

Proceedings of the 2nd International Precision Dairy Farming Conference



C O N F E R E N C E O N
PRECISION DAIRY FARMING

ROCHESTER, MINNESOTA, USA

18-20 JUNE

2019

**Organized by the
University of Minnesota**

Welcome to the 2019 Precision Dairy Conference!

On behalf of our conference planning committee, I welcome you to the second International Precision Dairy Farming Conference and the fourth U.S. Precision Dairy Conference.

Precision dairy technology is being adopted at a rapid pace in North America. Many farms now use sensor technologies for cattle health and reproduction management. The number of farms using robotic milking has grown substantially in recent years. There is also a lot of interest in data management and analysis, computer vision technology, automated feeding of calves and cows, inline sensors, smart barns, cow side tests, and more!

Precision dairy farm management has become an important topic in the dairy industry. Let us have a great time while learning more about it during the next two or three days.

Please visit with our sponsors and speakers while you are here. They have much to share with us. Some of them came from a long distance to tell us about their products and services, their research, or their farm. I know some of you attendees have also traveled many hours to get here. Thanks to all of you, near and far, for attending our event. Enjoy the networking opportunities, make new friends, and learn from each other.

Remember to use the *Whova app* to help you network and receive up to date information about the program.

Best wishes for an enjoyable and educational time at the 2019 Precision Dairy Conference!

Sincerely,



Marcia Endres
Conference Planning Committee Chair
Department of Animal Science
University of Minnesota

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June 18, Tuesday

7:30-4:30 Registration – North Lobby

7:30 – 8:30 Continental Breakfast – Exhibit Hall

1st Plenary Session – Suites 102-105

8:30-8:45 Welcome to the 2019 Conference – Marcia Endres

8:45-9:25 The New Digital World of Dairy Farming: Bridging the Data Gap - Aidan Connolly

9:30-10:30 Breakout Sessions

Suite 101 Use of Data in Dairy Systems

9:30-9:50 Harnessing the Power of Data for Better Cow Management – Sri Kantamneni

9:50-10:10 Accelerating Adoption of Precision Dairy Farming through Digital Innovation Hubs – Caroline van der Weerd

10:10-10:30 At-Market Sensor Technologies to Develop Proxies for Resilience and Efficiency in Dairy Cows – Claudia Kamphuis

Suite 106 Research with Sensor Data

9:30-9:50 Evaluation of a Cow Health Index for the Detection of Health Problems in Dairy Cows – Albert DeVries

9:50-10:10 Automated Disease Detection for Robotic Milking Systems Using Deep Learning and Recurrent Neural Networks – Meagan King

10:10-10:30 Determination of Relationships Between Rumination Time, Milk Fat Production, and Milk Fatty Acid Profile Using Real-Time Rumination Observation Data – Elle Andreen

10:30-11:00 Break and Refreshments – Exhibit Hall

11:00-12:00 Breakout Sessions

Suite 101 Sensors

11:00-11:20 Improving Dairy Cattle Management with Genomics and Sensor Data– Matthew Borchers

11:20-11:40 Use of an Accelerometer System for Identifying Cows At Risk For Suffering From Health Disorders in Early Lactation – Michael Iwersen

11:40-12:00 How Are We Using Sensor Technology on Our Farm? Diane Gertken

Suite 106 Applied Research Abstracts

11:00-11:20 Age-Related Changes in Body Shape May Affect the Accuracy of Biometric Measurements Performed on Three-Dimensional Models in Cattle – Joao Viana

11:20-11:40 Body Condition Score Change Throughout Lactation Utilizing an Automated Body Condition Scoring System: A Descriptive Study – Melissa Cantor

11:40-12:00 Comparison of In-Line Measurements with Conventional Single-Day Herd Tests – Robert Orchard

12:00-1:30 Lunch – Exhibit Hall

2nd Plenary Session – Suites 102-105

1:30-2:10 Experiences with Precision Farming in The Netherlands: A Farmer's Perspective on Data Ownership - Ron van Burgsteden

2:20-3:20 Breakout Sessions

Suite 101 Grazing Systems and Sensors

2:20-2:40 Performance of an In-Cow Sensor for Estrus Detection in Dairy Cattle During the Grazing Season – Judith Roelofs

2:40-3:00 Validation of an Ear-Attached Accelerometer for Grazing Behavior – Glenda Pereira

3:00-3:20 Ground Based and Remote Sensing Measurements for Automated Precision Grassland Management– Bernadette O'Brien

Suite 106 Using Sensors

2:20-2:40 Integrating Sensors and Standard Operating Procedures: A Reproduction Example – Arnold Habbers

2:40-3:00 Relationship between Actual Feeding Time and Time Predicted by Sensors in Transition Cows – Ray Nebel

3:00-3:20 Is It Possible To Detect Lameness in Dairy Cows Using Activity Sensors? – Lenny van Erp

3:20-4:20 Break and Refreshments (Exhibit Hall) and Poster Session (North Lobby)

3rd Plenary Session - Suites 102-105

4:20-5:00 Can We Use Sensors to Make Meaningful Animal Health Decisions? - Dave Kelton

5:30-7:30 Reception (Appetizers, cash bar) – Riverfront Plaza

June 19

7:30-12:30 Registration – North Lobby

7:30 – 8:30 Continental Breakfast – Exhibit Hall

4th Plenary Session – Suites 102-105

8:30-8:40 2nd Day Welcome and Announcements – Marcia Endres

8:40-9:20 Precision Agriculture: A Venture Capital Perspective - Kieran Furlong

9:30-10:30 Breakout Sessions

Suite 101 Informational and Applied Topics

9:30-9:50 TBD

9:50-10:10 A Practical Approach to Determine Daily Individual Cow Feed Efficiency and Income Over Feed Cost – Pedro Madero

10:10-10:30 Field Robotics (Not Ag!) Research and Development at the U of M – Junaed Sattar

Suite 106 Robotic Milking

9:30-9:50 Reducing Bimodality by Optimizing Treatment Time in AMS – Paul Peetz

9:50-10:10 Performance of an Automatically Milked Dairy Herd in a 4-Way Grazing System – Bernadette O'Brien

10:10-10:30 Factors Associated with Milk Production per Robot on Free-Flow Farms in the Upper Midwest United States – Mateus Peiter

10:30-11:00 Break and Refreshments – Exhibit Hall

11:00-12:00 Breakout Sessions

Suite 101 Calves

11:00-11:20 Are Accelerometers a Good Tool to Predict Diseases in Calves? – Sergio Calsamiglia

11:20-11:40 Fully Automated Individual Calf Rearing to Optimize Dairy Calf and Future Dairy Cow Performance – Harma Berends

11:40-12:00 Validation of a Partial Weight Scale on an Automated Milk Feeder for Estimating Daily Body Weight in Dairy Calves – Joao Costa

Suite 106 Robotic Milking

11:00-11:20 Update on the Use of Robotic Milking Around the World – Thierry Perrotin

11:20-11:40 The Largest Robotic Milking Dairy in The World: ANCALI, Chile - Past Experience and Forthcomings – Pedro Melendez

11:40-12:00 Planning and Design For Robotic Milking Facilities – Jeff Prashaw

12:00-1:30 Lunch – Exhibit Hall

5th Plenary Session – Suites 102-105

1:30-2:10 Large Scale Robotics: Is It Worth The Hype? - Brian Houin

2:10-3:10 Break and Refreshments (Exhibit Hall) and Poster Session (North Hall)

3:10-4:10 Breakout Sessions

Suite 101 Calf Feeders and Mastitis Research

3:10-3:30 Automated Milk Feeders for Calves at Our Dairy – Brian Houin

3:30-3:50 Unravelling the Terminology and Use of Methods in Data-Driven Mastitis Detection – Mariska van der Voort

3:50-4:10 An Automated In-Line Clinical Mastitis Detection System Using Measurement of Conductivity From Foremilk of Individual Udder Quarters – Russ Cavanaugh

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| 3:10-3:30 | Evaluating the Effects of Mean Stocking Density on Automatic Milking System Use and Total Milk Production in Holstein Cows – Amanda Lee |
| 3:30-3:50 | The Australian AMS Journey – Nicolas Lyons |
| 3:50-4:10 | Incomplete Milkings in Automatic Milking Systems – Nicolas Lyons |

6th Plenary Session – Suites 102-105

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| 4:15-4:30 | Conference Highlights and Wrap-Up – Henk Hogeveen |
| 4:30 | Adjourn the 2-day Conference |

June 20 Optional Farm Tour (separate registration)

| | |
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| 7:45-2:00 | One robotic milking (2 robots) and TMR feeding (Vector) dairy farm near Lanesboro, MN and one robotic milking dairy (4 robots) near Winona, MN. |
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Keynote Speakers

Aidan Connolly

Aidan Connolly is an unusual leader. He is currently President of Agritech Capital based in Wilmington, North Carolina. Despite nearly 30 years of business experience and employed in one company (Alltech) until recently, his role changed so often his experiences mirrors that of senior executives or global consultants. He has worked with a full range of executive and managerial challenges, including direct experience of Greenfield startups, high growth environments, turnaround issues, challenging economic environments and a wide range of political and economic systems. Connolly has worked in over 100 countries, lived in six of them and speaks five languages. He has worked in political associations, with state and national governments in the US, China, Europe and Brazil, international organizations such as the European Union and the United Nations. Connolly has appeared as a commentator on radio and television, often being cited for his knowledge of the animal feed industry. He holds positions as adjunct professor of marketing at the Smurfit School of Business, University College Dublin and the China Agricultural University in Beijing. He has published over 30 academic articles and is a regular contributor to social media where he is particularly active on LinkedIn and Twitter.

Ron van Burgsteden

Ron had the dream to be a farmer, just like six generations of his family before him. After finishing agricultural trade school, he took over the family farm which now includes 100 acres. The farm is located in Leusden, exactly in the middle of the Netherlands. Ron has witnessed the way that farming has changed over generations. Ron's father saw the change from milking by hand to milking with milking machines. Nowadays, Ron himself uses more technology than ever before and he runs his 70 cows and 50 youngstock all by himself. And he still has time to effectively manage the herd and spend time with family. Ron loves his job as never before.

Although Ron is a farmer and spends most of his time working on his farm, he is also active in a number of advisory and governance boards. Although these boards vary in nature, they are all about dairy farming. From 2005 until 2015 he was member and chairman of the Advisory board data management of CRV, the Dutch Dairy Herd Information cooperative (21,000 members, 195 million \$US turnover). From 1999 until 2014 he was member of the regional board of Royal Friesland Campina (the largest dairy processing cooperative in the Netherlands and 3rd largest cooperative dairy processor in the world). Currently he is member of Waterschap Vallei&Veluwe, the independent government body responsible for all regional water issues. He is also chairman of the Farmers Advisory board of JoinData. JoinData is a non-profit organization that was founded as result of the Dutch SmartDairyFarming project and has the main cooperatives in the dairy industry as its members.

Dr. David Kelton

David Kelton holds the DVM, MSc and PhD degrees, all from the University of Guelph. He is professor of veterinary epidemiology and the Dairy Farmers of Ontario Dairy Cattle Health Research Chair in the Department of Population Medicine, Ontario Veterinary College. He is a member of Scientific Committee of the Canadian Bovine Mastitis Research Network, the Canadian Representative to the International Dairy Federation Standing Committee on Animal Health and Welfare where he chairs the Working Group on Paratuberculosis, and President of the National Mastitis Council. He teaches dairy cattle health and management in the undergraduate, graduate and professional curriculum and is a member of several local, provincial and national working groups dealing with dairy cattle health and welfare. He has co-authored more than 200 manuscripts in refereed journals. His research interests include paratuberculosis, mastitis and lameness, with a focus on their detection and control in dairy herds and their impacts on health, productivity and welfare.

Kieran Furlong

Kieran Furlong is a Venture Partner with Finistere Ventures and works in the Discovery2Product (D2P) group at the University of Wisconsin, where he focuses on innovation and technology commercialization. He joined the University of Wisconsin in 2019 following a career that spanned venture capital, start-ups and the international chemical industry. Prior to D2P, Kieran headed the Finistere Ventures E.U. office, which he opened in 2017 in Dublin, Ireland and was Partner for the Ireland Agtech Fund. Finistere is a leading agtech venture capital firm based in California. He also serves on the board of ApisProtect – a start-up developing IoT hive monitors to improve beekeeping in the honey and pollination sectors. Kieran grew up in the rural south east of Ireland – a strong dairy region – and started his career with the global chemical firm, ICI. Following his career in the chemical industry, Kieran entered the world of start-ups. Kieran led the business development at Virent – a University of Wisconsin spin-out – including a successful partnership with The Coca-Cola Company in the development of the first commercial 100% bio-based PET bottle. Kieran has a degree in Chemical Engineering from University College Dublin, Ireland and an MBA from the Graduate School of Business at Stanford University where he was an Arjay Millar Scholar.

Brian Houin

Brian was born and raised on his family farm in Plymouth, Indiana. He graduated from Purdue in 2003 with a degree in Meteorology and a minor in Spanish. Even though he doesn't practice forecasting the weather, it gave him a passion for analyzing data. Faced with the challenge of staying competitive in the dairy industry, the Homestead Dairy family decided to embrace technology and build an automated calf facility with 8 feeders and a new robotic milking facility to take advantage of new technologies and improve efficiencies. They currently have 36 box robots milking 2200 cows.

Conference Planning Committee

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Without their support, this event would not be possible!

General Information

Conference Venue The Mayo Civic Center is located at 30 Civic Center Drive SE in Rochester, Minnesota. *Suites (Rooms)102-105, Suite (Room)101, and Suite (Room)106 will be used for conference sessions.*

Registration & Information Desk Located at the North Lobby, Mayo Civic Center. Registration will be open on Tuesday, June 18, 7:30 a.m. to 4:30 p.m., and on Wednesday, June 19, 7:30 a.m. to 12:30 p.m.

Conference App We are using the **Whova app** for this event. Download the app from the App Store or Google Play and click on the 2nd International Conference on Precision Dairy Farming. Your name has been uploaded as attendee to give you access. Please let us know if you have any issues getting it to work. The app is a fun way to network with attendees, share photos and stay posted on last minute changes to the event. Please turn notifications on.

Trade Show The Trade Show will take place in the Exhibit Hall at the Mayo Civic Center. We encourage you to visit the Trade Show during lunch and breaks.

Refreshment Breaks Breaks will take place in the Exhibit Hall at times shown on the conference schedule.

Breakfast & Lunch Breakfast and lunch will be served in the Exhibit Hall.

Reception & Cash Bar, June 18, 5:30-7:30 p.m. A reception with cash bar will be held in the Riverfront Plaza (near conference rooms).

Name Badges Your name badge is your admission to all presentations, to the Exhibit Hall for the trade show, breakfast, breaks and lunch, and to the reception on Tuesday night. Wear it at all times while at the event.

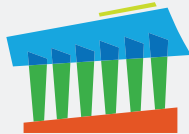
Certificate of Attendance Request a Certificate of Attendance at the registration desk if your organization requires one. They will not be automatically distributed to everyone.

Internet Access Complimentary wireless Internet access is available throughout the facility.

Emergency Calls Dial 911 (for emergencies only) if there is a need for an ambulance, the police, or the fire department.

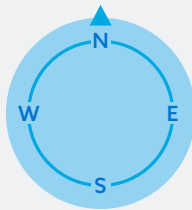
Shopping in Rochester Options located in close proximity to the Civic Center, include

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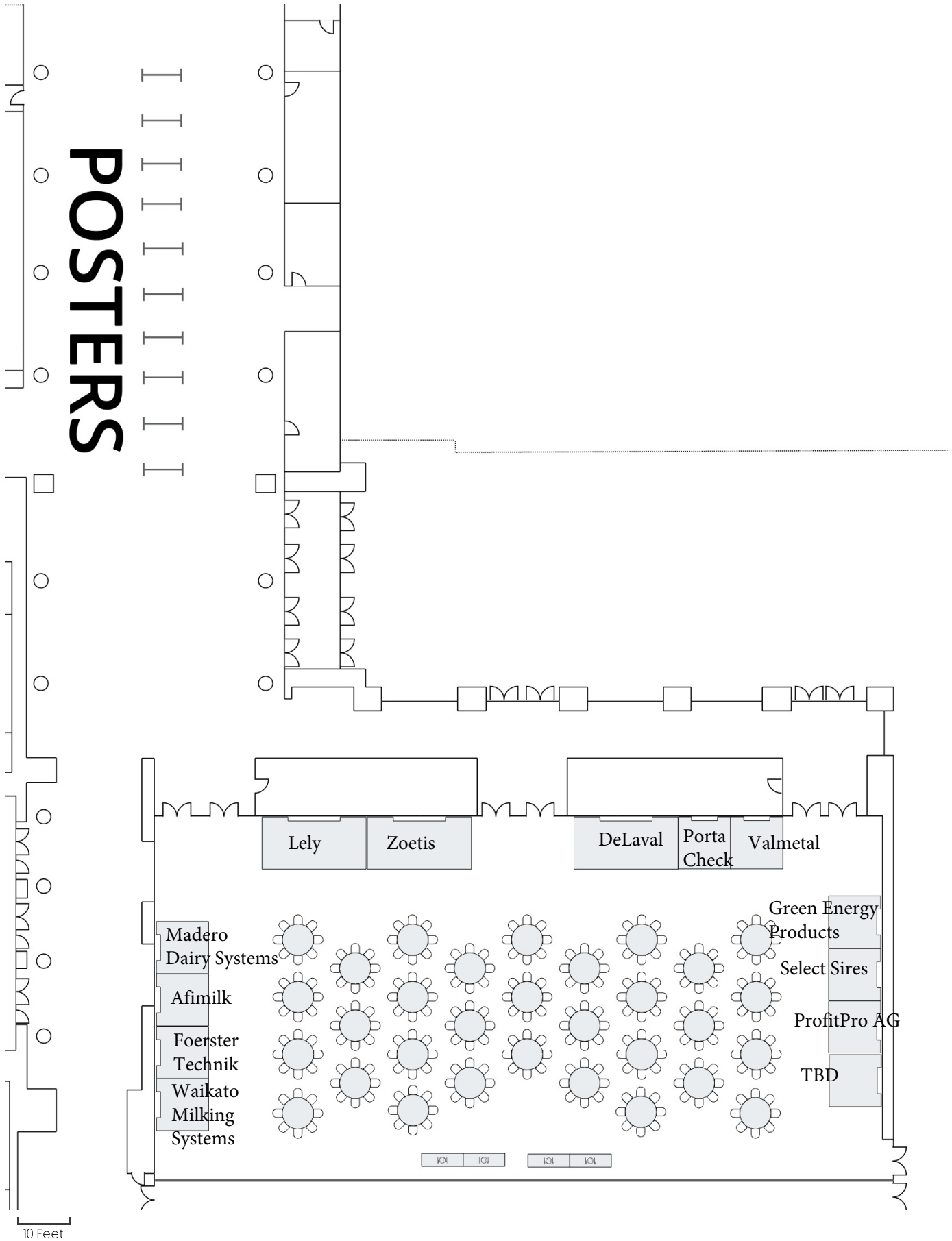


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The new Digital World of Dairy Farming – Bridging the data gap

Aidan Connolly
President, AgriTech Capital, North Carolina

By 2067 the dairy industry per capita consumption of dairy is expected to increase from 87 kg per person to 119 kg ([projections](#)). Compounded by a growing population, this means the world will need to produce 600 billion kilograms more milk. Today's dairy cow will either need to double her production, or we will need to dramatically increase cow numbers! In the last 25 years, we have increased milk production by [61%](#) (about 2% p.a.) but can we continue this trend and do so sustainably?

The difference between a high and low performing cow can be considerable. Milk production, judged by weight, is influenced by genetics and what cows eat (nutrition), but also by inconsistency in mixing of feed, eating behaviors such as sorting, other cows bullying, water quality (or lack of!) and environmental factors such as heat. In ever larger and more intensive production environments, with fewer people wanting to work on farms, managing is a bigger and bigger challenge. In such a setting dairy farming has focused on managing the average cow, not the individual.

A glaring gap for dairy farmers is data. Farms, especially large ones, don't know how much an individual cow eats, how much she drinks, how much she moves, her body temperature, stress, sickness, etc. Even individual milk production isn't always recorded in a consistent manner. How can farmers manage cow comfort, select the right ones for breeding and retaining, judge true profitability and raise the bar in terms of milk production?

Enter digital technologies with the power to fill that gap. The ability to use precise, real-time, smart data that can be monitored and converted to insights upon which farmers can base data driven decisions is a game changer. And, it's not just a game changer at farm level; consumer concerns for animal welfare and sustainability can also be addressed with digital technologies.

Sensors

More than any other technological advancement, sensors can fill in the data gap in dairy farming, particularly when animals are outside in a field. Before the use of technology, monitoring an individual cow's health was difficult, time consuming and cost-intensive. However, the use of sensors and wearable technologies allows farmers to monitor individual cows. No longer do producers have to work from herd averages but are able to determine illness or lameness more effectively, and react accordingly, quite possibly before milk production or the herd is affected.

Wearable sensors have proved to be vital in managing a cow's health and there is no shortage of companies producing this type of technology. Leaders such as SCR Dairy, which is assessed to have about 80% of the market share, produce all manner of wearables such as that worn on a cow's ears, neck, legs or tail. They can also be implanted subcutaneously or inside the rumen. Sensors also help to monitor cow comfort and welfare. Cows need to rest for an average of 11

hours a day, any less than this affects blood flow to the udder and can negatively impact milk yield. Sensors can detect a lack of locomotion and alert producers when it occurs in order to circumvent these negative effects.

Sensors can be used to detect disease signals that are otherwise hard for farmers to notice, such as mastitis. [AfiMilk](#), [Agricam](#), [DeLaval](#), [Fullwood](#), [Lely](#), [LIC Automation](#), [MastiLine](#) and [Wakaito](#) all claim to detect mastitis in cows and provide producers with early opportunities to combat the issue. Rumination is also vital to a cow's production and sensors designed to be located inside the rumen can do this most effectively by monitoring acidity levels through a digitally connected bolus. Companies that offer acid monitors like [Smartbow](#), which was a participant in the [Pearse Lyons Accelerator](#), allow farmers to detect digestive problems, such as ruminal acidosis. Other rumination sensors are provided by [Agis](#), [DairyMaster](#), [eCow](#), [Gentian Services](#), [ITIN-HOCH](#), [Lely](#), [Medria](#), [MoonSyst](#), [Moow](#), [Nedap](#), [Silent Herdsman](#), [SCR](#), [smaXtec](#), and [Well Cow](#).

Livestock Labs has created a tracking technology called [EmbediVet](#) which is implanted underneath the cow's skin using a local anesthetic. This tracker claims to be less annoying than wearable sensors and more accurate in gathering data and monitoring behavior. [Ingenera](#) offers a line of various sensor products designed to measure cow conformation, weight, udder health and other body metrics.

[Moocall](#) produces sensors that detect the heat cycle of cows by evaluating her responsiveness to a teaser bull. His proximity and behavior can determine her receptivity and alert the farmer's smart device if she is in heat. [Afirmilk](#) makes a pedometer for cows, alerting farmers of the best time for insemination on the basis that cows walk and move more as they come into estrus. Other heat detection sensor companies include: [Agis](#), [Boumatic](#), [CRV](#), [Dairymac](#), [DairyMaster](#), [DeLaval](#), [ENGS Systems](#), [GEA](#), [Gentian Services](#), [Ice Robotics](#), [Lely](#), [Moonitor](#), [Medria](#), [Nedap](#), [SCR](#), [Smartbow](#), [smaXtec](#), and [Fullwood](#).



Moocall also makes the [Moocall Calving sensor](#), a wearable that attaches to the cow's tail and monitors her contractions. Connected to the producer's mobile, it sends an alert one hour before active calving, allowing farmers to minimize time spent checking pregnant cows and increase

efficiencies in time management. More companies with calving sensors include [Cowcall](#), [smaXtec animal care GmbH](#), [Medria](#), [ENGS Systems](#) and the [Livestock Labs](#).

Outside of wearables on cows, there are other examples of sensors in the dairy industry. [SomaDetect](#) is a startup that has developed a sensor allowing farmers to know what is in the milk they produce. Specifically, there is an in-line sensor that measures milk fat, protein, somatic cell counts, progesterone, and antibiotics at every milking. Danish company [Foss Analytics](#) has a similar business model using sensors and NIR.

[ENGS systems](#) is implementing their free flow technology through the Advanced Milk Meter. It collects data on the cow's individual milk flow rate, quantity, temperature and electrical conductivity and transfers the data to a milk management program for farmers to use.

Artificial Intelligence

Big data promises precision agriculture, however if farmers can't interpret the data and use it to take action then the data is useless. Artificial intelligence allows producers to analyze the data that sensors and other hardware technologies collect. It can provide an interpretation and solution by mimicking human decision making and has the ability to completely transform how a dairy farm operates.

[SCR Dairy](#) is implementing cow, milk, and herd intelligence through their variety of sensors and artificial intelligence technologies. They offer sensors ranging from heat detection and calving to health monitoring sensors such as SCR's [SenseTime Solution](#) sensor which detects then charts a cow's daily activities, such as ruminating, eating and walking patterns. When paired with artificial intelligence software this provides users with early, proactive solutions to potentially concerning problems. Along with the capability to record information regarding reproduction, health and nutrition, the sensor provides farmers with solutions for each individual cow.



[Cainthus](#) has developed algorithms for facial recognition software that can monitor the cow's activity; there is no need for the cows to wear any sort of tracking devices and this software may eliminate the need for wearables all together, particularly for animals raised indoors. Using cameras stationed throughout the barn, the software alerts farmers when their cows show deviations from normalized behavior (such as feeding and drinking patterns). Cargill has a significant minority investment in Cainthus, assuming that this 'computer vision' approach will allow AI to supplant many of the sensor systems.

[Ida](#), "The Intelligent Dairy Farmer's Assistant," developed by Connecterra is a cow neck tag that gathers activity data on cows such as time spent eating, ruminating, idling, walking and lying down. Connecterra says it uses AI to interpret individual deviations in the cow's behavior and provide alerts or recommendations to the farmer.

Drones

There are opportunities for drones in the dairy industry, but they do often require additional technologies. Most simply, [drones](#) can be used to generally inspect the herd or fences or to aid in herding cows from fields to barns. The inclusion of other technologies creates greater opportunities. Visual sensors have proven to be instrumental in surveying land and measuring pasture growth. [PrecisionHawk](#) is using drones for the purpose of mapping, inspecting, and photographing pastures in order to detect growth.

Robots

Robotic milking machines are probably the most well-known application for robots in the dairy industry, increasing efficiencies and replacing expensive or unavailable labor. [Lely's Astronaut A5](#) and [DeLaval's Voluntary Milking System](#) not only cut labor costs, but allow cows to decide when they want to be milked. Robotic milkers (milkbots) clean the udders, identify the cow's teats and milk automatically.

DeLaval offers other robotic milking technologies, such as the [rotary platform](#) that allows farmers to maximize a herd's milking performance while providing a comfortable and safe environment for both cows and operators. [miRobot](#) provides a milking system also designed for larger operations. Both companies offer multi-stall automated milking operations to milk cows simultaneously, completing full parlors with only one operator. This new technology has allowed farmers to cut back on labor costs and get more milkings per day.

The [Lely Grazeway](#) system acts as a gateway to the pasture that only allows cows to graze after they have been milked. The cows step into the selection box, and the [Lely Qwes](#) cow-recognition system determines whether or not the cow can be let out to graze.

Before robots, cows were typically milked twice a day because of labor and time constraints. Now, cows can be milked three times a day or more, greatly increasing production and profits. And, as they are stationary for several minutes while milking, there is added opportunity for medical and health assessments using transponders or sensors; which can not only analyze the

speed, amount and quality of milk produced, but also how much the cow has eaten, heat cycle, etc.

Another possible use for robots include cleaning and sanitizing the barn, allowing for better biosecurity measures which will lead to healthier conditions for the cows. There might also be a place for robots in the calving process. While this might not be as useful for an outdoor herd, there could be potential for robotic assistance for cows kept indoors.

3D printing

There are multitudinous applications for 3D printing in the dairy industry. A primary application of 3D printing is in that of machine parts, which is of particular interest to rural farmers, saving valuable time and possibly money, depending on the part needed.

In some ways, 3D printing is already challenging the dairy industry with 3D printed foods. Cheese is one of the easier foods to duplicate through 3D printing, due to its easily changeable state from solid to liquid. [Study findings](#) suggest that printed cheese is less sticky, softer, and has better meltability than non-printed cheese. The concept of printed food may not appeal to all consumers; the challenge being to produce food that offers an advantage, such as lower cost, improved taste or healthier nutritional content.

Such is the case with “[Perfect Day](#),” a start-up company from San Francisco using 3D printing combined with gene sequencing to create a yeast fermentation product that looks and tastes like milk. The product is portrayed as a non-dairy alternative for vegans or dairy intolerant individuals.

Augmented Reality

Augmented reality can be defined as the integration of digital information with the user’s environment in real time. A recent [report](#) stated that sales for augmented reality are expected to rise from \$2.4 billion in 2018 to \$48.2 billion in 2025.

Studies have found that AR can be used to make food more [visually appealing](#) or to be effective in estimating proper [serving sizes](#). Apples’s [ARKit](#) can also be used to provide consumers with nutritional knowledge as this [video](#) demonstrates. Should this technology be more common, these applications could affect the dairy industry as certain aspects of food products, both good and bad, would now be more obvious to the consumer.

Outside of the consumer focus, augmented reality can be used to allow producers an alternative way to monitor and evaluate cows. This [video](#) (begin at 2:22) demonstrates how AR can allow a farmer to immediately see stats relating to the farm through the use of goggles. Information relating to each individual cow is overlaid through the glasses into the farmer’s field of vision. They can see information on everything in the facility, even evaluating the quality of the milk.

Could this technology not also be used in the veterinary field for inspection? Perhaps if combined with reliable sensor data, the vet could be able to deliver appropriate recommendations for disease management and reduce the need for direct farm call visits, thus lowering costs.

Virtual Reality

Virtual reality can be defined as an environment that can be interacted with in a seemingly real way through electronic equipment. Applications in the dairy industry vary from farm tours to veterinary training and the positive effects such as safety and efficiency are recognized.

New Zealand dairy cooperative Fonterra and solutions company Beca have partnered to develop a virtual reality [health and safety training technology](#) to allow employees to navigate the manufacturing and distribution sites without setting foot on the physical site, thus reducing onboarding times. Fonterra employees learn to identify potential hazards and experience hazardous situations in a realistic simulated environment, enhancing learning experiences without the risk of being in harm's way. This technology also reduces labor costs by replacing a number of the hands-on health and safety training positions.

Virtual reality is being used to teach veterinary students the reproductive and rectal tracts of the cow. Created by former vet, Sarah Baillie, the [Haptic Cow](#) is a fiberglass model of the rear of a cow that combines virtual reality with robotics. The VR aspect is provided by a computer that allows students to visualize an object within the cow virtually enabling them to practice fertility examinations such as pregnancy detection or determine reproductive concerns without putting them in a situation that can potentially be dangerous for both the cow and the student.

DeLaval is creating virtual reality footage of farms available also in 360 degrees, allowing viewers to scroll from side to side to view the entirety of the dairy barn in the film. The [Hamra Farm](#) in Sweden is showcased with the innovative techniques they implement on their farm, such as robotic milking machines, robotic brushes, robotic cleaners, as well as other innovative aspects of the farm. These "farm tours" will allow consumers to better understand where their dairy comes from. There is much discussion about animal welfare and giving consumers an opportunity to experience first-hand how a dairy farm operates will be a primary component to battle negative feelings toward the industry.

Blockchain

It is well known that consumers are increasingly becoming interested in where their food comes from and how it is produced. Blockchain can connect all aspects of the supply chain from producer to consumer and allow for food traceability and safety. The opportunities and challenges of blockchain have been described [before](#). From an agriculture and food perspective, offering this type of information to consumers will put products ahead of the competition and from a dairy industry standpoint, may not prove as challenging as other areas of agriculture, such as beef, which exchanges ownership more frequently.

Internet of Things

Together these eight technologies are creating opportunities within the dairy industry for increased efficiencies, profitability and production. The connectivity of these technologies is made possible through the Internet of Things (IoT)

[Agriwebb](#) is a company using IoT for full farm record keeping, including field management, inventory, operations, grazing and even biosecurity. [Stellapps](#) in India leverages IoT to offer all manner of products from general herd management to milk evaluation, payment processing and cold chain monitoring. [Dell Technologies](#) is also heavily involved in IoT applications and is working with dairy producer [Chitale](#).

Cargill is working with [SCiO \(Consumer Physics\)](#) to create [Reveal](#), an app designed to deliver content of feed within minutes. Previously, this type of technology was either time intensive (waiting on lab results) or expensive (specialized equipment cost thousands of dollars). Using a micro spectrometer with NIR calibrations, Cargill and SCiO offer this simple service using producers' own devices and results are available in a minute's time.

IoT is how another company, [SmartFarm Systems](#) is integrating various aspects of the dairy farm in one app. The software connects the producers bins to feed mills and helps with ordering feed and also connects to sensors on cows to monitor and track performance.

IoT technology such as [Keenan Intouch System](#) provides farmers with the nutritional information they need to ensure the best formulation possible. The feed mixer is designed to give uniformity to feed, allowing for improved digestion in the ruminant, creating rations that are both chemically and physically balanced. As an IOT system it allows producers and an international help desk to monitor feed waste and make necessary changes to improve efficiencies and decrease costs.

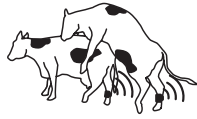
Using the Data

In the past, farm management applications have allowed farmers to make strategic management decisions based on the collection of farm data. Inevitably once nutritional decisions are being made, sciences such as nutrigenomics and decisions about smart nutrition are critical to taking advantage of this enhanced data and management information systems. Nutrigenomics research has shown that specific nutrients and inclusion of enzymes can greatly impact milk yield.

Previously, collected data has been generalized for an entire herd farm, rather than specific to each cow. Through the use of sensors, AI and other technologies, farm management apps like [FarmWizard](#) can provide individual data for each cow, allowing farmers to improve precision and accuracy when it comes to making managerial decisions. [Dairy Data Warehouse](#) and [Uniform Agri](#) also offer the opportunity for improved data collection, quality and analysis with a focus on enabling nutritionists to better advise their clients.

Dairying in 2050 won't look anything like Dairy farming of the recent past, let alone the since the first cow was domesticated. Changes are happening so fast the connected farm is likely to be the norm within the next 10 years. Capturing individual cow data and allows farmers direct access not only to current but also historical data and will made possible by implementing these 8 technologies and the interconnectivity of IoT. This will allow farmers to bridge the data gap and improve dairy production through digitization and the winners will be those who embrace this disrupted digital dairy landscape.

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ACCELERATING ADOPTION OF PRECISION DAIRY FARMING THROUGH DIGITAL INNOVATION HUBS

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Whereas ICT-related precision dairy farming (PDF) applications are advancing, the actual adoption thereof in practice does not always reflect their promising added value (Weerdt, van der, et al., 2017). That is not surprising, as adoption is an abstract concept, hard to grasp, let alone influence. But focusing on the supply-side of PDF applications more than on the demand from the intended users, does carry the risk that the gap between PDF applications and the farming sector grows, causing digital transformation to remain with just the frontrunners.

Closing the gap through Digital Innovation Hubs

A burgeoning phenomenon in the domain of digital transformation in different industry sectors, is the Digital Innovation Hub (DIH). These hubs, whether they are established formally or grow out of an informal initiative, aim to support and assist parties delivering digital applications to end-users. A DIH can for instance evolve around a university, some farmers and a feed company experimenting with a new young stock rearing approach, or originate from a fertility model that relies on data sharing between different owners of data.

In order to support and assist these parties, a DIH delivers services, preferably in a one-stop-shop concept (WG1, 2017). These services in turn relate to capabilities needed to deliver excellent technology, establish sustainable business plans and accurately address customers. For instance, a DIH can realize testing facilities for making improvements on the digital technology together with end-users; and provide training on marketing and creating appealing value propositions. This holistic perspective on PDF application development (from technology, business and user perspective), is found to be a promising way to safeguard adoption as delivery of actual value to daily practice on the farm is ensured (Weerdt, van der, et al., 2017). Adoption thus springs from continuous alignment of innovative applications with the context it is aiming to improve, and DIHs bring this context closer to the developers of these applications.

Realising adoption through DIHs: a focus on orchestration

Hubs are an important means through which ICT-related PDF applications can genuinely connect with their intended users. The reasons for this, is that DIHs are able to unite skills and capabilities from different contributors to the sector who take on different perspectives for the earlier-mentioned holistic view. As can be seen in

Figure 1, potentially a lot of actors can be related to a DIH. (A CC stands for Competence Centre, e.g. universities and research and technology centers).

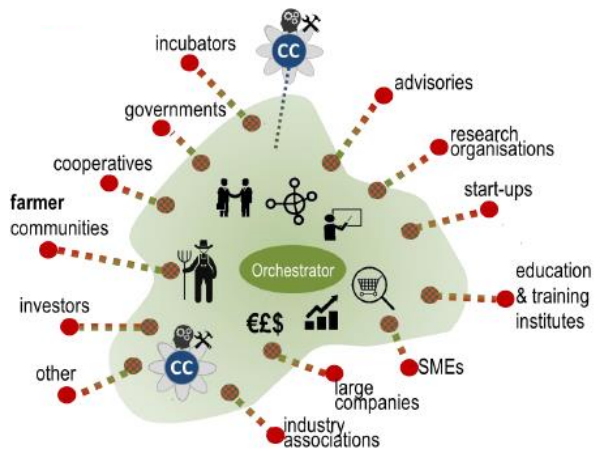


Figure 1: illustration of a Digital Innovation Hub and involved actors

Moreover, successful DIHs typically tend to grow: in number of applications, customers, but also in parties involved. This also means an increase knowledge transfer, best practice exchange and sharing of data, resulting in a potentially complex and extending infrastructure. The role of the Orchestrator (Figure 1) is to facilitate the process of initiating and extending DIHs. The orchestration challenges thus include: building capabilities and the DIH network, while guarding the holistic perspective as to ensure adoption by end users and customers.

Taking on the orchestration challenges and optimising adoption through DIHs

The European H2020 project SmartAgriHubs (<https://smartagrihubs.eu/>) is established to “[...]consolidate and foster an EU-wide network of Ag DIHs to enhance digital transformation for sustainable farming and food production”. The project evolves around DIHs and aims to take on the orchestration challenges mentioned above, not in the least by realising the ambition to attract 260 new DIHs besides the existing 140 DIHs in the current project network throughout Europe. The fundamental driver behind that is accelerating adoption by bringing digitalization closer to daily farm practice.

References

Weerdt, van der C.A., M.R. Vonder, G. Paradies, 2017, Connecting the business model’s value proposition to farmer adoption of precision farming apps, in: Proceedings of the 8th EC-PLF 2017 Conference, 340-347, Nantes, France

WG1, 2017, Digital Innovation Hubs: mainstreaming digital innovation across all sectors, Working Group 1, Roundtable on Digitising European industry, Final Version, June 2017.

At-market sensor technologies to develop proxies for resilience and efficiency in dairy cows

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Introduction

Currently, on-farm sensor technologies provide high-frequency repeated measures of, e.g., activity of individual animals. With these high-frequency sensor measurements, we moved forward from occasional snapshots of an animal's status, to a situation where we have continuous time-series of measurements. Until now, these measurements have largely been deployed for the detection of, e.g., a heat or mastitis event. However, little attention has been paid to their possible use for phenotyping complex traits, like resilience and efficiency (R&E). We hypothesize that these at-market sensor technologies can be used to develop proxies for R&E. As a first step, we compared curve-parameters of the 10% most and least resilient or efficient animals.

Materials And Methods

Data originated from the Dairy Campus, a Wageningen Research farm, and included data from 487 cows, or 487 lactations, between 2014 and 2015. Data included, albeit not continuously for all sensor technologies, sensor data on feed intake (through Roughage intake control bins), milk yield, activity, rumination activity, and live-weight.

For both R&E pragmatic definitions were used, where efficiency was expressed as feed efficiency, and computed for at lactation level as total input (DMI, in kg) over total output (milk yield, in kg). To be eligible for this feed efficiency computations, cows were required to have at least one RIC recording per week, for a minimum of 36 subsequent weeks. Resilience was defined to reflect a cow's ability to re-calve. To do so, lactations were divided into lactations where a cow was able to get in-calf again ("recalvers"), and those that were not ("non-recalvers"). Scoring for non-recalvers was done by counting the number of diseased days in the first 100 DIM, the more diseased days, the lower the ranking of the cow's lactation. For the recalvers, ranking was done based on inseminations and diseased days; those with just one insemination and no diseased days were ranked highest. Lactations were ranked according to their resilience or efficiency score.

The sensor measurements were aggregated to daily values. These daily values were made relative to the herd mean, and subsequently summarized these relative values into "curve-parameters" at lactation level. These curve-parameters involved the mean, and autocorrelation (lag1) of the relative curve of each lactation, the slope of the linear regression line through this relative curve, and the skewness and standard deviation of the residuals. These curve parameters were computed for all lactations (for both R&E). Subsequently, the 10% most and least resilient or efficient lactations were selected, and curve-parameters of these selected lactations were compared. Mean differences in these variables between groups were compared.

Results And Discussion

There were 98 lactations that had enough RIC recordings to compute efficiency at lactation level. These efficiency scores ranged from 0.48 (most efficient cows) to 1.19 (least efficient cows) kg DMI/kg milk. For ranking lactations for resilience, there were 128 lactations of non-recalvers and 359 lactations of recalvers. All lactations where cows were not in-calf received a lower resilience score than those lactations where cows were in-calf. Table 1 summarizes the mean values of curve-parameters for activity measurements of the 10% most and least resilient or efficient lactations. For activity, the mean values appear to be different between groups, although the ranges do overlap. Similar results were seen for the other sensors. These results imply that using a single sensor will be insufficient for a proxy for resilience or efficiency, and that combining sensors for this purpose is likely to be required. The lack of differences in mean values, and the overlap in the ranges, may also occur partly due to the very pragmatic definitions we used. Our current method to rank cows for resilience was based on the last lactation only, which has the consequence that cows in higher parities are likely to be underestimated for their resilience score compared to, e.g., heifers. This method could be improved by a scoring approach where cows with multiple lactations, that thus have shown the ability to re-calve several times, will receive more points than those that only make a first lactation. Concepts for such a method are under construction, and will be implemented in the future.

Conclusion

Comparing the curve-parameters of the 10% most and least efficient and resilient cows did demonstrate differences in means, although the ranges did overlap largely between the two groups. This implies there is little value in the use of individual sensors to develop proxies for resilience and efficiency so that combining sensors will be required to obtain good proxies.

Acknowledgement

The research leading to these results has received funding from the European Union's Horizon 2020 Framework Programme – GenTORE, under grant agreement n° 727213.

Table 1: Mean values (range between brackets) for activity measures, for the 10% most and least resilient or efficient lactations

| Curve-parameters | Resilience | | Efficiency | |
|--------------------|--------------------|-------------------|------------------|--------------------|
| | Top 10% | Lowest 10% | Top 10% | Lowest 10% |
| Mean | 100.7 (57.2-159.3) | 91.1 (37.6-207.3) | 116 (75.1-177.9) | 110.8 (79.4-154.4) |
| Autocorrelation 1 | 0.6 (-0.1-0.9) | 0.4 (-0.7-1.0) | 0.6 (0.2-1.0) | 0.7 (0.3-0.9) |
| Slope | -0.4 (-18.4-1.5) | -0.4(-10.8-3.1) | 0 (-0.2-0.3) | 0 (-0.1-0.2) |
| Skewness | 0.6 (-1.7-4.0) | 0.3 (-1.6-3.7) | 0.7 (-2.2-4.2) | 0.6 (-1.5-2.9) |
| Standard Deviation | 12.1 (0-39.2) | 12.0 (0-32.5) | 18.5 (8.9-39.3) | 17.0 (10.1-33.3) |

Evaluation of a Cow Health Index for the Detection of Health Problems in Dairy Cows

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Introduction

The DeLaval Cow Health Index (CHI) score is a new function in DeLaval DelPro software that is an indication of the health status of the cow. Each animal is given a CHI score after each milking. The CHI score is constructed from data on activity, milk yield, milk flow and conductivity collected by various sensors. Each combination of sensors results in a separate CHI score. Thus, CHI scores are always calculated even when data from one or more sensors are not available. The CHI score ranges from 0.0 to 5.0 (and even up to 8 depending on the number of sensors available). The idea is that the higher the CHI score, the greater the probability that the animal has a health problem. High CHI scores may indicate a variation of health events, such as emerging mastitis, ketosis, metritis, milk fever, or lameness.

One way to measure the predictive power of CHI scores is to see how well they signal emerging health problems without causing a high rate of false alarms. Therefore, the objective of this study was to investigate the sensitivity and specificity of various CHI scores to detect mastitis and ketosis.

Materials and Methods

The algorithms that calculate CHI scores were implemented on one dairy farm in the United States (farm B, average of 2800 cows) and one in Germany (farm K, average of 1929 cows). On both farms, three types of CHI scores were calculated named NO_ACT, NO_FLOW_COND, and COMPLETE. The COMPLETE scores included all sensor data on activity, milk yield, milk flow and conductivity. The NO_ACT scores included all sensor data except activity. The NO_FLOW_COND scores included all sensor data except milk flow and milk conductivity. Not all types of scores were available for all cows, but this depended on the sensors employed. On farm B, all types of CHI scores were available for at least 183 days. On farm K, all types of CHI scores were available for at least 178 days. The vast majority of data were collected in 2017. Events recorded by the dairy farmers were obtained as well. Here we will focus on mastitis (MAST) events which were available on both farms, and hoof trim (HOOF) events available on farm B and ketosis (KETO) events available on farm K.

Given an event, the highest CHI score within a time window around the event was calculated. Three time windows were investigated. Time windows varied from 5 days before to 2 days after the event (W5+2), from 5 days before to 1 day before the event (W5-1), and from 5 days before to 2 days before the event (W5-2). Thresholds for CHI scores were varied from 0.5 to 8 with steps of 0.5. A true positive (TP) was called when a CHI score \geq threshold within a window. A false negative was called when all CHI scores $<$ threshold within a window. Outside the window, every day a CHI score \geq threshold was a false positive (FP) and a CHI score $<$ threshold was a

true negative (TN). We calculated sensitivity ($TP / (TP + FN)$) and specificity ($TN / (TN + FP)$) for each combination of event, threshold, window, and type of CHI score. We also estimated specificity when sensitivity was set at 0.60 and at 0.80. Analyses were performed at the University of Florida with as little input from DeLaval as possible.

Results

Events of mastitis (196) and hoof trim (377) on farm B resulted in incidences per 1000 days of 0.34 and 0.65. On farm K, events of mastitis (1075) and ketosis (92) resulted in incidences per 1000 days of 3.49 and 0.30. Tables 1 (farm B) and 2 (farm K) show specificities given sensitivities of 0.60 and 0.80.

Table 1. Farm B. Specificities to detect mastitis (MAST) and hoof trim (HOOF) events given three types of CHI scores, sensitivities (SE) set at 0.60 or 0.80 and three time windows (W) around an event.

| Sensors | SE | MAST W5+2 | MAST W5-1 | MAST W5-2 | HOOF W5+2 | HOOF W5-1 | HOOF W5-2 |
|--------------|------|--------------|--------------|--------------|--------------|--------------|--------------|
| NO_ACT | 0.60 | 0.98 | 0.96 | 0.93 | 0.91 | 0.81 | 0.79 |
| NO_FLOW_COND | 0.60 | 0.99 | 0.98 | 0.96 | 0.94 | 0.85 | 0.82 |
| COMPLETE | 0.60 | 0.99 | 0.98 | 0.95 | 0.93 | 0.85 | 0.83 |
| NO_ACT | 0.80 | 0.94 | 0.88 | 0.80 | 0.83 | NA | NA |
| NO_FLOW_COND | 0.80 | 0.97 | 0.91 | 0.83 | 0.86 | NA | NA |
| COMPLETE | 0.80 | 0.97 | 0.91 | 0.84 | 0.86 | 0.74 | NA |

Table 2. Farm K. Specificities to detect mastitis (MAST) and ketosis (KETO) events given three types of CHI scores, sensitivities (SE) set at 0.60 or 0.80 and three time windows (W) around an event.

| Sensors | SE | MAST W5+2 | MAST W5-1 | MAST W5-2 | KETO W5+2 | KETO W5-1 | KETO W5-2 |
|--------------|------|--------------|--------------|--------------|--------------|--------------|--------------|
| NO_ACT | 0.60 | 0.95 | 0.93 | 0.90 | 0.99 | 0.98 | 0.97 |
| NO_FLOW_COND | 0.60 | 0.95 | 0.93 | 0.90 | 0.99 | 0.99 | 0.98 |
| COMPLETE | 0.60 | 0.95 | 0.93 | 0.90 | 0.99 | 0.99 | 0.98 |
| NO_ACT | 0.80 | 0.87 | 0.82 | N/A | 0.98 | 0.96 | 0.95 |
| NO_FLOW_COND | 0.80 | 0.87 | 0.82 | 0.77 | 0.98 | 0.97 | 0.96 |
| COMPLETE | 0.80 | 0.87 | 0.82 | 0.77 | 0.97 | 0.97 | 0.95 |

Specificities were 0.82 or greater when sensitivity was set at 0.80. Lower sensitivities resulted in greater specificities. Specificities were slightly greater for farm B than for farm K for mastitis. The combination of sensors as data sources for CHI scores had a negligible effect on specificities for mastitis and ketosis, but omitting activity data resulted in lower specificities for hoof trim events. These specificities appear to be high enough (Hogeveen et al., 2010) to warrant wider validation and implementation on dairy farms to detect emerging health problems.

Reference

Hogeveen, H., C. Kamphuis, W. Steeneveld, and H. Mollenhorst. 2010. Sensors and clinical mastitis - The quest for the perfect alert. *Sensors* 10(9), 7991-8009

Automated disease detection for robotic milking systems using deep learning and recurrent neural networks

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Automated milking systems (AMS) are currently used in over 30,000 dairy herds worldwide and in 10% of Canadian dairy farms. Not only do AMS record milking activity and yields, but they often include precision behavioural monitoring technologies for measuring cow behaviour, such as rumination time and cow activity. Additional software then creates reports and alerts to flag cows with deviations in their data and, thus, potential health problems. To date, no model has been transparently validated on-farm to report actual accuracy, specificity, and sensitivity to detect illness in AMS using milk and behaviour data.

With the abundance of data collected by AMS comes the need for reliable, validated algorithms to use these data for disease detection, but little research has been conducted to evaluate the use of precision behaviour and productivity monitoring for early detection of illness in AMS. Our objectives were: 1) to integrate all measurements from AMS to develop accurate illness detection models using recurrent neural networks; 2) to determine the relative importance of variables and their effect on model performance; 3) to assess the accuracy of our models.

Detailed disease events for individual cows were collected from 13 commercial AMS dairy herds in Ontario, Canada for the first 50 days of lactation. Health disorders assessed were clinical mastitis, displaced abomasum, subclinical ketosis, and lameness. Electronically recorded data included milk yield per visit and per day, number of milkings and robot visits per day, number of cows per robot, rumination time, and cow activity. Deep learning models were used to predict the daily probability of an animal being diagnosed with illness. Deep learning models use a series of connected neurons to identify complex relationships between predictor variables and the outcome of interest (disease probability). Farms were divided into 3 groups: 9 farms for training and model development, 2 farms to act as model-testing sets and 2 farms to serve as a hold-out validation set for model performance. Recurrent neural networks capture complex, time-dependent relationships and base predictions on individual animal patterns. Recurrent neural networks with varying numbers of long short-term memory cells were trained using different lengths of time windows when cows were classified as “sick” for 3, 5, 7, and 15 days centered around diagnoses. Models were evaluated using accuracy, sensitivity, and specificity.

Results presented below are solely for mastitis detection (Tables 1 and 2). Using a prediction window of 15 days centered around the day of mastitis diagnosis (7 d before, 7 d after, and the day of), models achieved 93% accuracy (7% false-positive and false-negative; Table 1). Using a more practical prediction window of 7 days, accuracy decreased to 85% (14-15% false-positive and false-negative; Table 1). Excluding behavior data reduced prediction accuracy by 5% units, and excluding daily variances reduced prediction accuracy by 7% units (Table 2).

These recurrent neural networks have improved performance compared to previous studies that use feed-forward neural networks for detection of mastitis. This suggests that long short-term memory models can capture temporal trends and patterns too complex to be represented by rolling averages and daily variances. Although the daily performance of the model was good, cases where cows were identified as being sick earlier are still contributing to the false-positive rate, while the reason for this misclassification may just be that the model is detecting disease early. Sensitivity and specificity may not be the best metrics for evaluation of these models' performance, and different metrics may be required to develop models which detect disease more accurately and earlier.

Future work will look at different measures of model accuracy and the timeliness of predictions. Models will be internally validated using cross-validation and hold-out validation, in addition to a future external validation with completely new data from new farms. We will also create detection models for other health disorders recorded during this study, either separately for each illness or combined to detect any type of illness present using one model. Finally, we will continue training models with different time windows when cows are classified as "sick", testing windows that only precede the day of diagnosis (whereas they currently surround the diagnosis).

Table 1. Performance of mastitis detection models using various time windows of data surrounding the day of diagnosis. Accuracy and positive predictive value (PPV) refer to the overall accuracy of predictions considering sensitivity (true positive cases detected) and specificity (true negative cases detected).

| No. days | Dataset | Accuracy (%) | Sensitivity (%) | Specificity (%) | PPV (%) |
|----------|---------|--------------|-----------------|-----------------|---------|
| 3 | Train | 83 | 83 | 83 | 83 |
| | Test | 82 | 83 | 83 | 83 |
| 7 | Train | 84 | 85 | 84 | 84 |
| | Test | 85 | 85 | 86 | 85 |
| 11 | Train | 84 | 84 | 85 | 85 |
| | Test | 79 | 79 | 79 | 79 |
| 15 | Train | 92 | 92 | 92 | 92 |
| | Test | 93 | 93 | 93 | 93 |

Table 2. Performance of mastitis detection models using a 7-day time window of data surrounding mastitis diagnosis. Accuracy and positive predictive value (PPV) refer to the overall accuracy of predictions considering sensitivity (true positive cases detected) and specificity (true negative cases detected).

| Variables | Dataset | Accuracy (%) | Sensitivity (%) | Specificity (%) | PPV (%) |
|--------------------|---------|--------------|-----------------|-----------------|---------|
| All variables | Train | 84 | 85 | 84 | 84 |
| | Test | 85 | 85 | 86 | 85 |
| No daily variances | Train | 84 | 84 | 84 | 84 |
| | Test | 78 | 79 | 80 | 80 |
| Milk traits only | Train | 79 | 79 | 80 | 80 |
| | Test | 80 | 80 | 81 | 81 |

Determination of relationships between rumination time, milk fat production, and milk fatty acid profile using real-time rumination observation data.

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Introduction

Rumination sensors have been readily adopted by commercial dairy producers to aid in detection of estrus and subclinical or acute illness. These systems generate real-time, high-resolution rumination data for individual animals, which presents an attractive opportunity to explore opportunity to use this data to manage nutrition. Relationships between rumination time and cow health status have been investigated by multiple researchers, but rumination time's relationship with milk fat concentration is less well-understood. Milk fat production is highly influenced by nutrition and rumen fermentation. Rumination is an essential part of the ruminant digestive process, and thus both contributes to as well as indicates rumen fermentation. Daily rumination time is also quite variable among individual animals, even after accounting for diet and other variables (Byskov et al., 2015). Therefore, we hypothesized that rumination may indicate disruptions to rumen fermentation, such as those that occur during milk fat depression (MFD) or subacute ruminal acidosis (SARA), and that lower-rumination cows would have lower milk fat due to these rumen disruptions. Both MFD and SARA reduce milk fat and thus farm profitability and are likely responsible for some of the variability in milk fat concentration observed within and between commercial herds. The milk fatty acid (FA) profile, particularly the odd and branched-chain (OBC FA) and specific *trans*-fatty acids, can be used as a non-invasive indicator of rumen fermentation, thus allowing relationships between rumination and rumen fermentation to be identified. The goals of this work were to quantify variation in rumination time between and within herds, and to determine relationships between rumination time and milk fat production and FA profile. Our overall goal is to improve on-farm usability of rumination data to increase milk fat yield and profitability.

Methods

Data were collected from five commercial dairy farms of 200 to 700 lactating Holsteins with an existing rumination sensing system, CowManager SensOor ear tags (CM; Agis Automatisering BV, Harmelen, the Netherlands) or SCR Hi-Tag neck collars (SCR; SCR Engineers, Netanya, Israel). A total of 1733 cows greater than 30 DIM from 4 farms in PA and 1 in NY were used. Rumination data were collected for 7 consecutive days leading up to a DHIA test. For each cow, rumination was summed by day then averaged over the 7-day observation period to obtain average daily minutes of rumination time (RT). Milk samples from the 7th day DHIA test were analyzed for fat content by mid infrared spectrum (Lancaster DHIA, Manheim, PA or DairyOne

DHIA, Ithaca, NY) and for milk FA profile via gas chromatography according to Rico and Harvatine (2013). Production and cow (DIM, parity, etc.) data were recorded from herd management software. Diet ingredients were recorded and sampled for reporting purposes. Statistical analyses were performed in JMP Pro v13.0 and R v3.4.4 (SAS Institute, Cary NC; R Core Team, Vienna, Austria). Partial R^2 's between rumination and individual milk fatty acids were calculated from linear models using the `lm` function of the `lme4` package in R v3.4.4 (Bates et al., 2015). Rumination data were analyzed using linear regression models built using the `Stepwise` function of JMP Pro to understand relationships between rumination time and milk fat production, and between rumination time and milk fatty acids. Models and other comparisons using only CM or SCR data were run in addition to models including data from both systems, as sensor or algorithm differences between systems may influence reported RT.

Results and conclusions

The mean RT across herds was 527 min/d (10th percentile = 433 min/d, 90th percentile = 609 min/d). For individual herds, mean RT ranged from 483 to 567 min/d. The mean SD across herds was 73 minutes and ranged from 47 to 90 min/d for individual herds, indicating the high variability of RT within herds. Milk fat concentration across all cows averaged $3.75 \pm 0.82\%$ (Mean \pm SD) but was highly influenced by Farm 1, which averaged 3.35% milk fat due to apparent biohydrogenation-induced MFD. Based on milk *trans*-10 C18:1, MFD was present in 55%, 7%, 2%, 5%, and 31% of cows on farms 1, 2, 3, 4, and 5, respectively.

Rumination was not directly related to milk fat production across farms or within each system and did not explain any additional variation in linear models predicting milk fat concentration. Rumination was however related to yield of total milk *de novo*, 16 carbon, and preformed FA and to multiple individual milk FA. The relationship between *trans*-10 C18:1 and RT was significant ($P < 0.001$) and positive with a partial R^2 (pR^2) of 2.97%, 4.24%, and 2.22% across all data, SCR, and CM data respectively. Rumination time was most strongly related to *iso* C15:0 ($pR^2 = 9.5\%$), C15:0 ($pR^2 = 11.6\%$), and *iso* C16:0 ($pR^2 = 14.5\%$) in SCR data and to *iso* C16:0 ($pR^2 = 2.75\%$), *trans*-5 C18:1 ($pR^2 = 2.78\%$), and *iso* C15:0 ($pR^2 = 2.81\%$) in CM data. Relationships between RT and FA were consistently stronger in SCR than in CM data. In conclusion, rumination time was related to milk FA profile of the odd and branched-chain and specific *trans*-FA but was not directly related to milk fat concentration. The profiles of the *trans* and odd and branched-chain FA have been demonstrated to change during both SARA and MFD, and thus further investigation into if rumination data may be used to predict or identify the presence of these conditions is warranted.

References

- Douglas Bates, Martin Maechler, Ben Bolker, Steve Walker. 2015. Fitting Linear Mixed-Effects Models Using `lme4`. J. of Statistical Software. 67:1-48.
- Rico D. E., Harvatine K. J. 2013. Induction of and recovery from milk fat depression occurs progressively in dairy cows switched between diets that differ in fiber and oil concentration. J. Dairy Sci. 96:6621-6630.

Use of an accelerometer system for identifying cows at risk for suffering from health disorders in early lactation

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Introduction

In dairy cows approximately 75% of diseases occur during the first month of lactation. Besides being detrimental from an animal welfare's perspective, disorders have a negative effect on farm economics because they cause losses in milk production, increase the risk of involuntary culling and death, increase treatment costs and impair reproductive performance. Unfortunately, too often early signs of diseases are overlooked or are not detectable by the farmer and/or veterinarian and animals will only be discovered when they already suffer from clinical signs of disease. Hence, several standard operating procedures (SOP) were recommended in the past, defining which animal, how and in which specific time period should be examined. Even if these procedures are standardized, the examination of animals is time consuming and their success relies on the experience and willingness of the farmer or on his or her personnel, if applicable to strictly follow the SOPs. Furthermore, in most farms animals have to be restrained for routine examination procedures, disrupting physiological behaviors and time budgets of the cows.

Nowadays, various sensor systems are available to assist the farmer in herd and health management decisions. Applying these technologies targets in an improved health monitoring to secure high levels of animal welfare, ensure food quality and safety as well as in optimizing work efficiency. The objective of this study was to evaluate if the output parameter of the accelerometer system SMARTBOW (SB, Smartbow GmbH, Weibern, Austria) are suitable for early disease detection in periparturient cows.

Materials and Methods

All study procedures were approved by the institutional ethics committee of the University as well as by the Slovakian Regional Veterinary Food Administration.

For study purposes, the SB system was installed on a commercial dairy farm, housing approx. 2,700 Holstein Friesian cows. Approximately 3 weeks prior to parturition, the ear-tag based 3D-accelerometers were permanently attached to the study animals in the middle of the right ear. Acceleration data (range -2 g to +2 g) of head and/or ear movements of the animals were recorded with a frequency of 10 Hz and sent in real-time to receivers (WallPoints) installed at a distance of about 20 m each, throughout the study pens. Receivers were connected with a local farm server on which data were processed. Based on machine learning algorithms commercial features (based on 1 Hz accelerometer) include estrus detection, rumination monitoring and localization of animals in the barn, so far.

In our study the 10 Hz data of the accelerometer system was used for retrospective analyses of activity levels, rumination and distinct behaviors of diseased animals compared with corresponding ‘healthy’ controls. For this, animals were matched by parity and calving date as best as possible. Animals were enrolled at drying off and followed up to 14 days in milk (DIM). Prior to commencing the study, SOPs were defined on animal examinations and disease definitions. Besides daily clinical examinations within the first 8 DIM, body condition scoring and metabolic testing [i.e. testing for non-esterified fatty acids (NEFA) within the last week prior to calving and testing for β -hydroxy butyric acid (BHBA) on days 3, 5 and 8 of lactation] were performed. All examinations were conducted by staff members of the University and farm workers had no access to the data. Findings [e.g. fever (rectal temperature $\geq 39.5^{\circ}\text{C}$)] and diagnoses [e.g. Hypocalcemia (recumbent cows with serum Ca < 2.0 mmol/L), Ketosis (BHBA ≥ 1.2 mmol/L), Metritis (watery, purulent or smelly uterine discharge with or without fever), Mastitis (swelling or pain in the udder, clots or flakes in milk)] were recorded.

Results

So far, data of approximately 150 diseased and corresponding 150 healthy control animals are available. As a preliminary result, the following graph demonstrates the average rumination time (minutes per hour) of animals suffering from any health disorders within the first 8 days of lactation compared with control cows in a period from 2 weeks prior up to 2 weeks after parturition.

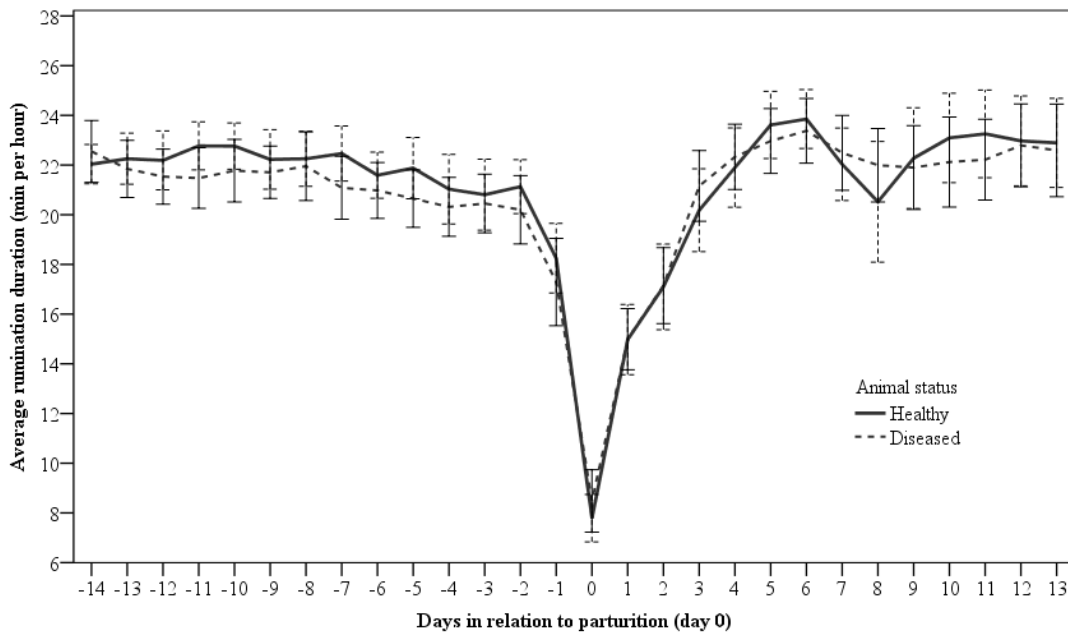


Figure: Average rumination time (min per hour) of animals suffering from health disorders in early lactation compared with corresponding healthy cows

Depending on the disease and the number of diagnoses within early lactation, differences in rumination activities were observed. Data analyses are currently in progress and the results will be presented at the conference.

Age-related changes in body shape may affect the accuracy of biometric measurements performed on three-dimensional models in cattle

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Introduction

Biometric parameters are largely used in dairy cattle to define phenotypic traits for breeding programs, and genetic improvement is directly related to the quantity and quality of phenotypic data available. Currently, however, evaluation of type traits in cattle is mostly based on visual, subjective scoring, which is inaccurate and prone to bias. The direct measurement with scales, on the other hand, is time consuming and requires physical contact with the animals. The use of sensors is an alternative to remotely acquire three-dimensional (3D) data from body geometry, and modelling tools can be used to extract a range of measurements from the data point cloud. The use of 3D technology-based large-scale fine phenotyping in cattle would positively impact production, health, and livestock well-being. In a previous study, our group used structured light scanning and a custom-design algorithm to obtain rump data in adult, lactating Holstein cows (Viana et al. 2016). The modeling model used in that study was based on the identification of reference points on skin surface. However, differences in rump geometry due to the amount of muscle tissue and subcutaneous fat could potentially interfere in the identification of reference points and thus reduce the accuracy of measurements. The aim of the present study was to validate this approach in *Bos indicus* calves.

Materials and Methods

This project was approved by the Embrapa Ethics in Use of Animals Committee (protocol CEUA #273/2017). Nelore breed calves (N=11) were monthly weighed from one month to 12 months old, and evaluated for biometric endpoints, including rump width, using a conventional metric scale. Acquisition of 3D data from the rump area was performed by structured infrared light scanning, using a portable sensor (iSense™, 3D Systems, Rock Hill, SC, USA) connected to a tablet computer (iPad Air 2, Apple Inc., Cupertino, CA, USA) equipped with real time scanning app (<https://itunes.apple.com/us/app/isense/id807510940>). The nominal resolution of the equipment at 0.5 m was 0.9 mm for the x/y axes and 1.0 mm for the z axis (depth). The points-cloud data was transformed in a geometric surface and stored as OBJ files (Figure 1A). The 3D images were then edited using the open-source software MeshLab (SourceForge, USA) to delete unspecific scans from nearby objects. The file containing only the x,y,z Cartesian coordinates of the points-cloud was exported and converted to a x,y,z matrix (.m file) using Matlab (<http://www.mathworks.com>). The algorithm script used was previously described (Viana et al. 2016). Briefly, it was based in a set of rules to identify, in the three-dimensional space, reference points corresponding to the tail and lateral prominences of the tuber ilium and of the tuber ischium. The values of rump width (RW) obtained from all calves at the ages of one, six, and 12 months, as calculated from the scan points-cloud or measured *in vivo* (reference standard), were used for comparisons. Differences between methods were determined by ANOVA. The association between the outcomes were

calculated using the Pearson's correlation method. Inconsistencies were defined as the proportion between the absolute difference of values calculated or measured for each calf, and the values calculated (e.g., $[(RW_{\text{calculated}} - RW_{\text{measured}})/RW_{\text{calculated}}] * 100$). The algorithm's results were also checked for coherence by plotting the reference points within the point cloud, and visually inspecting the resulting graphics (Figure 1B). Results are presented as mean \pm standard error, and a P-value of 0.05 indicated statistical significance.

Results and Discussion

There was no difference (36.4 ± 2.7 vs 36.2 ± 2.1 cm, respectively; $P > 0.05$) in rump width as measured *in vivo* or calculated from the scan points-cloud using the algorithm on data recovered from 12 months old calves. However, correlation between the results of the two techniques progressively decreased, as 3D models were obtained at earlier ages ($R = 0.92, 0.66,$ and 0.53 for 12, six, and one month, respectively). Higher correlations in older calves were associated with a lower proportion of misidentification of reference points, as observed in plotting graphics (0.0 vs 45.4% and 72.7% , respectively). When only results from 3D models with correct identification were taken into account, correlations were higher than 0.90 , regardless age (overall $R = 0.978$, average error of 1.5 ± 1.2 cm). The present results support the hypothesis that 3D image acquisition can be used to recover biometric data from cattle. The inconsistencies (average 5.4%) observed from measurements obtained *in vivo* were expected, as direct measurements with metric scales, used as reference standard, are also not precise, particularly in curved areas. However, differences in rump geometry, as observed during calf development, interfered in the accuracy of the algorithm-based estimation of reference points and, consequently, in measurements. Consequently, 3D data analysis algorithms shall be adjusted taking in account differences in geometry among cattle categories.

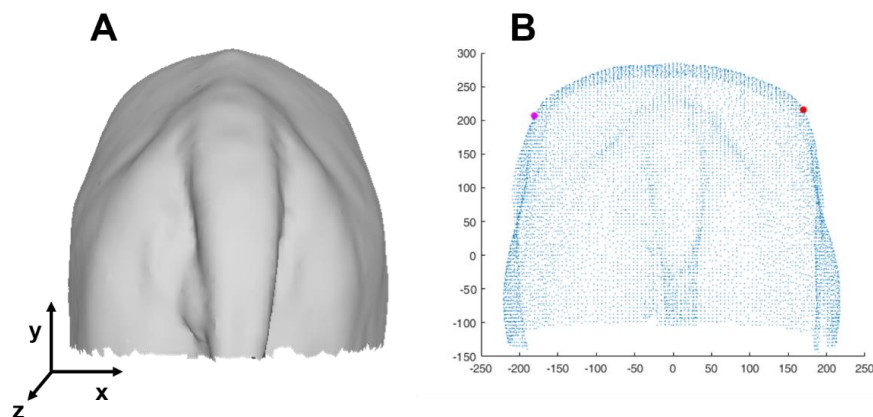


Figure 1. A: Three-dimensional image of the rump. B: Plotting of the point-cloud with reference points corresponding to the right and left tuber ilium prominences.

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References

Viana JHM, S Hinduja, PJS Bartolo. 2016. Estimation of biometric parameters from cattle rump using free-hand scanning and a 3D data processing algorithm. *Virtual Phys Prototyp* 1:1-6.

Body Condition Score Change Throughout Lactation Utilizing an Automated BCS Scoring System: A Descriptive Study

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Body condition scoring is a technique used to noninvasively assess fat reserves. It provides an objective estimate to describe the current and past nutritional status of the dairy cow and has been associated with increased disease risk and breeding success. Traditionally body condition scores are taken manually by visual appraisal on a 1 to 5 scale, in one-quarter increments. However, recent studies have shown the potential of automating the body condition scoring of cows using images. Therefore the objective of our research was to use a commercially available automated body condition scoring camera system to monitor body condition across the lactation period to evaluate differences between stratified parameters and to develop an equation to predict the dynamics of the body condition score.

The farm housed approximately 3,200 dry and lactating cows. Holstein cows (n = 2,343) used in this study were 2.1 ± 1.1 (mean \pm SD) lactation number, 186.1 ± 111.1 DIM, 3.42 ± 0.24 calving BCS, and $12,720 \pm 2028$ Kg of predicted milk yield (305PMY). The farm had two automatically recording BCS cameras (DeLaval International AB, Tumba, Sweden), one mounted on each of the two sort-gates at parlor exits (n = 2). The technology operated by filming a 3-D video, automatically selecting the best image, and generating a BCS score based on the classified algorithm based on Edmonson et al. (1989). All BCS were viewed and downloaded from DelPro Farm Manager (DeLaval International AB, Tumba, Sweden). Scores were reported on a 1 to 5 scale, in 0.1 increments. All lactating cows passed under the camera one time per day and their BCS was obtained. Statistical analyses were performed using SAS 9.3 (SAS Institute Inc., Cary, NC, USA). All descriptive statistics used to stratify factors related to ABCS were determined utilizing PROC MEANS and PROC UNIVARIATE. Lactation, DIM, and disease status were obtained from a data integration software (Bovisync, Dairy LLC, Eden, WI), which synced data entered by farm personnel from the on-farm computer. Milk production data was gathered from DelPro Farm Manager software (DeLaval International AB, Tumba, Sweden). Outlying ABCS were identified and removed. The variables included were DIM, lactation number, calving ABCS, calving month, diseased or non-diseased, and 305-d predicted milk yield (305PMY). Variables with $P < 0.05$ in the univariate models were offered to the multivariable model. The relationship of ABCS with all combined factors was analyzed using the MIXED procedure, where cow was used as a repeated subject. Variables were retained in the multivariable model if $P < 0.05$.

Mean ABCS for all scores collected was $3.29 (\pm 0.25$ ABCS; 1.50 to 5.00) and mean calving BCS was $3.42 (\pm 0.22$ ABCS; 1.55 to 5.00). The range of BCS at calving was 2.2 to 4.0 (3.42 ± 0.24 ABCS). The curves showed a decrease in ABCS until nadir followed by an increase in condition. After the loss of BCS post-calving, cows reached their calving ABCS in average by day 256, 3.42 ABCS (± 0.23 ABCS). On average, cows lost 0.24 ABCS (± 0.25 ABCS) by 71 DIM (Figure 1).

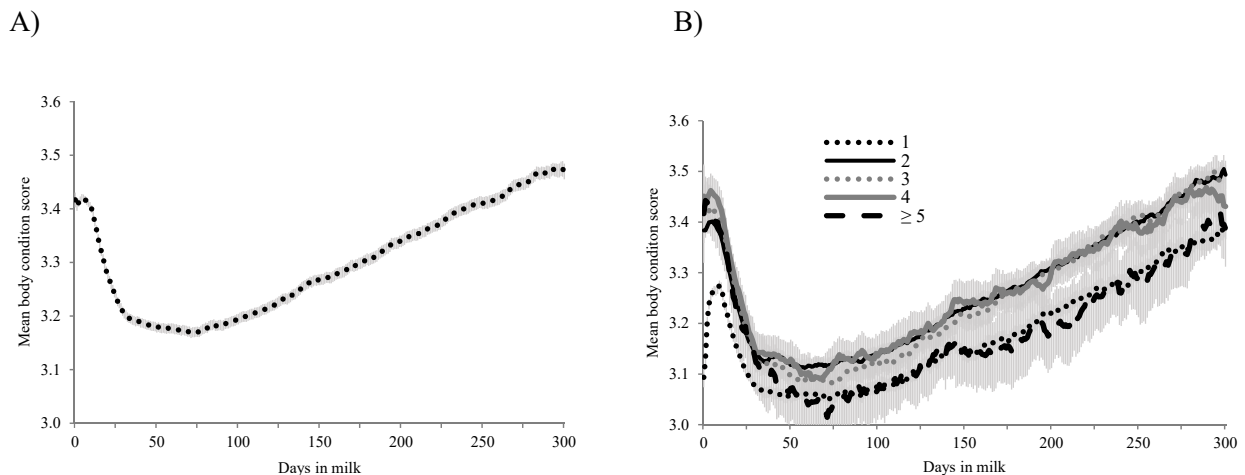
Thereafter cows regained condition and were at 3.47 ABCS (± 0.22 ABCS) at 300 DIM. As DIM progressed the number of records per day decreased which is agreeable with previous work (Banos et al., 2004), increasing the variability in the dataset in later DIM. When stratified by lactation number a similar ABCS path is seen across lactation in all lactations (Figure 1). Mean calving BCS was 3.43 (± 0.21), 3.38 (± 0.25), 3.44 (± 0.29), 3.45 (± 0.26), 3.42 (± 0.30 ABCS) for lactation numbers 1, 2, 3, 4, and ≥ 5 , respectively.

Days in milk, lactation number, calving ABCS, calving month, disease status, and 305PMY were all significant predictors of ABCS in each of their individual univariate models ($P < 0.0001$). Both DIM and calving ABCS had higher R^2 values, 0.11 and 0.16 respectively. When entered into the full multivariate model, calving month was not significant ($P > 0.05$) and removed from the model. All variables remaining in the multivariate model were significant ($P < 0.001$). The multivariate model that best explained the ABCS curve through lactation was found as:

$$ABCS_{ijk} = 1.4838 + -0.00452 * DIM_i + -0.03851 * Lactation\ number_j + 0.5970 * Calving\ ABCS_k + 0.02998 * Disease\ Status\ (negative)_l + -1.52E-6 * 305\text{-}d\ predicted\ milk\ yield_m + e_{ijklm}$$

Although other studies have evaluated and observed the impact and progression of BCS across lactation, this study aimed to determine these effects with a new, commercially available automated body condition scoring system. The automatization of BCS may provide additional information from the advantage of constant BCS monitoring that previous studies may have lacked from using only manual BCS. Descriptively, the BCS curve through lactation was like other studies utilizing manual scoring. Merging automated body condition scoring into future studies on commercial dairies may assist in providing protocols regarding management of an automated BCS system.

Figure 1. Mean (95% CI) automated body condition score (ABCS) of dairy cattle collected using a 3-D camera system at a commercial dairy in Indiana, USA. Data presented across days in milk to 300 days in milk (DIM) stratified by: (A) Overall¹ and (B) Lactation number.



Comparison of on-line measurements with conventional single-day herd tests

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Introduction

Previous theoretical studies have shown that frequent tests by on-line milk analysers (OMA), can provide better cow assessments than infrequent laboratory-based tests (Mein *et al.*, 2000). This is because the higher test error associated with OMA averages to zero with multiple tests and the true averages of parameters with high day-to-day variation are better estimated using tests taken over several days than with a single-day herd test (1DHT). Day-to-day variation for milk volume and fat is typically high (Mackle *et al.*, 1999). The theory, however, assumes tests are not affected by cow specific bias (CSB). CSB is a systematic error that causes cows to be consistently under- or over-evaluated relative to the herd, which reduces the accuracy of between-cow comparisons (Anderson *et al.*, 2016). This trial compared estimates of short-term (10d) cow average milk parameters by OMA and 1DHT. The aim was to determine whether the advantage of frequent tests by OMA, limited by CSB, outweighed the advantage of the precise tests of the 1DHT, which does not capture within-cow day-to-day variation.

Materials and Methods

Data were collected in June 2018 from a NZ herd of 208 cows milked twice per day. OMA prototypes (LIC Automation, NZ), including a new milk analyser technology, tested milk volume, fat, protein, lactose and SCC. Herd tests were conducted at twenty consecutive milking sessions. Data from cows that had eight or more milkings, with valid OMA and herd test results were included. OMA was evaluated at the individual milking level and the cow average level. 1DHT (a 1d cow average of two herd tests) was evaluated against the 10d cow average herd test. Precision was quantified using SD of error (SDE) and SD of relative error (SDRE). Spearman correlation was used to quantify the ability to correctly rank animals. Within-cow day-to-day variation in the milk parameters was quantified as the herd-average of the cow-SD of 24h herd test results.

Results and Discussion

The results of this trial are consistent with previous theoretical research. The performance statistics are shown in Table 1. OMA had better precision (SDE or SDRE) at the cow-average level than at the individual milking level for all parameters, indicating that some of the test error was averaged-out with repeated tests. The degree of improvement for protein, lactose and SCC (≥ 200 kcells/mL) suggests that for these parameters, CSB was negligible. However, for milk volume, fat and SCC (< 200 kcells/mL) the improvement was less than would be expected if there were no CSB. The precision of the 1DHT was numerically similar to the within-cow day-to-day SD, which supports the theory that day-to-day variation limits the precision of 1DHT for estimating the short term cow

average. Accordingly, the OMA provided an equivalent or better estimate than 1DHT of the 10d cow average for milk volume, fat and SCC (≥ 200 kcells/mL) – these parameters had high day-to-day variation. For protein and lactose, which had low day-to-day variation, the 1DHT was significantly better than the OMA. Even so, good precision and high Spearman correlations for all production parameters indicate that the OMA is a useful tool for identifying high and low producing cows. The within-cow day-to-day SD for SCC (< 200 kcells/mL) was smaller than reported by Orchard *et al.* (2018), and consequently 1DHT provided a significantly more precise estimate of the cow average than OMA. The CSB exhibited by OMA in the low SCC range was significant compared to the differences between cows. As a result, below 200 kcells/mL, the OMA had a poor Spearman correlation. The primary uses for an SCC analyser are to detect high SCC animals and those with subclinical mastitis. For these uses, accurate ranking of animals above 200 kcells/mL is most important. In this range, the OMA provided a significantly better estimate of cow average SCC than a 1DHT and had an equivalent Spearman correlation. Therefore, the OMA appears to be a valuable tool for monitoring individual cow SCC.

Table 1: Summary of results.

| | Indiv. test | | Cows | Cow average | | | | | | Within-cow SD ³ or CV |
|-----------------|-------------|--------------------------|------|--------------------------|------|---------|-----------------------------------|-------|---------|----------------------------------|
| | Milking | SDE or SDRE ¹ | | SDE or SDRE ¹ | | | Spearman correlation ² | | | |
| | | | | OMA | 1DHT | p-value | OMA | 1DHT | p-value | |
| Milk vol. | 2224 | 10.6% | 178 | 6.0% | 6.1% | 0.855 | 0.969 | 0.976 | 0.226 | 7.0% |
| Fat | 473 | 0.36 | 50 | 0.18 | 0.26 | 0.001 | 0.957 | 0.940 | 0.407 | 0.31 |
| Protein | 473 | 0.29 | 50 | 0.12 | 0.09 | 0.028 | 0.934 | 0.973 | 0.027 | 0.10 |
| Lactose | 473 | 0.18 | 50 | 0.09 | 0.05 | 0.000 | 0.935 | 0.957 | 0.303 | 0.07 |
| SCC $< 200k$ | 1951 | 66 | 157 | 42 | 26 | 0.000 | 0.309 | 0.948 | 0.000 | 21 |
| SCC $\geq 200k$ | 258 | 52% | 20 | 21% | 68% | 0.000 | 0.825 | 0.796 | 0.430 | 61% |

¹ SDE has units of g/100mL for fat, protein and lactose, and kcells/mL for SCC.

² Spearman correlation for fat, protein and lactose was based on kg yield.

³ Within-cow SD has units of g/100mL for fat, protein and lactose, and kcells/mL for SCC.

References

- Anderson, G.P.S., I.L. Zhang, A.M. Winkelman, B.L. Harris (2016). Comparison of records from in-line milk meters and conventional herd testing for management and genetic evaluation of dairy cow. 40th ICAR Biennial Session, Chile, 203-209.
- Mackle, T. R., A. M. Bryant, S. F. Petch, R. J. Hooper, and M. J. Auldist (1999). Variation in the composition of milk protein from pasture-fed dairy cows in late lactation and the effect of grain and silage supplementation. *New Zeal J Agr Res* 42(2): 147-154.
- Mein, G.A., M. Hannah, and T. Clarke (2000). Limits of error for permanently-installed milk meters used for herd recording or for daily herd management purposes. 32nd ICAR Biennial Session, Slovenia, 159-162.
- Orchard, R.G., G.P.S. Anderson, A.M. Winkelman (2018). Comparison of individual cow SCC estimates using an on-line SCC analyser and conventional herd tests. *ICAR Technical Series* 23:37-43.

Performance of an in-cow sensor for estrus detection in dairy cattle during the grazing season

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Accurate detection of estrus in dairy cows is crucial for a good reproductive performance when artificial insemination is used. Activity sensors are helpful in detecting estrus and increasing heat detection rates. Most of these sensors are placed on the cow, i.e. around the neck or leg, in the ear or on the tail head. Numerous studies have investigated the performance of these sensors (reviewed by Roelofs & van Erp-van der Kooij, 2015; Saint-Dizier & Chastant-Maillard, 2018). A fairly new activity sensor is an in-cow sensor, a bolus placed in the reticulorumen which measures temperature and activity with a 3D accelerometer continuously at 10 min intervals (smaXtec Basic, SmaXtec animal care GmbH, Austria). The aim of this study was to assess performance (sensitivity and positive predictive value) of the reticuloruminal bolus to detect estrus in dairy cows during the grazing season under field conditions.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 756943. The study was conducted from June – September 2017 on a dairy farm with a herd of 135 Holstein Frisians dairy cows in the Netherlands. During the research period the cows were pastured by a rotating grazing system, from 7 AM until 3 PM. The number of hours varied depending on weather circumstances.

Whole milk samples were taken twice weekly during milking and analyzed with a semi-quantitative ELISA kit for progesterone (Ridgeway Science, UK). Progesterone (P₄) served as golden standard for estrus. The P₄ pattern for each cow was assessed and true estrus was defined as low P₄ (less than 2 ng/ml) followed by high P₄ (around 20 ng/ml). Estrus alerts from the bolus were compared with true estrus. An estrus alert was considered as correct positive (CP) when it coincided with true estrus, as false negative (FN) when no alert was given two days before or after true estrus and as false positive (FP) when an alert did not coincide with true estrus. Sensitivity (%) was calculated as $CP/(CP+FN)*100$. Positive predictive value (PPV, %) was calculated as $CP/(CP+FP)$ (Roelofs et al., 2010).

A total of 131 true estrus periods were defined from P₄ profiles of 56 cows. Average 305-day milk production was $10,181 \pm 1693$ kg and cows were on average 65 ± 60 days in milk at the first true estrus in the study. Average parity was 2.7 ± 1.7 . Of the 56 cows, 13 were primiparous cows.

The overall sensitivity was 81% and the PPV was 74%, which is comparable with sensitivities and PPV's found in other studies using on-cow sensors to detect estrus (Roelofs & van Erp-van der Kooij, 2015). Sensitivity and PPV were higher in primiparous cows compared to multiparous cows (figure 1), which is in agreement with the results of a study using leg activity sensors to detect estrus (Chanvallon et al., 2014).

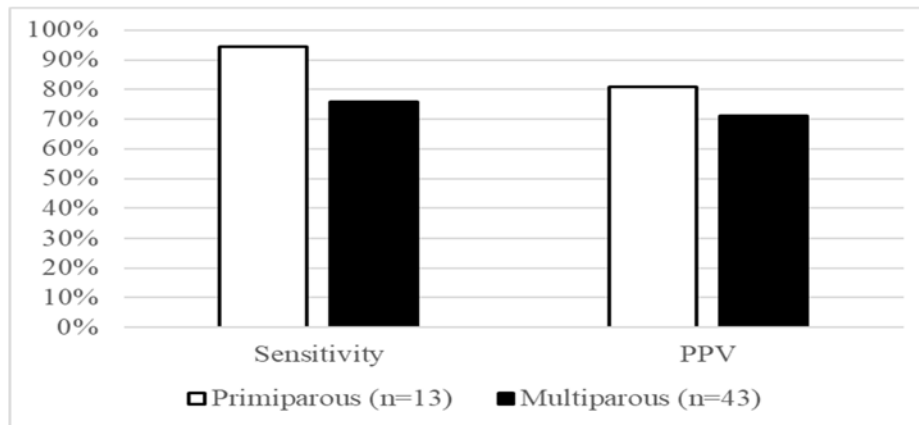


Figure 1. Sensitivity and positive predictive value (PPV) of primiparous and multiparous cows.

A total of 37 FP attentions were found in 26 cows. On two days a deviant number of FP attentions was found, 14 on one day and eight on another day. These high numbers could be explained by irregularities in the routine. According to the farmer a sudden change in weather occurred, which caused the cows to run to the shed. In the shed, they were nervous because of the bad weather. This could have led to an increase in activity and FP attentions. To correct for these commonly occurring irregularities in under field conditions, overall increase in herd activity can be taken into account when calculating the threshold to give an attention for an individual animal. This would decrease FP attentions and increase PPV to 87% in this study. Another 13 FP attentions were found in 5 cows that had abnormal P₄ profiles. Long periods of low P₄ were found, this could indicate cystic ovarian follicles (COF). COF can cause irregular estrous behavior which can explain the FP attentions in these cows (Vanholder et al., 2006). It is possible to correct for period since last estrus to decrease FP attentions caused by irregular estrus behavior (Firk et al., 2003). This would increase the PPV to 82% in this study.

This study has shown that an in-cow sensor performs well in terms of sensitivity and PPV for the detection of estrus in dairy cows during the grazing season.

References

- Chanvallon A., S. Coyral-Castel, J. Gatién, J-M. Lamy, D. Ribaud, C. Allain, P. Clément, P. Salvetti, 2014, Comparison of three devices for the automated detection of estrus in dairy cows, *Theriogenology*, 82:734-741.
- Firk R., E. Stamer, W. Junge, J. Krieter, 2003, Improving oestrus detection by combination of activity measurements with information about previous oestrus cases, *Livest. Prod. Sci.* 82:97-103
- Roelofs J., E. van Erp-van der Kooij, 2015, Estrus detection tools and their applicability in cattle: recent and perspectival situation, *Anim. Reprod.* 12:498-504.
- Roelofs J., F. López-Gatiús, R.H.F. Hunter, F.J.C.M. van Eerdenburg, Ch. Hanzen, 2010, When is a cow in estrus? Clinical and practical aspects, *Theriogenology* 74:327-344.
- Saint-Dizier M., S. Chastant-Maillard, 2018, Potential of connected devices to optimize cattle reproduction, *Theriogenology* 112:53-62.
- Vanholder T., G. Opsomer, A. de Kruif, 2006, Aetiology and pathogenesis of cystic ovarian follicles in dairy cattle: a review, *Reprod. Nutr. Dev.* 46:105-119.

Validation of an ear attached accelerometer for grazing behavior

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Introduction

Pasture-based dairy production systems are becoming more common in the global dairy industry (USDA, 2016), and grazing dairy producers may benefit from utilizing precision dairy technologies. However, the majority of work conducted with precision technologies has been in confinement systems. In a grazing herd, a halter with a noseband pressure sensor accurately recorded grazing behavior of cows (Werner et al., 2018). Grazing behavior may be difficult to define because grazing may be considered as both active and eating behaviors because cows may graze while standing or while walking. The objectives of this study were to develop a grazing algorithm for an ear attached accelerometer (Smartbow GmbH, Weibern, Austria) and to validate the ear attached accelerometer for grazing behavior.

Validation of grazing behavior

The study was conducted at the University of Minnesota grazing dairy in Morris, Minnesota, USA and at the Teagasc, Animal & Grassland Research and Innovation Centre in Moorepark, Fermoy, Co. Cork, Ireland. During May and June of 2017, ear attached accelerometers were attached to cows and three observers visually recorded behaviors of grazing cows for a total of 90 hours. The observational data from Minnesota and some additional data from Ireland was used to create a master dataset. From the dataset, 2/3 of the data was used for training the data and developing a grazing algorithm and 1/3 of the data was used for testing the ear attached accelerometers grazing algorithm. In addition to an acceleration sensor, the Smartbow ear attached accelerometer includes a radio chip, and temperature sensor. The ear attached accelerometer can monitor estrus detection and rumination by acceleration data from ear and head movements.

To validate the ear attached accelerometers grazing algorithm, a halter and noseband pressure sensor system (Rumiwatch, Itin and Hoch GmbH, Liestal, Switzerland) was utilized. The halter was comprised of a 3 axis accelerometer which recorded acceleration patterns and a noseband pressure sensor which detected jaw movements according to chewing activities (Werner et al., 2018). During September of 2018, data were collected from the ear-tag and halter system in Minnesota and Ireland.

In Minnesota, the ear attached accelerometers and the halter systems were attached to 12 crossbred cows for 4 days for each cow. Cows were offered pasture for 22 hours per day. Cows were milked twice per day in a swing-9 parabone milking parlor. The pastures were comprised of grasses and legumes that included smooth brome grass, orchardgrass, meadow fescue, alfalfa, red clover, and kura clover. Cows were stocked at a rate of 3 cows per hectare and were rotated to new paddocks every 2 days, with 3,796 kg of DM/ha available at the start of grazing.

The ear attached accelerometer and halter system were compared for number of grazing minutes per hour, during 150 hours under the Minnesota grazing conditions. A 2-sided paired t-test compared the percentage of time recorded for grazing behaviors by the halter and ear attached accelerometer. Pearson correlations evaluated associations between the halter and ear attached accelerometer for grazing behavior. For total recorded time, the percentage of time recorded for the ear attached accelerometer for grazing and non-grazing were 40.7 % and 59.3%, respectively (Table 1). Similarly, the percentage of time recorded by the halter system for grazing and non-grazing were 44.4 and 55.6%, respectively (Table 1). Correlation of grazing behavior was 0.95 ($P < 0.01$) for the ear attached accelerometer and halter system.

Conclusions

The results suggest that the ear attached accelerometer accurately monitored grazing behavior in a pasture-based system. Although this algorithm is not commercially available yet, there is great potential for the ear attached accelerometer to be utilized in pasture based dairy production systems to support farm management decision making.

Table 1. Percentage of time (\pm SD) and 95% confidence intervals for grazing or not grazing from the total recorded time (n=150 hours) from a 2-sided paired t-test.

| Behavior | Ear tag | 95% CL | Halter | 95% CL | P-value |
|-------------|-----------------|--------------|-----------------|--------------|---------|
| Grazing | 40.7 \pm 39.7 | 34.3 to 47.1 | 44.4 \pm 40.5 | 37.9 to 51.0 | 0.0003 |
| Not grazing | 59.3 \pm 39.7 | 52.9 to 65.7 | 55.6 \pm 40.5 | 49.0 to 62.1 | 0.0003 |

References

Werner, J., L. Leso, C. Umstatter, J. Niederhauser, E. Kennedy, A. Geoghegan, L. Shalloo, M. Schick, and B. O’Brien. 2018. Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *J. of Neuroscience Methods* 300:138–146.

Ground based and remote sensing measurements for automated precision grassland management

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Introduction

It is generally accepted that a grass-fed livestock production system can provide a significant comparative advantage in terms of cost competitiveness and environmental efficiency over an indoor-feeding system (Shalloo *et al.*, 2004). However, the potential of grazing has traditionally been restrained by the absence of user-friendly grass measurement systems, resulting in minimal availability of data for decision-making, low levels of expertise in production and utilization, resulting in low efficiencies. The automated capture of real-time measurement data would provide significant opportunities in developing easy to use decision support tools for grassland farmers to increase the efficiency of pasture-based systems.

Focus of Study

GrassQ is an ICT-Agri Era-Net funded EU project aimed at developing and combining precision grass measurement systems into web based decision support tools/platforms to aid precision grassland management. This concept is currently being developed and evaluated in a collaborative research consortium across four EU countries, Denmark, Finland, Ireland and Switzerland. Novel and conventional systems of measuring grass yield and quality are currently being developed and refined by research centres in these countries. The measurement techniques of focus include both ground based and aerial remote sensing methods. The measurement parameters of focus are compressed sward height (CSH, mm), herbage mass (HM, kgDM/ha), dry matter (DM, g/kg) and crude protein (CP, g/kg).

Ground Based Measurement Techniques

A robust measurement technique must be accurate, fast and reliable. The ground based measurement techniques focused on in this study include a rising plate meter (RPM) to predict herbage yield in the field and lab based near infrared analysis to predict the quality of fresh grass. The Grasshopper is an automated rising plate meter with inbuilt GPS capabilities which, via a Bluetooth link to the operator's smart phone, stores and processes measurement data in real time.

Initial evaluation of a protocol developed for grass measurement optimization indicates mean CSH can be predicted to $\pm 5\%$ SE using 35 samples/Ha. Region, sward and seasonal specific HM prediction models are being developed to further increase the accuracies of the RPM ($R^2 > 0.7$). Limited research has been conducted on the application of NIRS to predict un-dried fresh grass quality. Perennial ryegrass samples ($n = 1366$) were collected from trial plots and grazed paddocks over two grazing seasons at Teagasc Moorepark. The samples were scanned using a FOSS 6500 spectrometer at 2nm intervals in the range of 1100nm–2500nm and absorption was recorded as $\log 1/\text{Reflectance}$. Reference analyses were then carried out for both parameters and were combined with the spectral data. WinISI chemoetric modelling software was used to investigate a range of potential quality prediction equations of varying spectral treatments. Preliminary equations were ranked in order of the highest coefficient of determination (R^2) and lowest standard error of cross validation (SE_{cv}). The best performing calibrations ($R^2 > 0.94$, $SE_{cv} < 0.92$ g/kg and $R^2 > 0.9$, $SE_{cv} < 13.1$ g/kgDM for DM and CP respectively) were selected for further validation over the 2019 growing season. The measures outlined above (HM, DM and CP) can be uploaded to PasturebaseIreland (PBI) which represents a grassland database and a management decision support tool. Grass measurements are recorded on a regular basis and reports (grass wedge, distribution of growth and paddock summary reports) are automatically generated for management purposes.

Remote Sensing Measurement Techniques

An alternative technology of multispectral and hyperspectral remote sensing was carried out using a range of airborne methods including; unmanned aerial vehicles, manned aircraft and data from the European Union's Sentinel 2 satellite. Spectral models were developed from all data sets to enable grass quality and quantity prediction. Airborne surveys were carried out in conjunction with ground based measurements to enable non bias comparative analysis of each measurement system. Weather data for each survey was captured by an onsite meteorological station and included in each modelling process. Reference analysis for all prediction models was carried out in Moorepark's Grassland Laboratory and all sample locations were geo-tagged to enable in-depth spatial analysis of grass sward heterogeneity and spatial heat mapping of all measurement parameters. Spectral models were developed in Ireland using partial least squares and multi-linear regression, showing strong correlation for DM ($R^2 = 0.9$, $R^2 = 0.83$). Relatively accurate models were based on UAV images for CP ($R^2 = 0.8$) and CSH ($R^2 = 0.8$).

Conclusions

The prototype GrassQ web platform combining all of the data from the aforementioned models is nearing completion. The developed prediction models included in GrassQ will be validated in 2019 and comparative analysis will be carried out on each measurement systems. It is envisaged that GrassQ will highlight the benefits of targeted real-time precision grassland management.

Reference

Shalloo, L., P. Dillon, M. Rath and M. Wallace, 2004, Description and validation of the Moorepark dairy system model. *J. Dairy Sci*, 87, 1945-1959.

Integrating Sensors and Standard Operating Procedures: A Reproduction Example

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Introduction

Standard operating procedures (SOPs) are a common component of quality management programs; they help reduce the variation that occurs when different individuals perform the same task in different ways.

Dairies are a perfect place for adoption of SOPs because multiple employees often share responsibility for a single task (Stup et al, 2006).

Estrous synchronization followed by timed AI is a well-known example of a reproduction SOP. A survey among 103 large (average 613 lactating cows) US herds indicated that 77% of those herds used a reproduction SOP to set up cows for first service (Caraviello et al, 2006).

Automated estrous detection is a well-known example of precision technology and was considered the second most useful parameter from precision technology by US farmers (Borchers and Bewley, 2015).

However, automated estrous detection is just one step in the adoption of precision technology. Integrating it in current farm systems is also important. Dutch farmers rank 'poor integration of sensors with other farm systems and software' as the third main reason not to invest in sensors (Steenefeld and Hogeveen, 2015). US farmers indicate 'simplicity and ease of use' as the third most important criterium for evaluating precision dairy technology (Borchers and Bewley, 2015).

An easy to use system integrating sensors and reproduction SOPs can therefore be a next step in the adoption of precision dairy technology.

The objective of Nedap Reproduction Management is to be an all-in-one system that fully supports the entire reproduction program of every farmer.

General Reproduction Management

Reproduction management is a farm process that requires several tasks at operational, tactical and strategic level. The ultimate goal of reproduction management is to get a pregnant cow at a certain day in milk that remains pregnant until the next calving.

Estrous detection is a significant part of any reproduction program. Even a program that relies heavily on timed AI benefits from an early detection of open cows after insemination. And then there are farmers that inseminate cows that show heat during a reproduction SOP, so-called cherry-picking.

Technology for automated estrous detection in general simply show lists of cows that are in heat. Looking at reproduction programs, it is not that difficult to understand why these lists are of limited value to farmers that use reproduction SOPs. Estrous detection is just one part of their SOP and not every cow in estrous requires an action.

Integrating automated estrous detection with the rest of the reproduction program enables the farmer to focus on cows that require attention and inseminate cows in the ideal stage of the lactation.

Nedap Reproduction Management

At Nedap, we have developed a system that fully supports the reproduction program of every farmer. The main reason for developing this system is that we believe we can help farmers run a successful reproduction program by integrating sensor data and SOPs.

It started with observing what reproduction management really is for farmers. Every farmer has its own reproduction program. There is a difference in preparing cows for insemination,

use of different SOPs, use of natural heats, heifers vs cows, etc. However, the ultimate goal of each program is to get a pregnant cow.

With this in mind the system uses sensor data to monitor the reproduction status of every individual cow every day throughout the entire lactation. Together with the reproduction program of the farmer the system determines cows that are off track. These cows are put on check lists and are kept under surveillance until they are back on track.

Preparation period

Traditionally the period in between calving and start of the insemination period is called the voluntary waiting period (VWP). However, we believe a farmer should not be waiting in this period. This period should be used to prepare the cow for the coming insemination period. Sensor data is used to track the cyclicity of the cow.

Cows with unusual patterns in their cycle are automatically added to a check list for the reproduction specialist. These cows can then be enrolled in a SOP to restore their reproduction cycle. The goal is to have all cows ready for insemination at the end of the preparation period.

Farmers with a reproduction program based on SOPs have their cows enrolled in the correct SOP during this period.

Insemination period

Cows with heat alerts based on sensor data are automatically put on a worklist for insemination. Any cow with a heat alert that is in a SOP that includes cherry-picking is added to the list for insemination as well. Heat alerts of cows that are in a SOP with 100% timed AI are not shown to the farmer. This heat alert will not result in an insemination and therefore does not require any action.

Cows that are not inseminated within 21 days after the start of the insemination period are automatically put on the check list for the reproduction specialist for a checkup.

Gestation period

Cows are supposed to be pregnant during this entire period. Sensor data is used to check for cows that have potentially aborted. These cows are put on the check list for an additional pregnancy diagnosis. After a confirmed pregnancy loss, the farmer can decide what to do with this cow.

This period ends with a calving and the start of a new lactation and therefore a new preparation period.

At Nedap we believe that with Nedap Reproduction Management we have created a system that supports the full reproduction program of a farmer by integrating precision technology and SOPs.

References

- Borchers, MR, Bewley J. An assessment of farmer precision dairy farming technology use, prepurchase considerations, and usefulness. *J Dairy Sci.* 2015; 98:4198-4205.
- Caraviello, DZ, Weigel, KA, Fricke, PM, Wiltbank, MC, Florent, MJ, Cook, NB, Rawson, CL. Survey of Management Practices on Reproductive Performance of Dairy Cattle on Large US Commercial Farms. *J Dairy Sci.* 2006; 89:4723–4735.
- Steenefeld, W, Hogeveen, H. Characterization of Dutch dairy farms using sensor systems for cow management. *J Dairy Sci.* 2015, 98:709–717.
- Stup RE, Hyde J, Holden LA. Relationships between selected human resource management practices and dairy farm performance. *J Dairy Sci.* 2006; 89:116-1120.

Prediction of Dry Matter Intake of Dairy Cows that Occurs During the Transition Period

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Objective

Determine if an ear sensor technology (CowManager[®], Agis, Harmelen, Netherlands) can predict the change in feed intake of dairy cows that occurs during the transition period.

Justification

The transition from late gestation to early lactation is the most critical phase in the production cycle of dairy cows. At the cow level, dry matter intake (DMI) prediction can be used to identify low DMI cows and intervention programs can be developed to manage these at-risk cows.

Materials and Methods

Twenty-six multiparous Holstein cows were assigned beginning 28 days prefresh to electronic feeding stations (BioControl CRFI, Rakkestad, Norway) capable of measuring daily feed consumption and daily feeding time. Cows were also fitted with a sensor in the left ear that predicts daily eating time (ET), rumination time (RT), activity, high activity, resting time, and skin ear temperature. Three cows were removed from the experiment after calving due to metabolic disease resulting in 23 cows in the postfresh dataset.

Cows were fed a typical corn silage (40% DM basis), wheat straw (30%) based negative DCAD ration prefresh. After calving cows were switched to a fresh cow ration containing corn silage (31%), alfalfa haylage (22%), and 47% concentrate. Cows were milked 3x daily and DMI monitored from 21 d prefresh to 21 d postfresh. Cows were housed in a single row of sand bedded free stalls at a stocking density of ≤ 1 cow per freestall and assigned at random to an electronic feeding station.

Cows were fed a TMR once daily at approximately 0900 h where amount of feed refused and offered were recorded. Dry matter content of the TMR was determined twice weekly and DMI determined by multiplying DM concentration by feed disappearance. The electronic feeding stations recorded when a cow entered and exited her unique feed bin along with visit time and feed consumed. Data received from the ear sensor were ET and RT per hour over a 24-hr period.

Data were analyzed using the MIXED procedure of SAS (SAS Institute Inc., Cary, NC) to determine if actual daily feeding time estimated from the ear sensor differed from actual daily feeding time recorded by the electronic feeding stations. The STEPWISE procedure of SAS was used to develop an equation to predict DMI based on day relative to calving, sensor predicted ET and RT, and quadratic effects for all terms and interactions. Models were fit using forward stepwise regression to allow comparison between models using the Akaike information criterion (AIC). The model minimizing the AIC was chosen as the best fit.

Results

Prefresh DMI was 14.5 ± 0.1 kg (\bar{X} SE) which is within the range of literature reports for multiparous Holstein cows. Dry matter intake decreased linearly and quadratically ($P < 0.01$) as parturition approached with a modest 1-kg decline from 21 to 9 d prefresh followed by a rapid, 3-kg decrease from 8 to 1 d prefresh. Sensor overpredicted ET by 17 min compared to Biocontrol (212 vs 195 min; $P < 0.01$). Although method (sensor or feeding station) by day prefresh interaction was not significant, most of sensor's ET overprediction occurred 2-3 weeks prior to calving.

Both ET and RT decreased linearly as parturition approaches whereas DMI decreased linearly and quadratically. This indicates that eating rate changes during the prefresh period. Dry matter intake is a function of time spent eating at the feed bunk and eating rate, which changes during the transition period. During the prefresh period, eating rate decreased from approximately 80 g DM/min at 21 d prefresh to 70 g DM/min in the days leading up to calving. Therefore, it is the combination of declining ET and slower eating rate that contributes to the decrease in DMI of the prefresh cow.

The best fit model for predicting prefresh DMI using day prefresh, and sensor ET and RT included 8 parameters: intercept, linear and quadratic effects of day prefresh, linear and quadratic effects of ET, linear and quadratic effects of RT, and the interaction of ET and RT. Dry matter intake (kg) = $-4.38 + 0.3497 \times \text{Day} - 0.0097 \times \text{Day}^2 + 0.0581 \times \text{ET} - 0.00005 \times \text{ET}^2 + 0.0422 \times \text{RT} - 0.00003 \times \text{RT}^2 - 0.00006 \times \text{ET} \times \text{RT}$ ($r^2 = 0.44$).

Postfresh DMI was 22.1 ± 0.2 kg (\bar{X} SE) which is numerically greater than literature reports for multiparous Holstein cows. Dry matter intake increased linearly ($P < 0.01$) and quadratically ($P < 0.05$) during the first 3 wk of lactation with a rapid 7-kg increase from 1 to 12 d postfresh followed by a modest, 1-kg decrease from 13 to 21 d postfresh. Sensor overpredicted ET by 48 min compared to feeding stations (238 vs 190 min; $P < 0.01$). During the postfresh transition period eating rate increased from 110 to 140 g DM/min. Therefore, DMI during the 21-d postfresh period increases approximately 8 kg due to a 57 min increase in ET and a 29 g DM/min increase in feeding rate.

The best fit model for predicting postfresh DMI using day prefresh, and sensor ET and RT included 12 parameters: intercept, linear and quadratic effects of day postfresh, linear and quadratic effects of ET, linear and quadratic effects of day by ET, linear and quadratic effects of RT, postfresh day x RT, and the interaction of ET and RT x postfresh day. Dry matter intake (kg) = $1.78 - 0.614 \times \text{Day} - 0.038 \times \text{Day}^2 + 0.090 \times \text{ET} - 0.0002 \times \text{ET}^2 + 0.00024 \times \text{ET} \times \text{Day}^2 + 0.000013 \times \text{ET}^2 \times \text{Day} - 0.0000006 \times \text{ET}^2 \times \text{Day}^2 + 0.034 \times \text{RT} - 0.00004 \times \text{RT}^2 + 0.0029 \times \text{RT} \times \text{Day} - 0.000008 \times \text{ET} \times \text{RT} \times \text{Day}$ ($r^2 = 0.54$).

Summary

The transition period DMI prediction models using ET and RT may be used along with farm specific prefresh and postfresh pen DMI and days carried calf to develop DMI curves that can be used to monitor DMI at the cow and herd level.

Is it possible to detect lameness in dairy cows using activity sensors?

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Lameness in dairy cows is an important culling reason, a welfare issue and a cause of economic losses (Juarez et al. 2003) (Bielfeldt et al. 2005) (Klaas et al. 2003). When visually scored by farmers, lameness is greatly underestimated (Beggs et al. 2018). Changes in behaviour are associated with health issues. Activity monitoring systems can alert farmers to these changes, thus acting as an early warning system. The objective of this study was to determine whether activity meters could detect lameness in cows.

On a Dutch dairy farm 23 of 117 dairy cows were scored weekly for gait and body condition (BCS) during five weeks. Parity of cows was 1 (n=5), 2 (n=9) or 3-5 (n=8) and DIM was 49.1±45.2 days. Cows were housed in a freestall with slatted floor and cubicles, with ad lib. access to roughage and water. Cows had Nedap Smarttag neck and leg activity meters (Van Erp- Van der Kooij, Van de Brug, and Roelofs 2016), recording walking, lying, standing and eating time, stand-ups, leg and neck activity/15 min. BCS was recorded using 5-point scale at increments of 0.5 where 1=severe underconditioning, 3=normal and 5=severe overconditioning (Wildman et al. 1982). Gait scores were recorded while walking 5-10 m on a flat flooring using a 1-5 numerical rating system (NRS), where 1=normal and 5=severely lame (Flower and Weary 2006). To determine relationships between sensor data, BCS and gait scores, general estimating equations were used with subject variable 'cow' and within-subject variable 'week'. To determine the relationships between gait score and BCS a chi-square analysis was performed. Data were analysed using SPSS 25.0 (IBM Company inc., USA).

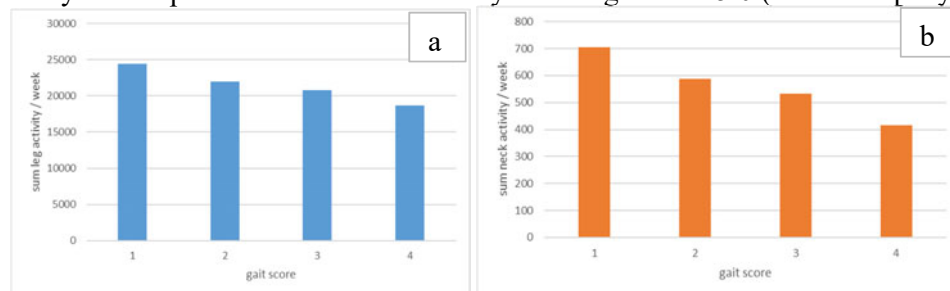


Figure 1: Leg (a) and neck activity (b) of 23 dairy cows with gait scores 1 (healthy) to 4 (lame)

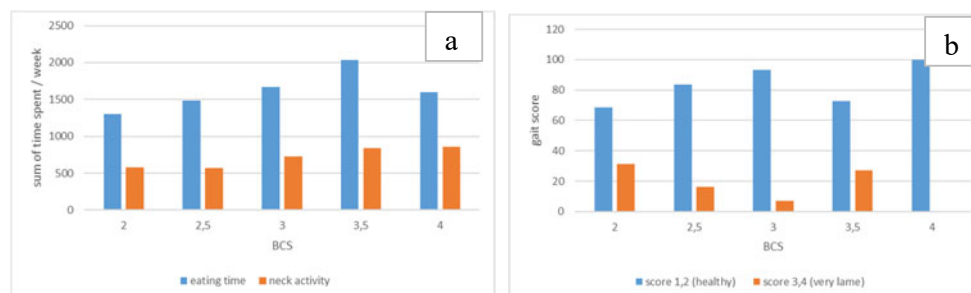


Figure 2: Eating time and neck activity per week (a) and gait score (b) for 23 dairy cows with BCS scores from 2 (underconditioning) to 4 (overconditioning)

We recorded 58% of gait score 1 (normal), 25% of gait score 2 and 17% of gait score 3-4 (lame). No cows were scored severely lame. A trend was found for gait score and general activity: cows with higher gait scores seemed to show less leg activity ($P=0.07$, Fig. 1a) and less neck activity ($P=0.07$, Fig. 1b). BCS varied from 2 to 4, with 25% of observations of BCS 3 (normal), 64% of BCS 2-2.5 (underconditioning) and 11% of BCS 3.5-4 (overconditioning). Cows with higher BCS showed longer eating times ($P=0.024$) and more neck activity ($P=0.010$, Fig. 2a). We found more lameness in cows with lower BCS (Fig. 2b).

Other studies also showed that lame cows had a lower leg or neck activity based on sensor data (Grimm et al. 2019) (Van Hertem et al. 2016) and that cows with lower BCS were less likely to be lame (Green et al. 2014). These results provide some evidence that lameness might be detected using activity meters, correcting for BCS. However, using simple statistics to relate activity to gait score and BCS, we fear to miss underlying behavioural patterns. Possibly by using more advanced machine learning techniques, combining data from different sources and teaching the computer to recognize behavioural patterns related to lameness, the success rate for detecting lameness from activity data would increase considerably.

References:

- Beggs, D. S., E. C. Jongman, P. E. Hemsworth, and A. D. Fisher. 2018. "Lame Cows on Australian Dairy Farms: A Comparison of Farmer-Identified Lameness and Formal Lameness Scoring, and the Position of Lamé Cows within the Milking Order." *J. Dairy Sci.* 102(2):1522–29.
- Bielfeldt, J. C., R. Badertscher, K. H. Tölle, and J. Krieter. 2005. "Risk Factors Influencing Lameness and Claw Disorders in Dairy Cows." *Livest. Prod. Sci.* 95(3):265–71.
- Van Erp- Van der Kooij, E., M. Van de Brug, and JB Roelofs. 2016. "Validation of Nedap Smarttag Leg and Neck to Assess Behavioural Activity Level in Dairy Cattle." Pp. 321–26 in *Precision Dairy Farming 2016*, edited by C. Kamphuis and W. Steeneveld. Leeuwarden: Wageningen Academic Press.
- Flower, F. C. and D. M. Weary. 2006. "Effect of Hoof Pathologies on Subjective Assessments of Dairy Cow Gait." *J. Dairy Sci.* 89(1):139–46.
- Green, L. E., J. N. Huxley, C. Banks, and M. J. Green. 2014. "Temporal Associations between Low Body Condition, Lameness and Milk Yield in a UK Dairy Herd." *Prev. Vet. Med.* 113(1):63–71.
- Grimm, Katharina, Bernhard Haidn, Michael Erhard, Marlene Tremblay, and Dörte Döpfer. 2019. "New Insights into the Association between Lameness, Behavior, and Performance in Simmental Cows." *J. Dairy Sci.* 102(3):1–16.
- Van Hertem, T., C. Bahr, A. Schlageter Tello, S. Viazzi, M. Steensels, C. E. B. Romanini, C. Lokhorst, E. Maltz, I. Halachmi, and D. Berckmans. 2016. "Lameness Detection in Dairy Cattle: Single Predictor v. Multivariate Analysis of Image-Based Posture Processing and Behaviour and Performance Sensing." 10(9):1525–32.
- Juarez, S. T., P. H. Robinson, E. J. DePeters, and E. O. Price. 2003. "Impact of Lameness on Behavior and Productivity of Lactating Holstein Cows." *Appl. Anim. Behav. Sci.* 83(1):1–14.
- Klaas, Ilka C., T. Rousing, C. Fossing, J. Hindhede, and J. T. Sørensen. 2003. "Is Lameness a Welfare Problem in Dairy Farms with Automatic Milking Systems?" *Anim. Welf.* 12(4):599–603.
- Wildman, E. E., G. M. Jones, P. E. Wagner, R. L. Boman, H. F. Troutt, and T. N. Lesch. 1982. "A Dairy Cow Body Condition Scoring System and Its Relationship to Selected Production Characteristics." *J. Dairy Sci.* 65(3):495–501.

CAN WE USE SENSORS TO MAKE MEANINGFUL ANIMAL HEALTH DECISIONS?

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INTRODUCTION

Monitoring the health and welfare of dairy cattle has traditionally been based on the daily physical interactions between people and cows. This interaction occurs during feed delivery, milking, moving cows from pens to parlor and the cleaning of stalls and housing areas. With the introduction of new automated technologies to milk cows (automatic milking systems (AMS) or robot milkers) and automated feeding and feed push-up systems, these people cow interactions are becoming fewer in number and duration. Fortunately, these new automated systems are often equipped with, or augmented by, sensor technologies that are purportedly able to detect changes in milk composition and or animal movement/behavior and are intended to ‘replace’ the human cow interaction for the purposes of disease detection. The question we have yet to answer is whether information from automated dairy systems can be used to make meaningful animal health decisions in our dairy herds.

FOCUS ON DAIRY CATTLE HEALTH AND WELFARE

Over the last decade we have seen an increasing focus on the welfare of our domesticated animals, including dairy cattle. This focus is the result of increased awareness and scrutiny from dairy producers, milk buyers, processors and retailers, milk consumers and the general public. In Canada we have a national set of requirements and best management practices for dairy cattle set out in the Code of Practice for the Care and Handling of Dairy Cattle, developed by an expert committee of the National Farm Animal Care Council (NFACC) and released in 2009 (<http://www.nfacc.ca/codes-of-practice/dairy-cattle>). Based on this code, the national dairy producer organization, Dairy Farmers of Canada, developed the Animal Care component of their national dairy customer assurance program, proAction (<https://www.dairyproaction.ca>). The Animal Care element includes a biannual second party audit of animal based measures (lameness, injuries to hocks, knees and necks, cow cleanliness and body condition) and compliance with standard operating procedures for animal care. In the United States of America, the National Milk Producers Federation has implemented the Farmers Assuring Responsible Management (FARM) Program, in many ways similar to the proAction program. Dairy processors are also actively promoting increased animal welfare through revisions to their animal welfare policies and support of educational programs such as Saputo’s Dairy Care programs at the University of Guelph and the University of Wisconsin.

As part of the recently completed Canadian National Dairy Study (NDS), a needs assessment was carried out in 2014 to create a list of the top management and disease priorities in the Canadian dairy industry, based on input from farmers, veterinarians, advisors, academics and government personnel involved in the dairy industry (1). All stakeholders unanimously ranked

animal welfare as the top management priority, and lameness as the top disease priority, demonstrating that those engaged in dairy production recognized the importance of dairy cattle welfare. Based on this needs assessment the NDS (similar to the National Animal Health Monitoring System studies in the USA) focused on collecting information about the health and welfare of the national dairy herd (<https://www.nationaldairystudy.ca>).

WELFARE ISSUES ON DAIRY FARMS

Welfare issues on dairy farms fall into a number of categories, including incidence and management of disease, prevalence and remediation of injuries, management of pain associated with routine procedures, and the decisions regarding end-of-life of animals of all ages. There is no doubt that many of the most common diseases of dairy cattle are painful. Moderate to severe lameness, mastitis and uterine disease are very often accompanied by manifestations of pain. It is less clear whether subclinical disease is also painful, although a 2015 study by Peters et al. concludes that cows with subclinical mastitis have a significantly lower thermal threshold than healthy cows, suggesting that subclinical mastitis is also associated with some degree of pain (2). Many studies have documented the prevalence of these painful diseases in dairy herds, with clinical mastitis being experienced by one in four cows at least once during a lactation, and mild to severe lameness commonly afflicting between 15 and 35 percent of cows in herds across the globe. Injuries to hocks, knees and necks are also painful and present a significant welfare concern. The Canadian NDS reported that on average 20% of cows housed in tie-stall or free-stall facilities have significant lesions on one or both hocks, while the prevalence is much lower (2%) in cows housed on bedded packs. This suggests that we have viable solutions for the prevention of these conditions, if we chose to implement them. In the shorter term, identifying animals with injuries and providing housing that will allow those injuries to heal is of paramount importance.

In keeping with the need to respect the Five Freedoms of animal welfare, Mellor recently reminded us that we need to deliver the associated Five Provisions of animal welfare (3). Specifically, the ‘freedom from pain, injury and disease’ is to be accomplished ‘by prevention or rapid diagnosis and treatment’ of these conditions.

DISEASE DETECTION

To be able to treat clinical or subclinical diseases of dairy cattle, the diseases first need to be detected. Traditionally people working on the farm (during milking, feeding, breeding, stall cleaning etc) have accomplished this through the frequent observation of, and interaction with, the dairy cattle in the herd. Although this has been the standard, there is evidence that disease detection (or at least the recording of disease events) is relatively poor (4,5). We reviewed dairy records from close to 3,000 farms in Ontario, Canada and found that the recording of most disease events was sporadic at best. Dairy farmers tend to focus on the few diseases that they are most concerned with. Over a one year period less than 70% of farms recorded any cases of

clinical mastitis, while less than 30% recorded any lameness events. Espadamala and co-workers assessed the detection of fresh-cow diseases on 45 California dairies and found them to be very inconsistent and rarely complete (6).

During the NDS, the actual lameness prevalence observed on 374 farms across Canada was compared to the farmer-estimated lameness on their farm. Over 80% of farmers under-estimated the prevalence of lameness, and some by as much as 80% (they only recognized one in five lame cows). This under-estimation has been reported by researchers around the globe, with most true prevalence estimates being about 3 times greater than farmer estimates. Based on these observations, the use of sensors to detect disease does not need to be perfect to surpass the current detection levels on many or most farms.

SENSOR-BASED SYSTEMS FOR DISEASE DETECTION

Over the last decade there has been more and more automation and technology introduced to the dairy barn to aid in management, and in some cases replace the labor that in some parts of North America is in short supply. Automatic milking systems were introduced in the early 90's and current adoption figures indicate that almost 20% of Canadian dairy cows are now milked by robots. This technology is welfare friendly in that it allow cows to be milked at intervals of their choosing, and adds flexibility to the daily schedules of farm owner-operators. Most of the systems are equipped with sensors that detect various components in the milk, evaluate cow behavior and alert the operator if cows fail to come to be milked. Other dairy farm technologies will automatically mix and deliver feed, push up feed, deliver clean bedding, clear alleyways, weigh cows, assess body condition, select animals to be bred or that are due to calve, and identify cows that need attention due to abnormal behavior or attributes – presumably sick cows.

These automated systems use various types of sensors. Milk sensors measure electrical conductivity, numbers of somatic cells either directly or indirectly, presence and relative amounts of enzymes and metabolites, and will soon be able to identify antigens or antibodies for specific diseases of interest as well as major species of mastitis causing bacteria. Sensors worn on the ear, neck or leg count steps, indicate whether a cow is standing or lying, describe the physical location of a cow in two dimensional space, measure body temperature, and detect swallowing and eructation as an indicator of rumination. Cameras are used to measure body condition and abnormal gait. Scales measure weight and rumen boluses measure rumen activity, temperature and pH. These sensors provide measurements at a high frequency, generating immense quantities of data (big data) that are easily stored on high capacity computer storage disks or in the digital cloud. Algorithms in the computer program transform the raw data into alerts using decision algorithms that range in sophistication from very simple to quite complex. These systems claim to be able to detect cows with mastitis, lameness, ketosis, and other common diseases of dairy cattle.

CHALLENGES OF SENSOR BASED DETECTION SYSTEMS

Based on clinical veterinary experience we know that diseases can be defined in different ways. While some diseases have pathognomonic signs, many others do not. There is considerable variation in the signs or disease indicators that the various sensor systems rely on to generate disease alerts. Mastitis detection can be based on electrical conductivity, presence of enzymes such as lactated dehydrogenase, numbers of somatic cells or the presence of specific bacteria in the milk. There are significant differences in the methods used to measure various mastitis indicators. As an example, a recent independent assessment of two different on farm methods to estimate milk somatic cell count (SCC) concluded that the optical enumeration technology was far more accurate than the automated gel reaction system (<http://www.canwestdhi.com/flipon17/index.html#p=10>). These variations in disease definition will pose challenges as we try to understand how sensitive or specific each detection system is.

The sensor systems we have generate large volumes of data on an ongoing basis, yet most of us lack the experience or expertise to utilize these data as well as we might like. Figure 1 depicts the daily SCC for one cow over a 4 month period. While we have become accustomed to interpreting monthly SCC, and are comfortable using those data to identify ‘new’, ‘chronic’ and ‘cured’ intramammary infections, we are less confident as to how to utilize these daily SCC data. Over the first 2 months of this cow’s lactation she maintains a low SCC, well below 50,000 cells/ml, but has one episode where the SCC climbs to over 600,000 cells/ml. This could be a misidentified recording (ID issues do arise and data points can be attributed to the wrong cow), or this could represent carryover of cells in the milk from a mastitic cow that was milked just prior (systems that use a milk collection device will often retain some milk in the device from one milking to the next, allowing a small amount of milk from one cow to mix with that of the next). If this is correctly attributable to this cow, then it might simply reflect a normal mammary gland response to a bacterial challenge by mobilizing somatic cells to clear the infection, and then returning to normal levels at the next milking. If this is a normal event, then should the operator be alerted to this short term SCC elevation? Might this stimulate an antibiotic treatment that is unnecessary? One month later the cow starts along a different path, with mild fluctuations in SCC, yet never once crossing the 200,000 cells/ml threshold that we commonly use to identify infected cows. Only a month later does her SCC increase to a level that would warrant intervention. The question here is whether an earlier intervention, at the beginning of March, prevented the establishment of this chronic infection? (We assume that this is all one event, but given that the SCC testing is of composite milk from all 4 quarters, it is equally possible that several events in different quarters are overlapping here.) This is just one example of the complexity that these daily measurements present to us as decision makers. We have a great deal to learn about how best to use these data to make the best and most prudent decisions for the cows.

While the aforementioned sensor-based disease detection systems are promising, they also have some significant challenges and short-comings. Currently there are many manufacturers, with proprietary sensors implemented on proprietary platforms, and few will communicate with one another. The result is that most current sensor systems are stand-alone and have decision algorithms that are simple, often using inputs from only a few (often 1) sensor on which to make

decisions. Very few have been independently validated, to provide assurance that they really do measure what the manufacturer suggests that they measure. With this increasingly crowded sensor marketplace, it may be a while before the full value of each of these sensors is realized.

IDENTIFYING ‘AT RISK’ INDIVIDUALS

As we seek to develop new or better disease detection systems we find that in many instances the technology is quite good at distinguishing ‘normal’ groups from ‘abnormal’ groups of animals. With larger studies we decrease the effect of individual variation on our estimates and conclude that there are differences in steps or lying time or lying bouts between lame and sound cows for instance. Unfortunately, when try to use these differences to identify individual animals that have slowly developed lameness, the individual day-to-day variation at the cow level masks the subtle changes to the point that we cannot identify the newly lame cow, or the alert comes far too late to be useful. We have a long way to go in our quest to develop algorithms that allow early detection of an abnormality without generating too many false-positive alarms. If the false-positives get too frequent, the technology is soon abandoned.

CAN WE REPLACE THE HUMAN IN DISEASE DETECTION

The explosion in sensor based disease detection systems will inevitably lead to the development of increasingly accurate decision support. With new analytic tools such as machine learning and deep learning to handle large data streams, the challenges we currently face will undoubtedly be resolved. As we move down that road we need to address a series of challenges. We need to understand how specific diseases are defined by each system and perhaps bring some uniformity to our disease definitions. We need to have independent validation of sensor systems to be sure that they actually do what the manufacturer or vendor claims. We are seeing some excellent work in this area (7), and this needs to continue. We need to increase the data sharing across systems so that we can better utilize all of the existing data to make better decisions using multiple inputs. Again, we are making strides in this area (8), but there is much work left to do. Finally, we will need to determine if the investment in each of these systems really does lead to effective and timely decisions that can generate cost-effective interventions. To do all of this we will need to continue to collect data from many cows in many herds, we will need these data annotated with accurate disease diagnoses, we will need open access to the data from different proprietary systems and we will need to apply the newest and best analytic tools available to us.

The final, and perhaps most important challenge we will need to address is the provision of support to the farmers and farm advisors who work with these systems on a daily basis. Far too often these systems are bought, installed and farmers are left to their own devices regarding how to best use the data that are generated. There are too few ‘experts’ available to provide support, and in general the training for farm advisors is lacking. Work out of Australia published in 2012 (9) indicates that even the best technologies will fail if there is not an effective support system around them.

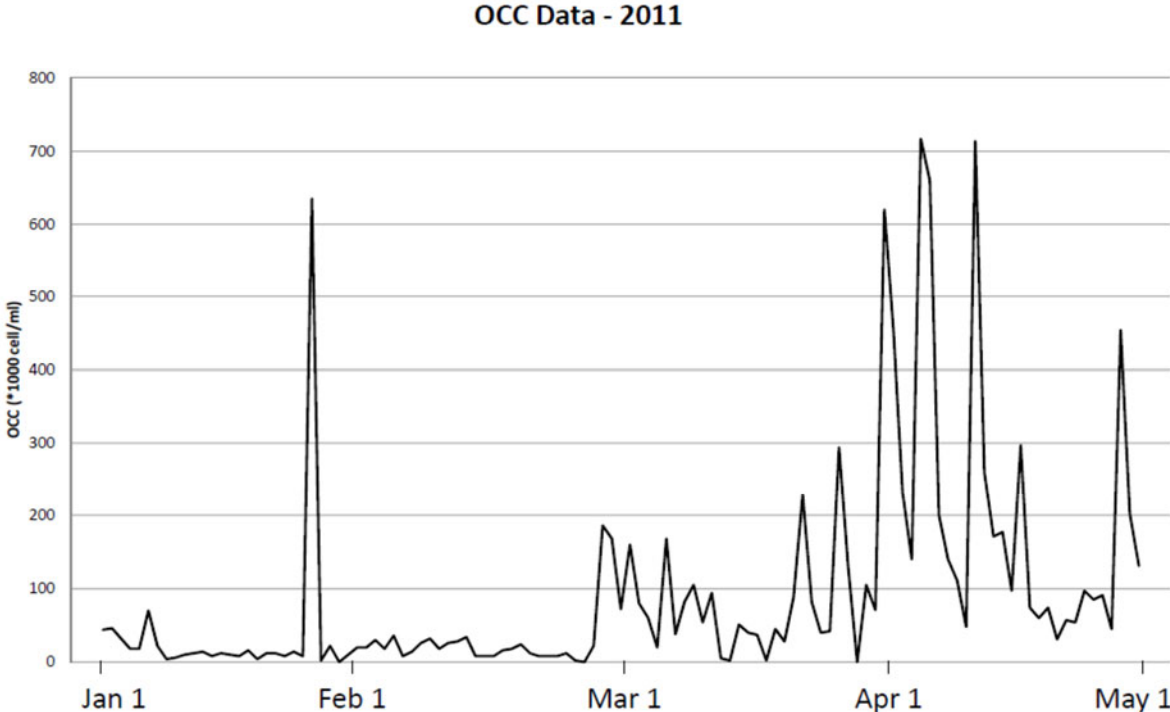
SUMMARY

We have an increasing number of technologies, sensors and systems that can measure many aspects of animal health and behavior instantly and many times per day. These are clearly useful in describing individual animal changes and changes in aggregated populations, but the decision algorithms for early and accurate detection of diseased individuals need improvement. There is little doubt that in the not too distant future, these sensor-based systems will be able to take on much of the disease detection currently done by people, but there is considerable work that needs to be done. We need to work towards data sharing, use of multiple inputs in our decision systems, require independent validation, and provide effective support to the users of these systems to make them sustainable.

REFERENCES

1. Bauman CA, Barkema HW, Dubuc J, Keefe GP, Kelton DF. Identifying management and disease priorities of Canadian dairy industry stakeholders. 2016. *J Dairy Sci* 99:10194-10203.
2. Peters MDP, Silveira IDB, Fischer V. Impact of subclinical and clinical mastitis on sensitivity to pain of dairy cows. 2015. *Animal* 9:2024-2028.
3. Mellor DJ. Moving beyond the ‘five freedoms’ by updating the ‘five provisions’ and introducing aligned ‘animal welfare aims’. 2016. *Animal* 6(10), 59; <https://doi.org/10.3390/ani6100059>.
4. Wenz JR, Giebel SK. Retrospective evaluation of health event data recording on 50 dairies using Dairy Comp 305. 2012. *J Dairy Sci* 95:4699-4706.
5. Espetvedt MN, Reksen O, Rintakoski S, Osteras O. Data quality in the Norwegian dairy herd recording system: Agreement between the national database and disease recording on farm. 2013. *J Dairy Sci* 96:2271-2282.
6. Espadamala A, Pallares P, Lago A, Silva-del-Rio N. Fresh-cow handling practices and methods for identification of health disorders on 45 dairy farms in California. 2016. *J Dairy Sci* 99:9319-9333.
7. Periera GM, Heins BJ, Endres MI. Technical note: Validation of an ear-tag accelerometer sensor to determine rumination, eating, and activity of grazing dairy cattle. 2018. *J Dairy Sci* 101:2492-2495.
8. Barker ZE, Vazquez Diosdado JA, Codling EA, Bell NJ, Hodges HR, Croft DP, Amory JR. Use of novel sensors combining local positioning and acceleration to measure feeding behavior differences associated with lameness in dairy cattle. 2018. *J Dairy Sci* 101:6310-6321.
9. Eastwood CR, Chapman DF, Paine MS. Networks of practice for co-construction of agricultural decision support systems: Case studies of precision dairy farms in Australia. 2012. *Agricultural Systems* 108:10-18.

Figure 1 – Composite milk somatic cell count measured at every milking for cow 2011 by an online somatic cell counter (OCC – Delaval, Sweden).



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A practical approach to determine daily individual cow Feed Efficiency and Income Over Feed Costs

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Madero Dairy Systems (MDS) has successfully incorporated highly specialized sensor-based computerized management systems in its own commercial dairy farm. As a result of this, a huge amount of information has been collected daily during the past 10 years, generating an extensive database, thus allowing on-farm research.

During every milking session, **electronic milk meters** provide precise *milk yield & flow*, **in-line milk analyzers** provide milk components *fat%*, *protein%*, *lactose%*, and **automated weighing scales** accurately measure *body-weight*. Real time **pedometers** monitor activity and rest time wireless throughout the 24-h a day anywhere in the barn, and **weather sensors** measure typical *humidity*, *temperature*, *wind speed* and *Temperature Humidity Index*. In the feeding area, **Portable & loader mounted NIR analyzers** are capable of measure the percentage of Moisture (Dry Matter), Starch, Crude Protein, Acid-Detergent Fiber, Neutral-Detergent Fiber, Ash, and Crude Fat in seconds with multiple analysis per load. These sensors coupled with novel connectivity features are able to generate on-farm and real time updated measurements every hour of every day.

During the past few years, MDS has been using this extensive database to study how the milk production and dry matter intake, as well as a set of different variables, affect the FE and therefore the dairy farm's income. Even though at the beginning this investigation was mainly focused in a general scale as total herd or specific groups results, the need to obtain individual cow's information came out. The methods available at that time to get the actual Feed Intake per cow required a huge investment, specially speaking of a large farm like Madero's.

By taking full advantage of the existing resources in the highly technological farm, analyzing the previously collected data and using multiple sources of information related to energy requirements and metabolism of dairy cattle, dry matter intake prediction models, energy values of milk along with its components and nutritional guidelines, an analytic tool was developed. This analytic tool is able to calculate the DMI estimate of every single cow of the herd taking into account its particular parameters.

As there was real and precise information of the herd and groups' DMI, the estimation was compared. It was found that the variations of what was actually being delivered and ingested to the estimated DMI were ranging between 1-5% in most of the cases, with a very few exceptions reaching the 10%. Taking the data from the previous years, MDS was able to extend the calculations of the individual estimated DMI of each one of the cows throughout their whole lactation.

The next step was to propose an index to equally evaluate all animals. Cumulative Income Over Feed Costs (IOFC) was proposed and calculated for all days under the 61-90 days 'optimal point', and then compared amongst cows and ultimately ranking them from most to least profitable cows.

The results of the experiment showed an estimation error within acceptable ranges. Therefore, the proposed index for selecting and classifying cows according to their FE and IOFC estimated, is a reliable and practical approach to be used in a commercial dairy farm as a useful precision dairy monitoring tool. In conclusion, the detailed levels of data mentioned has allowed MDS to keep improving decision making analysis, through comparing real measured data with theoretical and idealized approaches.

References

Ellis, Jennifer & Qiao, F & Cant, John. (2006). Evaluation of Net Energy Expenditures of Dairy Cows According to Body Weight Changes over a Full Lactation. *Journal of dairy science*. 89. 1546-57. 10.3168/jds.S0022-0302(06)72222-6.

Hutjens, Michael F. (2005). Dairy Efficiency and Dry Matter Intake. University of Illinois. Retrieved from <http://www.wdmc.org/2005/8Hutjens.pdf>

L.M. Jensen, N.I. Nielsen, E. Nadeau, B. Markussen, P. Nørgaard. (2015). Evaluation of five models predicting feed intake by dairy cows fed total mixed rations, *Livestock Science*. Volume 176. Pages 91-103. ISSN 1871-1413. Retrieved from <https://doi.org/10.1016/j.livsci.2015.03.026>.

Nutrient Requirements of Dairy Cattle. (2001).7th Edition. National Academies Press, Washington, DC.

S.J. Krizsan, A. Sairanen, A. Höjer, P. Huhtanen. (2014). Evaluation of different feed intake models for dairy cows. *Journal of Dairy Science*. Volume 97. Issue 4. Pages 2387-239. ISSN 0022-0302. Retrieved from <https://doi.org/10.3168/jds.2013-7561>.

Sjaunja, L.O. , Baevre, L , Junkkarinen, L , Pedersen, Jørn. (1990). A Nordic proposal for an energy corrected milk (ECM) formula. 27th Session of ICRPMA. 156-157.

Reducing bimodality by optimizing treatment time in AMS

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The milking process is a complex interaction of balancing udder health and milking machine efficiency. Efficiency is indicated by milk yield given during the time spend in the AMS. Milk letdown from the alveoli in the udder is provoked by brushing the teats, a tactile stimulus to trigger oxytocin release of the hypothalamus to the blood. When attaching the teat cup too soon or with an insufficient stimulus bimodality can occur. In that case, the cisternal milk is removed while alveolar milk let down has not yet started. Consequently, milking vacuum is applied while having limited milk flow, a risk for adverse teat (end) conditions. These AMS brush times are set at herd or group level. We hypothesize that bimodality can be reduced by adjustment of brush time.

Milk data from 26 randomly selected AMS-farms, which are located in Canada, Denmark, France, Germany, the Netherlands, United Kingdom and the United States of America, were examined at quarter level for the occurrence of bimodality during 80 consecutive days using semi-supervised classification (832,260 milkings of 4,809 cows). Aggregation of the quarter bimodality classification results in bimodal cow having at least 10% bimodality a week. This data was selected for 1) a spectral clustering analysis. Two weeks data of a subset of 857 bimodal cows was used for 2) the adjustment of brush time. This to exclude the impact of natural variation due to lactation stage. Fisher's exact test is used to check the effects of prolonged brush time with eight seconds (n=53) compared to without setting change (n=804).

Prevalence of bimodal cows per herd ranged from one to 46%. Mean and range of other relevant variables in the milking data are described in table 1.

Table 1: Mean, standard deviation and range of relevant variables in the milk data set.

| <i>Variable</i> | <i>Mean (std)</i> | <i>Range</i> |
|-------------------------------|-------------------|--------------|
| <i>Bimodality [%]</i> | 22 (13) | 1 – 46 |
| <i>Pre-treatment time [s]</i> | 56 (13) | 34 – 89 |
| <i>Connection time [s]</i> | 35 (28) | 13 – 124 |
| <i>Lactation number</i> | 3 (2) | 1 – 14 |
| <i>Days in lactation</i> | 146 (113) | 14 – 441 |
| <i>Interval [h]</i> | 9 (3) | 4 – 17 |

Farm level spectral clustering showed a different brush time between clusters of bimodality. Other significant effects were; multiparous and late lactation cows were more bimodal than primiparous and early lactation cows respectively. In addition, a longer milking interval reduced the occurrence of bimodality. Prolonged brush time results in a significant reduction of bimodal cows (odds ratio = 13). Milking efficiency was increased for bimodal cows with prolonged brush time, respectively dead milk time decreased (odds ratio = 1.9), average milk speed increased (odds ratio = 2.8) and yield per box time grew (odds ratio = 3.2).

Prolonged brush times for bimodal cows results in a reduced occurrence of bimodality, a more efficient milk process and might improve udder health. Ideally, the interaction between udder health and efficiency requires a cow individual brush time.

Performance of an automatically milked dairy herd in a 4-way grazing system

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Introduction

It is widely accepted that automatic milking can be integrated successfully where grazed grass represents different proportions of cow diet. However, few recent studies have reported on an almost complete grass based diet. In Ireland, it has been shown that the most competitive strategy for the farm business is to maximize the proportion of grazed grass in the cow diet, hence the importance and challenge of achieving this with an automatically milked dairy herd. The focus of the most recent automatic milking study has been to optimize the number of cows on the system in order to dilute the additional costs of investment (Shortall *et al.*, 2016). The study investigated the optimization of cow numbers, which could potentially lower milking frequency and maximizing the milk production output from the robot rather than from the individual cow. To focus on this approach, the key parameter of grazing strategy was examined, together with its effect on milking frequency (MF) at peak lactation, and cow movement around the system.

Description of System and Direction of Work

Cow number was 85 during the 2017 lactation. The herd comprised of 23 and 62 first lactation and mature cows, respectively and 74, 10 and 1 Friesians, Jersey/Jersey cross and Norwegian Red cows, respectively. An alternative grazing strategy (ABCD) compared to the previous system (ABC) was put in place. This involves a 4-way system which may better accommodate the larger herd size. More frequent gate change times may have a positive impact on grazing management and cow movement, but alternatively, time at grass needs to be maximized for the cow as well. But in a seasonally calved automatic milking production system, MF needs to be reduced during the peak milk yield period to accommodate increased herd size. However, too great a reduction in MF could significantly reduce milk yield and also, a potential carry-over effect could be incurred over the remainder of the lactation.

Grazing Management

With the 4-way grazing system, ABCD, cows have access to four different allocations of grass within a 24 hour timeframe. In theory, cows can pass through the yard four times per day, thus allowing them to be milked up to 4 times/day. However, permission to be milked is also dependent on duration since the last milking, which setting can be controlled, and expected milk yield. The cow movement to the robot and around the system is controlled by the grazing management parameters. The access to the different farm sections are as follows: Block A = 7am to 12 noon; Block D = 12noon to 6pm; Block B = 6pm to 11:30pm; Block C = 11:30pm to 7am. Cows received grass allocations across sections as follows: 6 kg DM/day, 6 kg DM/day, 2.5 kg

DM/day and 3 kg DM/day in Blocks A, D, B and C, respectively. Cow grazing areas had herbage yields of 1400-1550 kg DM/ha during the main grazing season in 2017 and achieved residuals of 5- 6cm, depending on the pre-grazing cover.

Concentrate Offered to Cows

The total amount of concentrate offered to cows over the 2017 lactation was 380 kg/cow. Cows received 4kg/cow/day at the commencement of the lactation, February to mid-March. Cows were then reduced to 1.5 until May, at which point, cows were reduced again to 0.5 kg/cow/day for the remainder of the lactation. In November, cows again received 2.0 kg/cow/day.

Results

Average milk yield and yield of milk solids (MS) produced per cow was 4,395 kg/cow and 365 kg MS/cow, respectively, over the 2017 lactation. Average fat, protein and somatic cell count levels were 4.67 %, 3.64% and 106×10^3 cells/ml, respectively. Milking performance and robot characteristics for the peak week of the herd milk production profile is shown in Table 1. With good management, a MF of 1.5 was maintained with a herd of 85 cows at peak milk production.

Table 1 Milking performance and robot characteristics for the peak week of herd milk profile

| Parameter | Peak week of herd milk profile (08-15 May 2017) |
|-----------------------------------|---|
| Milk output/robot/day | 1,932 kg |
| Milk yield/cow/day | 22.5 kg |
| MS yield/cow/day (kg) | 1.78 |
| Milkings/day | 131 |
| Milkings/cow/day | 1.5 |
| Av box time (min) | 8.0 |
| Milking time (milk flowing) (min) | 6.3 |

All cows did not visit all four grazing areas each day, but approximately 40% of the herd visited a minimum of 3 grazing areas; 61% of cows visited > 2 grazing areas per day. Cows had a better chance of new grass each day with 4-way grazing. However, while a 3-way grazing system requires similar skills and precision in management to that of a 4-way system, a slight reduction in labour time input is observed with a 3-way compared to a 4-way system.

Conclusion

Automatic milking can operate successfully with 85 per robot in a grass based, spring-calving milk production system, if managed correctly.

Reference

Shortall, J., L. Shalloo, C. Foley, R.D. Sleator and B. O'Brien, 2016. Investment appraisal of automatic milking and conventional milking technologies in a pasture-based dairy system. *J. Dairy Sci*, 99, 7700–7713.

Factors associated with milk production per automatic milking system on free-flow farms in the Upper Midwest United States

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Introduction

In conventional milking dairy farms, it is a common practice to focus on milk production per cow. However, in automatic milking system (AMS) farms we are also interested in how much milk each AMS unit produces a day. According to AMS manufacturers, a goal for milk production is 2,300 kg per AMS per day or greater. Management practices may play an important role on how much milk production can be achieved in each AMS unit. Therefore, the objective of this study was to investigate the association between management and housing factors with milk production per AMS on free-flow cow traffic farms.

Materials and Methods

We visited 36 free-flow AMS farms (Lely Astronaut, Lely, the Netherlands) in Minnesota and Wisconsin over the summer of 2018. During the visit, each producer answered a survey about general farm management practices. In addition, we collected retrospective daily data from the AMS software for one year. For this study, we used data for the 30 days (1,080 daily averages) prior to the farm visit to evaluate the association of those factors and management practices with milk production per AMS (kg/d). The MIXED procedure of SAS[®] 9.4 (SAS Institute, Inc., Cary, NC) was used to analyze the data. Factors evaluated in the analysis include barn design characteristics, such as number of AMS units per farm and per pen, new or retrofitted AMS facility, AMS location in the barn, use of automatic alley scraper, and ventilation system. General management practices included number of daily feedings, number of feeds offered in the AMS, cow fetching frequency, bedding frequency, use of automatic feed pusher, and presence of a fresh group. Data from the software were also included in the analysis, such as age of the cows, days in milk (DIM), concentrate offered per cow, number of cows per AMS, milkings, refusals, failures, milking speed, and milking time. A univariable linear mixed analysis was first conducted with each variable and milk production per AMS. Factors with a $P < 0.3$ were included in the initial multivariable linear mixed model. Backward stepwise elimination was used to remove nonsignificant factors until all remaining factors had a $P < 0.05$ in the final model. Farm was used as random effect.

Results and Discussion

Table 1 shows descriptive statistics for the factors associated with milk production per AMS. Results show that having multiple robots per pen tended to be associated with lower milk production ($P=0.09$, Table 2). As expected, a higher number of cows per AMS resulted in

greater milk production. Using an automatic alley scraper (present in 75% of the farms) resulted in an increase of 146 kg of milk per AMS compared to manual scraping. To our knowledge, this is the first study to look at number of feeds offered in the AMS in the US. There was a tendency for a positive association ($P=0.09$) between number of feeds in the AMS and milk production per AMS. Each type of feed was offered with a different purpose. For instance, a farm might have a pellet specially formulated for fresh cows. For each additional kg of concentrate offered in the AMS, there was an increase ($P < 0.05$) of 70 kg of milk per AMS unit. For each 0.1 increase in average milkings per cow per day there was an increase of 50 kg of milk per AMS. Refusals were negatively associated with milk production per AMS. This result may be expected, as each refused visit to the AMS takes time, which could be used to milk another cow. A higher milking speed resulted in more milk per AMS, as cows can be milked in less time. Milking time was also positively associated with higher milk production, probably because high producing cows might take more time to be milked.

Summary

Number of cows per AMS, use of automatic alley scraper, number of feeds offered in the AMS, amount of concentrate offered, milking frequency, how fast and for how long cows were milked, were the factors positively associated with milk production per AMS. Number of AMS per pen, and number of refusals had a negative association with daily milk production per AMS.

Table 1. Descriptive statistics of the variables associated with milk production/AMS (kg/d) on 36 free-flow AMS dairy farms in Minnesota and Wisconsin

| Variable | Mean | SD | Minimum | Maximum |
|------------------------------|-------------|-----------|----------------|----------------|
| AMS/pen | 1.89 | 0.74 | 1.00 | 4.00 |
| Cows/AMS | 59.04 | 4.96 | 47.63 | 69.43 |
| Feeds/AMS | 1.64 | 0.67 | 1.00 | 3.00 |
| Concentrate/cow (kg/day) | 5.56 | 0.87 | 3.43 | 7.43 |
| Milkings/cow/day | 2.82 | 0.22 | 2.50 | 3.35 |
| Refusals/cow/day | 1.27 | 0.58 | 0.40 | 2.34 |
| Milking speed (L/min) | 3.26 | 0.41 | 2.07 | 4.21 |
| Milking time (sec) | 306.53 | 29.67 | 260.57 | 352.77 |
| Milk production/AMS (kg/day) | 2224.19 | 340.08 | 1433.34 | 2880.13 |

Table 2. Multivariable analysis of farm-level factors and their association with milk production/AMS (kg/d) on 36 free-flow AMS dairy farms in Minnesota and Wisconsin

| Variable | Estimate | SE | P-value |
|--------------------------|-----------------|-----------|----------------|
| Intercept | -3424.56 | 168.88 | <.0001 |
| AMS/pen | -58.18 | 34.31 | 0.090 |
| Cows/AMS | 35.60 | 1.25 | <.0001 |
| Automatic alley scraper | 145.85 | 62.70 | 0.020 |
| Feeds/AMS | 69.87 | 40.78 | 0.087 |
| Concentrate/cow (kg/day) | 66.16 | 10.45 | <.0001 |
| Milkings/cow/day | 503.10 | 15.03 | <.0001 |
| Refusals/cow/day | -24.54 | 5.06 | <.0001 |
| Milking speed (L/min) | 245.32 | 14.28 | <.0001 |
| Milking time (sec) | 3.34 | 0.16 | <.0001 |

Are accelerometers a good tool to predict diseases in calves?

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Introduction

The early identification of sick calves can reduce costs and improve health and animal welfare. However, early identification of health problem in calves is difficult based only on subjective identification by farm personnel. Moreover, the intensification of the production systems decreases the human-animal interaction, which further complicates the visual and subjective diagnostic. Studies using wearable devices reported that the behavior could be useful to predict morbidity in calves (Svensson and Jensen, 2007). However, there is limited information on the reliability of these methods. The aim of this study was to verify if the use of accelerometers could be a good tool for early detection of diseases in dairy calves.

Material and Methods

A total of 325 Friesian male calves were enrolled in this study. There were four groups of calves (30±9 d and 65±15 kg) that arrived to the farm in March (n=85), June (n=85) September (n=80) and October (n=75). Calves were monitored throughout sixty days after their arrival to the farm with previously validated accelerometers (Fedometer [FEDO] system; ENGS, Rosh Pina, Israel; Wolfger et al., 2010) able to measure; daily duration (min/d) and frequency of attendance (n/d) to the feed bunk, steps count (n/d), lying time (min/d) and lying bouts (n/d). At arrival, calf ID, birth date and group entry date were recorded. Calves were observed daily by experienced farm personnel for evidence of sickness. All calves diagnosed as sick were treated for at least three days, and the date, the time of treatment, and the diseases treated were recorded. Data was analyzed by SAS software (v9.4) with individual animal serving as the experimental unit. To compare sick and healthy calves, a matched pair design was used, by which the day 0 was the day where calves were diagnosed as sick and three healthy calves on the same date, the same group, with a similar age (±4 d) and approximately the same weight at entry were defined as a matched pairs. Data from 10 d before to 10 d after the treatment event were analyzed. Data was analyzed using a multivariate logistic regression in SAS (PROC GLIMMIX) followed by PROC LOGISTIC and PROC FREQ to compute the area under the curve (AUC). The model included the fixed effects of the season, the age of entry and all behavioral measurements. Predictors were selected through a manual backward stepwise removal process until remaining predictors were significant. Equations with an AUC greater than 0.70 were chosen for the final prediction models. The sensitivity (Se) and the specificity (Sp) were calculated for each possible cut point (Dohoo et al., 2003), and the combination with the higher Se and Sp was selected. The rates of false positives (FPR), false negatives (FNR) and accuracy were calculated. The accuracy was defined as the proportion of healthy and sick calves diagnosed correctly.

Results

From a total of 325 calves, 33 (10%) were diagnosed sick. About half of calves (17; 51%) were treated against bovine respiratory diseases, and the rest had non-specific symptoms and received a general treatment based on antibiotics and anti-inflammatory. Only two calves died within the two first weeks in the farm (0.61%).

Comparison of healthy vs. sick calves. The difference in behavior began to be evident 10 d before the treatment event. Sick calves visited 20% less the feed bunk (days -10, -9, -6, -5, -3, -2, -1 and 0, $P<0.05$; days -8, -7, and -4; $P<0.10$) and spent less time at the feed bunk (days -10, -9, -1 and 0, $P<0.05$) than healthy calves. This difference disappeared after the treatment event, except on days 4 and 9, when sick calves visited less the feed bunk than healthy calves. Sick calves also did fewer steps than healthy calves during the 20 days around the disease (sick vs healthy: 1178 ± 100 vs. 1437 ± 59 steps/d), being differences significant except on d -9 ($P<0.10$). At the same time, sick calves made fewer lying bouts than healthy calves (sick vs. healthy: 17 ± 1.3 vs. 19 ± 0.8 changes/d), with significant differences ($P<0.05$) in days -6, -2, -1, 0, 2, 3, 4, 5 and 6. There were no differences between sick and healthy calves in lying time except on d -10, when the diseased calves spent more time lying than healthy calves (sick vs. healthy: 1057 ± 94 vs. 987 ± 50 min/d, $P<0.05$).

Diagnostic test and prediction models. All prediction models showed an AUC >0.60 . Only three of them had values under 0.70. The best prediction equation was found for d -1. Its application using the cut point chosen from the highest point of sensitivity (69%) and specificity (72%) had 72% accuracy, 55% FPR and 12% FNR. However, the usefulness of this prediction equation is limited because it provides an alarm only one day before the symptomatic diagnostic. An earlier predicting could be more useful to reduce the negative impact of the disease on production and welfare. Thus, the second best prediction equation was for d -10, with a sensitivity of 68%, a specificity of 68% and an accuracy of 67%. The FPR and FNR were 60 and 14%, respectively. Marchesini et al. (2018) observed that calves reduced their activity and rumination 3 to 6 d before suffering a respiratory disease. Knauer et al. (2017) also observed that they could detect a sick calf 4 d earlier of its diagnosis by the farm personnel. However, none of the previous studies provided information on the precision and accuracy of the method, nor on the incidence of FPR and FNR. Accelerometers were able to identify a sick calf at least 10 d before being diagnosed by farm personnel. However, under the conditions of this test, the rate of false positives was relatively high and may require further refinement.

References

- Dohoo, I., W. Martin, and H. Stryhn. 2003. Veterinary Epidemiology Research. AVC Inc., University of Prince Edward Island, Charlottetown, Canada.
- Knauer, W. A., S. M. Godden, A. Dietrich, and R. E. James. 2017. The association between daily average feeding behaviors and morbidity in automatically fed group-housed preweaned dairy calves. *J. Dairy Sci.* 100:5642-5652.
- Marchesini, G., M. Cortese, D. Mottaran, R. Ricci, L. Serva, B. Contiero, S. Segato, and I. Svensson, C., and M. B. Jensen. 2007. Short communication: Identification of diseased calves by use of data from automatic milk feeders. *J. Dairy Sci.* 90:994-997.
- Wolfer, B., K. S. Schwartzkopf-Genswein, H. W. Barkema, E. A. Pajor, M. Levy, and K. Orsel. 2015. Feeding behavior as an early predictor of bovine respiratory disease in North American feedlot systems. *J. Anim. Sci.* 93:377-385.

Fully automated individual calf rearing to optimize dairy calf and future dairy cow performance

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Introduction and Objective

The application of sensor technology and related data analysis is rapidly gaining interest in the dairy industry, as it has been shown that continuous monitoring animals can be beneficial for labour efficiency, animal health, welfare and productivity. Over the past decade, the dairy industry has shifted toward greater milk supply in early life because of observed benefits like greater growth and feed efficiency in early life, increased long-term survival (Bach, 2011), and lifetime milk production (Bach, 2012; Soberon et al., 2012). Despite the recently increased managerial focus on youngstock rearing, application of automation and sensor technology in youngstock has remained fairly limited to date. Only automated milk feeders for groups have been applied increasingly in recent years, since they allow for increased social facilitation among calves, reduction of labour, consistent and controlled milk supply, and a higher feeding frequency. Additionally, integration of nutritional and genetic insights could lead to further optimization of youngstock rearing and prediction of dairy cow survival and performance planning.

Ultimately, full automation of calf rearing would allow for in-depth monitoring of the development of calves as well as individual adjustment of nutritional and weaning strategies based on the individual health, nutritional needs and genetic potential. To this end, the current collaborative study was initiated with nutritional experts, sensor experts, geneticists and data scientists. The joint objective is to develop and validate applications supporting precision feeding of dairy calves to improve growth, health and welfare and to predict and optimize phenotypic performance, i.e. survival and milk production performance of dairy cows.

Technology and Data Collection

Five Dutch dairy farms with over 1000 dairy cows in total are equipped with calf rearing technology to allow individual and fully automated feeding and bodyweight monitoring until 4 months of age. Equipment was installed between September 2017 and January 2019. After birth, calves are housed in single pens and milk is supplied via an automated feeder (Calfrail®, Förster Technik, Engen, Germany). From 14 days onwards, calves are group-housed with access to milk, concentrate and water feeders (Förster Technik, Engen, Germany). Bodyweight is monitored using

a weighing scale (Gallagher Europe BV, Groningen, the Netherlands) in the concentrate feeders. For all calves, hair samples are taken to determine genomic breeding values. A digital logbook application is developed and used to insert all clinical health observations. All farms are provided with a protocol to standardize management of colostrum, housing, forage provision, health recordings, concentrate feed and milk replacer. The data are ingested in a data lake to be able to monitor the animals' performance and to extract data to be able to answer a wide range of research questions by applying data science and statistics.

Treatments

After birth, calves are randomly allocated to a 2x2 factorial design, including 2 levels of milk replacer and 2 levels of concentrate starter feed. A dairy-protein based milk replacer containing 22% protein and 17% fat (Kalvolac Power, Nutrifeed, the Netherlands) was provided ad libitum or restricted at 7 L per day at 150 g/L in a feeding frequency up to 7 feedings per day. A starter concentrate feed with 19% CP (Dairystart Vitaal, Agrifirm, the Netherlands) was provided ad libitum throughout the rearing period, or provided ad libitum until 10 weeks of age and subsequently restricted to 3 kg per day.

Preliminary findings

First preliminary results indicate that the application of automated calf rearing from birth leads to an increase in average daily gain until 12 weeks of age by 86 grams per day based on 488 animals. The effects on phenotypic performance in their productive life (insemination age, AFC, susceptibility to disease, milk production) are to be evaluated further in the years to come.

References

- Bach, A. 2011. Associations between several aspects of heifer development and dairy cow survivability to second lactation. *J. Dairy Sci.* 94:1052–1057.
- Bach, A. 2012. Ruminant Nutrition Symposium: Optimizing Performance of the Offspring: Nourishing and managing the dam and postnatal calf for optimal lactation, reproduction, and immunity. *J. Anim. Sci.* 90:1835–1845.
- Soberon, F., E. Raffrenato, R. W. Everett, and M. E. Van Amburgh. 2012. Prewaning milk replacer intake and effects on long-term productivity of dairy calves. *J. Dairy Sci.* 95:783–793.

Validation of a partial weight scale on an automated milk feeder for estimating daily body weight in dairy calves

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Monitoring early growth in neonatal dairy calves provides insight into the effectiveness of a producer's nutrition program, and helps monitor for sickness and rearing success. The objective of this study was to validate if a partial weight scale associated with an automated milk feeder (DeLaval, Combi, Tumba, Sweden) could accurately and precisely estimate calf weights when compared to bi-weekly weights of a calibrated electronic scale (gold standard; Brecknell PS1000, Avery Weigh-Tronix, LLC Brand, Fairmont, MN, USA).

Holstein heifers (n=20) born and raised at the University of Kentucky Coldstream Dairy Research Farm were enrolled on this study from birth until 2 weeks after weaning. Calves were weighed once within 24 h of birth, and placed in an individual pen (2.0 × 1.1 m) bedded with sawdust shavings for 2 days. After 2 days of age, calves were moved to a larger pen (4.57 × 10.67m) bedded with sawdust shavings. The pen contained a partial weight scale attached to the automated milk feeder and *ad libitum* access to a starter feeder (DeLaval, Combi, Tumba, Sweden), water, and chopped alfalfa hay. Calves could consume up to 10 L/d of milk replacer (Warm Front, Land O Lakes, Arden Hills, MN, USA) for 56 days. Milk replacer was reduced 50% across one week, and reduced an additional 20% across another week until complete weaning on day 70. The automated milk feeder had a radio frequency identification panel placed directly above the scale such that calves had to stand with both front hooves on the scale platform to access milk from the nipple. Calves were also weighed twice weekly until 2 weeks post-weaning on an electronic scale (Brecknell PS1000, Avery Weigh-Tronix, LLC Brand, Fairmont, MN, USA). All statistical analyses were performed in R (ver. 3.5.2).

An algorithm was create to summarize and clean the scale measurements of any non-biologically relevant data points (measurements of zero body weight, measurements lower than the 7-week body weight, or measurements with a deviation of more than 15% from the previous three measurements average). The relationship between the daily weight average from the partial scale and the electronic scale were analyzed using Pearson's correlation, linear regressions and Bland-Altman (1986) plots. Data from the partial weight scale were considered accurate if the Pearson's correlation coefficient and coefficient of determination (R²) were high or very high (> 0.70, Hinkle et al., 1988), if the slopes did not differ significantly from 1, and if mean bias from the Bland-Altman plots was within the 95% interval of agreement. We defined high precision as high Pearson's correlation and a high coefficient of determination (R²> 0.90). We observed high precision in the partial weight scale, with a very high Pearson's correlation coefficient (r= 0.99) and a very high coefficient of determination (R²=0.98; Figure 1). We observed high accuracy in the partial weight scale with the linear regression (y=1.01x-1.21) slope at 1.01 (CI: 1 – 1.03; P <0.0001) and a Bland-Altman plot distributed around zero (Figure 2). A regression of every calf's body weight against the partial weight scale (to determine the influence of the individual in the measurements) was calculated and high

precision and accuracy was also found (Figure 3). The mean differences in weights (using a paired t-test) between the partial weight scale and the electronic scale were 0.45 kg (CI: 0.22-0.69; $P < 0.001$). We found that the partial weight scale measurements, when associated with a data cleaning and summarization algorithm, were a precise and accurate measure for estimating body weight in dairy calves. We did not find influence of age or individual calf to be a source of variation in the findings.

Figure 1. Dairy calves (n=20) body weight measured by the partial body scale on an automatic milk feeder (x-axis) compared to the body weight measured by the electronic scale (y-axis). Data points symbolize body weight for each calf measured with both scales.

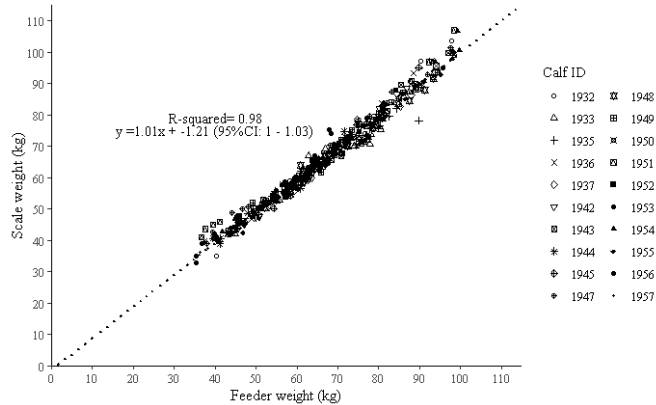


Figure 2. Bland-Altman plot illustrating agreement between the body weight measured by the partial body scale on an automatic milk feeder (x-axis) and by an electronic scale (y-axis). For this graph; x-axis is the mean of electric scale and feeder scale; and y-axis is the difference between electric scale and feeder scale.

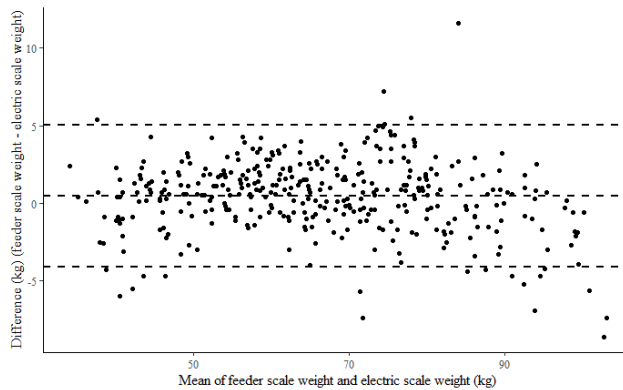
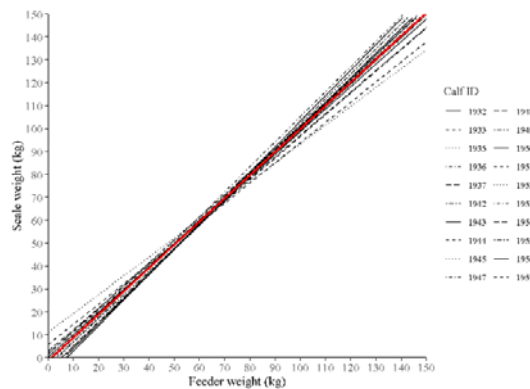


Figure 3. Regression of body weight by calf, comparing the body weight measured by the partial weight scale (x-axis) against the electronic scale (y-axis).

| Calf_ID | R-squared | Calf_ID | R-squared |
|---------|-----------|---------|-----------|
| 1932 | 0.98 | 1948 | 0.98 |
| 1933 | 0.93 | 1949 | 0.99 |
| 1935 | 0.93 | 1950 | 0.99 |
| 1936 | 0.98 | 1951 | 0.97 |
| 1937 | 0.98 | 1952 | 0.99 |
| 1942 | 0.99 | 1953 | 0.98 |
| 1943 | 0.98 | 1954 | 0.99 |
| 1944 | 0.97 | 1955 | 0.99 |
| 1945 | 0.99 | 1956 | 0.99 |
| 1947 | 0.99 | 1957 | 1 |



The largest robotic dairy of the world: ANCALI, Chile Past Experience and Forthcomings

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Agricola ANCALI is a large free-stall dairy farm situated in the south-central area of Chile (37.6 S; 72.3 W), characterized by temperate weather conditions and a Temperature Humidity Index > 73 during the summer months (December to February). It comprises of 8,929 ha, of which, 1,150 ha are established with corn for silage and grain, 650 ha with alfalfa, 450 ha with Ryegrass, and the rest in pasture. When the free-stall system was begun, the farm was milking 1,200 cows in a 40-unit rotary parlor (DeLaval®). In 2007, the dairy increased to 4,500 lactating cows using three 40-unit rotary parlors (DeLaval®). Then, in 2010 the farm built a new 40-unit rotary parlor and the number of milking cows increased to 6,000. In 2014 the herd size increased to 6,500 cows, with the same number of rotary parlors and the addition of 8 robotic systems (DeLaval VMS). In 2016, 7,000 cows were milked in the 4 rotary parlors and 16 robotic systems (DeLaval VMS). In 2017, the number of lactating cows decreased to 5,000 and 3 of the 4 rotary parlors were eliminated. Sixty-four robotic DeLaval systems were established. In 2018, the last rotary parlor was eliminated, leaving 4,500 cows to be milked in the 64 robotic systems with one conventional milking parlor (parallel) for fresh cows.

With this, Agrícola ANCALI became the largest robotic dairy of the world. The reasons for this evolution relate mostly to a lack of suitable personnel and poor labor efficiency. The results of this progression and change of mindset were more milk production (10%), greater labor efficiency (40%), greater longevity for cows (1 lactation), and thus more efficiency and profitability for the business.

The planning for installation of the robotic modules had to consider the design of barns and the normal behavior and movement of the animals. Two major challenges were (1) the conversion of the existing installations and (2) migration from the rotary parlors to the robotic systems. The second challenge involved training of the cows and preparation of the personnel (perhaps the most important aspect). Table 1 shows, the goals for production, the efficiency parameters for DeLaval VMS Robotic Systems, and current values that Agrícola ANCALI has achieved in the conversion to the robotic system for milking more than 4,000 Holstein cows. Today, Agrícola, ANCALI is a progressive dairy, with a total of 4,500 lactating cows under robotic system and a milk production of 65 million liters per year, which serves as a model for Chile and the rest of the world. Mindful of animal welfare (cow-comfort), the dairy maintains as a priority an efficient ventilation system to avoid heat stress during the summer months, use rubber mats on the floor, brushes for rooming, sand for bedding, photo period management and manure scraper.

In a Canadian study, 217 dairy producers were surveyed to share their experience on the transition from conventional to robotic systems. Producers perceived that robotic systems improved

profitability, the quality of their lives and their cows' lives, and had met expectations, despite experiencing some challenges during transition. Examples of challenges gleaned from the survey include learning to use the technology and data, cow training, and changing health management. Eighty-six percent of producers from this study would recommend the transition to robotic system for their peers. This supports the experience of ANCALI, the largest robotic dairy of the world (Tse et al., 2018).

Table 1. Goals and current values for production and efficiency parameters for DeLaval VMS Robotic Systems in Agricola ANCALI, Chile.

| Parameter | Goal | Current |
|-----------------------------|---------------|----------------|
| Production per VMS (kg/d) | > 2,400 | 2,670 |
| Production per cow (lt/d) | 40.0 | 43.3 |
| Days in Milk | < 180 | 166 |
| Milking per day <100 DIM | > 3.0 | 2.8 |
| Milking per day 100-200 DIM | > 2.5 | 2.8 |
| Milking per day >200 DIM | > 2.0 | 2.8 |
| MDI/cow/d* | < 1.4 | 1.1 |
| Time between milking (h) | < 12 | 8.5 |
| Conductivity | < 4.5 | 4.0 |
| SCC | < 150,000 | 128,000 |
| Milking time/cow | 6:00-7:00 min | 07:10 |
| Cleaning time/VMS/d | 1 hour | 00:48 min |
| Milking number/VMS/d | > 180 | 170 |
| Incomplete milking (%) | < 5 | 1.5 |

*MDI = Mastitis Detection Index

As Table 1 shows, most of the goals have been accomplished, giving great satisfaction to the managers and owners of the company. Two options are now open for discussion -- continue to increase the herd size while maintaining efficiency, or maintaining herd size and increasing the efficiency.

References

- Tse C, HW Barkema, TJ DeVries, J Rushen, E Vasseur, EA Pajor. 2018. Producer experience with transitioning to automatic milking: Cow training, challenges, and effect on quality of life. *J Dairy Sci*101:9599-9607

Centralized 12-robot, guided cow flow facility

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For three years running, I have had the honor of sharing with the readers in the dairy industry; both in Canada and the United States, with what I believe are cutting-edge robot dairy facilities. These designs are the culmination of decades of combined experience from dairy producers, veterinarians, nutritionists, builders, equipment manufacturers, and of architects/engineers like myself. I have received feedback from people all over the world that read these articles, both in print and digital formats. It is, without doubt, a team effort; and the ideas are flowing stronger than ever!

Previously, we have presented a design that encompasses nearly every luxury one can fit into a robot barn. We have also presented integrated, smart robotic facilities that hopefully will have some role in shaping the future of dairy farm planning and design. In the paper I would like to share what I believe is one of the most efficient facilities in several respects.

To begin, the milking area is centralized with all 12 robots in one room, which permits lower building costs as power, water, air, vacuum, and milk lines are going to one place. Delivery of teat dips whether pumped from the Milk House or a Utility Room adjacent to the robot room and ventilation systems minimized and going to one place.

Overall milk transport length is shorter leading to less risk for compromised milk quality and lower cleaning costs as opposed to a decentralized layout.

Labor input for working with and maintaining robots is as easy as it gets. Just the other day I spoke with a dairy producer that said centralizing the robots was a decision she was glad she made after visiting a retrofit robot barn that had little choice but to place robots in several areas.

Managing separation cows is also simplified as all the separation pens are in the center of the building.

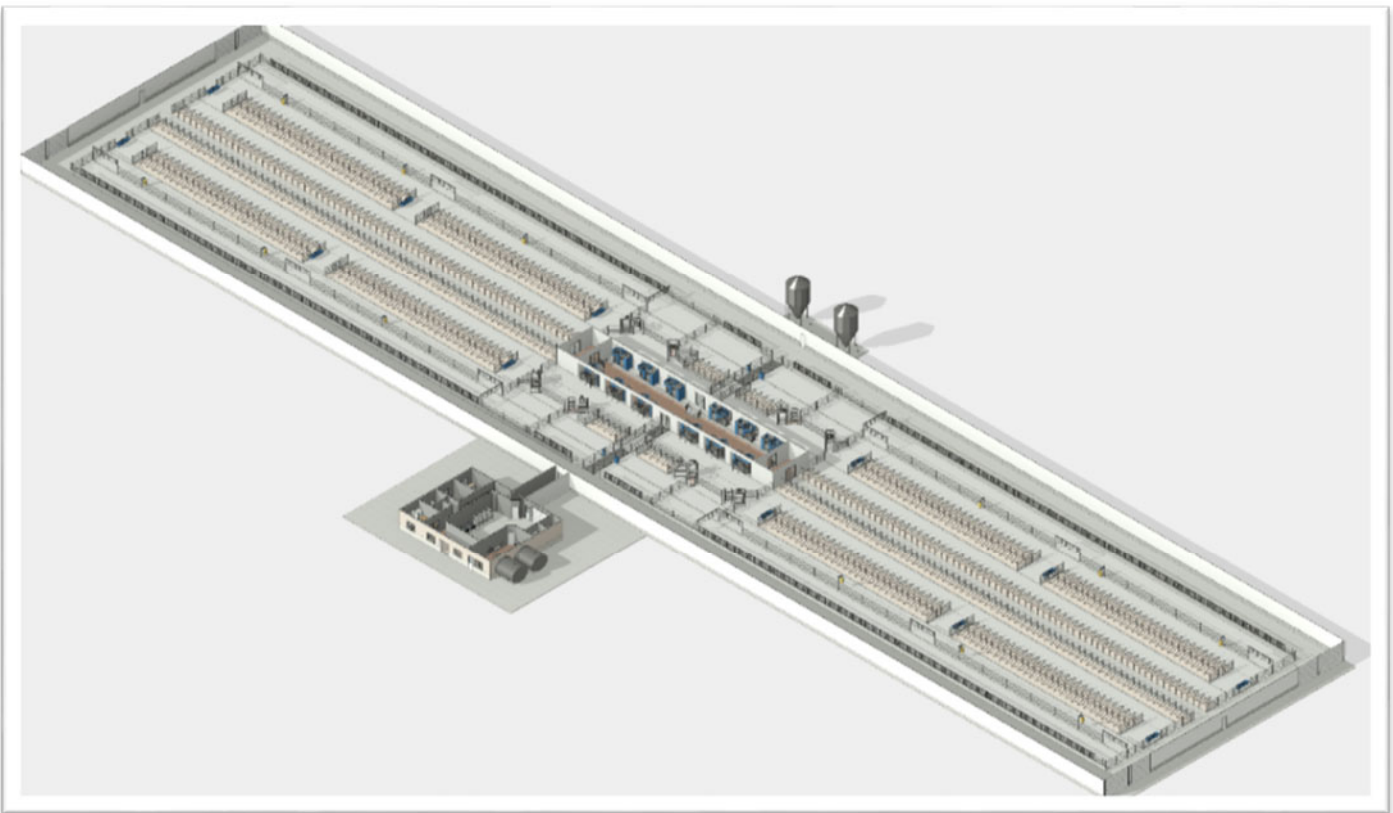
Of course, there are always trade-offs with nearly every decision. With centralization we are not able to sort cows quite as effectively as when each robot has a sort gate immediately at the exit. Cows must travel a greater distance to access the robots, however this is not an issue when alleys, stalls, and crossovers are planned with proper dimensions.

That said, the strengths far outweigh the weaknesses. This simplified and centralized layout can also be mirrored about the same Milk House to add up to 12 more robots.

The following 3D rendering and notations are intended to give the readers a clear understanding of the layout. I hope some of the concepts can be useful to those that may one day build their own robotic dairy.

DESIGN SUMMARY:

- 12 robots, 3/group
- Large, 720 cow capability (4 pens of 180 cows) Guided flow cow traffic to maximize robot capacity
- Centralized milking center
- Centralized, post-milk, long-term Separation Pens
- 6-row freestall bed cross-vent, 3-rows/group
- Extra alley added to maintain complete milk first, guided cow traffic flow



Large Scale Robotics: Is it Worth the Hype?

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Summary

- Homestead Dairy LLC was established in 1979 by 2nd generation owners Floyd and Dan Houin.
- When the next generation started working on the dairy Homestead Dairy began to focus on utilizing technology.
- In order to stay competitive in the dairy industry, Homestead Dairy LLC decided to build a brand-new robotic facility in 2017.
- Currently between businesses, Homestead and Legacy Dairies, we are milking 4800 cows, with 2100 cows in robots and 2700 in 2 conventional parlors.
- The cows and labor love the robots, which has improved herd health and milk production.

Introduction

Homestead Dairy was started by Elmer and Lena Houin in 1945 with 9 cows. In 1979, Floyd and Dan Houin purchased the farm and 110 cows from their parents and officially named the farm Homestead Dairy. Homestead Dairy slowly expanded through the 80's and 90's. In the year 2000, they built a brand-new double 25 parallel parlor milking around 1,000 cows. In 2004, they bought out a cousin's farm that was milking 600 cows in a double 8 herringbone parlor. In 2007, with the next generation involved, they purchased another dairy which had a double 8 parallel parlor. In 2015, with 4 from the next generation involved in the business and milking 3200 cows on 3 different facilities, the decision was made to build a brand-new dairy from scratch. After a lot of discussion, the Houin family decided to take a leap of faith into robots to build currently, the largest robotic dairy in the USA.

Utilizing Technology

After graduating from Purdue University in 2003 with a degree in Meteorology and a minor in Spanish, Brian Houin decided to come back to the family farm to work full time. Brian started managing the calves and being able to speak Spanish quickly became parlor manager. In being parlor manager, part of the routine was to manually record milk weights every month of the roughly 1,100 milking cows. After learning of the Afi-Farm program, which could do this automatically on a daily basis, and provide heat detection, Brian convinced family members to purchase the program. From the demanding math and analytics of the Metrology degree, began a passion for analyzing data. In 2006, he created his own benchmark spreadsheet to compare not only herd metrics against his own farm from year to year, but against industry standards. That has allowed Homestead Dairy to survive through the ups and downs of the industry.

In 2012, Homestead Dairy, which had only been AI breeding for 5 years, decided to start genomic testing all their females. They knew their genetics were below average and the genetic testing

allowed them a way to catch up genetically to their peers. Seven years later, the genetics of the herd has improved substantially, now being above average.

In 2015, Legacy dairy built 2 new automated calf feeding barns, followed by one in 2016 and one in 2017. Utilizing automated calf feeders has increased heifer growth and allowed Homestead Dairy to breed heifers 2 months sooner being the same size as raised in hutches.

Robotic Milking

When planning on the brand-new facility, the Houin family was first going to build an 80-stall rotary like most new construction. Talking things over, they decided to tour some robot farms in the US and Canada to see how they operate. It only took the first robot farm to see the difference in the cow's behavior. In talking about the labor issues, consumer perception, and cow comfort, they decided to go ahead and build a robotic facility. They started the first 6 robots on February 20th 2017. The family and team manually milked the cows for 3 days, before letting them on their own. Every 2 weeks they would start an additional 6 robots. By May of 2017, 24 robots were running. The robots were working well enough that 12 more were purchased, and by January of 2018, 2100 cows were milking on 36 Lely A4 robots. A year later, the farm has seen more milk per cow and better overall herd health in the robot barns compared to the conventionally milked cows. Reproduction is better and a lower cull rate can be found in the robotic dairy compared to the conventional. The way the cows are fed in the robot has allowed the feed costs to be similar between the robot cows and the conventionally fed cows. The maintenance cost per cow per month is lower in the robot barn as well, but that could be because of comparing an 18-year old parlor to a brand new parlor.

The biggest challenge to managing robots is forgetting everything you know about managing a dairy and starting over. With robots everything is done on a daily basis. Breeding, pregnancy checks, synchronization, dry cows, and vaccines are all done on a daily basis. Once everyone understands this, it actually makes it better, since every day is the same. The other challenge is some fresh heifers that do not adapt to the robots may never reach their full potential. How you manage fresh heifers is more critical in a robot barn compared to a conventional dairy.

Overall Homestead Dairy and its owners are extremely pleased with the decision to go to robotic milking and the results that have been shown. Currently having a robotic dairy and a conventional dairy work very well side by side, for cows that do not adapt, but Homestead Dairy will not be building another conventional parlor again.

Unravelling the terminology and use of methods in data driven mastitis detection

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Introduction

The development of sensor systems in dairy farming started in the early 90's, and with the introduction of automatic milking systems, the (still on-going) quest for sensors that automatically detect clinical mastitis was born. Sensors in general generate a large amount of data, but as such do not supply any information on which decisions can or should be taken. With the development of mastitis sensor systems, an increasing number of papers are published applying various data-driven methods to translate sensor data into useful information for mastitis detection. Literature does not only report a wide range of applied methods, but also there is wide variance in the applied gold standard, time window and the selection of sensor data. This makes the studies difficult, if not impossible, to compare. In addition, researchers tend to use different terminology for similar methods, which makes it even more difficult for non-specialised readers to have a clear understanding of the methods used and how they differ from each other.

In order to improve understanding of past and future work on automated, and data driven mastitis detection, a framework is needed to position the different data driven methods. Therefore, the objectives of this paper are to (1) provide a framework to assess and describe the methods used with regard to sensor performance in animal mastitis monitoring, and (2) review published peer-reviewed scientific papers on automated mastitis detection with respect to the methods applied.

Materials & Methods

Papers included in this review are all peer-reviewed and present data driven mastitis detection methods with the purpose to optimize mastitis detection in dairy farming. Papers in this review do not solely focus on mastitis, combine several methods, are based on parameters analysed in laboratories (e.g., somatic cell count), and use data from different types of sensors.

Proposed Framework

In existing literature on mastitis detection, a wide range of methods is applied to transform raw sensor data into information useful for decision taking. This paper proposes a framework which presents the three main method in data driven mastitis detection and their relation to each other (Figure 1). The three main methods are 1) filtering, 2) transformation, and 3) classification.

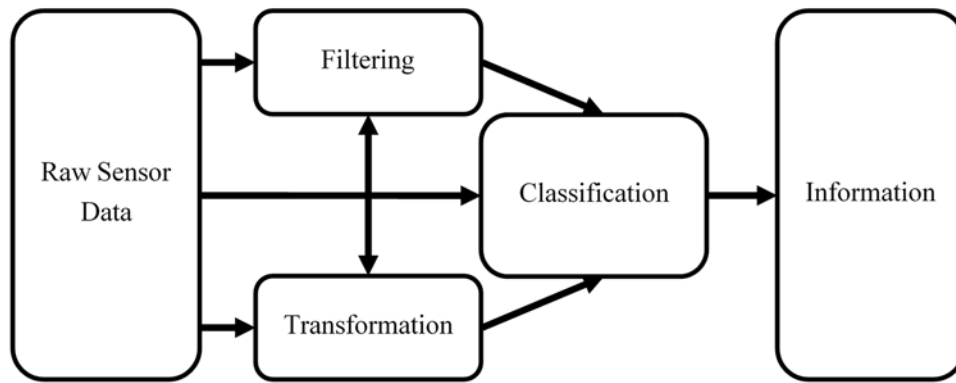


Figure 1. Framework describing the three main methods to convert raw sensor data into information in data driven mastitis detection.

Filtering is a pre-processing method that defines, detects and corrects errors of raw sensor data to minimize the impact on the succeeding subsequent analyses. Filter methods are used to, e.g., filter time series measurements with the purpose to remove the noise and underlying trends from a signal and estimate the true underlying value. Transformation methods are also classified as a pre-processing step that makes input data for classification more amenable. Filtering or transformation methods applied to the data can result in more suitable parameters for classification. Classification methods are always used to convert data into information. These methods apply algorithms that produce an alert when the measured sensor data (that are considered a proxy for cow health status) deviates from the expected measurements (being a proxy for a normal (healthy) status). The data used as input for a classification method can be either raw (non)sensor data, data from filtering or transformation methods, or a combination of these data.

Results and Discussion

About 39 papers have been published since 1992 that apply data driven methods to detect clinical mastitis from sensor data. Papers tend to use different terminologies for similar methods, which may be explained by the different domain expertise of the researchers (e.g., an animal scientist vs. a data scientist). From the papers, 11 used a classification method without applying filtering or transformation on the data. In 16 papers, pre-processing data took place with filtering methods, and in five papers transformation methods were applied. The remaining papers combined filtering and transformation before classification was applied. A variation of filtering methods have been used including moving averages, Kalman filters, linear regression updates, auto-regressive models, wavelet filters, and attribute weighting. Transformation methods mainly composed of standardization, normalization and mathematical transformations (i.e. Inter-quarter ratio). Simple thresholds were the first classification methods applied and today's popular classifications are Artificial Neural Networks, regression modelling, and decision trees.

With this paper we support the understanding of scientific literature on data driven methods applied in mastitis detection. The paper provides a clear overview of the methods used and allows to place the method, while reading the literature, in the proposed framework, even when different terminologies are used. It supports the same language and/or creates a clearer understanding between people with different background expertise.

An automated in-line clinical mastitis detection system using measurement of conductivity from foremilk of individual udder quarters

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Abstract

INTRODUCTION: Proper pre-milking procedures typically involve the fore-stripping of teats and observation of the milk ejected from each quarter. This step is to assist in the identification of abnormal milk. It is a laborious task and the results are subjective. If this process could be automated it would contribute to labour savings and animal health monitoring.

AIM: To assess a novel method for automatic in-line detection of clinical mastitis.

METHODS: For a brief period at the start of milking for each cow, electrical conductivity of foremilk was measured for each quarter in turn, using a single sensor installed in the long milk tube (LMT) about 1.5 m downstream from the milking-machine claw. Sequential separation of flow between udder quarters was achieved by control of pulsation to individual teatcups within a conventional cluster. The ratio of conductivity values between quarters was used as an indicator of mastitis status. The concept was evaluated initially in a pilot trial in a 200-cow herd milked in a 23-stall swing-over herringbone milking parlour. It was then tested rigorously in a field trial in a 640-cow herd milked in a 50-stall rotary milking parlour. Both trials were conducted in the Waikato region of New Zealand. In the latter trial, sensor results were compared with visual inspection of a commercial in-line mastitis filter fitted to each milking unit. These filters were inspected for clots immediately after every cow's milking, for 3 weeks. The dataset of approximately 27,000 individual milkings was tested against several published or potential alternative 'gold standards' for diagnosing clinical mastitis. As a gold standard, inline clot detection filters were used on every cow at every milking and then examined. Over 26,974 individual milkings were evaluated. A single observation of clots was defined as a 'gold alert'. Then a positive signal from the sensor for the system alerts. Using various forms of windowing the sensor alerts...e.g., one alert in three milkings, or so on...we calculated sensitivity (% of false negatives or # detected/# of gold standard positives) and false positives (# of detected positives that were not actual positives/total number of observations and expressed that as false positives per 1000 cow milkings). Then, we went one step further and questioned what frequency of clots in milk actually count as a valid gold standard positive. In other words, does just one milking with clots in it define the cow as clinical? Probably not. So, we used various combinations of observations, herd manager observations and SCC levels to get the various levels in Table 1 and the equations are on page 211 of the paper.

RESULTS: In the pilot trial, 12–14 clinical events were detected out of 19 true clinical quarters, with a false-alert rate of between three and five false electrical- conductivity alerts per 1,000 individual milkings. In the more rigorous field trial, sensitivity ranged from 68 to 88%, and the false-alert rate (false-alert epi- sodes per 1,000 individual milkings) ranged from 2.3 to 7.0.

CONCLUSION: The novel clinical mastitis detection system, based on separation of the flow and measurement of electrical conductivity from foremilk of individual udder quarters, has the potential to provide a new tool for helping farmers to monitor clinical mastitis in herds milked with conventional clusters.

KEY WORDS: *Mastitis, conductivity, clinical, detection, quarter*

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Evaluating the effects of mean stocking density on automatic milking system use and total milk production in Holstein cows

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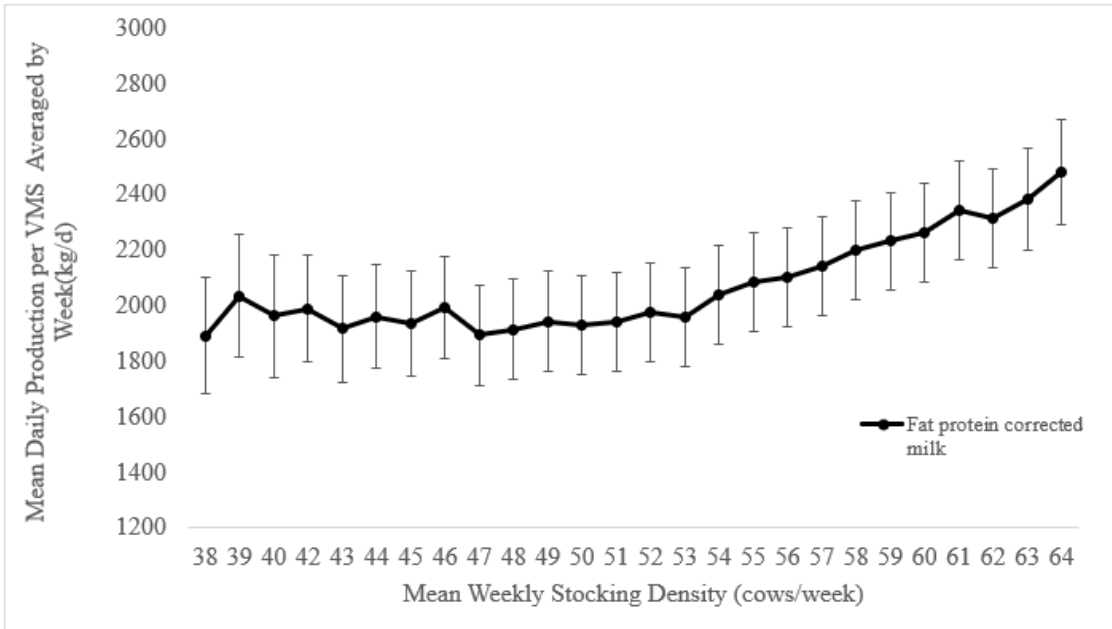
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Automatic milking systems (AMS) have become increasingly common since their first introduction. However, the number of cows that can be milked by a single AMS per day is based on company guidelines rather than empirically-derived recommendations. This suggests a need to determine the relationship between the number of cows milked daily by a single AMS and milk production per robot. The objective of this study was to evaluate the effects of stocking density, defined as number of cows milked by a single AMS within a day, on mean milking interval and mean weekly milk production variables.

A retrospective analysis of two AMS (Voluntary Milking System™, DeLaval, Tumba, Sweden) was performed on data collected between January 11, 2004 to May 23, 2006 and October 4, 2012 to September 16, 2018 at the Danish Cattle Research Center (Foulum, Denmark). Milking interval, total milk production and fat plus protein corrected milk (FPCM) were summarized by day and averaged across each week to determine weekly means. Variables were assessed by linear mixed models using the MIXED procedure of SAS 9.4 (Cary, NC, USA). Fixed effects of parity and week in milk were included in all models. In addition, we tested the polynomial effects of stocking density at a quartic relationship. Random effects were defined as AMS, week, and week nested within year. Fixed effects remained in the model regardless of significance. Mean stocking density was 56.3 ± 4.3 and 55.9 ± 4.6 cows (range: 38 to 64) for each AMS, respectively. When stocking density was 52 cows, mean milking interval per cow was 11.2 ± 0.1 h ($t = 199.4$; $P \leq 0.04$; range: 9.4 ± 0.3 to 11.2 ± 0.1 h). Mean total milk production per AMS increased until stocking density reached 60 cows per AMS. However, when stocking density reached 60 to 64 cows, milk production per AMS did not increase further ($t \leq -1.87$; $P \geq 0.06$). Mean FPCM per AMS were greatest when 60 to 64 cows were milked by a single AMS compared to < 60 cows ($t \geq 11.9$; $P < 0.001$, Figure 1). This suggests that total milk production and FPCM per AMS plateau around 60 to 64 cows. However, stocking density of 61 to 63 cows were not significantly different ($t \leq -1.79$; $P \geq 0.07$). Mean total milk production and FPCM per AMS was greatest when stocking density was 60 to 64 cows. Using milking interval and milk production variables as a way to compare effects of stocking density per AMS, indicates different values for each measurement. Mean milking interval may not be indicative of milk yield, suggesting milking interval may not be the best measurement to compare stocking densities. Stocking density was a significant factor effecting milking interval and milk

production variables. Therefore, results suggest that stocking density of 60 to 64 within a AMS is critical for maximizing milk production per AMS.

Figure 1: Relationship between mean weekly fat plus protein corrected milk per automatic milking system averaged by week versus mean weekly occupation rate, representative of mean total milk production and mean energy corrected milk variables.



THE AUSTRALIAN AMS JOURNEY

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Automatic Milking Systems (AMS) arrived in Australia in 2001 (Greenall et al., 2004), followed by 13 years of successful AMS R&D through the FutureDairy Project (Garcia et al., 2007). By February 2019, 54 dairy farmers from across all major dairy regions have decided to invest in the technology. This represents around 12,000 milking cows, milked by 186 robotic units, producing around 70 million litres/year. However, considering there are in Australia around 5,600 farms milking 1.56 million cows, adoption remains lower than expected. This is despite the growing interest in AMS both in Australia and Overseas, and a large number of success stories demonstrating benefits relating to labour, lifestyle, productivity and cow welfare. Furthermore, since 2001 there have been eight farms in Australia (~15% of installations) that have decommissioned their AMS installations or ceased milking. This rate of decommissioning is higher than experienced in more mature markets, but not surprising in early adoption phases.

In 2017 FutureDairy commissioned Nikon Rural Services to conduct in-depth interviews with farmers and service providers to understand more about the Australian AMS experience. The main findings related to: the complexity of AMS; the importance of communicating realistic expectations of what AMS can deliver; the need to manage risks pre- and post-commissioning; and the influence that operator temperament has on the preparedness and capacity of a person to adopt AMS rapidly and effectively. In response to these findings, in 2018 the Australian dairy industry established Milking Edge, a three year project run by the NSW Department of Primary Industries together with Dairy Australia and DeLaval. The overall objective is to ‘Support industry to consider, invest and operate AMS successfully’.

One of the aims of the project is to increase engagement with current AMS farmers. In December 2018 a Milking Edge information pack was sent to all 45 farmers that are either currently operating, or committed to AMS in Australia. The pack included a survey to capture figures related to the farm as well as gaining a greater understanding of the farmers’ expectations, business issues and priorities. So far we have received 21 farmer responses (47%), eight of which are from farmers who have not previously engaged with industry.

The top three farm management areas identified by operators as ‘Confident/On target’ were a) rearing and training animals (68%), b) feeding supplements (74%) and c) farm business management (79%). The confidence on feed management is not surprising given this is the main driver to encourage voluntary and distributed cow traffic in AMS. It is surprising that almost 70% of farmers indicated confidence in rearing and training animals, when previous reports have highlighted the underperformance of heifers as an issue on AMS farms. The 80% confidence in farm business management was also unexpected due to the relatively small proportion (25%) of AMS farmers who actively engage with industry financial benchmarking

programs. Only 50% of the farmers that felt confident in farm business management and 25% of those that did not indicated a desire to engage in financial benchmarking.

Areas that AMS farmers 'Would like to improve' were a) milk quality and animal health (37%), b) assessing robot and system performance (42%) and c) labour & routines (including maintenance) (47%). AMS farmers rely on sensors, reports and alerts to manage milk quality and animal health. Results from the AMS KPI Project run by NSW DPI indicate that AMS farms achieved a respectable average Bulk Milk Cell Count of 181,000 cells/ml. Recent research studies conducted by Khatun et al (2018) highlighted the potential to analyse robot generated data for multiple variables in order to improve mastitis detection. The study by Lyons and Kerrisk (2017) highlighted that Australian AMS farmers had the opportunity to increase system performance by a maximum of ~60%. All of the initial nine farmers that joined the AMS KPI Project highlighted the benefit of participating and that having access to those reports on a monthly basis allowed them greater control of their business and promoted better decision making. Lastly, despite case studies conducted by Future Dairy indicating AMS farmers had around 50% improvement in labour efficiency (cows/FTE) and improved start and finishing times, the preliminary results of a three-year study on financial data from AMS farms indicates that many AMS farmers either do not achieve those levels of labour efficiency, or that they adopt AMS for reasons other than labour efficiency.

The challenges within the Australian dairy industry in relation to cost and availability of skilled labour and the need to improve management and efficiency on-farm could drive increase adoption of AMS. A recent survey indicated that 60% of farmers and 80% of service providers believed there would be an increased adoption of AMS by 2025 (Gargiulo et al., 2018). Initiatives like Milking Edge are key as they provide support and assistance to farmers and service providers and encourage greater decision making around the consideration, purchase and implementation of AMS, minimising risk and maximising the likelihood of successful adoption and swift transition.

Garcia, S C; Fulkerson, W J; Nettle, R; Kenny, S and Armstrong, D, 2007, FutureDairy: a national, multidisciplinary project to assist dairy farmers to manage future challenges - methods and early findings. *Australian Journal of Experimental Agriculture*, 47, 1025-1031.

Gargiulo, J I; Eastwood, C R; Garcia, S C and Lyons, N A, 2018, Dairy farmers with larger herd sizes adopt more precision dairy technologies, *Journal of Dairy Science*, 101, 5466-5473.

Greenall, R. K., Warren, E. and Warren, M. 2004. Integrating automatic milking installations (AMIs) into grazing systems - lessons from Australia. In: *Automatic milking: a better understanding*, Lelystad, Netherlands, 273-279.

Khatun, M; Thomson, P C; Kerrisk, K L; Lyons, N A; Clark, C E F; Molfino, J and Garcia, S C, 2018, Development of a new clinical mastitis detection method for automatic milking systems, *Journal of Dairy Science*, 101, 9385-9395.

Lyons, N A and Kerrisk K L, 2017, Current and potential system performance on commercial automatic milking farms, *Animal Production Science*, 57, 1550-1556.

INCOMPLETE MILKINGS IN AUTOMATIC MILKING SYSTEMS

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Introduction

Automatic milking systems (AMS) rely on voluntary and distributed attendance of cows to the dairy facility throughout lactation. This generates variation in milking intervals (MI), defined as the period of time that elapses between two consecutive milking events, measured in hours. Farmers operating AMS need to manage variation in MI within and between cows.

In AMS a robotic arm locates and attaches a cup onto each individual teat. Success of this task depends on several cow and equipment factors, including localisation and insertion of the teats, which is related to the amount of milk in the udder. Unsuccessful attachment of the cups to one or more teats, and premature cup removal, are some of the causes of incomplete milkings (Lyons et al., 2014).

The aim of this work was to cluster cows according to the risk of having incomplete milkings and to characterize the groups regarding MI, peak yield (Lpeak) and days to peak yield (Dpeak).

Materials and methods

A database containing 773,483 records of automatic milking events for one year (July 2016 – June 2017) from four AMS herds was used (two from Australia, one from New Zealand and one from Chile). Each record contained identification number for herd, cow and lactation, as well as values of days in milk, MI and milk yield (MY, the total amount of milk harvested in one milking event, in liters/milking). Daily milk yield was calculated as the sum of MY within a day. Two ancillary variables were calculated: the phase of lactation (PL) (ascending, peak or descending) in which the studied milking event occurred and the cumulative number of milking events until the studied event (CM). An incomplete gamma function (Wood, 1967), was fitted for each lactation category (first, second and third or more lactation). This allowed us to extract lactation curve parameters and calculate Dpeak and Lpeak. The interval $Dpeak \pm 15$ days was called “Peak phase”. The “Ascending phase” was associated to the days from calving to start of peak phase. The “Descending phase” started after the peak phase and finished with dry off.

A mixed Cox model was fitted using package Coxme in RStudio (<http://www.r-project.org>) to estimate the risk of incomplete milking events as function of MI, PL, and CM by lactation category. The herd and lactation within herd effects were incorporated to the model as random to account for correlation among data from same lactation and herd. The best lineal unbiased predictor (BLUP) of lactation effects were used to rank lactations within herd. Furthermore, cows were divided in low, medium and high incomplete milking risk

categories, according to each of three equal groups into which a population can be partitioned applying the BLUP distribution. Finally, ANOVA was used to compare incomplete milking risk categories regarding average values of MI, Lpeak, and Dpeak.

Results

Interaction between PL and CM was significant. This implies that the rate of incomplete milking event varies according to CM and PL. For first lactations cows, the rate of incomplete milking differs between the peak and ascending phase. During the peak phase, with the course of the milkings, the rate of incomplete milking decreases, reversing this relationship in the ascending phase. For second lactation cows, at the peak phase the rate of occurrence of incomplete milking increases with CM in comparison with the descending phase. Finally, for cows with three or more lactations, the rate of occurrence of incomplete milking in the ascending phase decreases compared to the descending phase.

Regardless of the lactation category, the largest MI was observed in lactations with low risk of incomplete milkings. Cows with two or more lactations and high risk of incomplete milking had lower Dpeak than cows of low and mid risk of incomplete milkings. There was no difference in Dpeak according to risk of incomplete milkings for first lactation cows (Table 1). Risk of incomplete milking had no effect on Lpeak for any lactation category, except medium risk of incomplete milking for second lactation cows.

Table 1. Milk yield at peak (Lpeak), days to peak (Dpeak), and milking interval (MI) regard the likelihood of incomplete milking event according to lactation number.

| Risk of IM | 1 lactation | | | 2 lactation | | | 3 or more lactation | | |
|---------------|------------------------------|----------------------------|-------------------------|--------------------|-----------------|------------------|---------------------|-----------------|-----------------|
| | Lpeak (L/d ¹) | Dpeak (d ²) | MI (h ³) | Lpeak (L/d) | Dpeak (d) | MI (h) | Lpeak (L/d) | Dpeak (d) | MI (h) |
| LOW | 18.38 ^{a*} | 43 ^a | 18 ^a | 28.50 ^a | 52 ^b | 17 ^c | 35.81 ^a | 46 ^b | 16 ^c |
| MEDIUM | 18.64 ^a | 48 ^a | 13 ^b | 31.00 ^b | 52 ^b | 12 ^b | 34.69 ^a | 45 ^b | 12 ^b |
| HIGH | 19.43 ^a | 56 ^a | 11 ^c | 27.87 ^a | 44 ^a | 9.5 ^a | 34.22 ^a | 42 ^a | 9 ^a |

*^{a-c} Values within a column with different superscripts differ significantly ($P < 0.05$).

¹ Liters per day; ² days; ³ hours

Conclusion

There were differences in lactation curves among different risk groups for cows with two or more lactations.

Understanding the behaviour of type of milking will allow the development of management strategies to minimize the proportion of incomplete milkings and maximise the overall system performance.

References

Løvendahl and Chagunda, 2011. *Covariance among milking frequency, milk yield, and milk composition from automatically milked cows*. J. Dairy Sci. 94:5381–5392.

Lyons, N.A., Kerrisk, K.L. and Garcia, S.C., 2014. *Milking frequency management in pasture-based automatic milking systems: A review*. Livest. Sci. 159, 102-116.

Wood, P.D.P.: *Algebraic model of the lactation curve in cattle*. Nature 216, 164-165. (1967).

A dairy farm simulation model as a tool to identify priorities in technical and economical strategies to improve farm competitiveness

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Introduction

Dairy farmers and technicians have to make strategic decisions to ensure dairy farms economic sustainability. These decisions are difficult to assess because: 1) they depend on local conditions (prices, labor, investments, technical performance,...); and 2) the impact of the changes may require time to be observed. The integration of mathematical simulation models with current management software and other data acquisition tools may facilitate the decision making process. The objective of this study was to use a dairy farm simulation model to identify technical and economic priorities to improve farm competitiveness.

Material and Methods

A stochastic dairy farm simulation model was used (www.dairyfarm.es). This model integrates animal biology, diseases, nutrient supply, environmental effects farm management factors and accounts for income and costs. The simulation output is the result of the interaction of all these factors repeated daily for each animal during the simulation period (Calsamiglia et al., 2018). For this study, technical and economic data from 30 commercial dairy farms throughout Spain was collected. These farms were classified by farm location in Center, North-East, North-West and South Spain, and by farm size (< 120 cows, 120-320 cows and > 320 cows). The specific technical, economic and management data of each farm (milk yield and composition, reproductive indexes, environmental conditions, prices, labor costs, utilities...) were used to generate these farms in the simulator. A control simulation, under the current specific circumstances of each farm, was executed prior to the simulations of the technical and economic strategies proposed for the study. These strategies were: 1) Improvement in labor efficiency (ILE), considering adequate a ratio of 55 cows/worker. In the farms where the ratio was below the objective, ILE was simulated by reducing labor force, with the average salary within the farm; 2) Heat stress reduction (HSR) was simulated in farms with no cow cooling systems, considering an investment of 75 €/cow and an increase of 7 €/cow in electricity and water costs per each month of use. The degree of heat stress was estimated using the temperature-humidity index (THI) provided by the closest weather station to each farm; 3) Time-fixed artificial insemination (TFAI) simulation was performed in the farms which no current systematic use of hormones, and was planned at 77 days in milk (DIM) only for the first artificial insemination, considering a 50% fertility for primiparous cows and a 45% for multiparous, and a cost of 13 €/ treatment; 4) Short dry period (SDP) was set at 50 d in primiparous and 40 d in multiparous cows for the simulations, considering a 2% increase in milking costs as a result of the extension in DIM. All the simulations were run for a five year period. Therefore, the results reported correspond to the difference in the annual mean values of the simulated period for each strategy compared with the control within each farm.

Results and Discussion

Results of simulations (Table 1) indicate that ILE (141.2 €/cow/yr) was the most profitable opportunity, followed by the SDP, the TFAI and the HSR with 50.91, 39.91 and 11.83 €/cow/yr, respectively. However, this priority order was different in each region. Differences between regions were observed in the ILE. In the north-east, where salaries are highest, the optimization of labor improved profitability by 169.00 €/cow/yr; whereas in the north-west, where salaries are lowest, the benefit was also smallest (100.70 €/cow/yr). The use of heat stress abatement systems increased milk production, fat and protein content, and intake; and reduced open days and culling rate. Despite the initial investment, the HSR was profitable in the Southern region (75 €/cow/yr), but not in others. Farm size had small effects on the priorities except for the ILE. Farms with <120 cows, where there is more family labor, were less efficient and would benefit most from its optimization (165.50 €/cow/yr). Larger farms (>320 cows), where labor is mostly hired and more efficient, the benefit was lower (60.50 €/cow/yr). However, priorities vary not only among geographical areas and farm sizes, but also among individual farms due to their unique circumstances. Furthermore, these priorities are highly dependent on changes in prices of inputs and outputs, which requires simulations to identify priorities and take decisions ad hoc within each farm and the economic conditions.

Table 1. Net margin improvement (€/cow/yr) of different strategies by geographical area and by farm size.

| Item | ILE | HSR | TFAI | SDP |
|-------------------------------|-------|-------|-------|-------|
| Total farms average | 141.2 | 11.83 | 39.91 | 50.91 |
| Average by Geographical area: | | | | |
| Center | 137.2 | 5.67 | 51.60 | 45.56 |
| North-East | 169.0 | 0.25 | 44.43 | 56.89 |
| North-West | 100.7 | 1.50 | 25.20 | 51.57 |
| South | 151.3 | 75.00 | 36.60 | 49.43 |
| Average by farm size: | | | | |
| <120 | 165.5 | 12.50 | 29.29 | 52.09 |
| 120 - 320 | 124.4 | 9.80 | 38.50 | 46.20 |
| >320 | 60.50 | 15.25 | 57.60 | 60.50 |

Conclusions

Modeling dairy farms under different scenarios may point out priorities in the management strategies with better profitability. The integration of mathematical simulation models with current management software and other data acquisition tools may facilitate the decision making process.

References

1. Calsamiglia, S., S. Astiz, J. Baucells and L. Castillejos. 2018. A stochastic dynamic model of a dairy farm to evaluate technical and economic performance under different scenarios. *J. Dairy Sci.* 101:7517-7530.

Automated Calf Feeding in an Organic Production System

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Introduction

Whether conventional or organic, raising replacement dairy heifers is an expensive investment for a dairy operation (Heinrichs et. al., 2013). The nutrition, health, and management of replacement heifer calves may have a major impact on the profitability of the entire dairy operation. Organic producers, especially, may be faced with challenges such as higher feed costs and maintaining animal health. As the use of group housing for pre-weaned dairy calves has increased (USDA-NAHMS, 2016), automatic calf feeders have gained popularity. There are many advantages to utilizing automatic calf feeders in a group housing system such as accessibility to different feed programs, reduced labor, consistent hygiene, individual calf monitoring (Kack et. al., 2010), and socialization benefits for the calf (Chua et. al., 2002).

The WCROC's Automated Calf Feeding System

At the University of Minnesota's West Central Research and Outreach Center (WCROC) in Morris, MN, researchers have utilized and tested an automatic feeding system since 2017. The dairy herd at the WCROC is comprised of 300 milking cows, and the herd raises about 125 heifer calves each year. Heifer calves born at the WCROC are raised organically and housed in groups. At the WCROC, 40 calves are fed with a Holm & Laue (HL) HL100 Programmable Calf Feeder (Holm & Laue GmbH & Co KG, Westerronfeld, Germany). The HygieneStations are equipped with a forefoot weigh scale.

At the WCROC, organic whole milk was pasteurized and transported to the calf facility using a Holm & Laue Milk Taxi 260L where it was stored in a Milk Jug cooling tank (Calf-Star LLC, New Franken, WI). At 5 days of age, calves were fitted with an RFID tag for the autofeeder to identify each calf. Calves were then moved into a pen for 20 calves and were acclimated to the autofeeder.



Figure 1. The HL Milk Taxi which pasteurizes and transports the milk (left), the Milk Jug cooling tank where milk is stored (middle), and the Holm & Laue HL100 Programmable Automatic Calf Feeder (right).

Calves had an 8 L daily allotment of milk in 2 L increments. From 5 to 11 days of age, calves were “ramped-up” from 6 L to 8 L of milk per day. From 12 to 49 days, calves were fed on a “hold” program of 8 L of milk per day. From 50 days to weaning at 56 days, calves were on a “ramp down” program, which gradually reduced the milk allotment by 0.2 L per day to prepare them for weaning and encourage calf starter consumption.

The HL feeder at the WCROC allowed for consistent hygiene of the feeding system. After each calf visited the HygieneStation and consumed their allotment, the mixing bowl was rinsed and drained, the tubing to the nipple was rinsed, and the nipple was rinsed with a combination of water and hydrogen peroxide. Furthermore, the feeder was programmed to conduct a whole system wash cycle automatically three times per day.

The CalfGuide system at the WCROC has the ability to observe and download individual calf data. The data include drinking speed, visits to the HygieneStation, consumption of milk or milk replacer, and calf body weight. The HL feeder monitors individual calves and issues alarms on calves that have not been drinking milk allotments. This is of extreme importance for monitoring calf health and determining which calves require further observation and care.

Conclusions

Group-housed automatic calf feeding systems, whether in conventional or organic systems, allow for consistent and effective hygiene procedures, individualized calf monitoring, and social benefits for calves. Furthermore, labor may be reduced or reallocated to other areas of calf management to ensure the success of the calf program.

References

- Chua, B., E. Coenen, J. van Delen, D. M. Weary. 2002. Effects of pair versus individual housing on the behavior and performance of dairy calves. *J. Dairy Sci.* 85:360-364.
- Heinrichs, A. J., C. M. Jones, S. M. Gray, P. A. Heinrichs, S. A. Cornelisse, and T. C. Goodling. 2013. Identifying efficient dairy heifer producers using production costs and data envelopment analysis. *J. Dairy Sci.* 96:7355-7362.
- Kack, M., J. Ziemerink, Forster-Technik, Grober Nutrition. 2010. Benefits, Function and Operation of Computer-Controlled Calf Feeders. The First North American Conference on Precision Dairy Management, 2010. <http://precisiondairy.com/proceedings/s4kack.pdf>.
- USDA-NAHMS. 2016. Dairy cattle management practices in the United States, 2014. https://www.apis.usda.gov/animal_health/nahms/dairy/downloads/dairy14/Dairy14_dr_PartI.pdf.

Relations between milk yield and cow time budget

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Introduction

Precision Dairy Farming offers many opportunities for the dairy farmer to gain detailed insight and high production outputs based on new information technologies. One of these new technologies is the real-time location system (RTLS) which can provide a cow time budget based on classification of cow positioning within specific activity zones. Previous studies have shown changes in cow behaviors quantified with RTLS in relation to estrous, disease occurrence and feeding management changes (Peña Fernández et al., 2017; Veissier et al., 2017; Sloth et al., 2017). In the present study, the purpose was to do a first exploration of the relationship between milk yield and cow time budget to identify levels of cow behaviors with the highest milk production in one dairy herd.

Materials and methods

The dataset originated from a commercial automatic milking herd with 220 Holstein Friesian cows and included animal characteristics (parity, stage of lactation and stage of gestation), daily milk production and cow behaviors logged throughout the year 2016. The lactating dairy cows were housed in one large group in a free stall environment with slatted floors, deep straw cubicles, post-and-rail system along the feed bunk and free cow traffic with pre-selection for accessing the milking waiting area in front of the automatic milking system (AMS). The feed ration fed to the lactating dairy cows included a partial mixed ration (PMR) mixed and fed once daily and individually adjusted concentrate supplied in the AMS and concentrate boxes. Cows exhibiting more than 50 % overdue in milk allowance were collected and led to the AMS twice daily. Daily milk yields (kg) were provided by the AMS (one 5-box MiOne, GEA) while the cow behavior (time in walkways, distance traveled in walkways, time at feeding table and in cubicles) were provided by the GEA CowView system. Initial censoring out of outliers was performed at animal level deleting milk yield and cow behavior values outside a rolling 99 % confidence interval based on measurements latest minimum five and maximum ten historical days. Prior to modelling we calculated averages of the daily milk yield and cow behaviors on an animal-lactation-week basis starting at respective calving dates. The general null hypothesis on existence of a highest milk producing level of behavior in a herd was examined with a multivariable mixed model for average daily milk yield (MIXED procedure, SAS). The following fixed main effects were included and modelled as class variables: Parity, lactation month, gestation month, time spent in walkways, at feeding table, and in cubicles and distance traveled in the walkways. Tests for collinearity showed no indication for not applying this combination of fixed effects. Cow was fitted as random effect. Full model least-square mean values (LSMEANS, SAS) with 95%-confidence intervals were generated as estimates for fixed effects.

Results and discussion

Except for time spent in the cubicles (p -value= 0.074) all fixed effects were found significant (p -value ≤ 0.0031). According to estimated milk yields (see Figure 1a-1d), the highest yielding dairy cows in this herd proved indeed to be active spending on average 5.5-6.5 hours in the walkways traveling 225 or more meters per day, using only 10-11 hours of her time per day in the cubicles but 4.5-5.5 hours at the feeding table. Application of non-linear modeling instead would possibly have resulted in more accurate estimates.

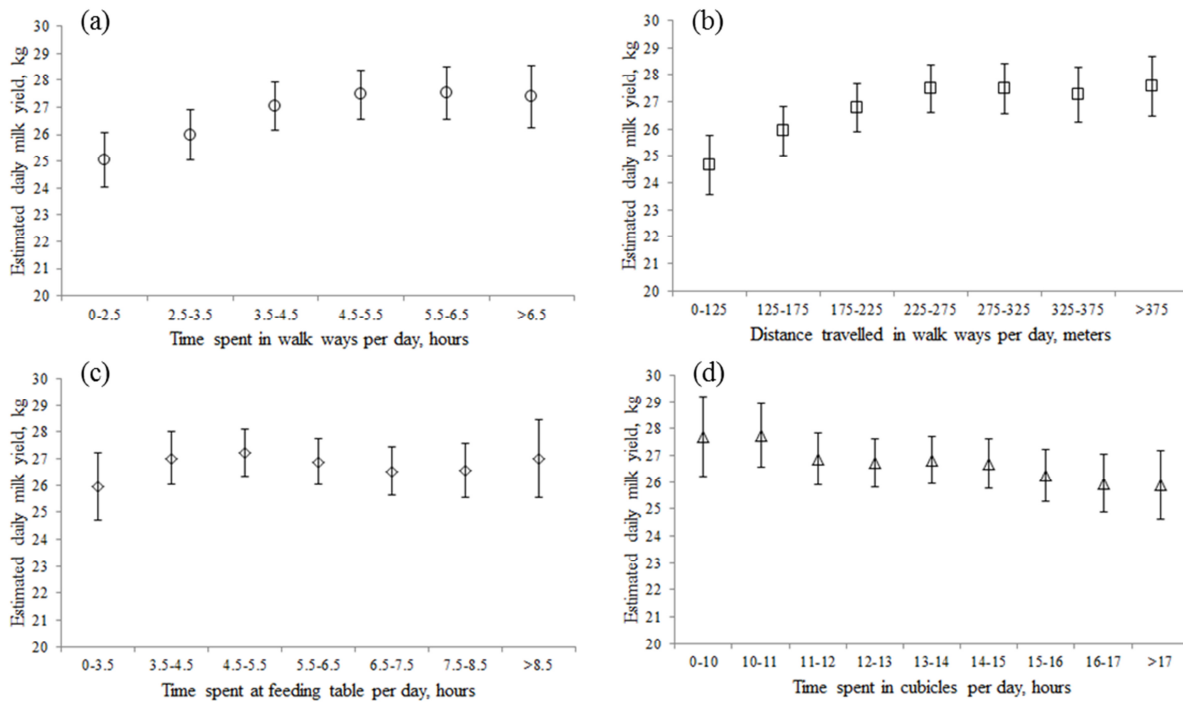


Figure 1a-1d. Least-square mean estimates of daily milk yield (kg) with 95% confidence intervals (error bars) for cow time budgets including: (a) time in walkways, (b) distance travelled, (c) time at feeding table and (d) time in cubicle, in one AMS herd.

References

- Peña Fernández, A., T. Norton, K. H. Sloth, S. Klimpel, D. Berckmans. 2017. Early detection of ketosis monitoring cow's behavioural activities and milk yield. Proc. 8th European Conference Precision Livestock Farming (EC-PLF), 12-14 Sept. 2017, Nantes, France. P. 200-210.
- Sloth, K. H., C. Coletti, A. Peña Fernández, D. Bossen, E. Tullo, I. Fontana, M. Guarino. 2017. Effect of feeding out frequency of mixed feed on feeding behaviour, feed intake, and milk production in an automatic milking herd. Proc. of the 8th European Conference Precision Livestock Farming (EC-PLF), 12-14 Sept. 2017, Nantes, France. P. 386-395.
- Veissier, I., M.-M. Mialon, K. H. Sloth. 2017. Short communication: Early modification of the circadian organization of cow activity in relation to disease or estrus. J. Dairy Sci. 100: 3969-3974.

DEVELOPING AN ONLINE AMS COMMUNITY

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One of the most significant technologies with the potential to create lasting beneficial change to dairy farming systems, and the wider industry is Automatic Milking Systems (AMS). The systems were introduced commercially in the early 1990's, and have since been adopted by farmers all around the world with adoption expected to continue to accelerate (Barkema et al., 2015).

Across the globe, farmers, researchers, industry experts and advisors investigate, develop and deliver relevant, timely and accurate information and resources related to AMS. However, geographical distance makes it difficult to collaborate, share information and learn from each other.

Most information is now sourced and transmitted online and there is potential for more innovative ways to connect, collaborate, share and source information that will promote and encourage positive change to on-farm practices.

A Community of Practice (CoP) is a group of people (such as farmers, advisors, service providers and researchers) with expertise in a particular field and a web based platform for collaborating and sharing information. Experts are drawn from a wide variety of backgrounds and organisations and are willing to collaborate and share information. A Community of Interest (CoI) is a group of people with a genuine interest in a particular field. The CoP aims to meet the information needs of the CoI.

Inspired by the US eXtension.org model, the ExtensionAUS platform was initiated in Australia in 2014 with CoP's for Crop Nutrition and Field Crop Diseases. By October 2018, the ExtensionAus platform had expanded to include a total of seven CoP's. With a growing international interest in AMS, and domain experts spread throughout the world, it was now the turn for an AMS Community of Practice!

The online AMS community was established as part of Milking Edge, an Australian dairy industry collaborative project run by NSW Department of Primary Industries in collaboration with Dairy Australia and DeLaval. The aim of the project is to 'support industry to consider, invest and operate AMS successfully'.

The objective of this AMS community is to bring together passionate and knowledgeable industry experts (including farmers, advisors, service providers and researchers) from all around the world to collaborate, share knowledge, research and solutions on all aspects related to AMS. The expertise and knowledge in AMS held by each expert is absolutely crucial to the success of this initiative.

In October 2018 Milking Edge put out a call for expressions of interest to join the AMS Community of Practice. In four months, 53 responses were received from people interested in being involved, with 43 were assessed to have the right set of technical skills and industry experience to join the AMS CoP. To date, 26 experts from Australia, New Zealand, US, Canada, Argentina, Uruguay, Ireland, UK, The Netherlands and Belgium have signed on as official AMS experts. Out of those 14 are working in the research and extension space, seven are service providers or consultants and five are AMS farmers.

AMS experts will develop and distribute relevant, high quality, web-based resources on topics requested by those interested in AMS (the Community of Interest) and/or recommended by AMS experts themselves. Some examples include technical articles, farmer case studies, videos, podcasts, webinars, newsletters and linkage to other articles or resources.

The AMS experts have already started collaborating on topics related to international AMS adoption rate, managing pasture, AMS for younger generations, commissioning robots and training animals. Future suggested topics include feeding cow in AMS, monitoring and managing milk quality, economics and financial behind AMS and layouts and design.

The online AMS Community of Practice was launched in January 2019 and can be found at <https://extensionaus.com.au/automaticmilkingystems/>. Everyone is invited to jump online and explore the resources, calendar of events, e-meet the AMS experts and ask them many questions.

Barkema, H W; von Keyserlingk, M A G; Kastelic, J P; Lam, T J G M; Luby, C; Roy, J-P; LeBlanc, S J; Keefe, G P; Kelton, D F, 2015, Invited review: Changes in the dairy industry affecting dairy cattle health and welfare, *Journal of Dairy Science*, 98, 7426-7445.

Development of Agri-Innovation Hub Ireland

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Introduction

Precision technologies in farming promise increased efficiency, improved product quality, reduced environmental impact, and overall improvements in animal health and welfare. World-wide there is huge interest in the application of precision technologies and ICT to agriculture. However, much of the work is fragmented, is not solution-driven and is focused on milk production and animal performance in indoor housing systems. Thus, Teagasc has embarked on a Precision Technology Programme that is focused on technologies that are of value to dairy farmers, suitable for pasture based systems and can add value to the end users. This programme is based on the concept of (i) development and testing of sensors for real-time data recording; (ii) communication and integration of the data from different sensors, analysis and interrogation of this data; (iii) conversion of this data to knowledge; and (iv) interpretation and use of this knowledge as inputs to decision support tools (DST) that can be used to make management decisions on-farm. The ultimate goal is to ensure that appropriate sensors are developed that collect useful, appropriate and accurate data and data that will make farm management easier, more accurate and more profitable, through converting this data to information and decisions and providing the outputs in a usable format in a time appropriate timeframe. In order to achieve this, the agri-tech sector needs multi-agency support at one location, including key specialisms in disciplines including dairy and pasture-technology, artificial intelligence, IoT (Internet of Things), robotics, big data and analytics.

The Agri-Innovation Hub Ireland Project

This project is associated with and located at the Moorepark Teagasc Animal and Grassland Research & Innovation Centre. The vision of Agri-Innovation Hub Ireland is to act as a single-entry point to promote and convert smart agri-tech enterprise opportunities and encompass (a) a knowledge centre of academics and industrialists who will be embedded in the centre to facilitate the proof of concept and commercialisation of research; (b) incubation facilities; (c) fast-track access to build capacity and scalability of start-ups and growing businesses through access to funding expertise, export accelerators and collaboration supports/brokerage; (d) Provision of experimentation and validation in pre-pilot scale, real-life agri-environments using the Teagasc test-bed infrastructures including access to elite genetics dairy cow herd, the automatic milking system and land available to trial IoT networks and concepts.

The key target market (users) for the Agri-Innovation Hub Ireland include national and international clients in the category of (a) start-up businesses by researchers who can commercialise their research and (b) agri-tech companies that need an incubator and business base. The convergence between ICT technologies and agriculture has resulted in a number of high potential start-ups (Source: AgFunder AgriFood Tech Investing Report, 2017). This hub increases the potential of high potential start-ups through access to incubation space, specific research outputs and access to national and international markets. Additionally, it will

represent an intense innovation base for existing agri-tech companies seeking an offsite venue for ideation and a potential soft landing space for foreign direct investment (FDI) where international companies wish to plug into a specialist agri-tech R&D base.

Together these components will deliver a new ecosystem of agri-tech entrepreneurship that is unique in Ireland. It is a model that combines best practice in commercialisation, technology innovation and knowledge facilities, thus generating potential for significant productivity in the agri-tech sector. While supports are currently available across a spectrum of enterprise agencies, technology specialists and education and knowledge providers, they can only be accessed on a stand-alone individual basis currently. The Hub will deliver concentrated and single access supports to escalate the growth path of agri-tech industry disruptors and assist agri-tech entrepreneurs in a supportive, innovative and synergistic enterprise environment.

Proposed Hub Infrastructure

The Hub infrastructure will include:

- Knowledge centre incorporating a research, academic and education centre, together with industry and government partners
- Incubation facilities to include 6 incubation units, a conference room, innovation workshops, entrepreneur residencies, etc. circulation foyer and service area
- Open innovation laboratory incorporating 12 x hot-lab stations
- Smart-farm test-bed available for trials and proof of concept, including a 325 cow herd available for studies, an integrated automatic milking and cow grazing system and land bank of 93 ha.

This infra-structure will provide manufacturers with a physical and knowledge space where they can design, simulate, and test products before making the first physical prototype, before setting up production lines, and before starting actual production. It will provide a much-needed continuum pathway structure to support agri-tech businesses to grow and scale. It will provide onsite support and mentoring on market strategists, funding/ financial engineering expertise and IP, as well as tailored supports for growth and access to investors. It will provide access to the recently funded SFI agri-tech centre (VistaMilk) with a €40 million research programme.

Management and timeline of project

This project has been funded by Enterprise Ireland which is a state agency responsible for supporting the development of manufacturing and internationally traded services companies. The Hub will operate as an independent entity financially (answerable to a board of directors) with the requirement of being self-financing after 3 years. Initially, it will mainly be managed by a chief executive officer and technical officer. It is planned to be ready to invite companies in by mid-2020.

DEVELOPMENT SCHEME FOR CATTLE BEHAVIOR ESTIMATION BY DEEP LEARNING IN AN EDGE DEVICE

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Real-time monitoring of cattle by information technology is demanded for early detection of estrus and diseases. There are many researches and products of state-estimation system focusing on change of activity amount, however, they can only detect a limited state in a barn [1]. Our approach is implementation of deep learning into an edge device to be worn on the cattle's neck or ear, which enables long-term and multi-state monitoring not only in a barn but on a grazing field because the deep learning can compress motion data down to motion flags with small data-size that can be communicated by the low power wide area (LPWA) wireless technology. This paper proposes and introduces a scheme to develop an edge device enabling estimation of several behavior by deep learning.

Training data for deep learning were acquired by the scheme shown in Fig. 1. This work only uses a tri-axis accelerometer for saving hardware cost and operation energy of the edge device. The acceleration data are once transmitted to an Android terminal, and the observer creates training data by adding labels of cattle's motion to the acceleration data. Then, the training data is accumulated in a cloud via 4G wireless communication.

Deep learning is performed using eight kinds of feature quantities shown in Fig. 2. The length and sampling rate of the each feature quantity is 100 samples and 50 Hz, respectively. Long short-term memory (LSTM) with the number of 128 output dimension was employed in the Sony's Neural Network Console. 58,734 and 14,684 data were used for learning and verification, respectively, and Fig. 3 shows the classification results. Average accuracy is 98.24 %, thus four kinds of behavior could be classified with high accuracy. Recall of lying and precision of feeding and drinking are less than 95 % due to incorrect labeling to feeding and drinking.

Sony's Spresense was applied as an edge device. Neural network structure and learned parameters (net.nntxt and parameters.h5 files) are converted to the standard NNP format (.nnp) by Neural Network Libraries (nnabla_cli.exe). The Spresense reads the neural network information from the NNP file and transmits an estimated motion flag over wireless communication. Bluetooth low energy (BLE) was used for demonstration, and standing motion could be detected and was indicated on the Android terminal as an example shown in Fig. 4.

[1] J. A. V. Diosdado, *et al.*, 2015, Classification of behavior in housed dairy cows using an accelerometer-based activity monitoring system, *Animal Biotelemetry*, Vol. 3:15, pp. 1-14.

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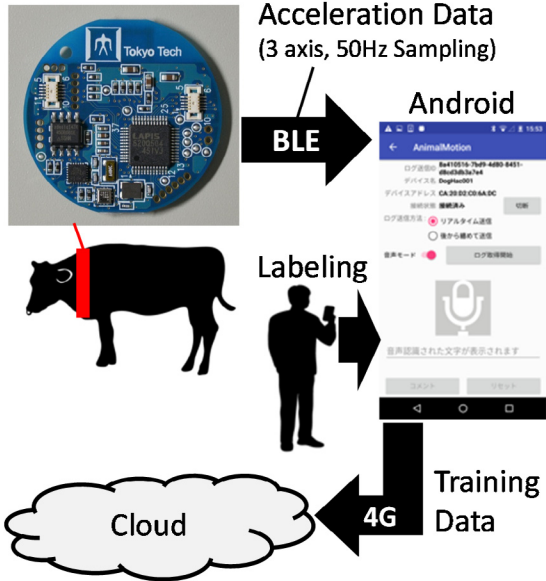


Fig. 1: Scheme of training data correction

$a_x(t), a_y(t), a_z(t)$: acceleration data of x, y and z axes at sample t

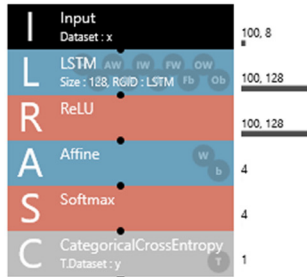
Moving Average $\overline{a_{x,y,z}}(t) = \sum_{i=0}^{N-1} \frac{a_{x,y,z}(t-i)}{N}$

Norm $|a| = \sqrt{a_x^2 + a_y^2 + a_z^2}$

Power $\sum_{i=0}^{W-1} \frac{(|a(t-i)| - g)^2}{W}$
(g: gravity acceleration)

Sensor Angle $\theta = \text{atan2}(\overline{a_x}, \sqrt{\overline{a_y^2} + \overline{a_z^2}})$
 $\psi = \text{atan2}(\overline{a_y}, \sqrt{\overline{a_x^2} + \overline{a_z^2}})$
 $\phi = \text{atan2}(\overline{a_z}, \sqrt{\overline{a_x^2} + \overline{a_y^2}})$

Fig.2: Feature quantity



| | Feeding & Drinking | Lying | Standing | Moving | Recall |
|--------------------|--------------------|---------------|---------------|---------------|----------------|
| Feeding & Drinking | 3593 | 61 | 0 | 0 | 98.33% |
| Lying | 189 | 3516 | 0 | 0 | 94.89% |
| Standing | 1 | 0 | 3691 | 5 | 99.83% |
| Moving | 0 | 0 | 1 | 3627 | 99.97% |
| Precision | 94.97% | 98.29% | 99.97% | 99.86% | Average |
| F-Measures | 96.62% | 96.56% | 99.89% | 99.91% | 98.24% |

Fig.3: Deep learning results

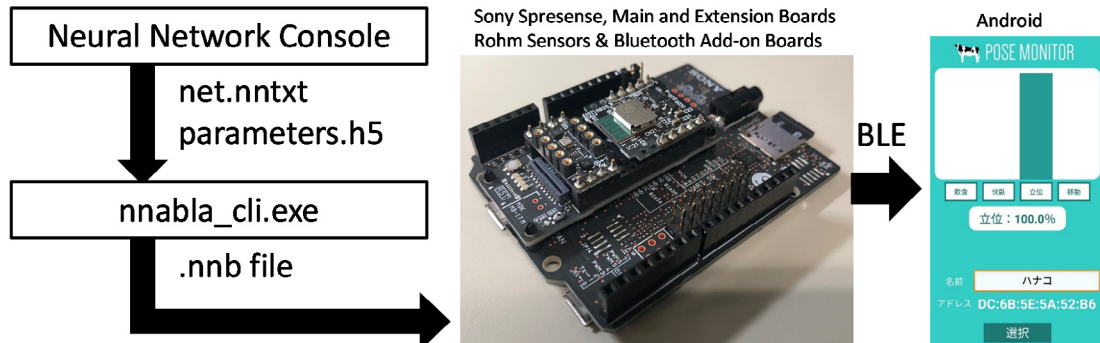


Fig.4: Edge AI implementation

Effect of meal size on Holstein bull calf growth and feeding behaviors in an automated feeding system

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Automated milk feeding systems for dairy calves provide the opportunity of feeding enhanced milk allowances and record feeding behavior of calves without increasing labor. Recorded data, such as milk consumption (L/d), drinking speed (ml/min), and frequency of visits can be used to detect deviations and to tailor the nutritional plan to the calf. Furthermore, automated milk feeding systems allow producers to individualize daily milk allowances, change meal sizes, concentration of the milk replacer offered, and allowed visits, which influences how calves use the feeder and other aspects of the environment. Therefore, it is imperative to determine the effects of these Automated milk feeding systems configuration on the calves. One of these aspects is how different meal size allocations have effects on calf performance and feeding behaviors development within the early milk feeding period.

The objective of this study was to determine the impact meal size plan has on calf growth and feeding behaviors (milk consumption and drinking speed), for calves allocated to 7 L/d of milk replacer during the first four weeks on an automated milk feeding system. Bull Holstein calves (n=52) at a (Mean \pm SD) 3 ± 2 days of age were transported from one dairy to a beef calf facility in central Kentucky and randomly enrolled by arrival date on this 2 X 2 factorial study from May 2018 to September 2018. Factor 1 was based on a minimum (**min.**) meal of either 0.5 L or 1.0 L per visit to the feeder, and Factor 2 was based on a maximum (**max.**) meal of either 2.0 L, or 4.0 L per visit. LowMinLowMax (N=12) had (0.5 L to 2.0 L) milk per visit, LowMinHighMax (N=14) had (0.5 L to 4.0 L) milk per visit, HighMinLowMax (N=13) had (1.0 L to 2.0 L) milk per visit and HighminHighMax (N=13) had (1.0 L to 4.0 L) milk per visit. Weights (Brecknell PS1000, Avery Weigh-Tronix, LLC Brand, Fairmont, MN, USA) and health scores, were taken once at arrival and once weekly until completion of the study. Calves were enrolled on the automated calf feeder program at 5(+/-) 4 days of age and the feeder automatically recorded the following behaviors: daily drinking speed (ml/min), milk consumption (L/d), and visits (rewarded received milk and unrewarded did not receive milk). Stocking density of the feeder was 15 to 20 calves per nipple. All calves had a 24 h distribution of 7 L/d milk replacer (20% crude protein 21% fat; CalfCare Plasma Starter, CalfCare, Manchester, Indiana, USA), with eligibility for more milk based on meal. Water and starter in a trough (Baghdad Feeds, Shelby, KY, USA) were provided *ad libitum* for the study duration.

Data analysis was performed using SAS version 9.4 (SAS, Cary, NC, USA). Normality was assessed by visual assessment and for all residuals output from the models to ensure good fit. A linear mixed model (PROC MIXED) was created for each dependent variable (weight, milk intake, visits (rewarded and unrewarded), drinking speed) to determine the effect of meal on performance and feeding behaviors. All models had calf treated as the subject and the repeated measure was

week, and the fixed effect of treatment and feeder enrollment age. For calf weight (kg) additional covariates were milk consumption, and initial body weight. For milk consumption (L/d) additional covariates were clinical Bovine Respiratory Disease (yes or no) and initial body weight. For drinking speed (ml/min) additional covariates were milk consumption.

At the end of the trial, calves weighed (LSM \pm SEM) (51.1 \pm 1.23 kg), LowMinHighMax (50.08 \pm 1.01 kg), HighMinLowMax (51.75 \pm 1.1 kg) and HighminHighMax (49.13 \pm 1.05) kg. Body weight was not associated with meal ($P = 0.33$) while milk consumption ($P < 0.01$), feeder week ($P < 0.0001$) feeder enrollment age ($P = 0.04$) and initial body weight were significant ($P < 0.0001$). However, milk consumption was significantly associated with meal ($P = 0.04$) as was Bovine Respiratory Disease ($P = 0.02$), feeder enrollment age ($P < 0.01$) and initial body weight ($P = 0.02$). Milk consumption was significantly different for LowMinHighMax (5.55 \pm 0.12 L/d) across all other treatments ($P < 0.02$), yet LowMinLowMax (5.26 \pm 0.14 L/d), HighMinLowMax (5.16 \pm 0.12 L/d) and HighminHighMax (5.2 \pm 0.11 L/d) were not different from one another ($P > 0.10$). Drinking speed across the trial was LowminLowMax (472.29 \pm 35.12 ml/min), LowminHighMax (445.92 \pm 27.80 ml/min), HighminLowMax (432.40 \pm 32.00 ml/min), and HighminHighMax (405.11 \pm 30.24 ml/min). Drinking speed was not associated with treatment ($P = 0.46$), but was associated with milk consumption ($P < 0.0001$), feeder week ($P = 0.02$) and there was a trend for feeder enrollment age to be associated with drinking speed ($P = 0.06$). Rewarded visits ($P = 0.36$) were also not associated with treatment, only feeder week ($P < 0.01$) and feeder enrollment age were significant ($P = 0.03$); calves visited the feeder an average 5 times per day across study treatments. Unrewarded visits were non-normal, and on average 1.5 across study treatments. Since unrewarded visits were so low, this variable was not further assessed.

In summary, milk consumption was affected by study treatment, with calves drinking the most milk for LowminHighMax whereas other plans were not different from one another. However, calf weight was not associated with meal, nor was drinking speed. This suggests meal size has a minimal effect on calf performance and feeding behaviors when calves are offered 7 (L/d) during the development of feeding behavior. In addition, average differences between meals for milk consumption were less than 0.5 L, suggesting that meal size differences were small and may not be biologically relevant. However, it is possible that a high stocking density of calves per nipple in this commercial setting affected the amount of low unrewarded visits seen on this study. Future research should determine if different meals have a different association with feeding behaviors for calves fed more milk per day. In addition, future research should determine if low stocking density facilities have a greater effect of meal size on calf feeding behavior. Calves allocated to 7 (L/d) milk replacer in a high density setting are minimally affected by different meal sizes in this particular setting.

Evaluation of an ear-attached accelerometer for detecting selected estrus events in dairy cows

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Introduction

Detecting cows in estrus as well as getting cows pregnant are two major challenges in herd management of dairy cows. With increasing herd size, farmers' available time for individual animal observations is decreasing. Furthermore, within the last decades the percentage of animals in estrus expressing 'stand-to-be-mounted' behavior has declined from 80% to 50%, with an average duration of this behavior of approx. 5 h. To achieve satisfactory estrus detection rates it is recommended to observe animals several times per day. This is quite time-consuming and requires the skills and knowledge of farmers and their employees of behavioral signs of cows in estrus, which are often not self-evident to paid farm workers.

Nowadays, several tools for estrus detection are available. The aim of this study was to evaluate the ear-tag based 3D-accelerometer system SMARTBOW (SB, Smartbow GmbH, Weibern, Austria) to detect estrus events in cows. For this, reproductive performance data were retrospectively compared with estrus alerts generated by the sensor system.

Materials and Methods

The study was conducted on a commercial dairy farm, housing approx. 2,700 Holstein-Friesian cows. Cows were kept in freestall barns with pens for approx. 250 animals, each equipped with full concrete floors and high bed cubicles. All animal related events [e.g., estrus, artificial insemination (AI), clinical diseases, treatments] were entered into the herd management software DairyComp 305 (DC305, Valley Agricultural Software, Tulare, USA) by farm personnel. First lactation animals were kept on another farm site, thus, only multiparous cows were included in this study. The voluntary waiting period was set at 50 days in milk (DIM). Cows detected in estrus by visual observation and by use of an automated monitoring device were inseminated by two AI technicians based on the a.m.-p.m. rule. Cows not detected in estrus and bred by 64 DIM were subjected to a standard Ovsynch protocol. Pregnancy diagnosis was performed between day 39 and 45 after AI by ultrasound and confirmed approximately 90 d after AI.

For study purposes, two pens of the farm were equipped with the SB system. The accelerometer was attached to the study animals in the middle of the right ear. Acceleration data (range -2 g to +2 g) of head and/or ear movements of the animals were recorded with a frequency of 1 Hz and sent in real-time to the receivers. Receivers were connected with a local server on which data were processed and analyzed. When activity and behavior changes exceeded a defined threshold, an estrus alert was generated.

Inseminations resulting from an Ovsynch protocol were excluded from statistical analyses. An estrus followed by AI that resulted in pregnancy was defined as ‘golden standard’ (GS), representing the highest reference level in our study. In addition to GS we defined estrus events with an interval of 18 to 25 d as ‘recorded estrus’ (RE) events, independent of whether estrus was followed by AI or pregnancy. For the evaluation of the performance of the SB system, GS and RE events were determined retrospectively, based on reproductive performance data (i.e., estrus, insemination) entered into DC305 and matched with generated estrus alerts by SB. If an estrus alert coincided with a GS or RE event, the alert was classified as ‘true positive’ (TP). In the case that no estrus alert was generated during a GS or RE event, it was classified as ‘false negative’ (FN). An estrus interval was classified as ‘true negative’ (TN), when no estrus alert occurred, and as ‘false positive’ (FP), when an estrus alert occurred during an estrus interval.

Results

For the evaluation of the estrus detection performance of SB, a total of 316 GS events in 316 cows and 263 RE events divided by 142 estrus intervals in 116 cows were used. Estrus was detected in 306 of 316 GS events with the accelerometer system, resulting in a sensitivity of 96.8%. Additional results for RE are presented in the following Table.

Table: Test characteristics of the SMARTBOW (SB) system for detecting estrus events

| Events ¹ | Cows | SB results | True (+) | False (-) | Statistics ² % | | | |
|---------------------|------|--------------|------------------|-------------------|---------------------------|------|------|------|
| | | | | | Se | Sp | PPV | NPV |
| GS | 316 | Alert (+) | 306 ^a | n.a. ³ | 96.8 | n.a. | n.a. | n.a. |
| | | No Alert (-) | 10 ^a | n.a. | | | | |
| RE | 116 | Alert (+) | 254 | 6 | 96.6 | 97.7 | 95.8 | 93.8 |
| | | No Alert (-) | 9 | 136 | | | | |

¹GS = golden standard events; RE = recorded estrus events

²Se = Sensitivity $[\text{TP}/(\text{TP}+\text{FN}) \times 100]$; Sp = Specificity $[\text{TN}/(\text{TN}+\text{FP}) \times 100]$;

PPV = Positive predictive value $[\text{TP}/(\text{TP}+\text{FP}) \times 100]$;

NPV = Negative predictive value $[\text{TN}/(\text{TN}+\text{FN}) \times 100]$

³n.a. = not available

Conclusion

The sensitivity, specificity, positive and negative predictive values of the SMARTBOW system for detecting recorded estrus events were 97%, 98%, 96%, 94%, respectively. Hence, the system is considered as suitable for an automated detection of estrus events of indoor housed multiparous dairy cows. Further studies should be conducted in heifers and primiparous cows and should investigate the effect of different conditions of housing conditions.

Conflict of interests

The authors declare no conflict of interests. Any results and interpretation of this study were not influenced by the company Smartbow.

Factors associated with milk production per cow on free-flow automatic milking system farms in the Upper Midwest United States

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Introduction

Automatic milking systems (AMS) are common in Europe and have grown in popularity recently in the US. Management can be different among AMS farms, even within the same cow traffic system. Cow traffic refers to the way cows are allowed to move around their pen. A free-flow cow traffic system allows the cows to have free access to all the areas of the pen. Siewert et al. (2018) reported associations between management factors and milk production per cow in free-flow farms. However, for their study, data from 2013-2014 were used. Therefore, the main objective of this study was to investigate the factors associated with milk production per cow using a more recent dataset.

Materials and Methods

We visited 36 free-flow AMS farms (Lely Astronaut, Lely, the Netherlands) in Minnesota and Wisconsin over the summer of 2018. During the visit, each producer answered a survey about general farm management practices. In addition, we collected retrospective daily data from the AMS software for one year. For this study, we used data for the 30 days (1,080 daily averages) prior to the farm visit to evaluate the association of those factors and management practices with milk production per cow (kg/d). The MIXED procedure of SAS[®] 9.4 (SAS Institute, Inc., Cary, NC) was used to analyze the data. Factors evaluated in the analysis include barn design characteristics, such as number of AMS units per farm and per pen, new or retrofitted AMS facility, AMS location in the barn, use of automatic alley scraper, and ventilation system. General management practices included number of daily feedings, number of feeds offered in the AMS, cow fetching frequency, bedding frequency, use of automatic feed pusher, and presence of a fresh group. Data from the software were also included in the analysis, such as age of the cows, days in milk (DIM), concentrate offered per cow, number of cows per AMS, milkings, refusals, failures, milking speed, and milking time. A univariable linear mixed analysis was first conducted with each variable and milk production per cow. Factors with a $P < 0.3$ were included in the initial multivariable linear mixed model. Backward stepwise elimination was used to remove nonsignificant factors until all remaining factors had a $P < 0.05$ in the final model. Farm was used as random effect.

Results and Discussion

Descriptive statistics for the factors associated with milk production per cow are shown in Table 1. Amount of daily concentrate in the AMS was associated with increased milk production per cow (Table 2). For every additional kg of concentrate offered, cows increased milk production by 1.3 kg. Milkings and refusals were also associated with daily milk production per cow. For each 1 unit increase in milkings per day, cows produced about 9 kg more milk. On the other hand, refusals had a negative association with milk production. For each unit increase in refusals, there was a decrease in milk production of approximately 0.4 kg. As expected, higher milking speed resulted in higher milk production. For each additional kg of milk milked per minute, milk production per day increased by 4.2 kg. Milking time was also associated with higher milk production, potentially a result of proportion of high producing cows that take longer time to get milked.

Summary

Days in milk, the amount of concentrate cows consume in the AMS, milking frequency, how fast and for how long cows are milked, were all factors associated with higher milk production. The amount of refusals was the only factor negatively associated with milk production per cow.

Table 1. Descriptive statistics of the variables associated with milk production/cow (kg/d) on 36 free-flow AMS dairy farms in Minnesota and Wisconsin

| Variable | Mean | SD | Minimum | Maximum |
|------------------------------|-------------|-----------|----------------|----------------|
| DIM | 172.14 | 26.25 | 130.30 | 276.93 |
| Concentrate/cow (kg/day) | 5.56 | 0.87 | 3.43 | 7.43 |
| Milkings/cow/day | 2.82 | 0.22 | 2.50 | 3.35 |
| Refusals/cow/day | 1.27 | 0.58 | 0.40 | 2.34 |
| Milking speed (L/min) | 3.26 | 0.41 | 2.07 | 4.21 |
| Milking time (sec) | 306.53 | 29.67 | 260.57 | 352.77 |
| Milk production/cow (kg/day) | 37.63 | 4.43 | 28.15 | 46.63 |

Table 2. Multivariable analysis of farm-level factors and their association with milk production/cow (kg/d) on 36 free-flow AMS dairy farms in Minnesota and Wisconsin

| Variable | Estimate | SE | P-value |
|--------------------------|-----------------|-----------|----------------|
| Intercept | -27.54 | 2.20 | <.0001 |
| DIM | 0.01 | 0.006 | 0.046 |
| Concentrate/cow (kg/day) | 1.28 | 0.17 | <.0001 |
| Milkings/cow/day | 8.93 | 0.25 | <.0001 |
| Refusals/cow/day | -0.43 | 0.08 | <.0001 |
| Milking speed (L/min) | 4.16 | 0.24 | <.0001 |
| Milking time (sec) | 0.06 | 0.003 | <.0001 |

References

Siewert, J.M., J.A. Salfer, and M.I. Endres, 2018. Factors associated with productivity on automatic milking system dairy farms in the Upper Midwest United States. *J. Dairy Sci.* 101:8327-8334.

How often should we measure reticulorumen temperature and pH in dairy cows? Evaluation of multiple recording intervals from an automated reticulorumen bolus

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Automated reticulorumen temperature and pH boluses (ARB) have been used on early diseases detection or on physiological responses monitoring (*i.e.* estrus, calving onset signals, and heat stress). However, battery life and pH measurement drifts are major limitations for long-term use of ARB. The aim of this study was to compare five different reticulorumen temperature and pH recording intervals to the standard 10 min recording interval on ARB. Sixteen lactating Holstein dairy cows were enrolled in this study and had their reticulorumen temperature and pH measured every 10 minutes by an ARB (iNVOTEC Animal Care, smaXtec, Graz, Austria). Reticulorumen temperatures were recorded in 10 min intervals for 213 ± 99 days. The 10-minute dataset was set as the gold-standard and used to generate datasets with five alternative recording intervals: 20, 30, 60, 120, and 240 min. The same 16 animals also had their reticulorumen pH recorded for eight days during a SARA experiment. During that trial, cows were fed a balanced TMR *ad libitum* for three days and on the fourth day cows had their feed allowance reduced by half. On the fifth day, cows received a grain mix to induce SARA and were allowed to recover for 3 days. During and after the recovering period, cows had *ad libitum* access to feed and water. Mean, minimum, and maximum daily reticulorumen temperature and pH were generated for each recording interval. In addition, we calculated daily time above elevated temperature and SARA. Elevated temperature was defined as reticulorumen temperatures above 40°C, following AlZahal et al., 2011. The relationship between the recording intervals of temperature and pH were analyzed using linear regressions and Bland-Altman plots. Data from the alternative recording intervals were considered accurate if the coefficient of determination (R^2) were above 0.90 (Hinkle et al., 1988), if the slopes did not differ significantly from 1, and if mean bias from the Bland-Altman plots was within the 95% interval of agreement; reported in Table 1. When analyzing mean daily temperature, data recorded in intervals longer than 30 min were not considered accurate. In addition, the alternative recording intervals were not accurate in registering minimum daily temperatures. Maximum daily temperatures and time above 40°C were only accurate when recorded in intervals were no longer than 20 min. Briefly, those accuracy losses when longer temperature measurements intervals were taken can be explained due to the animal water intake. Authors have reported a drop on reticulorumen temperature following water intake, and some of them have also described that the recovering time for the baseline temperature has ranged from 20 to 90 min, depending on the amount of water ingested and its temperature (*i.e.* Cantor et al., 2018). On this study, the mean daily reticulorumen pH, data from all alternative recording intervals met the accuracy criteria and its values agree with those reported by literature under different evaluation techniques (Gozho, 2005). Reticulorumen pH recording intervals up to 60 min were accurate only when recording time below pH 5.6. Those results can be understood considering that the induced SARA condition kept the reticulorumen pH < 5.6 during part of the day and then, each cow has had its own recovering time to a physiological pH baseline. Thus, considering the individual variations on feed intake or on SARA recovering time, those pH drifts were not accurately detected by ARB when measured

in longer intervals. Reported SARA challenges reduced the average daily rumen pH and increased the day time of the rumen pH below 5.6 for at least 180 min (Gozho et al., 2005), which also could justify the reason of none of the alternative recording intervals on this study were accurate in measuring minimum and maximum daily reticulorumen pH. In conclusion, there is a possibility to record reticulorumen temperature and pH less frequently. However, as data recorded hourly doesn't seem to affect SARA detection, elevated temperature could only be accurately detected when reticulorumen temperature was recorded in intervals no longer than 20 min. As some alternative recording intervals seem not to affect data quality, future research should investigate if the recording reticulorumen pH and temperature less frequently can affect the accuracy of individual pH recordings and bolus battery life.

Table 1: Coefficients of determination and slopes for five different reticulorumen temperature and pH recording intervals in comparison to temperatures recorded every 10 minutes.

| Item | Alternative interval (min) | | | | |
|---------------------------------------|----------------------------|------------|------------|------------|------------|
| | 20 | 30 | 60 | 120 | 240 |
| <i>Mean daily Temperature (°C)</i> | 39.05±0.31 | 39.05±0.31 | 39.05±0.34 | 39.06±0.39 | 39.05±0.51 |
| R ² | 0.987 | 0.956 | 0.827 | 0.621 | 0.361 |
| Slope similar to 1 | Yes | Yes | Yes | Yes | Yes |
| <i>Minimum daily temperature (°C)</i> | 35.04±1.42 | 35.35±1.40 | 35.98±1.42 | 36.73±1.47 | 37.51±1.47 |
| R ² | 0.839 | 0.706 | 0.482 | 0.218 | 0.08 |
| Slope similar to 1 | No | No | No | No | No |
| <i>Maximum daily temperature (°C)</i> | 40.15±0.38 | 40.13±0.38 | 40.08±0.38 | 40.01±0.37 | 39.91±0.38 |
| R ² | 0.993 | 0.985 | 0.951 | 0.877 | 0.716 |
| Slope similar to 1 | Yes | No | No | No | No |
| <i>Time above 40°C (h)</i> | 3.44±3.75 | 3.57±3.79 | 4.09±3.85 | 4.96±3.95 | 6.68±4.16 |
| R ² | 0.997 | 0.992 | 0.963 | 0.876 | 0.664 |
| Slope similar to 1 | Yes | No | No | No | No |
| <i>Mean daily pH</i> | 6.15±0.28 | 6.15±0.28 | 6.15±0.28 | 6.16±0.28 | 6.16±0.28 |
| R ² | 1.000 | 0.999 | 0.998 | 0.991 | 0.964 |
| Slope similar to 1 | Yes | Yes | Yes | Yes | Yes |
| <i>Minimum daily pH</i> | 5.64±0.33 | 5.66±0.33 | 5.71±0.33 | 5.77±0.34 | 5.84±0.32 |
| R ² | 0.985 | 0.961 | 0.931 | 0.850 | 0.748 |
| Slope similar to 1 | No | No | No | No | No |
| <i>Maximum daily pH</i> | 6.61±0.26 | 6.61±0.26 | 6.58±0.27 | 6.54±0.28 | 6.50±0.30 |
| R ² | 0.985 | 0.984 | 0.967 | 0.924 | 0.870 |
| Slope similar to 1 | No | No | No | No | No |
| <i>Time below pH 5.6 (h)</i> | 3.80±5.27 | 3.71±5.09 | 4.88±5.28 | 5.68±5.25 | 8.00±5.60 |
| R ² | 0.971 | 0.990 | 0.929 | 0.839 | 0.475 |
| Slope similar to 1 | Yes | Yes | Yes | Yes | No |

References

- AlZahal, O., H. AlZahal, M. A. Steele, M. Van Schaik, I. Kyriazakis, T. F. Duffield, and B. W. McBride. 2011. The use of a radiotelemetric ruminal bolus to detect body temperature changes in lactating dairy cattle. *J Dairy Sci* 94(7):3568-3574.
- Cantor, C. M., H. J. Costa, and M. J. Bewley. 2018. Impact of observed and controlled water intake on reticulorumen temperature in lactating dairy cattle. *Animals* 8(11).
- Gozho, G. N., J. C. Plaizier, D. O. Krause, A. D. Kennedy, and K. M. Wittenberg. 2005. SARA Induces ruminal lipopolysaccharide endotoxin release and triggers an inflammatory response. *J Dairy Sci* 88:1399-1403.
- Hinkle, D. E., W. Wiersma, and S. G. Jurs. 1988. *Applied statistics for the behavioral sciences*. 2nd Ed., Houghton Mifflin Co, Boston, Massachusetts, USA.

Milk Haptoglobin Detection Based on Enhanced Chemiluminescence of Gold Nanoparticles

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Bovine mastitis (BM) is one of the most frequent diseases in dairy cattle, having a large adverse effect on farm economics, including increased treatment costs, decreased milk yield, escalation of somatic cell counts (SCC), increased risk of removal from the herd or even death. The mammary gland inflammation is usually classified upon its severity into subclinical, clinical and chronic forms, and is dependent on the nature of the causative pathogen, immunological health and lactation state of the animal. Traditionally, the detection of BM depends on the efficiency and reliability of the methods designed to estimate SCC, indicate inflammation, identify the causative microorganisms or measure the biomarkers associated with the onset of the disease. The latter incorporates a group of serum acute phase proteins (APP) that are used as predicting diagnostic biomarkers for health evaluation of cattle herd. These proteins are marginally change their distribution as a response to infection, inflammation or trauma. Specifically, Haptoglobin (Hp) can provide sufficient clinical status of dairy cows experiencing clinical BM, while both serum and milk Hp concentrations are dramatically increased (up to 10-fold) with respect to healthy udder quarters. Hp is usually diffused by damaged or permeable mammary vascular cells, thus increasing the overall concentration in milk. Hiss et al. have shown that not only hepatically derived Hp can circulate onto milk, but Hp can also be locally synthesized within the mammary gland, thus increasing the overall concentrations. Milk Hp is commonly detected by commercial immunoassays, e.g., enzyme-linked immunosorbent assay (ELISA) based on hemoglobin (Hb) binding capacity, which are cumbersome, expensive and time-consuming.

Chemiluminescence (CL) is an attractive opto-chemical reaction with diverse analytical applications in biotechnology, food and pharmaceutical industries, clinical assays and environmental monitoring, utilizing the extensively studied luminol-hydrogen peroxide reaction. Despite the pronounced advantages of high-sensitivity, simplicity, rapid analysis and insignificant background luminescence signal, CL suffers from low photon intensity that corresponds to lower detection limits in complex matrices. CL reactions can be enhanced with the aid of catalyst in the form of enzyme, dye, ions or metal nanoparticles. Specifically, gold nanoparticles (GNPs) were extensively used for gas and liquid phase redox reactions due to unique physical and chemical properties that affect the catalytic response, easily functionalized and attain sufficient stability. So far, numerous biosensors and bioassays were developed based on enhanced luminol-H₂O₂ CL reaction presenting a repertoire of novel possible applications.

In the present work, we have designed and fabricated a liquid-phase CL system for sensitive detection of Hp concentrations in bovine milk, by utilizing the high binding affinity of Hb. The analytical performance of Hp detection by the inhibition of peroxidase-like activity of luminol-H₂O₂-Hb CL system as a response to Hb-Hp complex formation was investigated under optimized experimental conditions, as schematically illustrated in Figure 1. Moreover, we show the enhancement effect, by at least 10-fold, of catalytically active cross-linked GNPs on CL intensity. The relationship between CL signal decrease and Hp concentration within different milk samples was proportionally obtained. We show the influence of different SCC levels and pathogen types (i.e., *CNS* and *Streptococcus dysgalactiae*) on the secreted Hp in milk with respect to the healthy udder. The resulting sensing concept offers simple, cost-effective, label-free and reliable systematic analysis of Hp biomarker for BM,

initiating a positive effect on animals' health.

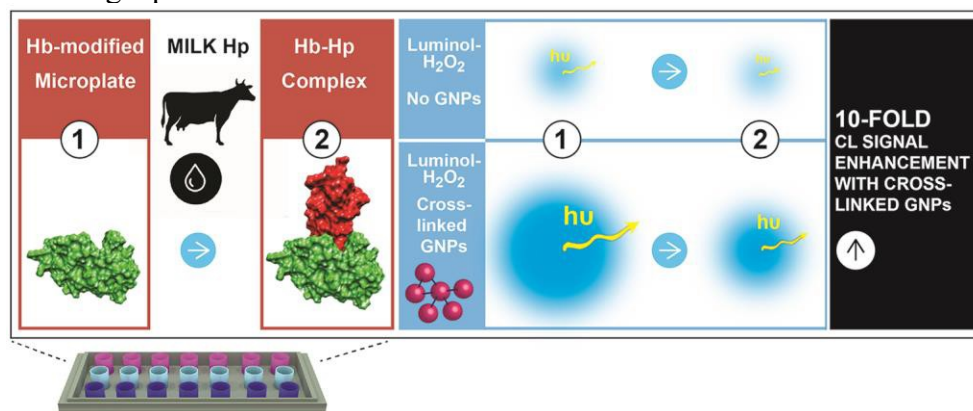


Figure 1. A schematic illustration of the Hp sensing concept within luminol-H₂O₂-Hb CL system based on enhanced CL using cross-linked GNPs. The plate assay is modified with Hb as a bioreceptor for specific binding with Hp found in milk. The resulting Hb-Hp complex inhibits the peroxidase-like activity of Hb within the CL system proportionally to Hp concentration. Minute concentrations in milk are enhanced by the addition of cross-linked GNPs onto the luminol-H₂O₂ reaction solution to amplify the CL signal for highly sensitive detection of the target molecule.

Practical Challenges and Potential Approaches to Predicting Clinical Mastitis On-Farm Using Individual Cow Data

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Practical Challenges

Mastitis is an extremely costly disease in the US dairy industry. Despite this great cost, mastitis is not common on dairy farms, with estimates of its incidence less than 1 in every 2000 cow-lactation days (McDougall et al. 2007). Predicting clinical mastitis (CM) is then of utmost importance to farmers because early detection can prevent or expedite treatment of the disease, preventing lost milk (Milner, Page, and Hillerton 1997). When building models that use data to predict whether a cow has CM, International Standard ISO/FDIS 20966 (Automatic milking installations—requirements and testing) of the International Standard Organization (ISO) includes an annex describing a minimum sensitivity (Se) of 80% with specificity (Sp) greater than 99%. For ISO standards, that cover broad categories, Se = 80% and Se = 99% is appropriate. However, the nature of the calculations of Se and Sp allow for the value of the standard to diminish as the incidence rate of the targeted variable decreases. Table 1 shows the confusion matrix seen in a model with Se = 80% and Sp = 99% with an incidence rate of 50% compared to 5%. Consider positive predictive value (PPV) in the two scenarios: the likelihood of a predicted CM case actually being CM. The PPV decreases by 18% as the incidence rate decreases to 5%. Consider that, in dairying, false positive CM cases are much costlier, as the cost of treating unnecessarily is much greater than that of waiting.

Potential Approaches

Our work proposes the use of a cost matrix for assessing models built to predict mastitis using individual cow data. A cost matrix is simply a method for weighting the results of a given model based on an estimate of each decision's net gain or loss. To show the benefit, consider the cost of a true positive (TP) case equal to the milk saved in the current lactation by treating the cow along with residual milk saved in future lactations, estimated at +\$132 USD (Bar et al. 2008). The cost of a false negative is \$0 because we are comparing models to the alternative, which is no model, and no model would necessarily always predict to do nothing. The cost of a false positive (FP) is estimated as the cost of lost milk and treatment costs, -\$165 USD (Bar et al. 2008). We see that the ratio of money gained per TP is near equal to the amount lost per FP. This indicates that a successful model in this paradigm must produce a ratio of TP:FP greater than that of the farm's calculated costs of CM treatment as we estimated above. Further, simply applying the ISO standard does not ensure a practical model in-farm, as the PPV can vary depending on the incidence rate of CM on-farm.

Sparse data, data with disproportionately few positive cases, is a challenge in data science. While techniques like neural networks and other machine learning methods have become popular, gaining insights in sparse datasets is often about improving data aggregation and handling.

Because the positive case data is disproportionate, aggregating data with outside sources can improve accuracy, as models will improve super-linearly with each new positive case. An easy trap to fall into with sparse data is to train on a subset with an unrepresentative CM incidence rate, making training easier. This model will not perform in the real world, as the data is not a proper representation. The practice of real-world, held-out data as a final validation of data can prevent some of these errors. Despite the increased access to computer processing and more advanced analytical techniques, the ISO standards are still held as the gold standard and rarely matched. The lack of high Sp in CM prediction papers suggests the difficulty of the problem and the need for better analytical techniques, data collection, and cross-validation if we want to create models that will be practical on-farm.

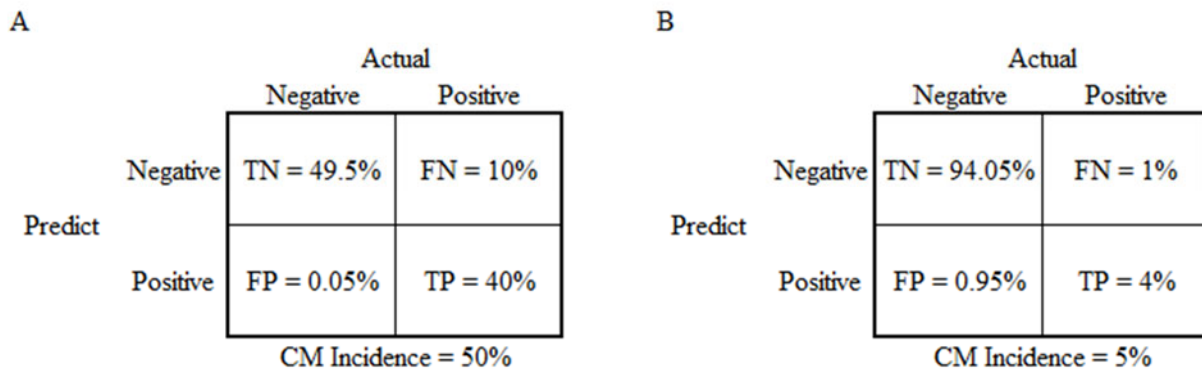


Figure 1. Confusion matrices for models with specificity = 99% and sensitivity = 80%; TN = True negative; FN = False negative; FP = False positive; TP = True positive. A) incidence rate in the prediction set = 50% and percentage of cases to fall in each category are shown. B) Incidence in the prediction set = 5%.

- Bar, D., L. W. Tauer, G. Bennett, R. N. González, J. A. Hertl, Y. H. Schukken, H. F. Schulte, F. L. Welcome, and Y. T. Gröhn. 2008. “The Cost of Generic Clinical Mastitis in Dairy Cows as Estimated by Using Dynamic Programming.” *Journal of Dairy Science* 91 (6): 2205–14.
- Khatun, M., P. C. Thomson, K. L. Kerrisk, N. A. Lyons, C. E. F. Clark, J. Molfino, and S. C. García. 2018. “Development of a New Clinical Mastitis Detection Method for Automatic Milking Systems.” *Journal of Dairy Science* 101 (10): 9385–95.
- McDougall, S., K. E. Agnew, R. Cursons, X. X. Hou, and C. R. W. Compton. 2007. “Parenteral Treatment of Clinical Mastitis with Tylosin Base or Penethamate Hydriodide in Dairy Cattle.” *Journal of Dairy Science* 90 (2): 779–89.
- Milner, P., K. L. Page, and J. E. Hillerton. 1997. “The Effects of Early Antibiotic Treatment Following Diagnosis of Mastitis Detected by a Change in the Electrical Conductivity of Milk.” *Journal of Dairy Science* 80 (5): 859–63.
- Steenefeld, W., L. C. van der Gaag, W. Ouweltjes, H. Mollenhorst, and H. Hogeveen. 2010. “Discriminating between True-Positive and False-Positive Clinical Mastitis Alerts from Automatic Milking Systems.” *Journal of Dairy Science* 93 (6): 2559–68.

Production parameters of free-flow automatic milking system farms in the Upper Midwest United States

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Introduction

Box-style automatic milking systems (AMS) have increased in popularity over the last decade in the US. It is estimated that in the Upper Midwest (including Iowa, Minnesota, Michigan, and Wisconsin) alone there are over 400 farms with these systems in place (Siewert et al., 2018). A free-flow cow traffic system allows the animals to move freely around the pen, with free access to the stalls, feeding area, and the AMS. Our objective was to describe the main production parameters collected by the AMS software in free-flow farms to use as a benchmark for producers and also dairy consultants.

Materials and Methods

We collected 1-year of retrospective daily data from 36 free-flow AMS farms (Lely Astronaut, Lely, the Netherlands) in Minnesota and Wisconsin (13,050 farm days). All the farms were visited once over the summer of 2018 and the data were collected from the AMS software at each farm. The MEANS procedure of SAS[®] 9.4 (SAS Institute, Inc., Cary, NC) was used to analyze the data.

Results and Discussion

Results can be found in Table 1. The average number of AMS per farm was 2.8 (± 1.6). Number of cows per AMS unit was 57.6 (± 5.4), which is within the common management practice of keeping that number between 55 and 65 cows. Cows were on average 47 months old with 171 (± 25.5) days in milk.

Daily milk production per cow was 37.3 (± 4.3) kg and daily milk production per AMS was 2,153.0 (± 350.6) kg. Siewert et al. (2018) reported average milk production per cow of 33.2 (± 5.3) kg and per AMS of 1,861.1 (± 380.4) kg with data from 2013 and 2014. It appears there has been a numeric increase in milk production on AMS farms in the Upper Midwest US over the last few years.

Farms averaged 2.8 (± 0.2) successful milkings per cow per day, 1.15 (± 0.5) refusals per cow per day, and 5.37 (± 3.53) failures per AMS/day. Number of milkings and number of failures found in this study are in agreement with numbers found by Siewert et al. (2018). Number of refusals, on the other hand, was higher in the present study (1.15 vs. 0.81). Number of milkings was

positively associated with milk production (Tremblay et al., 2016), therefore a higher number of milkings/cow/day is preferable but it needs to be optimized. Refusals could be seen as positive because it means cows are voluntarily visiting the AMS frequently. Failures should ideally be close to 0; it has been suggested by the manufacturers that there should be less than 5 failures per AMS per day.

Milking speed in this study was 3.07 (± 0.4) L/min. Milking speed is a parameter that can help producers in different ways. Cows with high milking speed spend less time milking, which could allow a higher number of cows per AMS. The same parameter may also be used to decide whether cows should be culled or not.

Table 1. Descriptive statistics of one-year of daily data from 36 free-flow automatic milking system farms in Minnesota and Wisconsin

| Variable | Mean | SD | Minimum | Maximum |
|---------------------------------|-------------|-----------|----------------|----------------|
| AMS/farm | 2.83 | 1.57 | 1.00 | 8.00 |
| Cows/AMS | 57.64 | 5.40 | 44.98 | 67.34 |
| DIM | 171.33 | 25.48 | 129.45 | 252.95 |
| Cow age (mo) | 47.01 | 4.89 | 41.3 | 64.99 |
| Milk/cow/d (kg) | 37.27 | 4.34 | 28.07 | 44.08 |
| Milk/AMS/d (kg) | 2151.98 | 350.59 | 1477.32 | 2837.91 |
| Milkings/cow/d | 2.80 | 0.21 | 2.55 | 3.21 |
| Refusals/cow/d | 1.15 | 0.54 | 0.54 | 2.31 |
| Failures/AMS/d* | 5.37 | 3.53 | 0.52 | 8.31 |
| Concentrate/100 kg of milk (kg) | 15.02 | 2.84 | 9.25 | 19.94 |
| Concentrate/cow/d (kg) | 5.52 | 0.89 | 3.68 | 7.43 |
| Rest feed (kg) | 0.30 | 0.14 | 0.13 | 0.62 |
| Milking speed (L/min) | 3.07 | 0.36 | 1.99 | 3.79 |
| Milking time (s) | 322.70 | 30.09 | 270.62 | 375.78 |

*Median reported due to the non-normality of the data.

References

Siewert, J.M., J.A. Salfer, and M.I. Endres, 2018. Factors associated with productivity on automatic milking system dairy farms in the Upper Midwest United States. *J. Dairy Sci.* 101:8327-8334.

Tremblay M., J.P. Hess, B.M. Christenson, K.K. McIntyre, B. Smink, A.J. van der Kamp, L.G. de Jong, and D. Dopfer, 2016. Factors associated with increased milk production for automatic milking systems. *J. Dairy Sci.* 99:3824-3837.

Robotic milking investment decision tool and simulated profitability

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Introduction

Robotic milking systems (RMS) are an increasingly appealing investment for dairy farmers who are considering a major facility upgrade, technological solutions for eliminating milking labor needs, or multi-generational succession plans. Many of the modern precision technologies, including activity monitoring systems and tailored feed supplements to individual cows, work well with RMS. Continuously tightening agricultural labor markets indicate that farmers will be competing for workers amid the rising benefits from urban centers and declining living conditions in rural towns. The prospect of freeing management resources from milking chores appears particularly suitable for a new generation of well-educated, technologically-savvy farmers who cherish their family-farming traditions and simultaneously want to adapt to the farming environment of today and the future.

However, the adoption of RMS comes with significant risks. Milking robots are large financial commitments, especially when combined with new facility construction that may offer the maximum advantage of RMS technology. Any adopter of RMS must learn the new technology and be willing to change many aspects of management, including allocation of owner-operator time. The ability to learn and continuously make improvements will be important. The increased volatility in the dairy and feed markets also makes it harder to assess the investment potential for RMS.

Decision-tool

Building on the earlier works of Dikhusen et al. (1997) and Hyde and Engel (2002), an economic model of RMS investment has been developed. It is a partial budget model that sums changes in revenues and costs associated with RMS investments and summarizes the resulting changes in partial cashflow as the equivalent annuity value. The investment value is contrasted between RMS and conventional (parlor) milking system (CMS). The earlier version of the model is described in Salfer et al. (2017). The model has been made available as an online decision-making tool, named Robot vs Parlor, at <https://z.umn.edu/robotparlor>.

The tool asks the user to enter the current situation of his dairy operations and also provide his assumptions regarding investment costs, expected lifespan and repair cost of robots, and changes in milking outputs and labor needs. For convenience, the tool offers over 10 sets of starting values that fit typical farm descriptions. The main determinants of profitability are the increased

milk revenue, increased feed cost, increased repair cost, decreased labor cost, increased debt service obligation, and increased tax deductions through interest and depreciation. The sensitivity of results is assessed for varying levels of milk outputs, labor savings, robots' lifespan, the amount of investment, and repair costs.

Simulations

The profitability uncertainties of the investment are modeled in three areas: market prices, robots' lifespan, and the success in RMS technology utilization. To accommodate the challenge of describing the parameters of uncertainty used in these simulations, the user is asked to adjust parameters to match the simulated distributions of the prices, lifespan, and technology utilization within their expectations. The simulated distributions of the "futures" are then translated into simulated distributions of outcomes for the partial cashflow and the net annual impact.

Certain aspects of the simulation results may be anticipated. For example, the profitability for RMS would be more variable than that of CMS due to strong effects from changes in milk output, labor efficiencies, and the robots' uncertain lifespan. The distribution of return on investment may also be skewed, which can have varying implications for farmers with different attitudes toward risks. The comparison between RMS and CMS is partly driven by the evolution of the wage rate as RMS may be best classified as a labor-saving technology. The agricultural labor wage has been increasing rapidly in recent years, and the rate of increase also depends on the location of the farm and the economic situation of the surrounding region.

The simulation component of the decision-making tool is being developed and improved at this time. The goal is to identify the key risks associated with an investment in RMS and present the implications of those risks to the farmer in a user-friendly and accessible manner.

Conclusions

RMS technology can offer dairy producers an attractive investment opportunity for various reasons. Assessing the profitability and risks associated with such an investment, however, may pose challenges. To help producers overcome such challenges, a RMS and CMS investment decision-making tool has been developed. Based on user-provided data entries, the tool calculates the net annual impact of the investment under RMS and CMS. Sensitivity analysis and simulation analysis help inform the user of known risks in the investment. The tool continues to be improved based on user feedback regarding usability and accuracy.

References

- Dijkhuizen, A.A., R.B.M. Huirne, S.B. Harsh, and R.W. Gardner. 1997. Economics of robot application. *Computers and Electronics in Agriculture* 17:111–121.
- Hyde, J., and P. Engel. 2002. Investing in a Robotic Milking System: A Monte Carlo Simulation Analysis. *Journal of Dairy Science* 85:2207–2214.
- Salfer, J.A., K. Minegishi, W. Lazarus, E. Berning, and M.I. Endres. 2017. Finances and returns for robotic dairies. *Journal of Dairy Science* 100:7739–7749.

TECH KISS: TECHNOLOGY DOING WHAT FARMERS WANT

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The dairy industry is the third largest rural industry in Australia, behind beef and wheat. New South Wales (NSW) is the second largest dairy producing state in Australia, with an annual production of 1.1 billion litres coming from 626 dairy farms which have predominantly year-round calving, pasture-based production systems. The challenges associated with increasing herd sizes and milk production per cow, together with the difficulty of attracting and retaining skilled labour, mean that monitoring and managing cows has become more complex and requires enhanced management ability. Technology can aid in the day-to-day running of farming operations by automating tasks and providing early alerts, and can generate key indicators for herd performance. Yet, despite there being a large number of technological innovations available, the rate of uptake and utilisation of technology on dairy farms is not well understood.

Research to date has focused on the technology itself, and not on its integration within the farming systems. The focus has been on the collection of data, but not its collation and use, especially across multiple technologies and multiple commercial platforms. A survey conducted in 2015 (Gargiulo et al, 2018) provided information about the current and intended technology investments of dairy farms in Australia, but there was no assessment of whether technology was doing what farmers wanted. There is an urgent need to move from ‘technology works’ to ‘information works’; from collection of data, to use of information; from telling farmers what they can do with technology/data, to asking them what they want to do and helping them find very simple solutions; from stand-alone technologies to integrated technologies and from use by only key people to everyone on farm being involved.

The TechKISS project is supported by the NSW Dairy Industry Fund, and is exploring how NSW dairy farmers are adopting technologies that assist with day-to-day animal health and management tasks. The project aims to identify and share the key things that lead to success – how farms achieve the outcomes they want. The target technologies are electronic cow ID, in-line milk metering and analysis, automatic drafting, automatic feeding systems, activity meters and the relevant linking software.

The first objective of the project was to conduct a desktop audit of these target technologies, in consultation with major equipment providers, to create the TechMatrix. This is a list of products available in Australia with an outline of the main characteristics of each. The list includes about 80 products from 20 manufacturers. It is presented in the same format as the EU 4D4F TechWarehouse.

The market place of dairy technologies is very complex in Australia. Some are local and others are imported mainly from the Northern Hemisphere. Several products are the same but under different brand names. Some products have a spectrum of optional functionalities. Each technology tends to have its own software and two-way transfer of data between different brands is not a given (may occur automatically, manually or not at all). Until now Australian dairy farmers have had to find this information from many different sources, so the TechMatrix becomes an important central resource for the industry.

The second objective was to understand on-farm adoption and adaptation of the target technologies from the farmers' perspectives (102 responses and 39 individual interviews). Service providers (such as vets and nutritionists) provided insight about their use of data from the target technologies and opportunities to value-add to their advice (35 interviews).

About 60% of NSW dairy farms use at least one of the focus technologies, but only 7% use all of them. There is very strong interest in automating immediate tasks and much less on using rich data streams for making herd level management decisions. In the last two years there has been a strong uptake of activity meters (26% of farms, particularly larger farms). These are mostly collars, purchased primarily to improve and simplify heat detection as well as provide cow health alerts, and satisfaction with them is high. An unexpected finding is that 21% of farms in NSW do not use any herd management software (these were all smaller herds of less than 300 cows).

Technology is used in many combinations, with different protocols and for different reasons; it also seems that many people don't realise the full potential functionality of the technology they have. Having said that, technologies have usually met farmers' expectations and once comfortable, farmers tend to look to extend functionality and/or the scope of the tasks that can be automated.

Engagement of service providers in NSW with the target technologies appears to be relatively low. Although most believe technology is the way to go, they find it difficult to access data from herd management software, as they are faced with multiple software packages and versions, each requiring a different approach. This limits their use of data to provide advice. To date no-one has pursued a commercial opportunity to provide independent advice about management of technology or data on-farm.

TechKISS will now produce a series of case studies to wrap the lived experience on NSW dairy farms into an independent industry resource that other farmers can use to help get the technology to work for them. By doing so the Tech-KISS project will increase NSW dairy farmers' awareness of the opportunities for improved productivity through the better use of technology and contribute to increasing farmers' confidence to grow their businesses.

Gargiulo, J I, Eastwood, C R, Garcia, S C and Lyons, N A, 2018, Dairy farmers with larger herd sizes adopt more precision dairy technologies, *Journal of Dairy Science*, 101, 5466-5473.

Abstract: The Economics of Automatic Milking Systems and the Iowa Experience

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Introduction

Installation of Automatic Milking Systems (AMS) in Iowa continues to grow. Approximately 5% of Iowa dairy producers currently use AMS. In order to assist dairy producers and lenders make informed decisions on the economic variables associated with AMS consideration, a partial budget spreadsheet tool was developed by the ISU Extension and Outreach dairy team. In addition, in 2012 and 2015 producers in Iowa were surveyed regarding their user experiences with AMS. There are two very important things to note when comparing AMS versus conventional parlor milking. First, many factors are “highly variable” meaning that slight changes in milk price or projected change in milk production, for instance, can significantly change the financial impact. Second, there is a wide variation in results from producers implementing AMS in terms of milk production and other responses. AMS can be more profitable than other milking systems but the answer depends on the actual on farm performance of the AMS system on a particular farm versus other alternative milking systems that farm might employ or be able to employ.

Herd and Financial Assumptions

Herd size is important in calculating the number of AMS needed. One AMS can handle an estimate 55-70 milking cows. An additional 10% to 12% herd size can be added when including dry cows. Thus, a 72 cow total herd per AMS is typical, depending upon milk production system. Milk price should be estimated as a long term, projected average. Estimated cost per AMS should include new building or modifications to existing structures to house the robot and adequate alleys for cow flow. Area to house the AMS averages \$25,000 per AMS. On average, each AMS costs around \$225,000.

AMS installed in the early 2000's are still in operation. So, “years of useful life” is an unknown variable. Ten years of useful life is a very conservative estimate while more than 15 years may be risky, especially with the rapid development in AMS technology. The value of AMS after its useful life is also not clearly defined at this time. Interest rate on money should represent the cost of interest paid to a bank; or the opportunity cost of the owner's money; or a combination of both over the life of the loan and/or AMS. Insurance rate is the rate per \$1,000 of value of AMS. Value of AMS used for interest and insurance is the full investment value less salvage value.

Labor Changes

One of the leading interest factors of AMS is the reduction of labor. Current hours of milking for the designated herd size in a current milking system need to be compared to the anticipated hours of milking labor after the AMS is installed. Management of labor tends to decrease, too.

Herd Management Software

The herd management software includes rumination data, milk conductivity, and cow activity. This information can lead to savings from heightened heat and mastitis detection and faster identification of sick cows. Pregnancy rates tend to increase. There will likely be an increase in

records management with the AMS to utilize data that might not be available with other milking systems.

Milk Production, Fat, Protein and Quality Changes

Producers may experience losses in milk production six to nine percent lower from 3x milking. From 2x milking, one could expect a three to five percent increase or more. Iowa surveys show a 10% increase on herds not building new facilities. This is a huge variable of AMS financial impact. Somatic Cell Counts (SCC) and bacteria counts tend to increase in the first few months after adoption to the AMS but tends to drop to initial levels or even 20% lower after the adoption period. Milk fat and protein tends to increase.

Feed Costs and Intake Changes

Feed cost per pound and intake level changes are seldom accounted for but can be significant. Milk production and feed intake have a positive correlation. AMS utilize a pelleted feed during milking which may increase feed cost depending but dependent on current TMR. However, feed costs could decrease relative to previous feeding practices since cows are fed more individually with AMS. Producers feeding both a parlor herd and an AMS herd, share feed cost at about \$0.005 higher per lb. DM for the AMS herd.

Culling and Herd Replacement Changes

Producers report a 0-2% decrease in culling percent on average. Higher changes in turnover rate should be expected for herds with poor feet and legs or possibly herds with genetic potential for lots of reverse tilt udders.

Utilities and Supply Changes for Milking

AMS systems may increase electrical usage up to 300 kWh per cow per year. Water usage may decrease for small herds using only one AMS, but water usage is more comparable or higher for herds using two or three AMS. Chemical, teat dip and supply costs tend to be higher.

Quality of Life Experiences with AMS

Not all reasons to install an AMS are financial. Quality of life factors also weigh in as major reasons due to family labor issues, especially labor cost, dependability, availability and flexibility.

Cash Flow Relative to Profitability of AMS

Quite often, AMS has a break-even net financial impact or profit impact. However, even with a break-even profit impact, the implementation of an AMS can give a quite different picture when cash flow is concerned. For many producers, it is like having to prepay your labor for the next 15 years but the banker often make it a 7 year repayment. Thus, the cash flow impact for the first seven years is quite different than the last 8 years when no more payments need to be made.

Summary

AMS usage continues to grow. Many variables determine if AMS can improve profitability over a present system. Milk price, milk production increase and life of the AMS are only a few of the major variables that affect a partial budget comparison of a present milking system versus an AMS. And, even if the AMS can improve profit, the cash flow impact can be quite different.

The use of an activity system to monitor transition cow health on a commercial dairy farm: A case study.

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Introduction

The use of activity monitor systems are becoming increasingly common on dairy farms. While these systems were originally developed as a reproduction management tool, they are increasingly being used as tools for monitoring cow health. Modern activity systems can provide dairy producers with information on cow activity, rumination and eating time, health alerts, temperature, and other critical information for managing individual animals and groups of animals. The transition period of a dairy cow, often defined as the period from 3 weeks before until 3 weeks after calving, is a challenging time for the health, production, and profitability of the dairy cow (Drackley, 1999). In 2014, dairy farmers reported that 20% of cows left the herd within the first 50 days post-calving (USDA-NAHMS, 2018). Metabolic and reproductive health issues associated with the transition period; including displaced abomasum, ketosis, milk fever, dystocia, metritis, and retained placenta, are common causes for early removal of cows from the herd. The main objective of this case study was to evaluate the effectiveness of rumination and activity data from a commercially available activity monitor system during the pre-calving period in detecting cows that suffered health events during post-calving period and potentially left the herd prematurely.

Methods

Holstein dairy cows (n = 422) on a 650-cow dairy farm in southeastern Pennsylvania were fitted with commercially available activity monitor system (SCR; SCR Engineers, Netanya, Israel) from approximately 45 days pre-fresh to 60 days post-fresh. The herd averaged 88 pounds of milk per cow per day with 3.6% fat and 3.0% protein during the study period. Average daily activity and rumination data on individual cows were collected from April 2017 through February 2018. Farm personnel provided calving date, health events, date cow was sold or died, and other relevant health and performance data through on-farm computer records (Dairy Comp 305, Valley Ag Software, Tulare, CA). Based on farm records, cows were divided into 3 groups as determined by their health status following calving. Groups were defined as, 1) NO EVENT = cows that had no early lactation health events reported and remained in the herd for a minimum of 60 days post-calving, 2) RECOVERED = cows with one or more early lactation health event reported but recovered and remained in the herd, and 3) LEFT = cows with one or more early lactation related health events reported and were culled or died within the first 30 days post-calving. For purposes of this study; early lactation health events included metritis, displaced abomasum, retained placenta, ketosis, and milk fever. Preliminary results are presented in the current abstract, statistical analysis of the data are being conducted and will be reported in the final presentation during the conference.

Results and Conclusion

Average daily rumination (Figure 1) and activity (Figure 2) patterns for all cows are shown from 30 days pre-calving until 45 days post-calving. Pre-calving, daily rumination for the herd averaged 490 minutes per cow per day. Average daily rumination and activity patterns were similar across the three groups; however, there were apparent differences in the activity and rumination patterns between groups, during the pre-calving and post-calving periods. Most notably, rumination was numerically lower in cows in the RECOVERED group compared to cows in the NO EVENT group (data not shown). Additionally, activity levels pre-calving were numerically lower for the LEFT group compared to cows in either the NO EVENT or RECOVERED groups (data not shown).

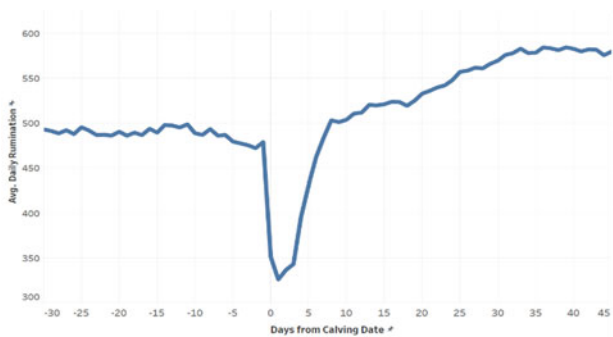


Figure 1. Average daily rumination, all cows.

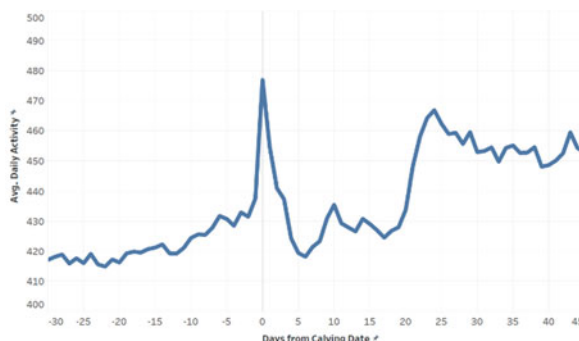


Figure 2. Average daily activity, all cows.

Results indicate that activity and rumination data during the pre-calving period could potentially be used as a tool to help farmers detecting cows that may be at a higher risk of becoming ill or leaving the herd during the first 60 days in milk. This early warning could provide farmers with an opportunity to implement best management strategies for these at-risk animals, allowing them to cope better with transition period challenges, and therefore, decrease the risk of becoming sick or leaving the herd.

References

Drackley, J.K. 1999. Biology of Dairy Cows During the Transition Period: the Final Frontier? *Journal of Dairy Science* 82(11): 2259-2273.

USDA-NAHMS. 2018. Dairy 2014: Health and Management Practices on U.S. Dairy Operations, 2014. Available: https://www.aphis.usda.gov/aphis/ourfocus/animalhealth/monitoring-and-surveillance/nahms/nahms_dairy_studies.

Validation of the RumiWatchSystem to monitor feeding and locomotive behaviors in an organic grazing dairy herd

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Introduction

Many precision technologies may accurately record feeding behavior; however, grazing behavior may be difficult to define because grazing may be considered both active and eating behavior because cows may graze while standing or while walking. Because many precision technologies do not monitor grazing behavior, grazing has not been researched as extensively. Recently in Ireland, a halter and pedometer system (Rumiwatch, Itin and Hoch GmbH, Liestal, Switzerland) were validated for grazing behavior with 92% accuracy (Werner et al., 2018). Alternative grazing environments may provide opportunity for variation in monitoring behaviors. The objective of the study was to validate a halter and pedometer for monitoring feeding and locomotive behaviors by direct visual observation in a grazing dairy herd in Minnesota, USA.

Validation of Rumiwatch

The study was conducted at the University of Minnesota West Central Research and Outreach Center organic dairy in Morris, Minnesota from May to June 2018. Lactating crossbred dairy cows (n = 12) were offered pasture for 22 hours per day and milked twice per day. The pastures were comprised of grasses and legumes that included smooth brome grass, orchardgrass, meadow fescue, alfalfa, red clover, and kura clover. Cows were stocked at a rate of 3 cows per hectare and rotated to a new paddock every 2 days, with 4,834 kg of DM/ha available at the initiation of grazing.

The halter system can classify data as feeding behaviors, including ruminating, eating, drinking and other. In addition, the halter can classify jaw movements as grazing bites or rumination chews. The pedometer, a 3-axis accelerometer, monitors locomotive behaviors such as standing, lying and walking. Data from the halter and pedometer were collected in 10 Hz resolution, and the RumiWatch Converter V.0.7.3.36 transformed data into minute and hour summaries. Observational data were recorded by 3 trained observers on Samsung tablets, using the Pocket observer app (The Observer XT, Version 14.0, Noldus Information Technology, Leesburg, VA). Data from the visual observations were minutes and hour summaries.

The first experiment determined agreement between visual observation and the halter and pedometer. For this experiment, 144 hours of feeding and locomotive behaviors were evaluated. The second experiment evaluated correlation of grazing bites and rumination chews and 1,205 minutes were evaluated between visual observation and the halter system.

Pearson correlations and concordance correlation coefficient (PROC CORR of SAS), bias correction factors (Cb), location shift (V) and scale shift (μ) (epiR package of R software)

evaluated associations between direct visual observations and halter observations (Table 1). Correlations for feeding behavior between visual observations and the halter system were 0.84 ($P < 0.01$) for ruminating, 0.76 ($P < 0.01$) for eating, 0.39 ($P < 0.01$) for drinking, and 0.57 ($P < 0.01$) for other behaviors. Correlations for locomotive behaviors between visual observations and the pedometer were 0.83 ($P < 0.01$) for standing, 0.91 ($P < 0.01$) for lying, and 0.38 ($P < 0.01$) for walking. The correlation between visual observation and the halter system for grazing bites and rumination chews were 0.46 ($P < 0.01$) and -0.04 ($P = 0.79$), respectively. Together grazing bites and rumination chews had a correlation of 0.68 ($P < 0.01$) compared to visual observation.

Conclusions

The results suggest the RumiWatchSystem may accurately monitor rumination and eating, as well as standing and lying behaviors. Behaviors such as drinking and walking were seldom observed and may be difficult to accurately monitor in grazing dairy cattle.

Table 1. Results of feeding and locomotive behaviors from RumiWatch compared to direct visual observations¹ of 12 crossbred dairy cattle

| Item | n | Correlation | <i>P</i> -value | Correction bias | CCC | Location shift | Scale shift |
|-------------------------|-----|-------------|-----------------|-----------------|--------|----------------|-------------|
| Rumination | 144 | 0.84 | 0.01 | 0.99 | 0.83 | -0.12 | 0.88 |
| Eating | 144 | 0.76 | 0.01 | 0.93 | 0.71 | 0.39 | 0.91 |
| Drink | 144 | 0.39 | 0.01 | 0.89 | 0.34 | -0.39 | 0.72 |
| Other | 144 | 0.57 | 0.01 | 0.90 | 0.51 | -0.46 | 0.92 |
| Standing | 134 | 0.83 | 0.01 | 0.87 | 0.73 | -0.53 | 0.93 |
| Lying | 134 | 0.91 | 0.01 | 0.99 | 0.91 | 0.05 | 1.02 |
| Walking | 134 | 0.38 | 0.01 | 0.53 | 0.20 | -1.26 | 0.65 |
| Rumination chews | 43 | -0.04 | 0.79 | 0.18 | -0.007 | -0.08 | 10.9 |
| Grazing bites | 171 | 0.46 | 0.01 | 0.76 | 0.35 | 0.63 | 1.64 |
| Overall bites and chews | 214 | 0.68 | 0.01 | 0.84 | 0.57 | 0.43 | 1.54 |

¹Visual observations and Rumiwatch were compared on an hourly basis, for feeding and locomotive behaviors. For rumination chews and grazing bites, comparison was conducted on a 5-minute basis.

References

Werner, J., L. Leso, C. Umstatter, J. Niederhauser, E. Kennedy, A. Geoghegan, L. Shalloo, M. Schick, and B. O'Brien. 2018. Evaluation of the RumiWatchSystem for measuring grazing behaviour of cows. *J. of Neuroscience Methods* 300:138–146.

Value of Information in Early Lifetime for Prediction of Net Profit from Calf Selection Assessed with Regression and Random Forest Methods

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Introduction

Prediction of future cow profitability based on early available calf information is a valuable tool to dairy farmers for raising the best replacement heifers. Cow profitability is determined by a combination of genetic and environmental factors. Disease events and reduced calf growth negatively impact the likelihood of a heifer to calve and reduces milk production (Schaffer et al. 2016; Chester-Jones et al. 2017). Dairy farmers routinely record body weights and health treatment records to monitor calf growth and health, but few use these records beyond the rearing period. Furthermore, genetic predictions are available for calves as the average genetic value of the parents or through genomic testing. For dairy farmers considering culling surplus heifers, identification of the best animals to raise remains subjective. Linear regression models may be used to predict net profit, but linear assumptions may not hold. The machine learning method of random forest (RF) does not assume data distributions and thrives on large datasets with many predictors. Each method can be used to generate predictions to help cull the lowest heifers, however costs are incurred with each piece of additional information. Therefore, our objective was to determine the value of genetic and phenotypic information in early lifetime for prediction of net profit from calf selection with regression and random forest methods.

Materials and Methods

Data were collected on 3,256 heifer calves born between April 2012 and November 2014 that survived beyond 120 days of age from a single farm in Florida. These records contained genetic parent average estimates and genomic estimates, ordinal variables of health treatment records for respiratory, digestive, otitis, other health events and a combination of all health events and body weights. These data were obtained from the farm's herd management software. The response variables were survival to first calving and cumulative milk production through the second lactation. All animals were allowed 5 years to complete their second lactation. Two models were created for each prediction method. A mixed linear regression model was used for the continuous response of milk production through the second lactation for heifers that calved. The second model was a mixed logistic regression model for the binary response of survival to the first lactation. The RF method was trained with the same response variables in the two-model approach for the continuous and binary response. Predictions by each model were obtained through 10-fold cross-validation with 5 replications of different random splits for unseen test data. The expected net revenue of milk production through the second lactation from selection is the product of predicted milk production given first calving, the probability of survival to first calving and the fraction of heifers calves retained. In addition, costs were applied to each information source for all heifer calves. Net profit is the expected net revenue from selection minus the cost of information, which is equivalent to the value of information.

Results and Conclusion

Net profit from 3 sources of information and both prediction methods are shown in Figure 1. Net profit was very similar between the regression and RF methods in this dataset, indicating similar predictive ability. At low culling levels, the cost of genomic predictions was greater than net revenue, resulting in negative net profit. At higher culling levels, genomic predictions, health and growth combined resulted in the greatest net profit. When 20% of heifer calves were culled, net profit ranged from \$123 to \$256 per retained heifer. Additional sources of information may increase the predictive ability, but are cost dependent. This approach can be expanded to better predict lifetime net profit from selection using other data sources from precision dairy farming and improved prediction methods.

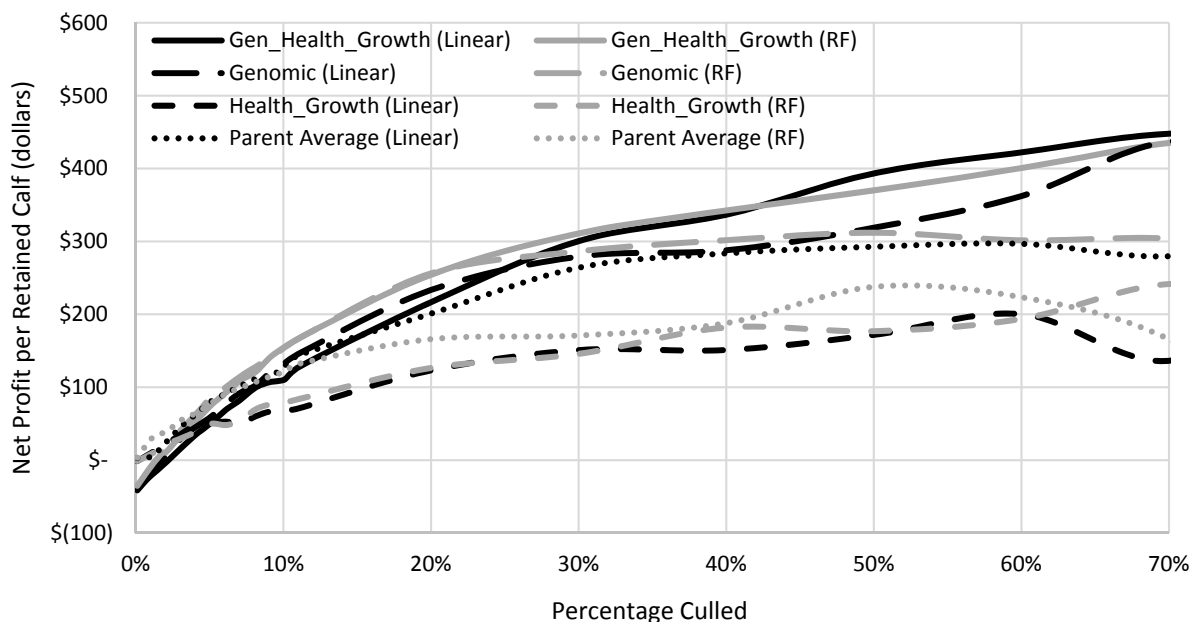


Figure 1. Net profit through the second lactation from culling surplus calves based on predictions from linear regression (Dark) and random forest (Light) methods using data sources of genomic estimates and health and growth (solid), only genomic estimates (long dashed), only health and growth (short dashed) and only parent average genetic estimates (dotted).

References

- Chester-Jones, H., B. J. Heins, D. Ziegler, D. Schimek, S. Schuling, B. Ziegler, M. B. de Ondarza, C. J. Sniffen, and N. Broadwater. 2017. Relationships between early-life growth, intake, and birth season with first-lactation performance of Holstein dairy cows. *J. Dairy Sci.* 100:3697-3704.
- Schaffer, A., R. Larson, N. Cernicchiaro, G. Hanzlicek, S. Bartle, and D. Thomson. 2016. The association between calffood bovine respiratory disease complex and subsequent departure from the herd, milk production, and reproduction in dairy cattle. *JAVMA.* 10:1157-1164.

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