' = 2$, which has lower accuracy. Similar trends are observed in the resultant communication energies, as shown in Figure 23. Figure 23(a) illustrates the net energy cost for local communication between devices, i.e., net $E_{CO} + E_{LO}$. While an increase in E_{CO} and decrease in E_{LO} is expected with increase in N', we observe a net increase in the local communication energy due to higher impact of E_{CO} (as $P_{CO} > P_{LO}$). On the contrary, a drop in E_{CL} is observed with increase in N', owing to improved accuracy and fewer packet transmissions to the cloud (Figure 23(b)). The net communication energy (E_C) is then calculated using Equation (11) and depicted in Figure 23(c). Since the magnitude of local communication cost is significantly lower when compared to the cost for cloud communication, the value of E_C mimics the value of E_{CL}. Moreover, the value decreases with increase in the coalition size N', thereby improving the network efficiency. Similar to the packet transmissions, the energy costs further decrease with increase in the ε value.



(a) (b) (c)

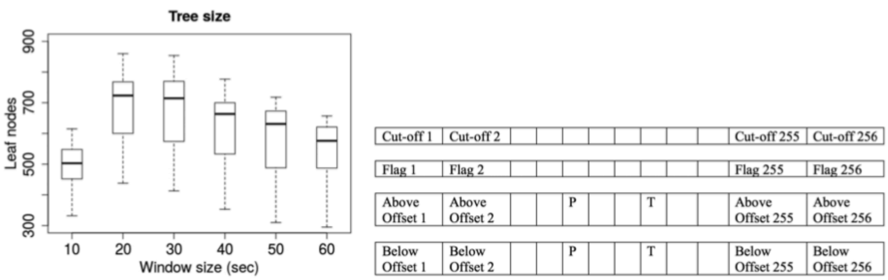
Fig. 24. Effect of ASMM on (a) Localization error (b) P_{CL} (c) Net E_{Cl} for $windowSize = 60$ and $N' = 5$.

While the cooperation significantly improves the classification accuracy, the number of state transitions detected by the system (resulting into P_{CL}) is quite high. As such, our pilot study incorporates four state changes ($M_0 \rightarrow T_0 \rightarrow P_0 \rightarrow T_1 \rightarrow M_1$) and should result into exactly four packet transmissions to the cloud. This implies that our system detects untimely state changes (within-the-state errors) that are short-lived (suggested by high accuracy) but occur frequently (suggested by value of P_{CL}). We expect the ASMM approach to address such errors by mapping the sequence of activities to the farm topology and reducing the within-the-state errors. We consider the coalition groups for $N' = 5$ for the analysis, as they allow highest accuracy of classification along with minimum E_C. As mentioned above, we use the eight decile value based on the distribution of errors to calculate threshold $\mathcal{T}$ for each state (depicted as T_t, P_p, and M_m in Figure 7). ASMM accepts a change in state detected by the cooperation only if it is consistent with the topology (follows the state transition diagram) and continues for a period assigned by $\mathcal{T}$. Figure 24 shows the effect of ASMM on the location accuracy, $P_{CL,}$ and E_{CL}.[4] As can be seen, the accuracy for all three states does not alter significantly (Figure 24(a)) and closely resembles the values achieved after cooperation (see Figure 21). Note that the localization accuracy is calculated in terms of percentage, as we consider high-level localization of cows in three discrete regions. On the contrary, the median of number of packets transmitted to the cloud reduces remarkably to 20, i.e., 4 packets per node as desired (Figure 24(b)). That is, ASMM eliminates all the untimely state transitions. Resultantly, it leads to a significant drop in the value of E_{CL}. As shown in Figure 24(c), the value of E_{CL} drops to less than 10%, compared to Figure 23(b), i.e., a reduction of 90%. The error in classification can be explained by early or delayed detection of state changes, owing to the use of $\mathcal{T}$ parameter.

6 DISCUSSION AND FUTURE WORK

In the previous section, we evaluated the performance of the IEM2.0-CASMM model for different values of the input parameter. The analysis shows that while the stand-alone IEM classifier can achieve a reasonable level of accuracy (>90% for $windowSize = 60$ and $\varepsilon = 0.2$) for all three activity states along with very low frequency of classifications (a reduction of >96% for $windowSize = 60$ and $\varepsilon = 0.2$), it results in a considerable number of unnecessary and expensive packet transmissions to the cloud. The CASMM method improves the accuracy of IEM-based classification (~99% for $N' = 5$, $windowSize = 60$, and $\varepsilon = 0.2$) through cooperation between devices with very low overhead energy costs of the order of 10^{-4} and facilitates accurate localization via ASMM. The ASMM eliminates the unnecessary packet transmissions to the cloud, thereby improving the overall energy efficiency of the WSN operation by 90%. The analysis, thus, confirms the suitability of

[4]ASMM has no effect on the local communication between the devices.



(a) (b)

Fig. 25. (a) Effect of *windowSize* on the size of *DT* (b) Array-based implementation of DT.

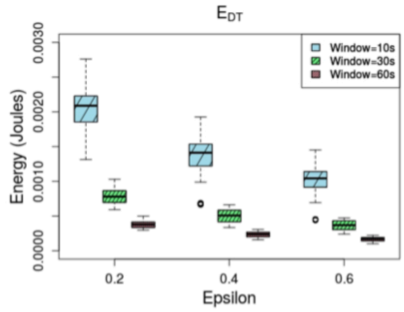
using the IEM2.0-CASMM approach for activity recognition and localization of the cows. In this section, we assess the feasibility of implementing the IEM classifier *DT* on-board the sensor devices. We discuss an array-based implementation of the IEM algorithm and present a memory analysis for the same. In comparison to *DT*, implementation of CASMM only requires a few variables, such as N', state vector, and $\mathcal{T}$ to be maintained by the device. In addition, we evaluate the energy cost associated with the *DT*-based classification (E_{DT}) for different values of the input parameters. Last, we present the proposed future work.

6.1 Memory Analysis

Figure 25(a) shows the effect of *windowSize* on the size of *DT* in terms of number of leaf nodes. As can be seen, the number of nodes increase as we move from *windowSize* 10 to 20s and follows a downward trend thereafter with further increase in the *windowSize*. Accordingly, while a median value of ~700 is obtained for $windowSize = 30$, it decreases to 580 for $windowSize = 60$. However, the number of leaf nodes is as high as 850 nodes for certain cases with $windowSize = 20/30$. We use this upper case to calculate the memory requirements for IEM-based *DT* and verify its feasibility for sensor-based execution. We present an array-based implementation of a *DT* with 850 leaf nodes, as shown in Figure 25(b). We require four arrays of length 850 each. The first array holds the cut-off values used at the decision nodes in *DT* to split the data into two subsets. As mentioned in Section 4.2, the range of the acceleration values of cows is −2g to +2g. We scale down the measurements such that they range between −1g and +1g. The cut-off values can then be represented as $0.int$ and would require 2 bytes per reading; that is, a total of $850 * 2$ bytes is required for the first array. The second array is used to store flags that indicate whether the cut-off value sets a constraint on the windowed min or max. Each flag requires 1 bit, adding up to $850 * 1/8$ bytes. The third and the fourth arrays provide link to the child nodes—left child and right child. If the child is a leaf, a label "P" for paddock, "T" for transit, or "M" for parlour is assigned to the appropriate index variable. Otherwise, the variable contains an offset value for the pointer to the first array for subsequent decisions along the *DT*. Each entry in both arrays requires 1 byte to store the value and totals to $850 * 1 * 2$ bytes for both arrays. The net memory required for the IEM implementation, thus, equals 3.4KB ($1KB = 1024bytes$). The CM5000 mote used in our prototype, for instance, features a program flash memory of 48KB. This analysis, thus, validates the suitability of IEM for on-board implementation on the resource-constrained sensor devices. Furthermore, the generic nature of the implementation suggests that IEM can also be incorporated in the commercially available wearable sensor devices such as RumiWatch [32] and SmartBow [6].

Operator	Data type	E_{op} (mean)	E_{op} (variance)	E_{op} (error)
<	float	4.23E-8	8.17E-17	2.92E-17
≥	float	4.08E-8	5.35E-17	0.0
assign	float	8.27E-8	5.29E-18	2.30E-9

(a)



(b)

Fig. 26. (a) Energy consumption per operation [41] (b) Effect of *windowSize* and ε on E_{DT}.

6.2 Computation Energy Cost

While we discuss the optimization of network communication cost in Section 5, it is important to evaluate the energy consumed by on-board analysis to ensure that it does not significantly impact the sensing and communication tasks. The conventional approach to evaluate the power consumption involves periodic measurement of remaining battery level on physical hardware, as presented in Reference [38]. Although this approach provides accurate analysis, it has several limitations, including potential hardware and human failures, complexity and size of WSN, as well as inherent dynamism of the environment. Alternatively, the use of modelling has been proposed to evaluate the power consumption of WSN applications. In Reference [39], for instance, the authors use Colored Petri Nets (CPN) tools to automatically generate consumption models for given NesC [40] (programming language used in TinyOS) operators, structures and functions to, in turn, estimate the energy cost of an entire application. While this approach may have slightly less accuracy, it provides flexibility and agility to evaluate energy consumption in complex application scenarios in a timely and cost-effective manner. We, therefore, adopt the approach presented in Reference [39] for calculating the energy cost associated with DT-based classification.

Using the CPN tools, DT-based classification can be modelled as a sequence of relational operations, i.e., ≥ comparisons. The power consumption for each classification can, thus, be calculated as the product of the total number of operations to traverse the DT (N_{op}) and energy consumed per operation (E_{op}). The value of N_{op} is governed by the tree size and is typically calculated as the log base 2 of the total number of nodes in a tree (see Figure 25(a)). To estimate E_{op}, the CPN models discussed for NesC operators in Reference [39] make use of an auxiliary function, namely *addEnergy*. The function is assumed to follow a normal distribution and generates a random value for each instruction's power consumption using given energy mean and variance values. The values of mean and variance are specific to each operator and have been estimated using measurements. We obtain these values for relational and assignment operations from a Github repository [41], as shown in Figure 26(a). The net energy for classification (E_{DT}) per node is then calculated using the following equation:

$$E_{DT} = (N_{op} \cdot E_{op}) \cdot N_{class},$$

where N_{class} is total number of classifications on a given node. The value of N_{class} can be calculated as the percent readings that are classified from each trace (see Figure 17). Figure 26(b) illustrates the effect of *windowSize* and ε on E_{DT}. As expected, the energy consumption decreases with increase in values of both window size and ε, owing to fewer classifications. Furthermore, the value of E_{DT} is of the order of $10^{-3} J$ for different values of the input parameters. For a $windowSize = 60$, the median value of E_{DT} is below 0.0005, thus, validating the suitability of IEM (v. 2.0) for sensor-based execution.

6.3 Future Work

In this work, we present proof-of-concept for our WSN-based localization approach. In the future, we intend to deploy the trained IEM2.0-CASMM model on wearable sensor devices to test the approach in real time. Moreover, we wish to address the scalability of our approach across a larger set of devices. We also plan to assess the impact of CASMM on the response time of the system. Since the initiating node in a coalition waits for a response from all the participating devices before making a decision, a large coalition size may lead to an increase in response time. In this case, a deadline by which all responses must be received may be used to meet the application response time requirements. A trade-off between the quality of result and application deadline should, thus, be considered. Furthermore, since accuracy of individual nodes affects the combined performance of a coalition, we wish to study the effect of selection of nodes for forming a coalition. In addition, we wish to design handover of the analysis to other nodes in the vicinity as the energy level of participating nodes depletes below a given threshold.

7 CONCLUSION

In this article, we show the suitability of using the IEM-2.0 approach for classifying Mixed Gaussian signals (especially with unequal distributions) and analyze the performance of our IEM2.0-CASMM-based localization approach for animal-activity recognition and localization in dairy farms. The performance evaluation is based on real-world mobility data of cows and shows that the IEM2.0-CASMM approach can achieve a localization accuracy of 99% with very low frequency of classifications. With such high accuracy of localization, a location-aware event-driven communication approach is used to transfer sensor data to the cloud. Such an approach consumes energy of the order 10^{-4} and significantly improves the energy efficiency of the WSN operation. Furthermore, memory analysis for the approach shows that it requires only 3.4KB of the program flash and is suitable for implementation on wearable sensor devices. On-board implementation of IEM2.0-CASMM on animal wearables would allow uninterrupted context-aware sensing in Cooperative WSN, as cows move around a farm despite the lack of continuous Internet connectivity. This, in turn, would facilitate real-time LBS within the farm as well as early detection of behavior anomalies that may indicate health-related issues. As IEM is applicable for classification of generic Mixed Gaussian signals, our approach can be extended to different WSN applications.

REFERENCES

[1] T. Wang, Z. Peng, J. Liang, S. Wen, Md Z. A. Bhuiyan, Y. Cai, and J. Cao. 2016. Following targets for mobile tracking in wireless sensor networks. *ACM Trans. Sen. Netw.* 12, 4 (2016). DOI: http://dx.doi.org/10.1145/2968450

[2] CERES TAG. 2018. What is ceres tag. Retrieved from cerestag.com.

[3] T. Wark, D. Swain, C. Crossman, P. Valencia, G. Bishop-Hurley, and R. Handcock. 2009. Sensor and actuator networks: Protecting environmentally sensitive areas. *IEEE Perv. Comput.* 8, 1 (2009), 30–36. DOI: http://dx.doi.org/10.1109/MPRV.2009.15

[4] A. Maddumabandara, H. Leung, and M. Liu. 2015. Experimental evaluation of indoor localization using wireless sensor networks. *IEEE Sens. J.* 15, 9 (2015), 5228–5237.

[5] T. Stoyanova, F. Kerasiotis, C. Antonopoulos, and G. Papadopoulos. 2014. RSS-based localization for wireless sensor networks in practice. In *Proceedings of the 9th International Symposium on Communication Systems, Networks Digital Sign (CSNDSP'14)*. 134–139.

[6] SmartBow. 2014. User manual: E093 SmartBow eartag. Retrieved from smartbow.com. (accessed Oct. 2017).

[7] F. Bonomi, R. Milito, J. Zhu, and S. Addepalli. 2012. Fog computing and its role in the internet of things. In *Proceedings of the 1st Edition of the MCC Workshop on Mobile Cloud Computing*. 13–16. DOI: http://dx.doi.org/10.1145/2342509.2342513

[8] B. Zhou, Q. Li, Q. Mao, W. Tu, and X. Zhang. 2015. Activity sequence-based indoor pedestrian localization using smartphones. *IEEE Trans. Hum.-Mach. Syst.* 45, 5 (2015), 562–574. DOI: http://dx.doi.org/10.1109/THMS.2014.2368092

[9] DAIRYMASTER. 2013. What is moomonitor+. Retrieved from moomonitor.dairymaster.com.

[10] HerdInsights. 2015. How HerdInsights works. Retrieved from herdinsights.com.

[11] E. I. Gaura, J. Brusey, M. Allen, R. Wilkins, D. Goldsmith, and R. Rednic. 2013. Edge mining the internet of things. *IEEE Sens. J.* 13, 10 (2013), 3816–3825. DOI: http://dx.doi.org/10.1109/JSEN.2013.2266895

[12] K. Bhargava, S. Ivanov, C. Kulatunga, and W. Donnelly. 2017. Fog-enabled WSN system for animal behavior analysis in precision dairy. In *Proceedings of the International Conference on Computing, Networking and Communications (ICNC'17)*. 504–510. DOI: http://dx.doi.org/10.1109/ICCNC.2017.7876180

[13] L. Mainetti, L. Patrono, A. Secco, and I. Sergi. 2016. An IoT-aware AAL system for elderly people. In *Proceedings of the International Multidisciplinary Conference on Computer and Energy Science (SpliTech'16)*. 1–6. DOI: http://dx.doi.org/10.1109/SpliTech.2016.7555929

[14] X. Huang, Y. Li, Y. Wang, X. Chen, Y. Xiao, and L. Zhang. 2018. CTS: A cellular-based trajectory tracking system with GPS-level accuracy. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 4, Article 140 (2018), 140:1–140:29 pages. DOI: http://dx.doi.org/10.1145/3161185

[15] R. Mohamed, H. Aly, and M. Youssef. 2017. Accurate real-time map matching for challenging environments. *IEEE Trans. Intell. Transport. Syst.* 18, 4 (2017), 847–857. DOI: http://dx.doi.org/10.1109/TITS.2016.2591958

[16] X. Li, D. Zhang, Q. Lv, J. Xiong, S. Li, Y. Zhang, and H. Mei. 2017. IndoTrack: Device-free indoor human tracking with commodity Wi-Fi. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 3, Article 72 (2017), 72:1–72:22 pages. DOI: http://dx.doi.org/10.1145/3130940

[17] B. Xie, K. Chen, G. Tan, M. Lu, Y. Liu, J. Wu, and T. He. 2016. LIPS: A light intensity–based positioning system for indoor environments. *ACM Trans. Sen. Netw.* 12, 4 (2016). DOI: http://dx.doi.org/10.1145/2953880

[18] Q. Yuan and I. M. Chen. 2013. 3-D localization of human based on an inertial capture system. *IEEE Trans. Robot.* 29, 3 (2013), 806–812. DOI: http://dx.doi.org/10.1109/TRO.2013.2248535

[19] D. Ayllón, H. A. Sánchez-Hevia, R. Gil-Pita, M. U. Manso, and M. R. Zurera. 2016. Indoor blind localization of smartphones by means of sensor data fusion. *IEEE Trans. Instr. Meas.* 65, 4 (2016), 783–794. DOI: http://dx.doi.org/10.1109/TIM.2015.2494629

[20] Z. Chen, Q. Zhu, and Y. C. Soh. 2016. Smartphone inertial sensor-based indoor localization and tracking with iBeacon corrections. *IEEE Trans. Industr. Inform.* 12, 4 (2016), 1540–1549. DOI: http://dx.doi.org/10.1109/TII.2016.2579265

[21] OpenFog Consortium Architecture Working Group. 2017. OpenFog reference architecture for fog computing. Retrieved from openfogconsortium.org.

[22] S. Sarkar, S. Chatterjee, and S. Misra. 2015. Assessment of the suitability of fog computing in the context of internet of things. *IEEE Trans. Cloud Comput.* PP, 99 (2015). DOI: http://dx.doi.org/10.1109/TCC.2015.2485206

[23] R. Tan, G. Xing, B. Liu, J. Wang, and X. Jia. 2012. Exploiting data fusion to improve the coverage of wireless sensor networks. *IEEE/ACM Trans. Netw.* 20, 2 (2012), 450–462.

[24] S. Gomes Soares, A. F. da Rocha, T. M. G. de A. Barbosa, and R. A. de Matos Araújo. 2010. Embedding a neural network into WSN furniture. In *Proceedings of the 10th International Conference on Hybrid Intelligent Systems*. 219–222.

[25] D. Goldsmith and J. Brusey. 2010. The Spanish Inquisition protocol: Model-based transmission reduction for wireless sensor networks. In *IEEE Sensors*. 2043–2048. DOI: http://dx.doi.org/10.1109/ICSENS.2010.5690285

[26] E. I. Gaura, J. Brusey, and R. Wilkins. 2011. Bare necessities—Knowledge-driven WSN design. In *Proceedings of the IEEE Concerence on Sensors* 66–70. DOI: http://dx.doi.org/10.1109/ICSENS.2011.6127213

[27] R. Rednic, E. Gaura, and J. Brusey. 2009. ClassAct: Accelerometer-based real-time activity classifier. In *Proceedings of the Sensors & Instrumentation KTN: Wireless Sensing Demonstrator Showcase (WiSIG'09)*. 1–6.

[28] M. Abo-Zahhad, O. Amin, M. Farrag, and A. Ali. 2014. Survey on energy consumption models in wireless sensor networks. *Open Trans. Wireless Comm.* 1, 1 (2014), 63–79.

[29] C. J. Rutten, A. G. Velthuis, W. Steeneveld, and H. Hogeveen. 2013. Invited review: Sensors to support health management on dairy farms. *J. Dairy Sci.* 96, 4 (2013), 1928–1952. DOI: http://dx.doi.org/10.3168/jds.2012-6107

[30] M. Alsaaod, C. Römer, J. Kleinmanns, K. Hendriksen, S. Rose-Meierhöfer, L. Plümer, and W. Büscher. 2012. Electronic detection of lameness in dairy cows through measuring pedometric activity and lying behavior. *Appl. Animal Behav. Sci.* 142, 3 (2012), 134–141. DOI: http://dx.doi.org/10.1016/j.applanim.2012.10.001

[31] M. Trotter et al. 2012. Monitoring and managing landscape variability in grazing systems. In *Proceedings of the 15th Precision Agriculture Symposium*. 42–48.

[32] J. Werner et al. 2017. Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *J. Neurosci. Meth., Elsevier* (2017). DOI: http://dx.doi.org/10.1016/j.jneumeth.2017.08.022

[33] Advanticsys. 2017. MTM-CM5000-MSP. Retrieved from advanticsys.com.
[34] Invensense. 2014. MPU-9255 product specification (rev. 1.0). Retrieved from stanford.edu.
[35] Wiki. 2015. TinyOS documentation wiki. Retrieved from tinyos.stanford.edu/tinyos-wiki.
[36] Raspberry Pi Foundation. 2016. Raspberry Pi 2 model B. Retrieved from raspberrypi.org.
[37] Md. B. Uddin and C. Castelluccia. 2010. Toward clock skew–based wireless sensor node services. In *Proceedings of the 5th ICST Wireless Internet Conference (WICON'10)*. 1–9. DOI: http://dx.doi.org/10.4108/ICST.WICON2010.8503
[38] K. Shinghal, A. Noor, N. Srivastava, and R. Singh. 2011. Power measurements of wireless sensor network node. *Int. J. Comput. Eng. Sci.* 1, 1 (2011), 8–13.
[39] Antônio Dâmaso, Davi Freitas, Nelson Rosa, Bruno Silva, and Paulo Maciel. 2013. Evaluating the power consumption of wireless sensor network applications using models. *Sensors* 13, 3 (2013), 3473–3500. DOI: http://dx.doi.org/10.3390/s130303473
[40] David Gay, Philip Levis, Robert von Behren, Matt Welsh, Eric Brewer, and David Culler. 2003. The nesC language: A holistic approach to networked embedded systems. *SIGPLAN Not.* 38, 5 (May 2003), 1–11. DOI: http://dx.doi.org/10.1145/780822.781133
[41] Antônio Dâmaso, Davi Freitas, and Nelson Rosa. 2013. nesc2cpn. Retrieved from github.com/sensor2model-group/nesc2cpn.

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