# Conference on Precision Dairy Farming

## Hyatt Regency
## Lexington, KY
## May 30 - June 1, 2017

### A Conference on Precision Dairy Technologies

CONFERENCE & EXPO ON
PRECISION DAIRY FARMING 2017
Hyatt Regency, LEXINGTON, KY
May 30-June 1

*Organized by University of Kentucky and University of Minnesota*

# Precision Dairy 2017

*Organized by:*

University of Kentucky

University of Minnesota
Driven to Discover

# Welcome to the Precision Dairy 2017 Conference and Expo!

On behalf of the organizing committee, we welcome you to the third U.S. Precision Dairy Conference in Lexington, Kentucky.

Adoption of precision technology is really picking up in the U.S. We see quite a bit of growth on cow sensor technologies for disease and heat detection. There is also a lot of interest in data management, precision feeding, automatic milking, inline sensors, calf feeders, and more!
Precision dairy management is the wave of today and the wave of the future. Let's have a great time while learning more about it.

Please visit with our sponsors and speakers while you are here. They have much to share with us. Some came from a long distance to tell us about their research, their farm, or their products. I know some of our 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.

Best wishes for an enjoyable and educational time at the Precision Dairy 2017!

Sincerely,

Jeffrey Bewley, Chair
Department of Animal and Food Sciences
University of Kentucky

Marcia Endres, Co-Chair
Department of Animal Science
University of Minnesota

# Table of Contents

# Agenda

***All events are located in the Patterson Ballroom on Lower Level "B" of the Hyatt Regency Hotel (see hotel map on page 103)***

| Tuesday, May 30th | |
|---|---|
| **Time** | **Topic** |
| 11:00 AM to 1:00 PM | Registration and Trade Show |
| **Session 1 – *Led by Dr. Jeffrey Bewley*** | |
| 1:00 PM | Opening and Welcome |
| 1:10 PM | Integrating Automated Detection of Estrus in Reproductive Management Programs for Dairy Cattle – *Dr. Julio Giordano* |
| 1:55 PM | Ketosis Detection Using Sensor Technology and Integrated Process Data - *Dr. Dana Tomic* |
| 2:20 PM | Lameness Alerting Sensor - *Vivi Thorup* |
| 2:45 PM | Break and Trade Show |
| **Session 2 – *Led by Elizabeth Eckelkamp*** | |
| 3:00 PM | Opportunities for Managing Milk Quality Using Precision Technologies - *Dr. Christina Petersson-Wolfe* |
| 3:45 PM | Producer Panel - Robotics |
| 4:30 PM | Usage of Combined Sensor Information in the Lely Robots in the Daily Practice of the Producer - Arjen van der Kamp |
| 4:55 PM | Transition to Precision Dairy – Jason Troyer |
| 5:20 PM | Cash Bar and Trade Show |
| 6:30 PM | Dinner |
| **Wednesday, May 31st** | |
| 6:30 to 8:00 AM | Continental Breakfast |
| 7:00 AM | Trade Show Opens |
| **Session 3 – *Led by Dr. Bradley Heins*** | |
| 8:50 AM | Welcome and Announcements |
| 9:00 AM | Automated Calf Feeder Systems: What We Learned from Farms in the Upper Midwest USA - *Dr. Marcia Endres* |
| 9:45 AM | Producer Panel – Calf Feeders |
| 10:35 AM | Technology Implementation – *Doug and Mark Stensland* |
| 11:00 AM | Break and Trade Show |

| Session 4 – *Led by Dr. Tyler Mark* | |
|---|---|
| 11:25 AM | Heat Detection with smaXtex – *Dr. Sina Stein* |
| 11:50 AM | Edge Computing and Dairy Farming: Opportunities and Challenges - *Chris Gans* |
| 12:15 PM | Lunch and Trade Show |
| 1:30 PM | New Milk Analysis Technologies to Monitor Management and Improve Herd Performance - *Dr. Heather Dann* |
| 2:15 PM | Genetic and Phenotypic Analysis of Milk, Fat, and Protein Production Based on Real Time Daily Milk Analysis – *Dr. Gil Katz* |
| 2:40 PM | Transportation to UK Coldstream Dairy |
| **Session 5 – *Led by Dr. Jeffrey Bewley*** | |
| 3:25 PM | Overview of UK Coldstream Dairy Technologies and Current Research |
| 5:00 PM | BBQ Dinner |
| 6:30 PM | Transportation to Hyatt Regency Lexington |
| **Thursday, June 1, 2017** | |
| 6:30 to 8:00 AM | Continental Breakfast |
| 7:00 AM | Trade Show Opens |
| **Session 6 – *Led by Dr. Marcis Endres*** | |
| 8:50 AM | Welcome and Announcements |
| 9:00 AM | The Value of Precision Dairy Farming: Going Beyond Labor Savings - *Dr. Henk Hogeveen* |
| 9:45 AM | Producer Panel – Wearables and Stand Alone |
| 10:30 | Break and Trade Show |
| **Session 7 – *Led by Karmella Dolecheck*** | |
| 11:00 AM | Farm Decision Making: Unlocking the Power of Data and Analytics - *Mike Jerred* |
| 11:25 AM | Maximizing Returns from Technology Investments - *Tammie Guyer* |
| 11:50 AM | Wrap-up and Thank You – *Dr. Jeffrey Bewley and Dr. Marcia Endres* |
| 12:00 PM | Adjourn |

## Speakers

**Dr. Julio Giordano, Cornell University**
Dr. Julio Giordano is Assistant Professor of Dairy Cattle Biology and Management in the Department of Animal Science at Cornell University. His expertise is in dairy cattle reproduction, health, and the implications of herd performance on the economics of dairy farms. His basic research focuses on the elucidation of physiological mechanisms controlling reproductive function and changes in physiological parameters during disease in dairy cattle. His applied program incorporates novel technologies to develop new and simplify established reproductive and health management programs for dairy cattle. Through the integration of these basic and applied research components, Dr. Giordano's laboratory strives to enhance the reproductive performance, health, and productivity of cows thus, the economic viability of dairy farms.

**Dr. Dana Tomic, Smartbow**
Dr. Dana Tomic is Innovation and Strategy Manager at Smartbow GmbH. She received her PhD in technical sciences from the Vienna University of Technology (TU Wien). Dana joined Smartbow in 2015, and is contributing to the design of the Smartbow's Big Data Platform and the Digital Strategy. She was the leader of the innovation initiative dadafi.io<http://dadafi.io> and is leading the R&D project agriProKnow.

**Vivi Thorup, IceRobotics**
Dr. Vivi M. Thorup works in precision livestock farming with a particular interest in animal lameness and behaviour. She is Lead Data Analysist at IceRobotics (South Queensferry, United Kingdom) since 2015. At IceRobotics, she develops novel algorithms for detecting health and welfare states of livestock for the CowAlert dairy cow monitoring system, further, she ensures effective design and management of experiments and provides support to costumers within the international research community. Prior to that, she spent 13 years in science in France and Denmark, e.g. developing a model for estimating the energy balance of individual dairy cows based on frequent body weights and body condition scores. She is also chairman of the working group 'Activity Based Welfare Monitoring' in the EU COST Action 'DairyCare'.

**Dr. Christina Petersson-Wolfe, Virginia Tech**
Dr. Christina Petersson-Wolfe is an Associate Professor of Dairy Science at Virginia Tech. She completed her B.S. (Dairy & Animal Science) at Penn State University, M.Sc. (Epidemiology) at the University of Guelph and Ph.D. (Animal Science) at Ohio State University in 2006. Her research interests are focused around mastitis prevention, disease detection and animal well-being. Currently, she has a heavy Extension appointment where she works directly with stakeholders in the field, while also maintaining an active research program.

**Arjen van der Kamp, Lely International**
In 1985 I was born on a farm in the middle of the Netherlands. During my youth I had a fascination for technique and agriculture, so it was not a surprise that I went to study Agricultural engineering which I graduated from in 2010. As part of my study I did an internship at Lely Industries and after graduation I was offered a job at Lely as engineer. As engineer I focused on algorithm development. In 2013 I joined my parents as partner of our farm and at the same moment I changed jobs within Lely and started working for Farm Management Support at Lely International being responsible for the support on the Lely Management software and for Data analysis projects. Here I'm combining my knowledge of data with working on farm to be able to support other farmers.

**Jason Troyer, RJT Dairy Farm**

Jason Troyer lives in Northwestern Pennsylvania. He works on a 215-cow dairy farm with his parents and sister. In the fall of 2015 they installed two AMS Galaxy robots. He grew up on the family dairy farm. After high school, he went to college for four years. After college, he came back to the farm to work full time. His current responsibilities include being the herdsman, maintaining the robots, and helping in the fields. He will by presenting on the transition from milking 115 cows in a double four parlor to 215 cows in a robotic milking system.

**Dr. Marcia Endres, University of Minnesota**

Dr. Marcia Endres is a Professor in the Department of Animal Science at the University of Minnesota with an extension/research appointment. Her research interests include dairy management, welfare and behavior. She has studied how various housing and management systems can influence health, welfare and performance of dairy cattle. In recent years, she has also conducted research and outreach on precision dairy technologies, including robotic milking systems, automated calf feeders and individual cow behavior sensors. She chaired the first US Precision Dairy Conference in 2013 and co-chaired 2015 and 2017 conferences. She teaches two classes in dairy herd management. Dr. Endres has published over 310 popular press articles, 105 scientific abstracts, 120 conference proceedings and 45 peer-reviewed scientific manuscripts. She serves as director on the PAACO (Professional Animal Auditor Certification Organization) board, the national organization that certifies animal welfare audits and auditors, and is Vice-President elect of the Dairy Cattle Welfare Council. Dr. Endres received her Ph.D. from the University of Minnesota, M.Sc. from Iowa State University, and a Veterinary Medicine degree from University Federal of Parana, Brazil.

**Doug and Mark Stensland, Stensland Family Farms**

Doug Stensland is a herd health and robotic operations manager on a dairy in Larchwood, Iowa. Doug has been doing dairy for as long as he can remember, from carrying 5 gallon buckets, to managing the robotic milkers. He has been married to his high school sweet heart Mona for nearly 40 years now. They and their four children run their family business, Stensland Family Farms. He believes the advances in technology on the farm have allowed their dairy to become more efficient which in turn has benefited the herd as they are able to more closely monitor their health and catch any issues before they become too serious. Doug's states that all the advancements on the farm have truly left him blessed; to be able work so closely with all of his family as well as leaving him with a sense of hope that the farm will thrive for generations to come.

**Dr. Sina Stein, smaXtec**

Dr. Sina Stein is agricultural head of the smaXtec product management team and is based at the company’s headquarters in Graz/Austria. She first discovered her passion for dairy cows growing up on her family farm. Sina received her B.S. degree in Agricultural Business and her M.S. in Animal Science from the University of Goettingen. While working on her doctorate at the Department for Animal Nutrition and Animal Health at the University of Kassel, Sina focused on the early detection of subclinical metabolic disorders in transition dairy cows with the help of sensor technologies. After 5 years of working as a Research Assistant she decided to gain experience in the dairy industry and joined smaXtec. She is now responsible for all research activities at smaXtec focused on making continuous and ongoing improvements to the smaXtec product range. Sina still loves to be out in the field, supporting smaXtec farmers all over the world with her expert knowledge of dairy cows and the smaXtec system. Sina´s presentation will give you closer insights into how the smaXtec solution can make a farmer´s life easier and more specifically how estrus detection works using smaXtec technology.

**Chris Gans, Dairy Quality Inc.**
Dairy Quality Inc. is the manufacturer of instant, on farm milk quality testing equipment using smartphone technology. Currently, Dairy Quality's milk quality control devices are distributed and sold in every major dairy market in the world. Chris Gans, the Vice President of Sales and Chief Marketing Officer, has been with Dairy Quality for 3 years. Prior to joining Dairy Quality, Chris worked in the IT industry; specifically, in the data storage solutions and analytics market. Most recently, Chris has been working with the Southeast Quality Milk Initiative (SQMI) organization on a 25-farm pilot project in Kentucky, Tennessee and Virginia to analyze the challenges and opportunities in the use of a hand-held, milk quality testing devices. This partnership will help to determine the importance of the ability to capture raw testing data and transfer it to cloud based data storage for retrieval and integration with herd management systems.

**Dr. Heather Dann, William H. Miner Agricultural Research Institute**
Heather Dann is a research scientist at the William H. Miner Agricultural Research Institute in Chazy, NY. She grew up on a dairy farm in New York where she developed a passion for dairy and an appreciation for research. She received a B.S. degree from Cornell University, a M.S. degree from the Pennsylvania State University, and a Ph.D. degree from the University of Illinois. For the past 13 years, her research at Miner Institute has focused on dairy cow nutrition and management. In addition to research activities, she is active in training and mentoring undergraduate and post-graduate students through a variety of experiential learning programs at Miner Institute.

**Dr. Gil Katz, afimilk**
Gil Katz, sponsored by afimilk. Dr. Gil Katz received his B.Sc. degree in Chemistry from the Hebrew University of Jerusalem in 1991 where he continued for his M.Sc. and his PhD in Theoretical Chemistry in 2002. At the course of his PhD., Gil was leading the group of scientists and engineers that developed the first real time in-line milk analyzer. From 2002 until 2006 Gil was a post doctorate fellow at Northwestern University at the Department of Chemistry working on quantum dynamics in condensed phase. For the last 10 years, Gil is the CSO at afimilk, directing a multidisciplinary research group (including physics, chemistry, biology, computer science, math, statistics, veterinary medicine, epidemiology, physiology and nutrition). The research focuses on properties of raw milk and on pattern behavior of individual and groups of dairy cows. This work is manifested to big data research performed from top to bottom, from new technology for acquiring new data, data-mining methodology, predictive models and algorithms to extract new knowledge and information from data. Gil has numerous scientific publications (peer reviewed journals and books) in fields varying from physical chemistry to food, dairy and animal science.

**Dr. Henk Hogeveen, Wageningen University**
Being raised on a dairy farm, Henk Hogeveen graduated as MSc from Wageningen Agricultural University in 1989. His PhD research was carried out at the Department of Herd Health and Reproduction of the Faculty of Veterinary Medicine of Utrecht University. After that he worked from 1994-2001 at several Dutch research institutes. Since 2001, Henk Hogeveen is working in academia, currently as personal professor at the chair group Business Economics of Wageningen University and the Department of Farm Animal Health of the Faculty of Veterinary Medicine of Utrecht University, where he focuses on the support of decisions on animal health. Since his PhD Henk has been interested in the integration of new technology in dairy farm management.

**Mike Jerred, Cargill Animal Nutrition**
Mike Jerred is a Global Technology Manager - Dairy for Cargill Animal Nutrition where he leads global dairy technology application and deployment. He has been in this role for 7 years after spending 9 years as Dairy Brand Manager. Prior to that he was the Dairy Specialist in the Upper Midwest region of the United States and has been with Cargill for 22 years. His current position allows him to connect his passion for the dairy industry with his interest in global markets along with diet formulation and dairy management software development. Current projects include: MAX™ system and Dairy Enteligen™. His various roles in Cargill have given him the opportunity to visit dairy operations in over 25 countries. Raised on a dairy farm in central Wisconsin, Mike earned a B.S. and M.S. degree from the University of Wisconsin – Madison in Dairy Science where he worked primarily in the area of high quality forage utilization. Prior to his work at Cargill, he worked for 3 years as a dairy nutritionist in western Wisconsin and 2 years managing the dairy farm where he was raised.

**Tammie Guyer, Dairy Records Management Systems**
Tammie Guyer received her B.S.in Agricultural Systems Technology from Cornell University and currently serves as the Assistant Manager of User Support Services with Dairy Records Management Systems (DRMS) in Raleigh, NC, where she provides support for PCDART, PocketDairy, PocketMeter, and other DRMS products and services. Tammie's main focus is working with PCDART and its interface with milking and heat monitoring systems. She frequently travels to conferences to train producers, technicians and consultants on the newest aspects of DRMS software. Prior to DRMS, Tammie owned her own business as a computer trainer and support technician in Texas. She has served as a research support specialist with Cornell University and conducted research on the Cornell Net Carbohydrate and Protein System, a ruminant nutrition model. Tammie grew up on a small dairy farm in New York State.

# Producer Panelists

**Dore Baker: Robotics**
Dore Baker is from Chaney's Dairy Farm, located in Glasgow, Kentucky. Dore originally grew up on a dairy farm in Western New York. The current farm has about 60 cows, which is enough to keep the robot full. Chaney' s Dairy Farm was not originally a dairy farm when established in 1886, but dairy was incorporated in 1940 with two Jersey cows. This dairy has been using robots since June 14, 2016.

**Kyle Abel: Robotics**
Kyle Able is from Abel Acres HD, located in Loyal, Wisconsin. Abel Acres HD has 689 animals on their farm. They milk 125 robotically and 185 through a double six flat barn/step up parlor. The rest of the animals are either dry cows (50) or young stock for replacements. Kyle is a third generation farmer, but has been farming full time himself since May of 2010, when he graduated from UW Madison Farm and Industry Short Course. Kyle has been using the DeLaval milking robot since August 16, 2016.

**Eddie Gibson: Robotics**
Eddie Gibson is from EdMar Dairy Farm, located in Walton, Kentucky. This dairy owns 55 cows total. They have been farming for 35 years and have been using the Lely milking robot for 2 years in November, 2017.

**David Corbin: Automated Calf Feeder**
David Corbin is from Corbin Dairy Farm, located in Taylor County, Kentucky. They have a total of 293 cows. David has been farming for about 60 years and has been using the calf feeder technology for about 5 years.

**Michael Hunt: Automated Calf Feeder**
Michael Hunt is from H&S Dairy, located in Morgantown, Kentucky. They have a total of 275 cows on the dairy and have been farming since 1981. Michael has been using the calf feeder technology since September 2015.

**Jerry Gentry: Automated Calf Feeder**
Jerry Gentry is from Gentry Dairy Farm, located in Pulaski County, Kentucky. The farm has a total of 65 cows. Jerry has been in the dairy industry for 68 years and has been using the calf feeder technology for two years.

**Stacy Sidebottom: Wearables**
Stacy Sidebottom is from Sidebottom Dairy Farm, located in Greensburg, Kentucky. The farm has a total of 240 cows. Stacy has been farming since 1981, but started milking in 1985. Stacy has been using the Alta Genetics CowWatch neck and leg technologies for 1.5 years.

**Jeff Core: Wearables**
Jeff Core is from Keightley and Core Jerseys, located in Salvisa, Kentucky. The dairy has a total of 250 cows. Jeff Core has been farming for about 50 years and has been using the Select Sires CowManager technology for about 3 to 4 years.

**Joey Clark: Wearables**
Joey Clark is from the University of Kentucky Coldstream Dairy, located in Lexington, Kentucky. The farm has a total of 119 cows. Joey has been the herdsman at the University of Kentucky for 11 years and has been using multiple technologies for 7 years.

# Conference Planning Committee

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## Sponsors

***We are extremely grateful to all of our sponsors! Without your support, this event would not be possible.***

***All sponsor booths are located in the Patterson Ballroom on Lower Level "B" of the Hyatt Regency Hotel*** ***(see hotel map on page 103)***

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# Integrating Automated Detection of Estrus in Reproductive Management Programs for Dairy Cattle

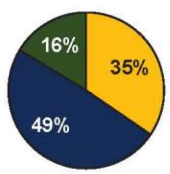
**Julio Giordano, DVM, MS, PhD**
**Assistant Professor**
**Dairy Cattle Biology & Management**
Cornell University
Department of Animal Science

# Outline

1. **Role of estrus detection and automated estrus detection (AED) in reproductive management**
2. **Research on integration of AED in reproductive management**
3. **Potential strategies to incorporate AED in management programs**

# Estrus Detection in Dairy Herds

| Study | Use of Estrus Detect. % of farms |
|---|---|
| Caraviello et al., 2006 | 100 (n = 153) |
| Skidmore and Ferguson, 2013 | 100 (n = 16) |
| Scott and Giordano, (unpublished) | 1st AI: 67 (n = 55)<br>2+ AI: 100 (n = 55) |

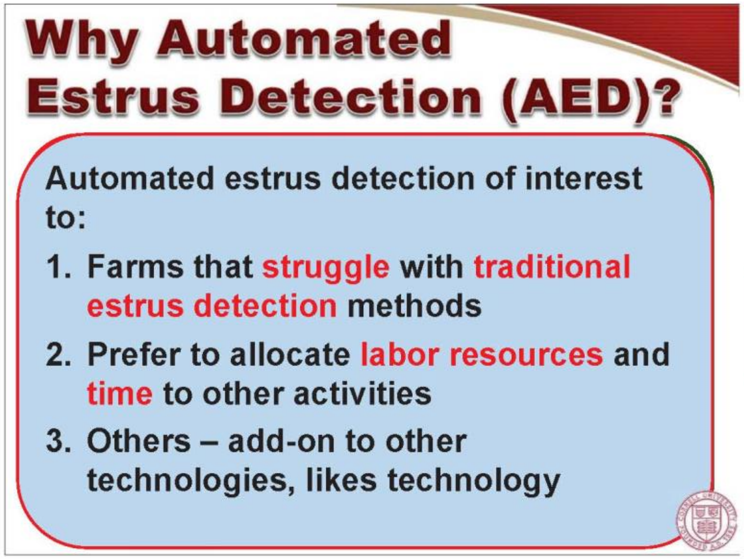


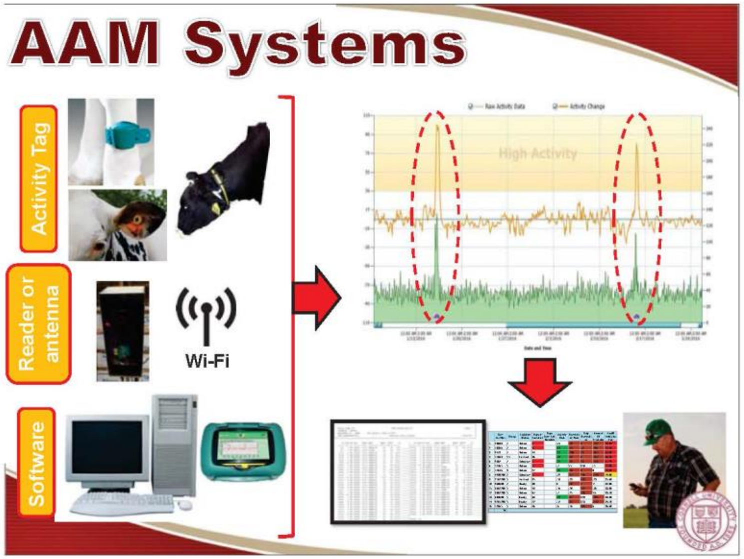

N = 55 farms
63,238 cows
Scott and Giordano, (unpublished)

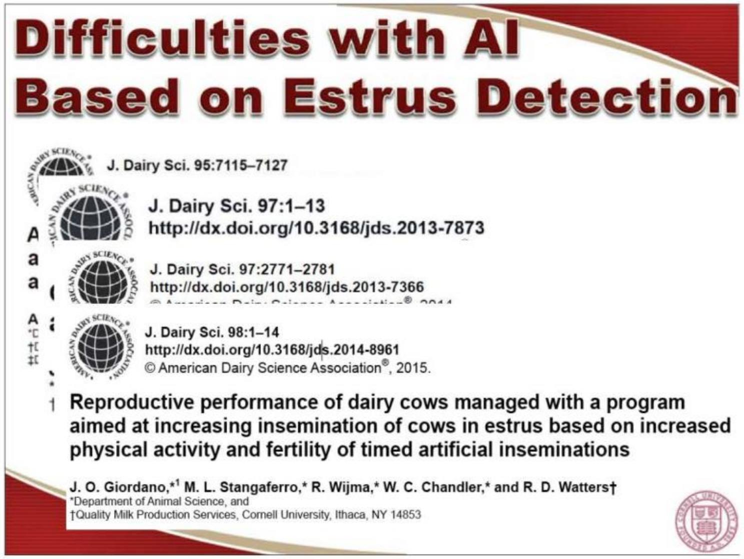
# Why Automated Estrus Detection (AED)?

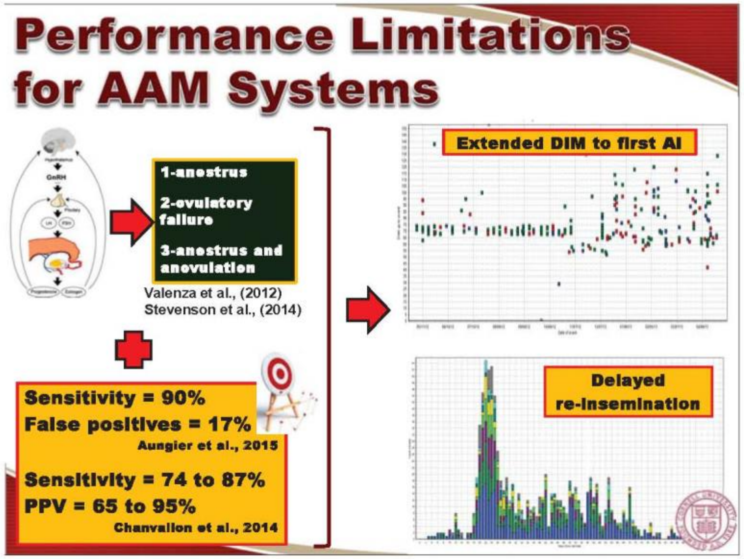
**Difficulties with traditional methods**
- Poor compliance
- Subjectivity of method
- Variation among cows
- Labor intensive and repetitive

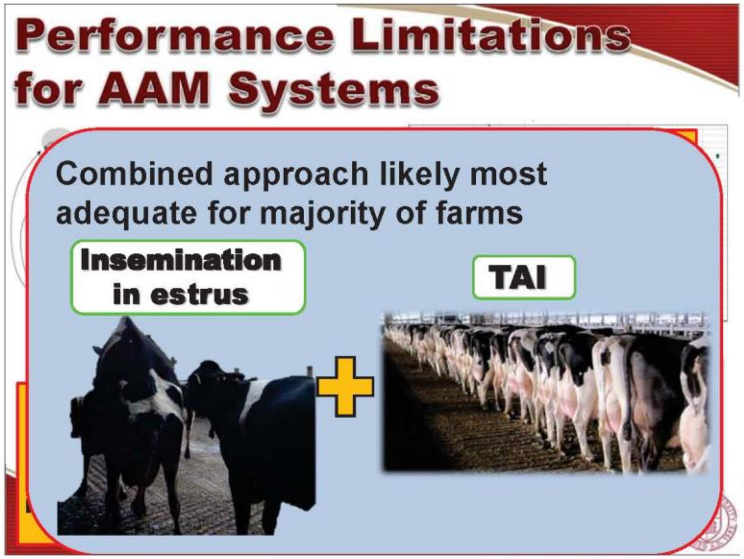
**Potential benefits of AED systems**
- Continuous monitoring
- Objective evaluation of behavior or physiological status
- Elimination or substantial labor reduction

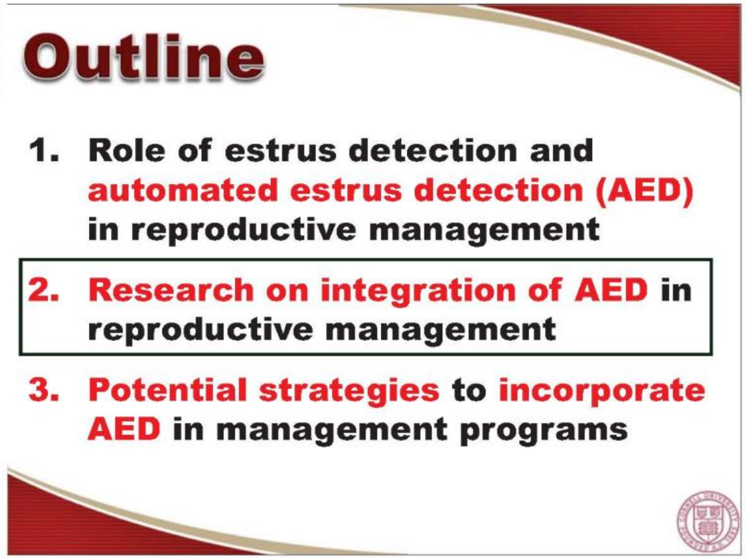

Why Automated
Estrus Detection (AED)?
Automated estrus detection of interest to:
1. Farms that struggle with traditional estrus detection methods
2. Prefer to allocate labor resources and time to other activities
3. Others – add-on to other technologies, likes technology

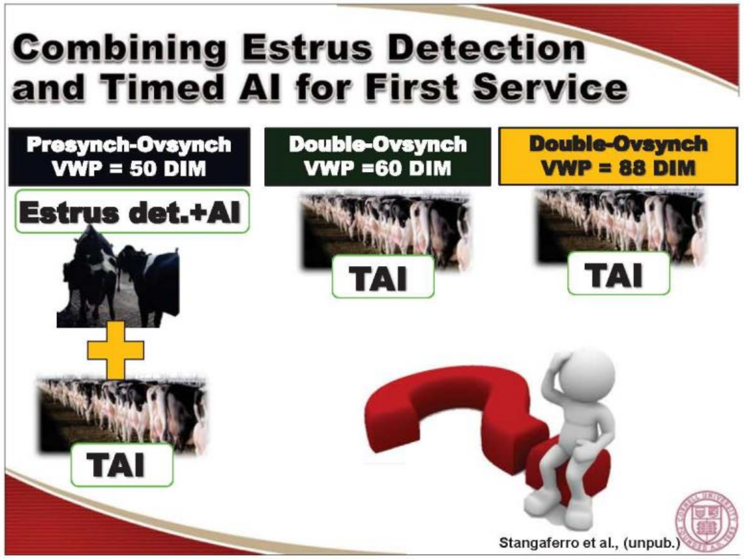

AAM Systems
Activity Tag
Reader or antenna
Wi-Fi
Software
High Activity

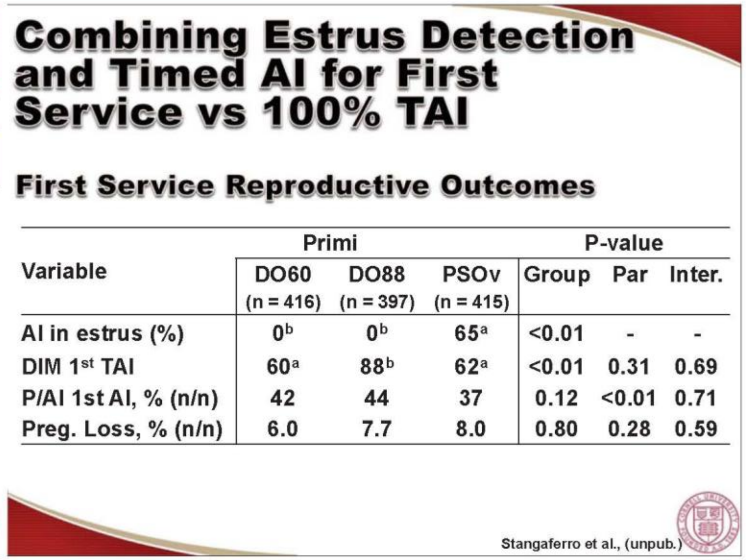

Difficulties with AI
Based on Estrus Detection
J. Dairy Sci. 95:7115–7127
J. Dairy Sci. 97:1–13
http://dx.doi.org/10.3168/jds.2013-7873
J. Dairy Sci. 97:2771–2781
http://dx.doi.org/10.3168/jds.2013-7366
J. Dairy Sci. 98:1–14
http://dx.doi.org/10.3168/jds.2014-8961
© American Dairy Science Association®, 2015.
Reproductive performance of dairy cows managed with a program aimed at increasing insemination of cows in estrus based on increased physical activity and fertility of timed artificial inseminations
J. O. Giordano,*1 M. L. Stangaferro,* R. Wijma,* W. C. Chandler,* and R. D. Watters†
*Department of Animal Science, and
†Quality Milk Production Services, Cornell University, Ithaca, NY 14853


Performance Limitations
for AAM Systems
1-anestrus
2-ovulatory failure
3-anestrus and anovulation
Valenza et al., (2012)
Stevenson et al., (2014)
Sensitivity = 90%
False positives = 17%
Aungier et al., 2015
Sensitivity = 74 to 87%
PPV = 65 to 95%
Chanvallon et al., 2014
Extended DIM to first AI
Delayed re-insemination



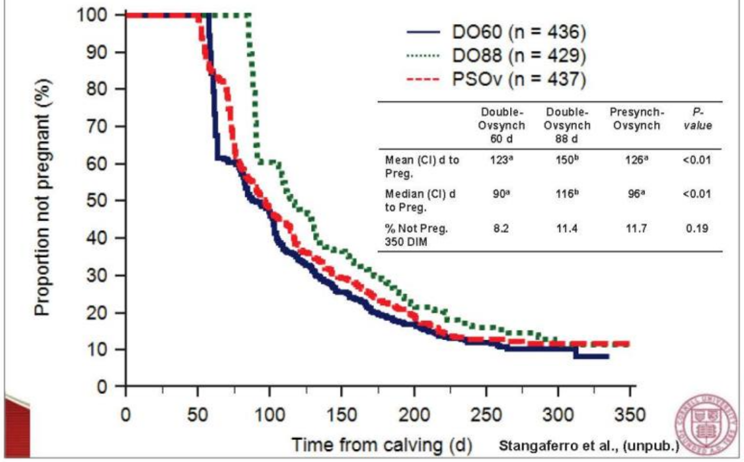




| Variable | Primi | | | P-value | | |
|---|---|---|---|---|---|---|
| | DO60 (n = 416) | DO88 (n = 397) | PSOv (n = 415) | Group | Par | Inter. |
| AI in estrus (%) | 0[b] | 0[b] | 65[a] | <0.01 | - | - |
| DIM 1st TAI | 60[a] | 88[b] | 62[a] | <0.01 | 0.31 | 0.69 |
| P/AI 1st AI, % (n/n) | 42 | 44 | 37 | 0.12 | <0.01 | 0.71 |
| Preg. Loss, % (n/n) | 6.0 | 7.7 | 8.0 | 0.80 | 0.28 | 0.59 |

**Integrating Automated Detection of Estrus in Reproductive Management Programs for Dairy Cattle**
***Dr. Julio Giordano, Cornell University***

## Time to Pregnancy During Lactation




| | Double-Ovsynch 60 d | Double-Ovsynch 88 d | Presynch-Ovsynch | *P-value* |
|---|---|---|---|---|
| Mean (CI) d to Preg. | 123[a] | 150[b] | 126[a] | <0.01 |
| Median (CI) d to Preg. | 90[a] | 116[b] | 96[a] | <0.01 |
| % Not Preg. 350 DIM | 8.2 | 11.4 | 11.7 | 0.19 |

## Combining Estrus Detection and Timed AI for First Service

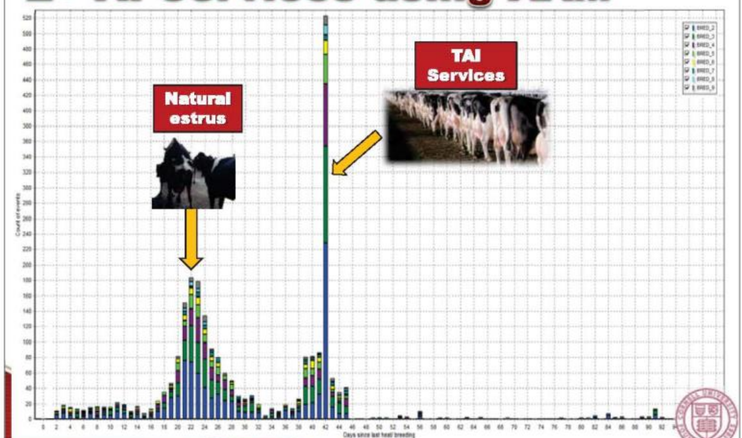
**(Stangaferro et al., unpublished)**

### Summary:

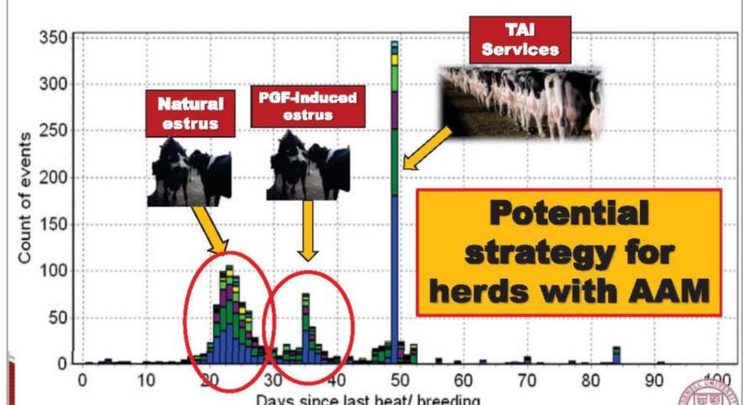
**Combining detection of estrus with activity monitors (and some visual observation) and TAI through a Presynch-Ovsynch protocol resulted in similar time to pregnancy during lactation than Double-Ovsynch (DO) with a VWP of 60 days and reduced time to pregnancy when compared with DO with a VWP of 88 d. However, results for DO with a VWP of 88 d should be taken with caution because conception rate was not improved as expected by extending the duration of the VWP at this farm.**

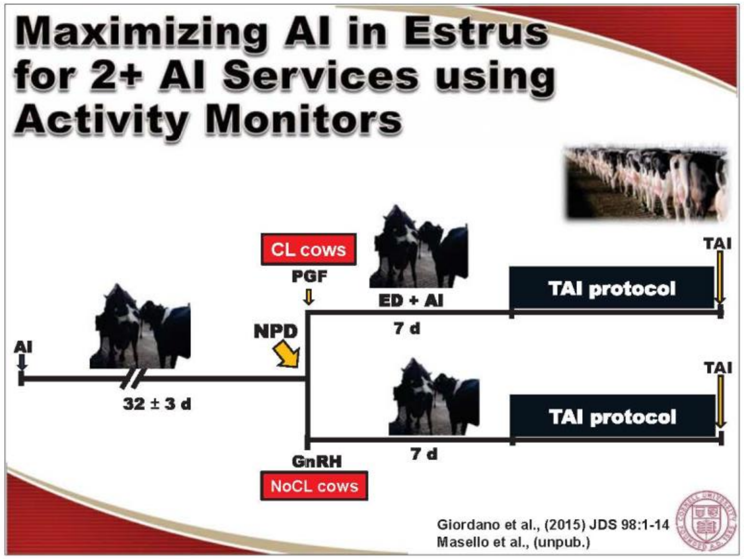
**Economic impact of each strategy needs to be determined.**

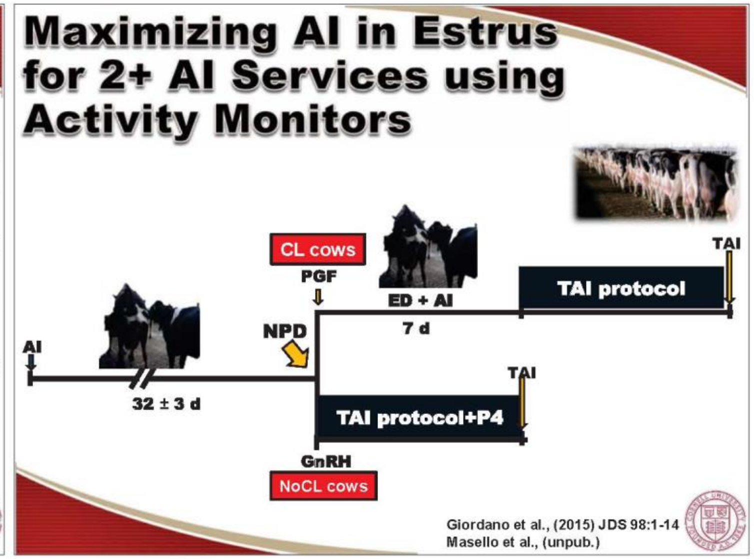
## Maximizing AI in Estrus for 2+ AI Services using AAM




## Maximizing AI in Estrus for 2+ AI Services using AAM




Maximizing AI in Estrus for 2+ AI Services using Activity Monitors
CL cows
PGF
ED + AI
7 d
TAI protocol
TAI
AI
32 ± 3 d
NPD
TAI
7 d
TAI protocol
GnRH
NoCL cows
Giordano et al., (2015) JDS 98:1-14
Masello et al., (unpub.)


Maximizing AI in Estrus for 2+ AI Services using Activity Monitors
CL cows
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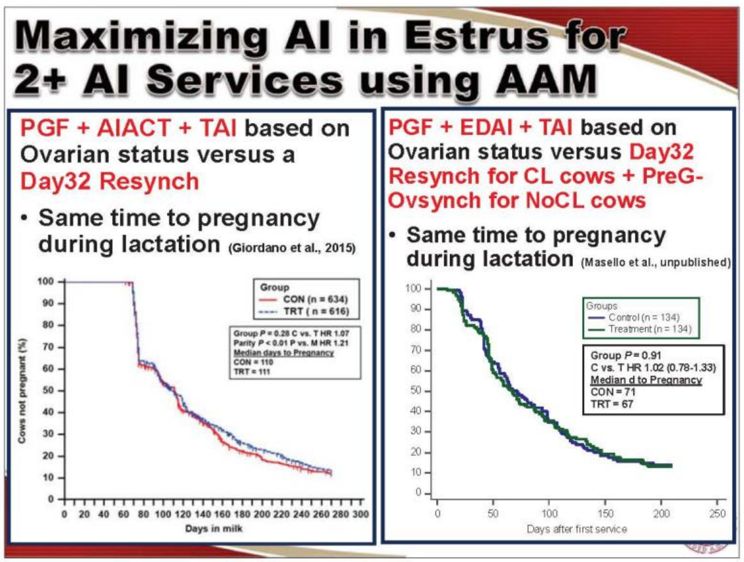
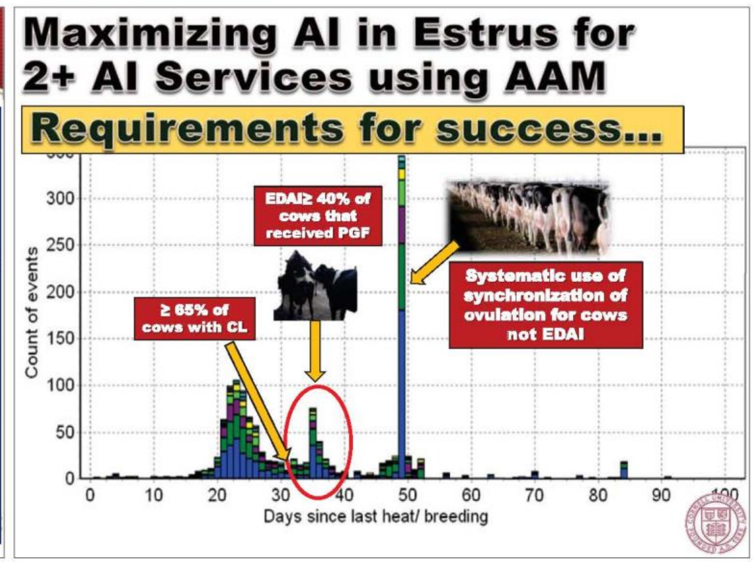
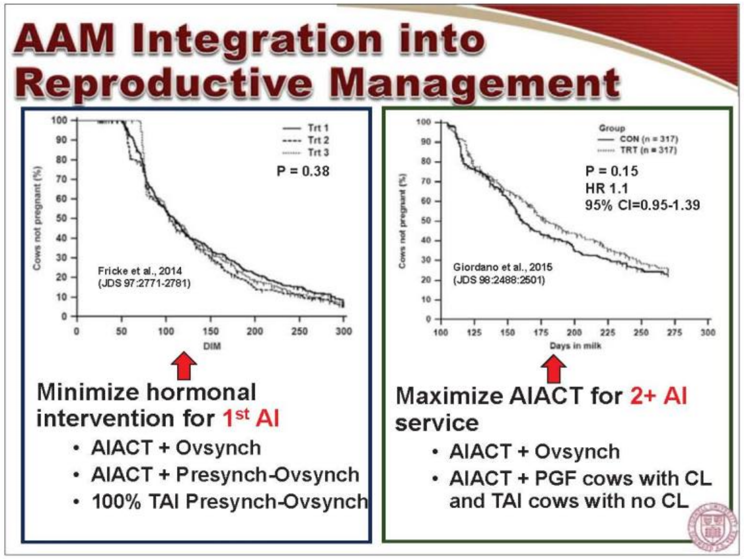
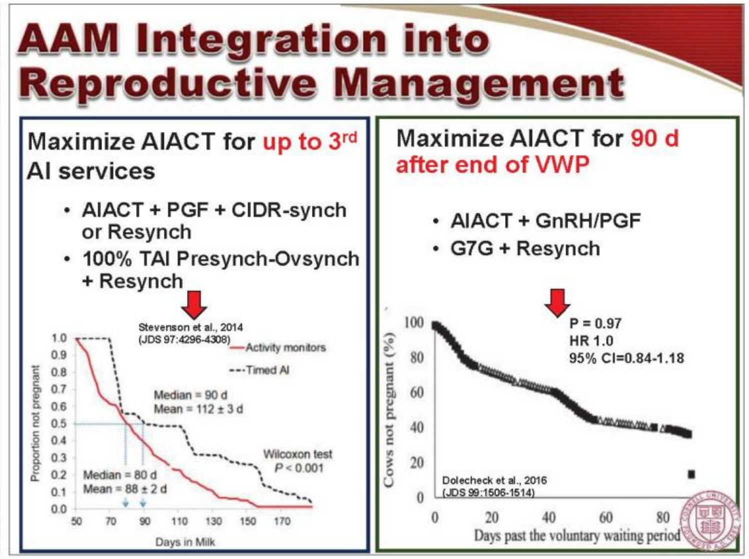
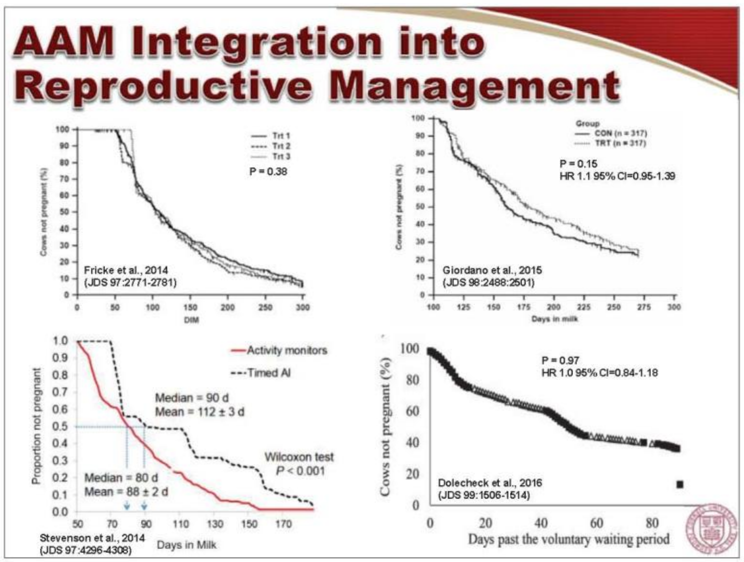

Maximizing AI in Estrus for 2+ AI Services using AAM
PGF + AIACT + TAI based on Ovarian status versus a Day32 Resynch
• Same time to pregnancy during lactation (Giordano et al., 2015)
Cows not pregnant (%)
Days in milk
Group
CON (n = 634)
TRT (n = 616)
PGF + EDAI + TAI based on Ovarian status versus Day32 Resynch for CL cows + PreG-Ovsynch for NoCL cows
• Same time to pregnancy during lactation (Masello et al., unpublished)
Groups
Control (n = 134)
Treatment (n = 134)
Group P = 0.91
C vs. T HR 1.02 (0.78-1.33)
Median d to Pregnancy
CON = 71
TRT = 67
Days after first service


Maximizing AI in Estrus for 2+ AI Services using AAM
Requirements for success...
EDAI≥ 40% of cows that received PGF
≥ 65% of cows with CL
Systematic use of synchronization of ovulation for cows not EDAI
Count of events
Days since last heat/ breeding


AAM Integration into Reproductive Management
P = 0.38
Fricke et al., 2014
(JDS 97:2771-2781)
Minimize hormonal intervention for 1st AI
• AIACT + Ovsynch
• AIACT + Presynch-Ovsynch
• 100% TAI Presynch-Ovsynch
Group
CON (n = 317)
TRT (n = 317)
P = 0.15
HR 1.1
95% CI=0.95-1.39
Giordano et al., 2015
(JDS 98:2488:2501)
Days in milk
Maximize AIACT for 2+ AI service
• AIACT + Ovsynch
• AIACT + PGF cows with CL and TAI cows with no CL


AAM Integration into Reproductive Management
Maximize AIACT for up to 3rd AI services
• AIACT + PGF + CIDR-synch or Resynch
• 100% TAI Presynch-Ovsynch + Resynch
Stevenson et al., 2014
(JDS 97:4296-4308)
Activity monitors
Timed AI
Median = 90 d
Mean = 112 ± 3 d
Wilcoxon test
P < 0.001
Median = 80 d
Mean = 88 ± 2 d
Proportion not pregnant
Days in Milk
Maximize AIACT for 90 d after end of VWP
• AIACT + GnRH/PGF
• G7G + Resynch
P = 0.97
HR 1.0
95% CI=0.84-1.18
Cows not pregnant (%)
Dolecheck et al., 2016
(JDS 99:1506-1514)
Days past the voluntary waiting period


AAM Integration into Reproductive Management
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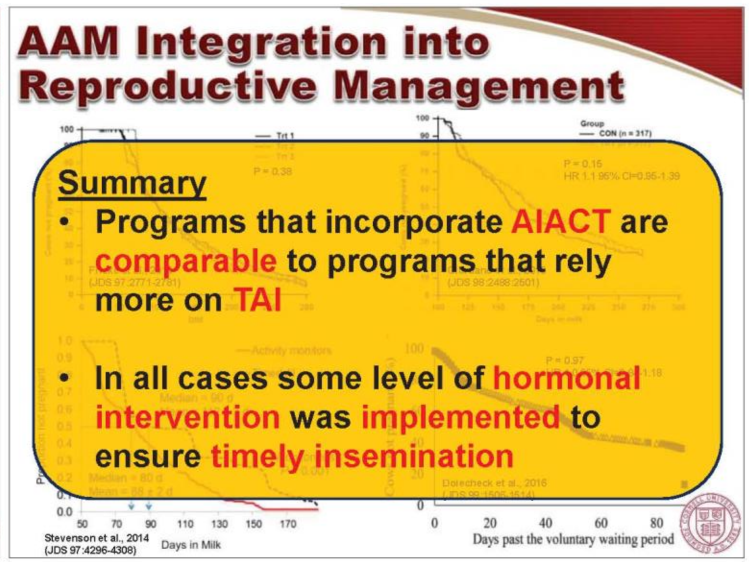
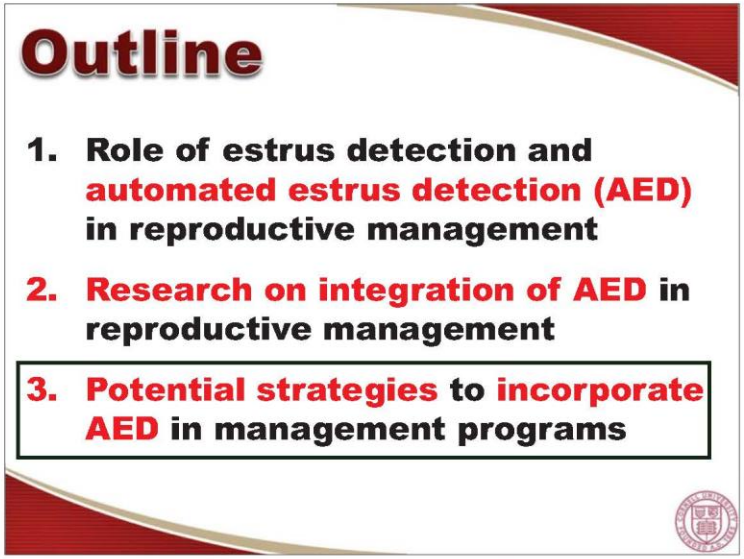
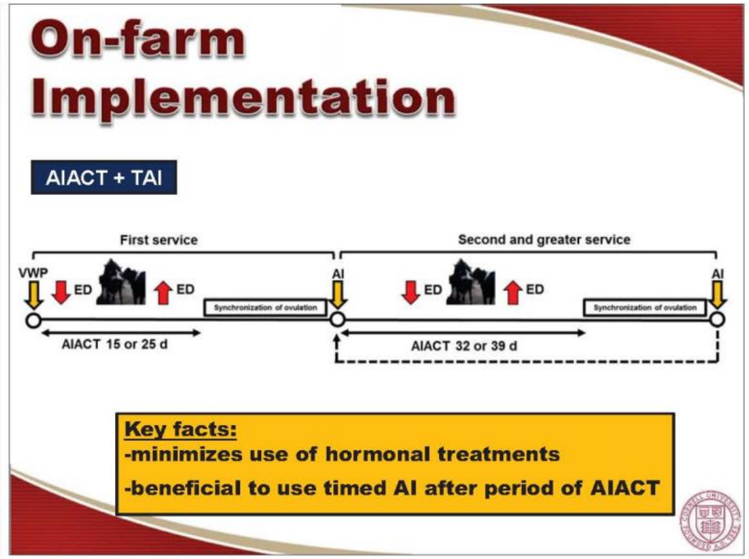
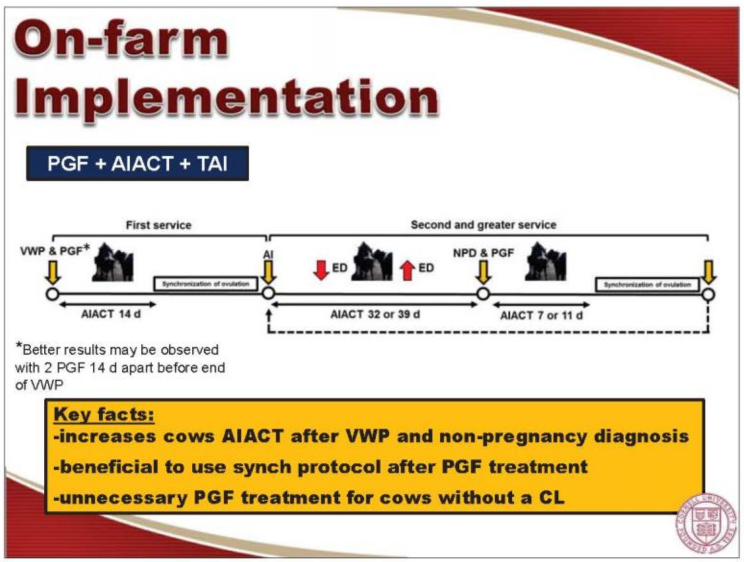
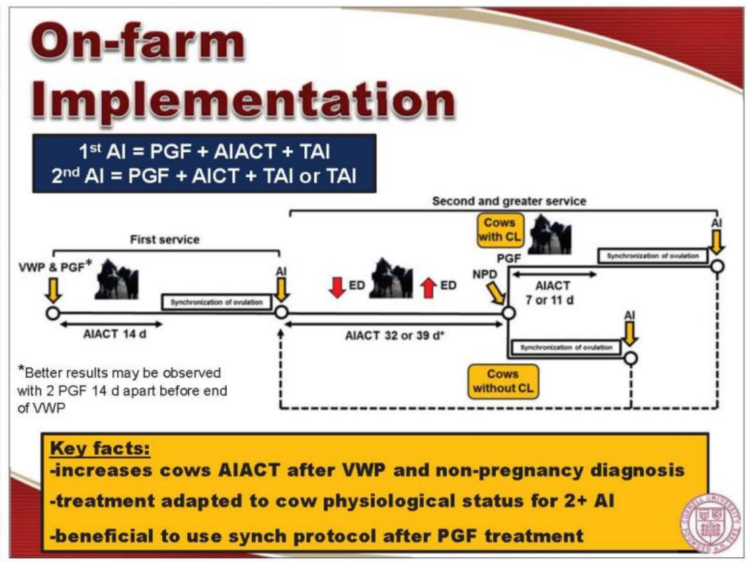

AAM Integration into Reproductive Management
Summary
• Programs that incorporate AIACT are comparable to programs that rely more on TAI
• In all cases some level of hormonal intervention was implemented to ensure timely insemination
Stevenson et al., 2014
(JDS 97:4296-4308)
Days in Milk
Days past the voluntary waiting period

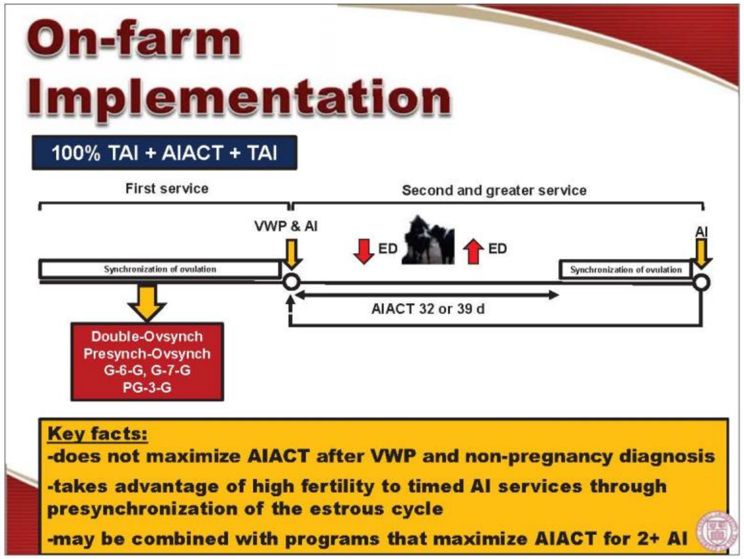
**Integrating Automated Detection of Estrus in Reproductive Management Programs for Dairy Cattle**
***Dr. Julio Giordano, Cornell University***

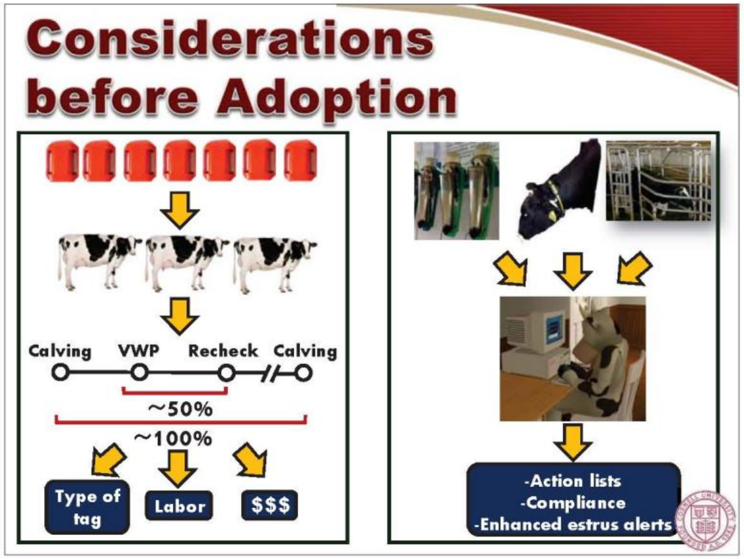


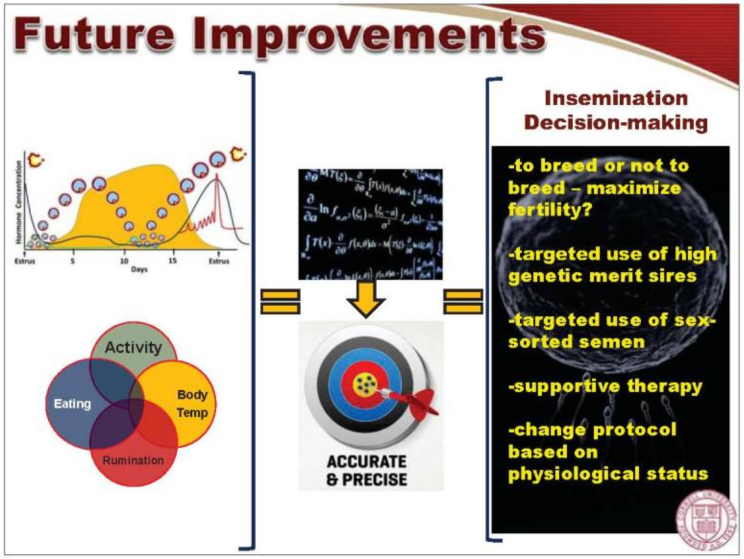



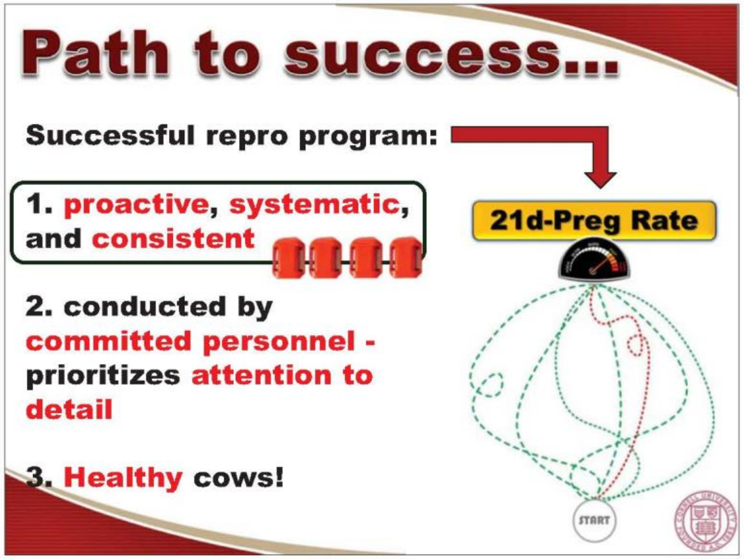




On-farm Implementation
100% TAI + AIACT + TAI
First service
Second and greater service
VWP & AI
ED
ED
AI
Synchronization of ovulation
Synchronization of ovulation
AIACT 32 or 39 d
Double-Ovsynch
Presynch-Ovsynch
G-6-G, G-7-G
PG-3-G
Key facts:
-does not maximize AIACT after VWP and non-pregnancy diagnosis
-takes advantage of high fertility to timed AI services through presynchronization of the estrous cycle
-may be combined with programs that maximize AIACT for 2+ AI

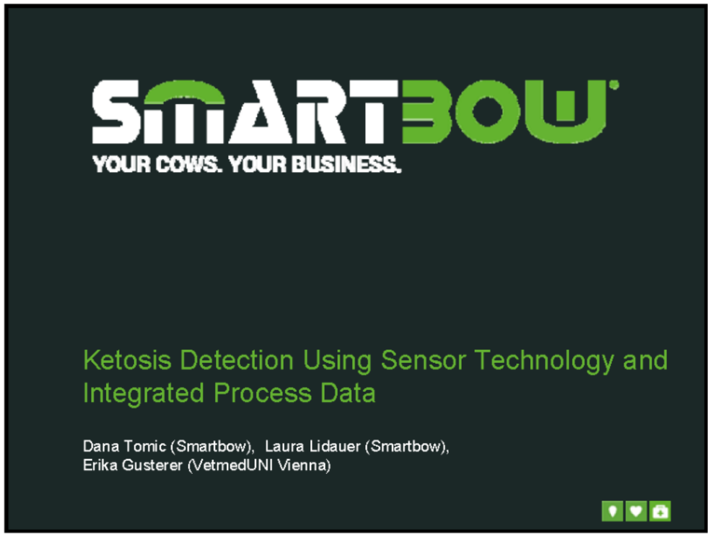

Considerations before Adoption
Calving
VWP
Recheck
Calving
~50%
~100%
Type of tag
Labor
$$$
-Action lists
-Compliance
-Enhanced estrus alerts


Future Improvements
Insemination Decision-making
-to breed or not to breed – maximize fertility?
-targeted use of high genetic merit sires
-targeted use of sex-sorted semen
-supportive therapy
-change protocol based on physiological status
Activity
Eating
Body Temp
Rumination
ACCURATE & PRECISE


Path to success...
Successful repro program:
1. proactive, systematic, and consistent
2. conducted by committed personnel - prioritizes attention to detail
3. Healthy cows!
21d-Preg Rate
START


Thank you!
Cornell University
Department of Animal Science
Julio Giordano
http://blogs.cornell.edu/giordano/
jog25@cornell.edu

**Ketosis Detection Using Sensor Technology and Integrated Process Data**
***Dr. Dana Tomic, Smartbow***






# KETOSIS

SMARTBOW
YOUR COWS. YOUR BUSINESS.

The most important metabolic disease in cattle with serious consequences

- occurs in cattle when energy demands (e.g. high milk production) exceed energy intake and result in a negative energy balance. Ketotic cows often have low blood glucose (blood sugar) concentrations.

Primary ketosis

- *Starvation ketosis*
- *Overfeed ketosis*

Secondary ketosis

- *Following a primary disease, e.g. milk fever, mastitis, metritis, ruminal acidosis, or a displaced abomasum*

Alimentary ketosis

- *Wrong feeding*
- *High butyric acid content in silage - faulty fermentation)*

Clinical Form

- *↓ Appetite; ↓ Rumination; ↓ Omasum activity; Rumen standstill*
- *↓ Milk output*
- *Constipation, dark, clotted faeces, also possibly diarrhoea*
- *Emaciation; apathy*
- *Ketosis smell*

Subclinical Form

- *No symptoms of the clinical form*
- *Ketone body in blood, urine, milk ↑↑↑*
- *Glucose ↓*

# EFFECTS OF KETOSIS

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Incurred Costs *(Geishauer et al., 2000)*

- *Subclinical: 50 € / disease*
- *Clinical: 125 € / disease*

Milk yield loss

- *Loss of 60-70 kg of milk in 14 days (Lucey and Rowlands, 1983)*
- *5.7 kg of milk loss per day in the first 49 days of lactation (Lean et al., 1994)*

Fertility loss

- *First ovulation 10 days later comp. to healthy animals (Schilling, 1976)*
- *Fertility rate: 42% (healthy animals: 92%) (Refsdal, 1977)*
- *Time and interim duration significantly increased by 12 and 6 days, respectively (Klug et al., 1989)*

Health loss

- *82.4% of the ketosis cows at least one other disease (Markusfeld, 1985)*
- **Increased risk of ketosis occurring as a result of**
  - *abomasum displacements*
  - *Afterbirth retention*
  - *mastitis*
  - *previous ketosis (Erb and Grohn 1988).*
- **Trigger disease for:**
  - *Ovarial cysts (Andersson et al., 1991)*
  - *Claw disease (Schuler et al., 1990, Staufenbiel 2001)*
  - *Recumbency (Staufenbiel 2001)*
  - *Displaced abomasum (Staufenbiel 2001)*
  - *Mastitis (Danuser et al., 1988)*

# KETOSIS

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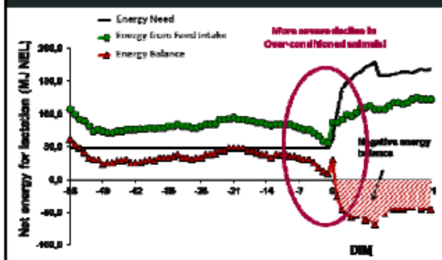



Increase in glucose requirements:

- *Pregnancy: 30%*
- *Peak lactation: 75%*

Primary ketosis

- *2-8 weeks. p.p. → peak lactation*
- *Lactation peak: 4-6 wk. p.p.*
- *Max feed intake ~. 8 wk. p.p.*

Indicated by increased concentration of ketone bodies

- *acetone*
- *acetoacetate*
- *Beta-hydroxybutyrate (BHB)*
  - *Detectable in blood, milk, urine*

Subclinical

*≥ 1.2 mmol / L and ≥ 1.4 mmol / L, (Geishauser et al., 1998; Duffield et al., 2009)*

Clinical

*≥ 3 mmol / L (Oetzel, 2004)*


# KETOSIS

SMARTBOW
YOUR COWS. YOUR BUSINESS.

Therapeutic possibilities

- *Correct feeding / offer tasty food*
- *Treat primary disease*
- *Glucose infusion; Glucocorticoids*
- *Glucoplastic substances (propylene glycol, sodium propionate)*
- *Raspberry juice / Rumen stimulants*
- *Stimulate more activity*
- *Vitamin B, Vitamin E / Selenium*

Prophylaxis

***Correct feeding***

- *Avoid fatty A.P. (calving at BCS 3.5)*
- *Divide drying time in 2 phases*
  - *TS to 4 weeks A.P. → Roughing*
  - *3 weeks A.P. To birth → daily 0.25kg more KF*

***Monitor***

- *Milk protein as an indicator of energy supply*
- *Ketone bodies (milk, urine)*

***Prevent***

- *Preventive treatment with propylene glycol*

Forecast

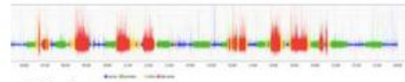
- *Primary ketosis:* **favorable prognosis**
  - *- Usually healing without direct consequences and consequential damage*
  - *- Indirect effects (emaciation, hepatic impairment, ..) are partly limiting*
- *Secondary ketosis,* ***depending on primary disease***

## OUTLINE

- The SMARTBOW system
- Imperative of Preventing Ketosis
- **Practical Insights from Rumination Monitoring**
- Improving Prevention by Sensors & Integrated Process Data
- Conclusions and Future Work

## RUMINATION MONITORING

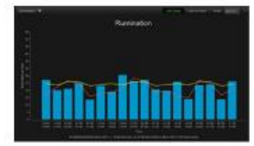
- Movement of ears during characteristic jaw movements



- Algorithm gives out 2 different alerts:
  - Urgent rumination alert: drop of rumination activity within 24 hours
  - Long term rumination alert: drop of rumination activity over more than 1 day

- System captures rumination times and trends on herd level

  *Minutes per day*




## RUMINATION ACTIVITY

- Evaluated at several experimental farms and universities

  *(UK, VetmedUni)*

- Publication in the Journal of Dairy Science (UK):
  - *A validation of technologies monitoring dairy cow feeding, ruminating, and lying behaviors, Borchers, M.R. et al. Journal of Dairy Science, Volume 99, Issue 9, 7458 – 7466*

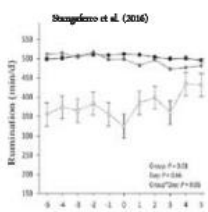

***"Visually recorded rumination activities were strongly correlated with the Smartbow (r = 0.97, CCC = 0.96)"***

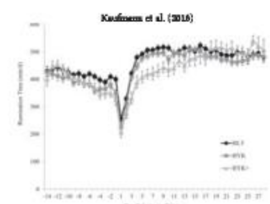
- *Reiter et al. (2017). Evaluation of an ear tag based accelerometer for monitoring rumination in dairy cows. (submitted for publication)*

***Very good accuracy of Smartbow detection of rumination activity compare to real time and video recorded rumination activities detected***
***( r=0,99, P<0.01)***

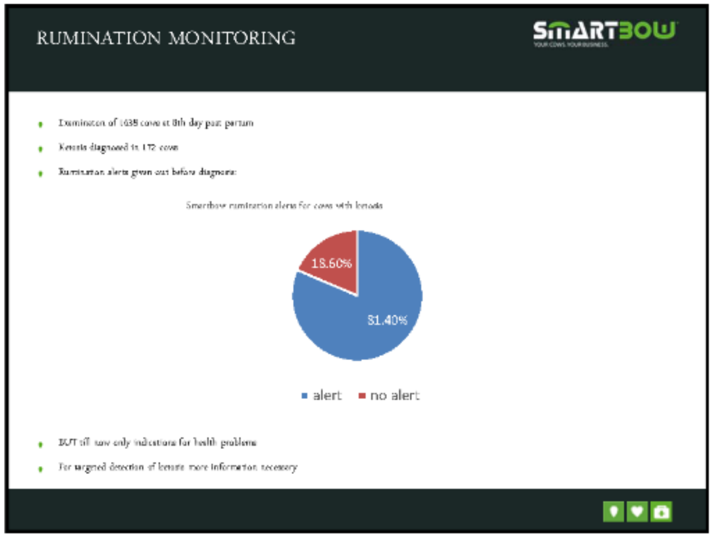
## RUMINATION MONITORING

- Promising results of various studies using rumination monitoring for disease detection and health prevention
  - **Metabolic diseases**




  - **Mastitis**
  - **Metritis detection (Stangaferro et al., 2016)**
  - **Health disorders around calving (Kaufmann et al., 2016; Calamari et al., 2014)**


RUMINATION MONITORING
Examination of 1638 cows at 8th day post partum
Ketosis diagnosed in 172 cows
Rumination alerts given out before diagnosis:
Smartbow rumination alerts for cows with ketosis
18.60%
81.40%
alert
no alert
BUT till now only indications for health problems
For targeted detection of ketosis more information necessary


OUTLINE
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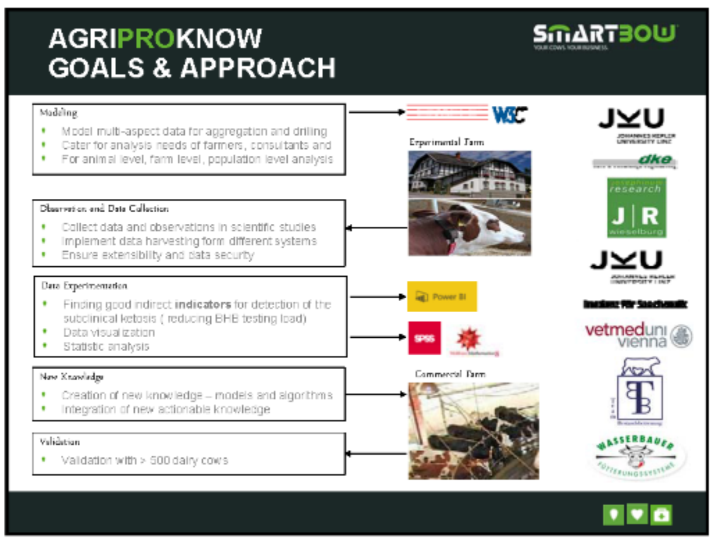
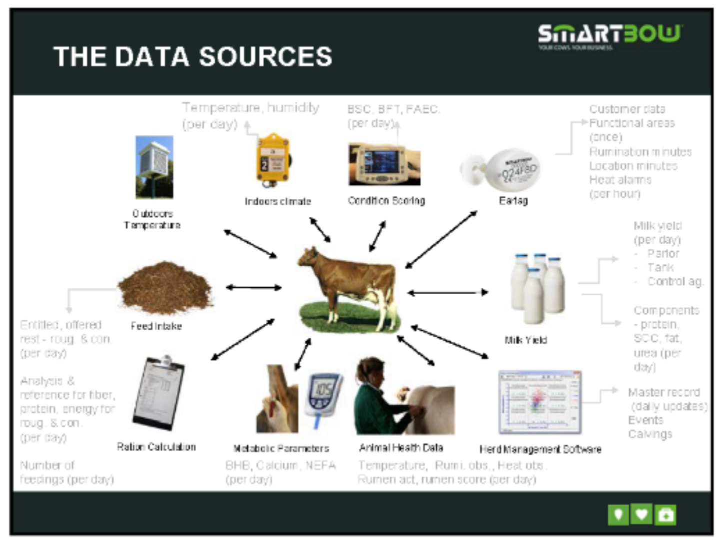
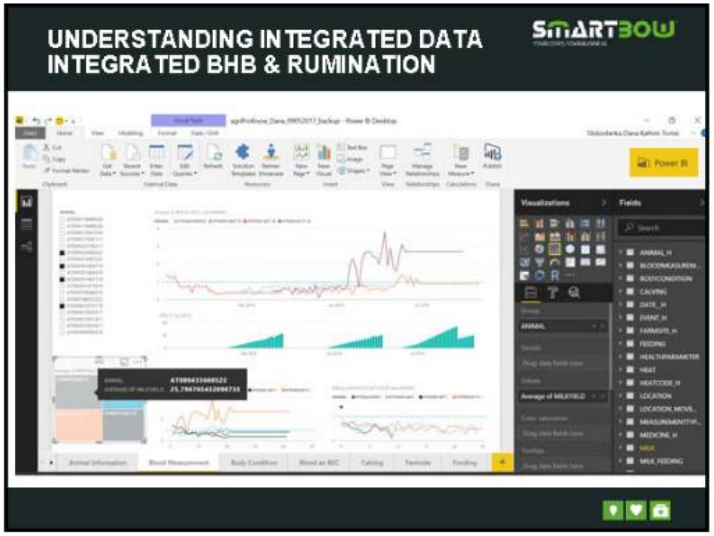
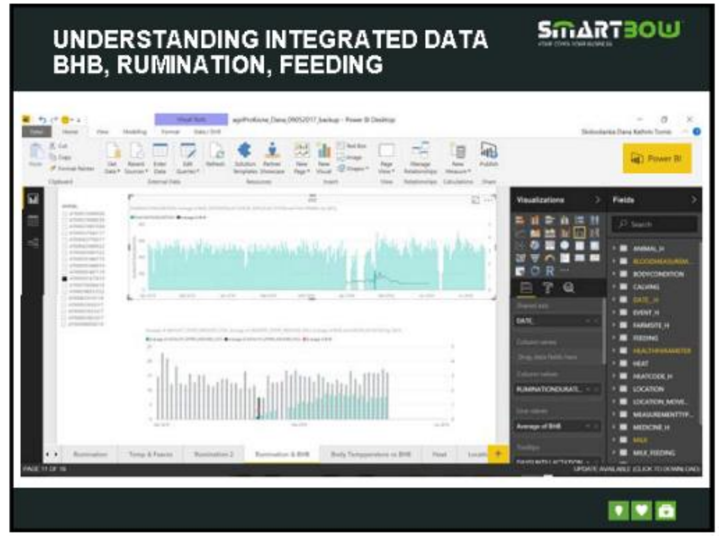
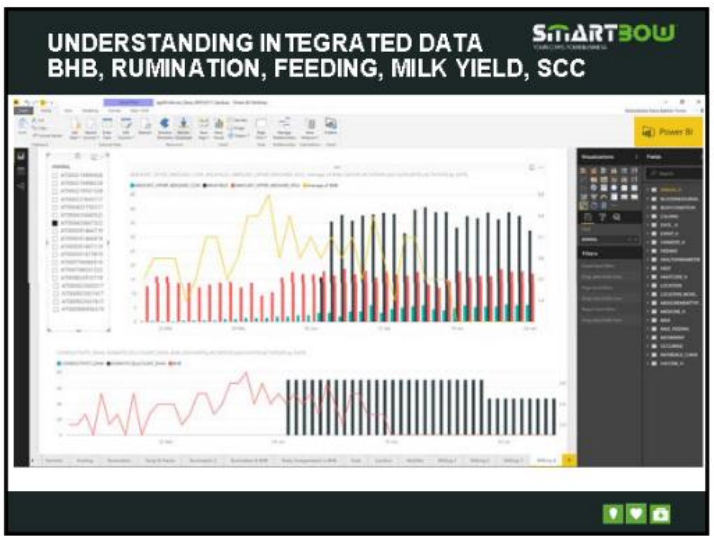

AGRIPROKNOW
GOALS & APPROACH
Modeling
Model multi-aspect data for aggregation and drilling
Cater for analysis needs of farmers, consultants and
For animal level, farm level, population level analysis
Observation and Data Collection
Collect data and observations in scientific studies
Implement data harvesting form different systems
Ensure extensibility and data security
Data Experimentation
Finding good indirect indicators for detection of the subclinical ketosis ( reducing BHB testing load)
Data visualization
Statistic analysis
New Knowledge
Creation of new knowledge – models and algorithms
Integration of new actionable knowledge
Validation
Validation with > 500 dairy cows
Experimental Farm
Commercial Farm
Power BI
SPSS
vetmeduni vienna

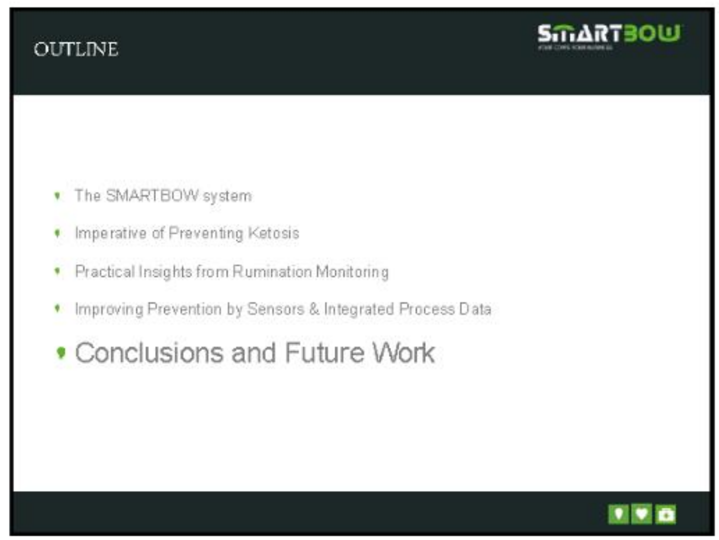

THE DATA SOURCES
Temperature, humidity (per day)
BSC, BFT, FAEC. (per day)
Customer data
Functional areas (once)
Rumination minutes
Location minutes
Heat alarms
(per hour)
Outdoors Temperature
Indoors climate
Condition Scoring
Eartag
Milk yield (per day)
- Parlor
- Tank
- Control ag.
Components - protein, SCC, fat, urea (per day)
Feed Intake
Entitled, offered rest - roug. & con. (per day)
Milk Yield
Analysis & reference for fiber, protein, energy for roug. & con. (per day)
Ration Calculation
Metabolic Parameters
Animal Health Data
Herd Management Software
Master record (daily updates)
Events
Calvings
Number of feedings (per day)
BHB, Calcium, NEFA (per day)
Temperature, Rumi. obs., Heat obs.
Rumen act, rumen score (per day)

8


UNDERSTANDING INTEGRATED DATA
INTEGRATED BHB & RUMINATION
SMARTBOW


UNDERSTANDING INTEGRATED DATA
BHB, RUMINATION, FEEDING
SMARTBOW


UNDERSTANDING INTEGRATED DATA
BHB, RUMINATION, FEEDING, MILK YIELD, SCC
SMARTBOW


OUTLINE
SMARTBOW
The SMARTBOW system
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## SOME DATA MANAGEMENT ISSUES

Sources

- > 30 types
- 1st study > 6 months of analysis
- 2nd study > 12 months of data

Data Warehouse

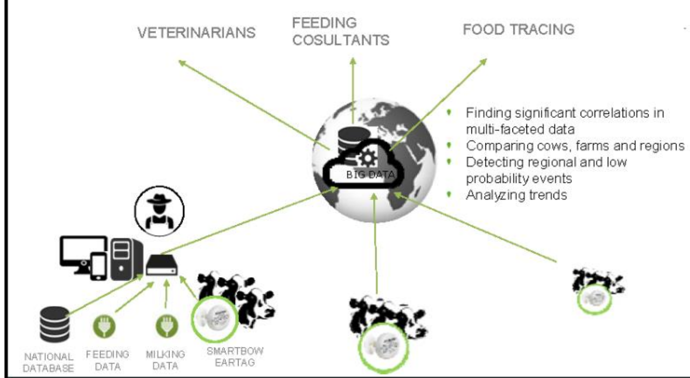
- 21 Tables
- > 150 Attributes
- Complex queries for cow, farm, region comparisons

Many important lessons learned in data quality & availability!

So far the focus on modelling, query design, data visualization, understanding of integrated data

Next steps include rigorous data analysis for models creation and validation

## OUR GOAL - DELIVERING INSIGHTS




- Finding significant correlations in multi-faceted data
- Comparing cows, farms and regions
- Detecting regional and low probability events
- Analyzing trends

## SMARTBOW FUNCTIONS IN DEVELOPMENT

- Identification in the milking parlor
- Birth detection
- Lameness detection
- Temperature measurement
- Grazing
- Ketosis alarm
- Feeding behavior
- Calf health, drinking behavior
- Wrong group detection

- Eartag LIFE
- New Interfaces



# THANK YOU!

ENDLESS POSSIBILITIES WITH SMARTBOW

YOUR COWS. YOUR BUSINESS.

SMARTBOW

## REFERENCES


- *Calmari, L., Soriani, N., Panella, G., Petrera, F., Minuti, A., Trevisi, E. (2014): Rumination time around calving: An early signal to detect cows at greater risk of disease. Jounal of Dairy Science 97, page 3635–3647.*
- *Kaufmann, E.I., LeBlanc, S.J., McBride, B.W., Duffield, T.F. and DeVries, T.J. (2016): Association of rumination time with subclinical ketosis in transition dairy cows. Journal of Dairy Science 99, page 5604 – 5618.*
- *Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016a): Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part I.Metabolic and digestive disorders. Journal of Dairy Science 99, page 7395 – 7410.*
- *Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016b): Use of rumination and activity monitoring for the identification of dairy cows with health disorders: Part II. Mastitis.*
- *Stangaferro, M.L., Wijma, R., Caixeta, L.S., Al-Abri, M.A. and Giordano, J.O. (2016c): Use of rumination and activity monitoring for the identification of dairy cows with health disorders: PartIII.Metritis.*
- *Lean, I. J., Bruss, M. L., Troutt, H. F., Galland, J. C., Farver, T. B., Rostami, J., Holmberg, C. A., Weaver, L. D. (1994): Bovine ketosis and somatotropin: risk factors for ketosis and effects of ketosis on health and production. Research in Vet. Sci. 57: 200-209*
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- *Klug, F., Franz, H., Rehbock, F. (1989): Ketose bei Milchkühen: Tierzüchterische und tiergesundheitliche Aspekte. Tierzucht. 43: 26-29*
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- *Shilling, E. (1976): Zur Fortpflanzung der Kühe nach dem Kalben unter Berücksichtigung fütterungsbedingter Stoffwechselstörungen. Tierzüchter 28, 310-312*
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# Lameness Alerting – the End to the Silent Epidemic?

Dr. Vivi M. Thorup
Lead Data Analyst, IceRobotics

Precision Dairy Farming 2017, May 30th, Lexington, Kentucky

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- About IceRobotics
- The DASIE project
- Lameness background
- Data collection
- Methods
- Results
- The future
- Conclusions

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## IceRobotics Ltd

- A technology producing company based in South Queensferry, Edinburgh, Scotland
- 20 staff, 6 nationalities
- Specialists in livestock behaviour monitoring
- Support researchers and farmers
- First IceTag sold in 2005
- First IceQube sold in 2009
- CowAlert launched in 2011

3

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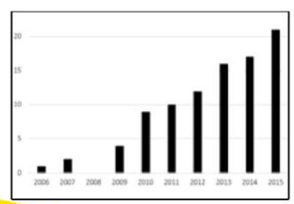
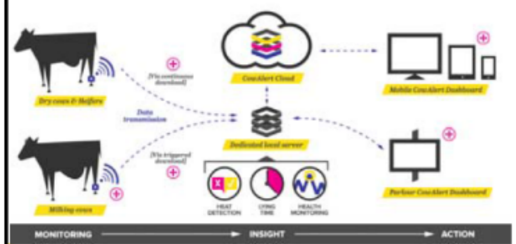
## IceTags and IceQubes = animal science tools



2006-2015: 92 peer-reviewed papers

## The CowAlert System

COWALERT BY ICEROBOTICS




- CowAlert on 200+ farms
- 50+ million "cow days" of data from commercial farms in the UK, Netherlands, Germany, Poland, USA, and Australia
- Cloud storage
- Heat, fertility and health alerts
- Whole herd monitoring
- Dry cow monitoring

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## DASIE project

COWALERT BY ICEROBOTICS

- Dairy Animal Sensor Integrated Engineering
- August 2014 – 2017
- Supported by the UK government
- 4 partners
- Data from 6 commercial farms & 1 research herd

Innovate UK Technology Strategy Board

ICEROBOTICS müller Harper Adams University Kingshay

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**Lameness prevalence world-wide, recent studies**
(¹Score ≥ 3: lame, unless otherwise stated)

COWALERT

| Lameness prevalence[1] | Scale | Data collection year | Country | No. of farms or cows | Study |
|---|---|---|---|---|---|
| 37% (range 0-79%), score ≥ 2 | 0-3 | 2006-2007 | UK | 205 farms | Barker et al, 2010 |
| 34% (range 0-82%) | 1-5 | 2004-2005 | Germany & Austria | 103 farms, 3514 cows | Dippel et al, 2009 |
| 38%, for 32 random cows/farm | 1-5 | 2008-2009 | Denmark | 42 farms, 1340 cows | Thomsen et al, 2012 |
| 23% (range 2-62%) | 1-5 | 2005 | Finland | 87 farms, 3499 cows | Sarjokari et al, 2013 |
| 28% Canada, 33% California, 55% Northeast USA | 1-5 | 2007-2008 Canada 2010 USA | Canada & USA | 42 farms, 79 farms | [illegible]eyserlingk et al, 2012 |
| 10%, score > 2 | 1-5 | 2012-2013 | USA | [illegible] farms, [illegible] cows | Foditsch et al, 2016 |
| 19% | 1-5 | 2007 | [illegible] | 40 farms, 3400 [illegible] | Katsoulos & Christodoulopoulos, 2009 |
| 32% (range 0-98%) | [illegible] | [illegible] | The Netherlands | [illegible] | de Vries et al, 2015 |
| 37% in large farms 13% in small farms | [illegible] | 2004 | [illegible] | [illegible] farms, 10899 cows | Tadich et al, 2010 |
| 33% (range 7-53%) | 1-5 | [illegible] | China | 38 farms | Chapinal et al, 2014 |
| 28% | [illegible] | [illegible]-2007 | Turkey | 38 farms, 5078 cows | Yaylak et al 2010 |
| 33% (range 9-64%), score ≥ 1 | 0-2 | 2007 | Czech Republic | 14 farms, 807 cows | Sarova et al, 2011 |
| 27% in 2010 39% in 2011 | 1-5 | 2010-2011 | Hungary | 25 farms | Gudaj et al, 2013 |
| 10%, score ≥ 1 | 0-5 | 2001-2002 | Switzerland | 290 farms, 4621 cows | Bielfeldt et al, 2005 |
| 34%, score = lameness present | binary | 2005-2011 | Spain | 28 farms, 3499 cows | Perez-Cabal & Alenda, 2014 |
| 43%, score>1 | 1-3 | 2003-2004 | Poland | 11 farms, 1330 cows | Olechnowicz et al, 2010 |

**28% = too many lame cows in the world!**

## Lameness – a Silent Epidemic?

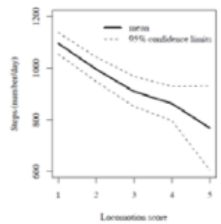
COWALERT BY ICEROBOTICS

- High prevalence
- World-wide presence
- On average, farmers notice 20-25% of lame cows[1]

[1]Archer et al, 2010 In Practice 32: 492-504

## Lameness affects Behaviour

- Lying time: 119%
- Number of lying bouts: 103%
- Number of steps: 95%
- Leg activity: 80%
- Feeding time: 60%





Blackie et al, 2011 Applied Animal Behavioral Science 134: 85-91
Thorup et al, 2015 Animal 9: 1704-12
Thorup et al, 2016 Frontiers in Veterinary Science: 10 May
Wadsworth et al, 2016 Proc. PDF Conference, Leeuwarden, NL: 315-19


## Lameness Reduces

- Yield: 270-857 l milk lost over a lactation
- Oestrus behaviour, e.g. mounting period shortened from 5.2 to 1.8 h
- Reproductive performance, e.g. the first ovulatory oestrus delayed by 19 days
- Cow lifetime: increased risk of culling (HR=1.45 for MS≥3, HR=1.74 for MS≥4)


Bicalho et al, 2007 JDS 90: 4586-91
Huxley, 2013, Livestock Sci 156: 64-70
Petersson et al, 2006 Anim Repro Sci 91: 201-214
Walker et al, 2010 Rep Dom Anim 45: 109-117


## Reasons to Detect Lameness

Lameness impacts the way a cow
- Walks
- Rests
- Eats
- Expresses oestrus

Lameness reduces
- Cow welfare
- Farm profit



## Automatic Lameness Alerting

We want to alert for lame cows, such that cows in need can be detected early, receive treatment and farmers can save time and money

# Cows & IceQubes

COWALERT BY ICEROBOTICS

| Farm | Herd size | Milk yield | Cows with IceQubes |
|---|---|---|---|
| Harper Adams University[1] | 360 | 9,829 | 117 |
| A | 240 | 7,229 | 237 |
| B | 1,500 | 11,194 | 500 |
| C | 150 | 8,740 | 137 |
| D | 467 | 9,180 | 462 |
| E | 610 | 8,727 | 606 |
| F | 200 | 6,744 | 181 |

[1]Research herd, cows wore IceQubes on 3 legs

In total 2,240 cows with IceQubes

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# IceQube Output

COWALERT BY ICEROBOTICS

Motion Index

Lying time ← Transitions → Standing time

Step count

+ Transition timestamps

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# The Reference Data

COWALERT BY ICEROBOTICS

- Visual mobility scoring at 7 farms in 2016
- 1 of 2 trained observers
- Scale 1-5[1] (1 = perfect mobility, 5 = severely lame)

[1]Chapinal et al, 2009 JDS 92: 4365–74

# Mobility Scores

COWALERT BY ICEROBOTICS

| | Visual mobility score | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | Total |
| Number of observations | 412 | 4810 | 1382 | 146 | 5 | 6755 |

- Cows at HAU scored weekly, the rest only once
- Lameness definition: MS > 3
- Highly imbalanced ratio of non-lame/lame observations

## Building a Lameness Model

- Input = IceQube data (lying time, number of lying bouts, steps and MI) + farm KPIs
- Balance non-lame and lame observations (smoting)
- Data split in training (75%) and test data (25%)
- Machine learning method
- Train model (on 75% of data)
- Test model (on 25% of data)
- Output = a lameness probability per cow per day

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## Detection Rates

Current model:

- Correctly identified lame cows: 62% (sensitivity)
- Correctly identified non-lame cows: 96% (specificity)

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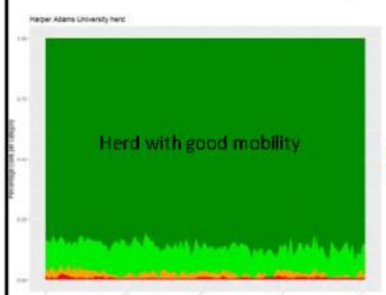
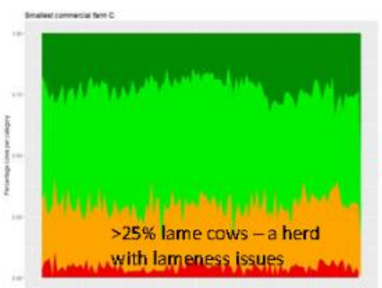
## Herd Mobility

- ➢ Trend in herd mobility across time
- ➢ An automated daily mobility score for all IceQubed cows




## The Future

Validation study with another golden standard: Lameness expert to claw diagnose and measure pain response of ~70 cows on each commercial farm and compare with our automated mobility score.

We hypothesise that our automated mobility score will correlate even better with pain response and claw diagnosis than with the visual mobility score.

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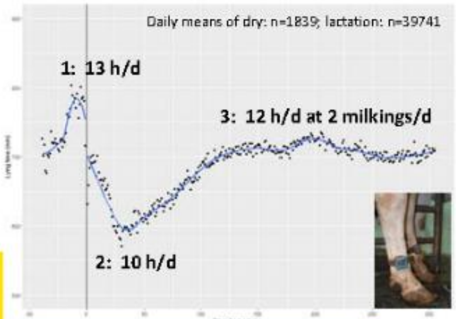
## Further Development




Lactation stage affects behaviour => integrate calving date to improve lameness detection rate

Thorup et al, 2016 Proc. 4th DairyCare Conference, Lisbon, Portugal, p 16

## Conclusions

- Lameness is not a classical epidemic – but a severe problem which MUST be addressed on every farm
- CowAlert detects lameness automatically
- CowAlert provides an automated mobility score
- Validate automated mobility score using claw diagnosis and pain response as golden standard
- Continue to improve detection rate through additional context such as lactation cycle and parity

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## Thank you for listening

v.thorup@icerobotics.com
www.icerobotics.com
www.cowalert.com

## Scotland & UK

| | Scotland | United Kingdom |
|---|---|---|
| Dairy farms | 2,123 | 13,355 |
| Dairy cows | 276,000 | 1,898,000 |
| Herd size | 180 | 143 |
| Yield/cow | - | 7,912 litres |

UK: 14 m tonnes of milk/year = 2.3% of world production
USA: 87 m tonnes = 14.6%


FAOstat 2012
www.emap.org.uk/HeatMap.aspx
www.gov.scot/Topics/Statistics/Browse/Agriculture-Fisheries/agritopics/Cattle
http://dairy.ahdb.org.uk/resources-library/market-information/farming-data/average-herd-size
www.gov.uk/government/statistical-data-sets/structure-of-the-livestock-industry-in-england-at-december

*Managing health and well-being*


*Managing health and well-being*

## Background

- Disease prevention & treatment constant focus
- Costs range from ~$200-300/case (Kelton et al., 1998)
- Clinical state easily identified
- True cost is unknown
  - Subclinical state

*Managing health and well-being*

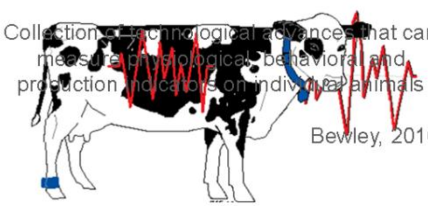
## Background

- Historical focus on treatment (von Keyserlingk et al., 2009)
  - Physical observations
  - Cow-side tests
  - Need more rapid and continuous measures
- Recent proactive movement
  - Advancement in technologies

….Precision Dairy Farming

*Managing health and well-being*

## Precision Dairy Farming



*Managing health and well-being*

## Objective

- Discuss current state of knowledge regarding disease identification
  - Lactating
  - Non-lactating
  - Young stock
- Understand limitations of current research
- Propose future research needs

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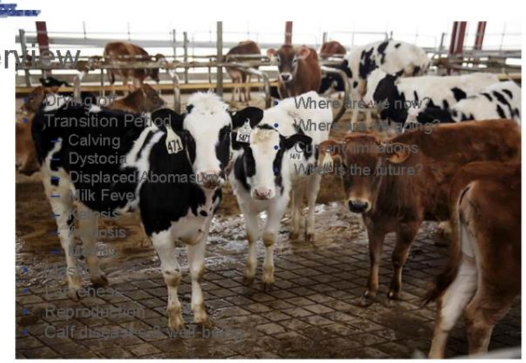
*Managing health and well-being*

## Overview



- Drying off
- Transition Period
  - Calving
  - Dystocia
  - Displaced Abomasum
  - Milk Fever
  - Ketosis
  - Acidosis
  - Metritis
- Mastitis
- Lameness
- Reproduction
- Calf diseases & well-being

- Where are we now?
- Where are we going?
- Current limitations
- What is the future?

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*Managing health and well-being*

## Overview

- Drying off
- Transition Period
  - Calving
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---

*Managing health and well-being*

## Drying off

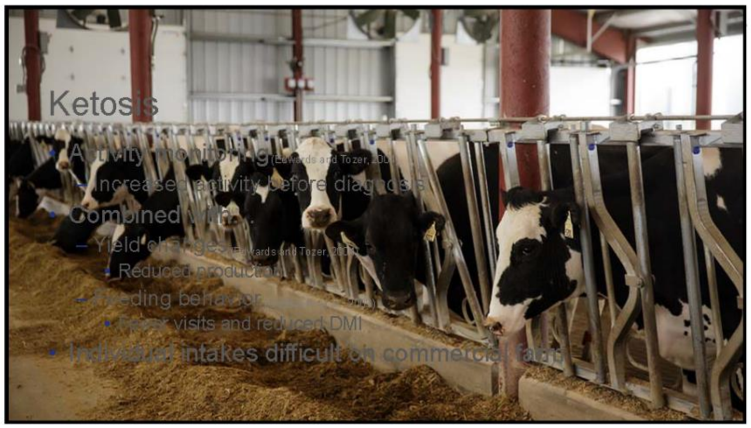
- Abrupt cessation is US industry norm
- Milk leakage and discomfort are concern
- Increase risk of IMI with > 17.5 kg/d (Rajala-Schultz et al., 2005)
- Primiparous animals show reduced risk of IMI with gradual cessation (Gott et al., 2016)
- Role in tailoring drying off approach
  - Production and age


*Managing health and well-being*

Herd Navigator

## Ketosis

- Variety of cow-side tests for BHBA
  - Urine, Milk, Blood
- Se and Sp vary
  - Precision Xtra test strip
- Fat:protein ratio & yield helpful (Heuer et al., 1999)
- In-line system for BHBA
- No cow-side NEFA test available


*Managing health and well-being*

## Mastitis

- Daily use of CMT and EC
- Monthly testing of SCC
- More recent focus
  - Introduction of in-line analyzers
    - Milk components
      - LDH
      - Little day-to-day variation in lactose
  - Addition of EC to milk component data
  - Behavior

Herd Navigator

*Managing health and well-being*

ADSA

## Mastitis

- 37 sensor systems adopted by producers
- 73% of studies have validated algorithm to detect
- < 50% of the systems provide alert
- Se: 55-89%
- Sp: 56-99%
- Currently none meet guidelines for standalone detection

(Rutten et al., 2013)

*Managing health and well-being*

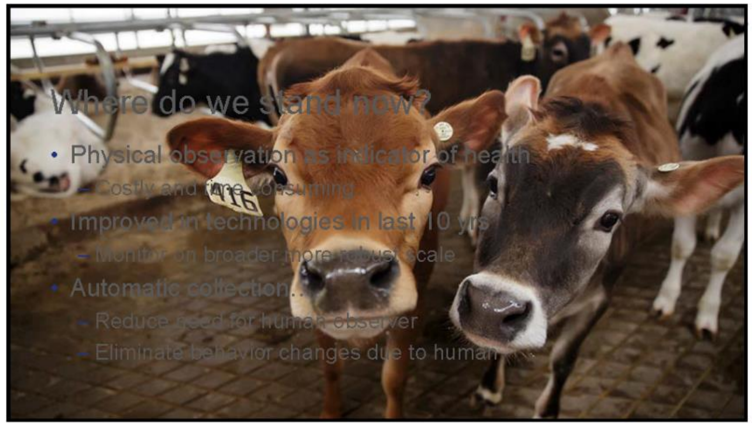
ADSA

## Lameness

- Increased lying times (Ito et al., 2010)
  - >14.5 h/d in deep bedded stalls
- Increased lying bouts
  - > 90 min
- Increased frequency of bouts around calving (Calderon and Cook, 2011)
- Changes in behaviors from baseline can be useful

## Calf diseases & well-being

- Use of feeding behavior to detect disease
- Fewer unrewarded visits in sick calves
  - Associated with reduced ADG (Svensson and Jensen, 2007; Murray et al., 2016))
- Traditional diet compared to ad lib (De Paula Vieira et al., 2008)
  - Increased standing time
  - Increased unrewarded visits



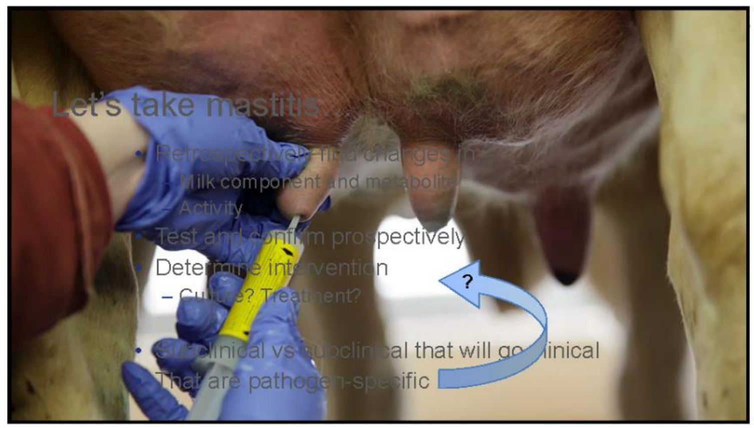
## Where do we stand now?

- Physical observation as indicator of health
  - Costly and time consuming
- Improved in technologies in last 10 yrs
  - Monitor on broader more robust scale
- Automatic collection…
  - Reduce need for human observer
  - Eliminate behavior changes due to human




## Can we…

- Find disease-specific alerts?
- …Using 1-2 devices?
- Distinguish subclinical & clinical disease?
- …Determine whether intervention varies?
- Identify cows with multiple diseases?
- …Determine whether intervention differs?



## Where will we be in 20 years…

- Ability to monitor feeding behavior
- 2 wearable devices + in-line milk analysis
- Disease-specific alerts
  - High Se & Sp
- … incidence of disease
- Reduced antimicrobial use
- Better cow well-being




**Usage of Combined Sensor Information in the Lely Robots in the Daily Practice of the Producer**

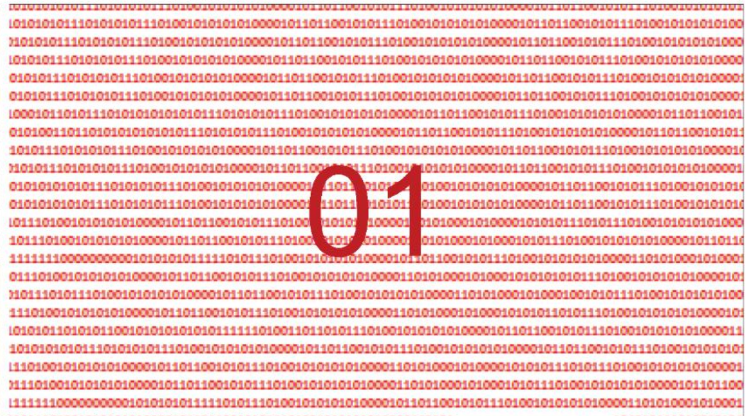
*Arjen van der Kamp, Lely International*

## Precision dairy farming to unburden the dairy farmer

A.J. van der Kamp, A. Gouw


## Content

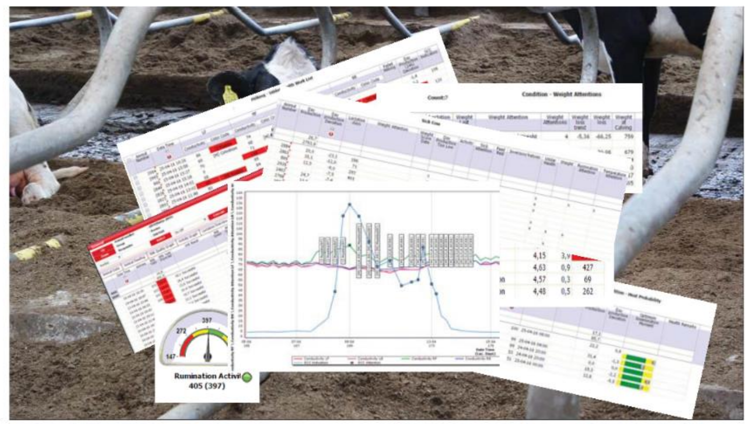
- Introduction
  - Automation
  - Sensor usage
- Health report
  - Results
- Further development
- Wrap up




## Sensors on AMS farms

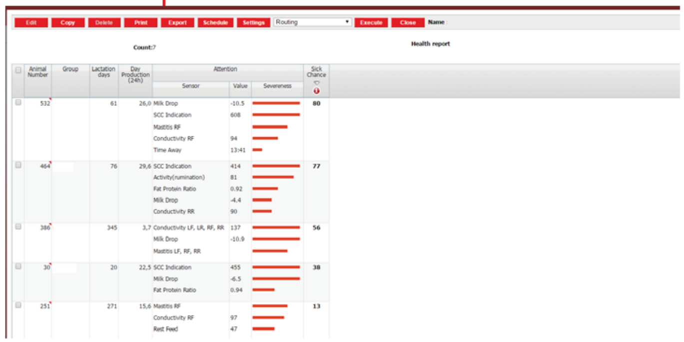
| Type of sensor system on the farm | % of AMS farms using the sensor system |
|---|---|
| Milk color sensor | 60 |
| SCC sensor | 17 |
| Electrical conductivity | 93 |
| Weighing platform | 27 |
| Rumination activity sensor | 9 |
| Activity meters for dairy cows | 41 |
| Fat and protein sensor | 20 |
| Milk temperature sensor | 46 |

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



What does a dairy farmer expect when investing in sensors?

# Health report




| Animal Number | Group | Lactation days | Day Production (24h) | Attention: Sensor | Value | Severeness | Sick Chance |
|---|---|---|---|---|---|---|---|
| 532 | | 61 | 26,0 | Milk Drop | -10.5 | | 80 |
| | | | | SCC Indication | 608 | | |
| | | | | Mastitis RF | | | |
| | | | | Conductivity RF | 94 | | |
| | | | | Time Away | 13:41 | | |
| 464 | | 76 | 29,6 | SCC Indication | 414 | | 77 |
| | | | | Activity(rumination) | 81 | | |
| | | | | Fat Protein Ratio | 0.92 | | |
| | | | | Milk Drop | -4.4 | | |
| | | | | Conductivity RR | 90 | | |
| 386 | | 345 | 3,7 | Conductivity LF, LR, RF, RR | 137 | | 56 |
| | | | | Milk Drop | -10.9 | | |
| | | | | Mastitis LF, RF, RR | | | |
| 30 | | 20 | 22,5 | SCC Indication | 455 | | 38 |
| | | | | Milk Drop | -6.5 | | |
| | | | | Fat Protein Ratio | 0.94 | | |
| 251 | | 271 | 15,6 | Mastitis RF | | | 13 |
| | | | | Conductivity RF | 97 | | |
| | | | | Rest Feed | 47 | | |

# Results

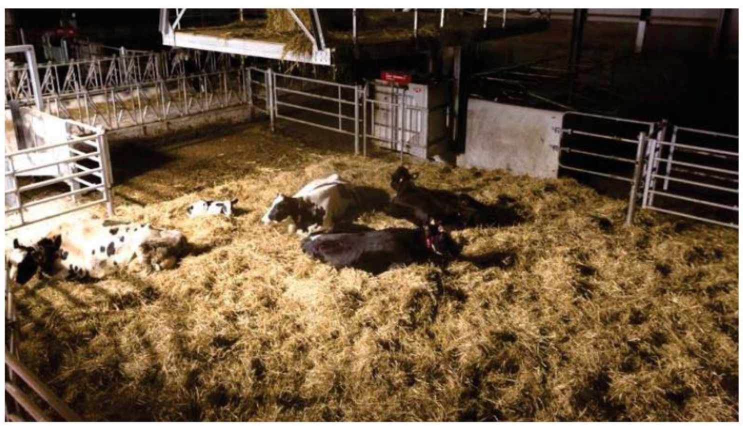
- Positive predictive value of 'Diagnosed sick'
  - 0.11 & 0.06 for single sensor performance
  - 0.39 for Sensor integrated attentions
- Positive predictive value of 'Want on report'
  - 0.24 & 0.14 for single sensor performance
  - 0.71 for Sensor integrated attentions

*When cow health counts, probabilities matter. R. van der Tol, P. Kool, A. van der Kamp, Proceedings Precision Dairy Farming 2016*

# Results

**'This is the only report I currently use for finding attention cows'**

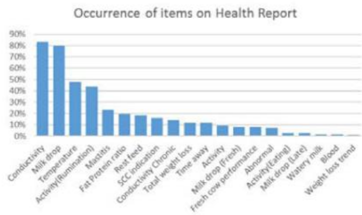
Are we satisfied?

## Research

- 1 Day of Health report data
- 517127 observations
  - 125299 cow 'transactions'
- Used a subset of 24230 cow 'transactions'

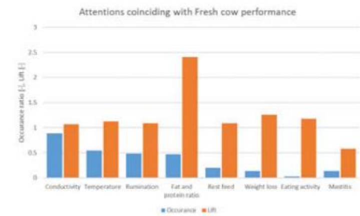
# Results




- Incidence of attentions
  - –Conductivity and milk drop very important
- Dependent on install base

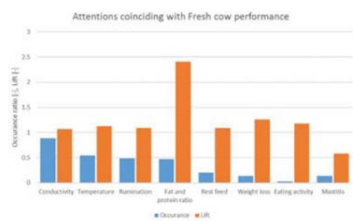
# Fresh cow performance

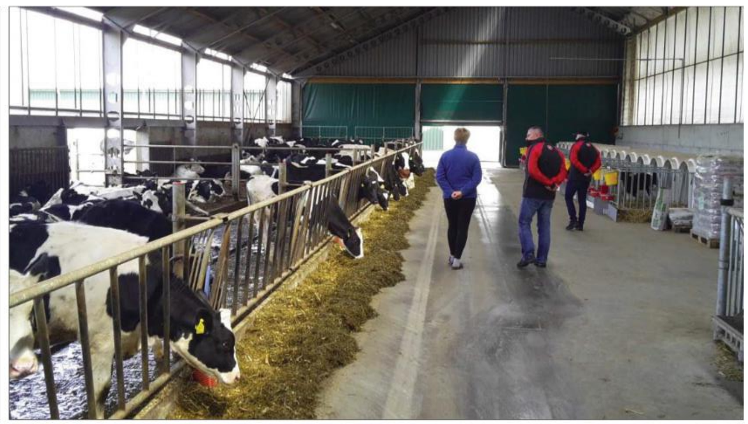
- Occurrence
  - –How often do the attention appear together
- Lift
  - –Added value of the parameters




# Fresh cow performance

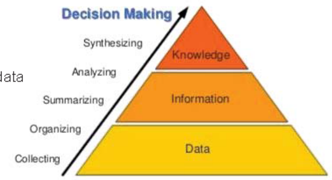
- High lift with Fat and protein ratio
  - –Strong combination and good indicator for mastitis
- Positive lift for indicators of post-calving issues



# Wrap up

- Use Precision Dairy farming technologies to make farmers' life easier
- Data integration to create information
- In future management software will unburden the dairy farmer.
- Dairy farmer
  - No need to understand overcomplicated sensors/data
  - Getting the most out of your investment




***Converting data into information is just the first step in Precision livestock farming***

**Transition to Precision Dairy**
*Jason Troyer, RJT Dairy Farm*

# RJT Dairy Farm

Jason Troyer

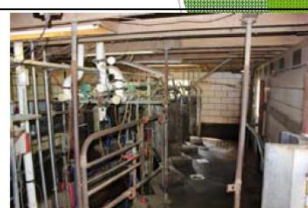
Precision Dairy 2017

## History of The Troyer Farm

The dairy was established in 1978 when Jason's grandfather and father moved from Ohio bought the farm and cows and started milking. They then sold out in the government buyout in 1985 and his father sold milk equipment until 1991. In the spring of 1992 he bought 50 cows and we were back in business again. Jason came home from college in 2007. In 2009 we built a new dairy barn and by 2015 had grown the herd to 150 milking cows. That same year Jason and his family decided on installing 2 AMS Galaxy Astrea 20.20's and grew the herd to 220 cows.

## RJT Farm: Before Robots

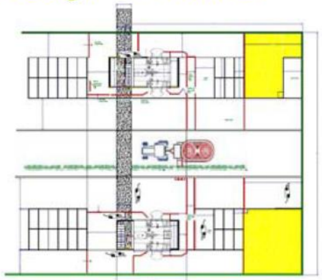
- Parlor: milked in a double 4 sawtooth herringbone parlor, built in the 1960's. It originally had 4 swing units and a high line but had been upgraded to 8 units and a lowline in the late 90's
- Hr's Milking: 6hr 2x
- Full Time Employees:3 along with family
- Part Time Employees 1
- Milking cows: 150



## RJT Farm: Presently Milking with Robots

- Milking with AMS Galaxy Astrea 20.20- 4 milking boxes, 2 arms.
- Hr's Milking: Robots milk 24 hr's a day.
- Full Time Employees:1 along with family
- Part Time Employees 1
- Milking cows: 220

## Barn Design / Features



• Barn – 100'x200' Freestall barn built in 2009 and added 72' in 2015 for robots and sort pens and 100' in the back for dry cows and heifers
• Milk Cows -- 260 stalls, 4 row with sand bedding
• AMS Galaxy Astrea 20.20 - 4 milking boxes, 2 robot arms

## Barn Design / Features

## Precision Dairy Features

• Astrea 20.20 – AMS Galaxy USA
• Smart Phone Access & Control
•Saturnus Cow management Software
•Saturnus App
•Text messaging cow alerts


## Precision Dairy Features

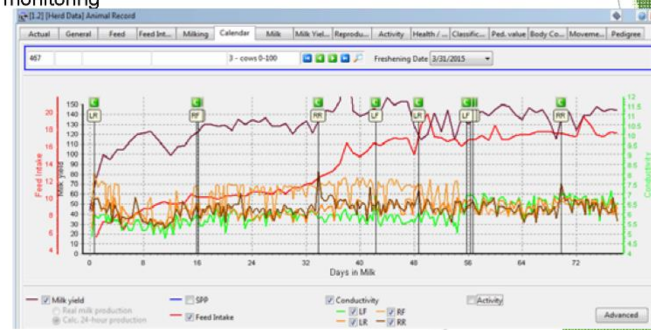
• Astrea 20.20 Automatic Milking System – AMS Galaxy USA
• 1 Motoman Industrial Robot Arm – Preps and attaches in 2 boxes and milks 120 + cows
• Low maintenance / high durability more than 270,000 arms in operation world wide in various industrial applications
• Steam cleaning system – cleans teat cups after every milking
• Superior teat preparation

## Astrea 20.20 Macro Key Performance Indicators

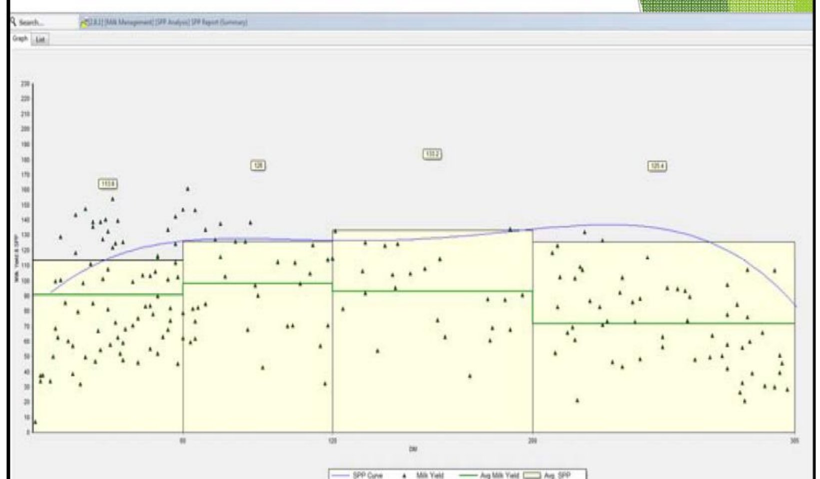
- Saturnus 20.20 Management Software
  - Daily pulse of production & cow flow through the robot
  - Daily attention cows are highlighted allowing the dairyman to only manage the small percentage of cows that need it most

## Astrea 20.20 Micro Key Performance Indicators

- Saturnus 20.20 Management Software
  - Individual Cow Production Curve
  - Feed Curves for freshening and production based tables
  - Milk Quality Sensors for individual quarters for daily health monitoring



- Fresh
- Serviced
- Open
- Pregnant
- Dry
- Do not breed



## What did precision dairy do for our farm?

- Expanded herd from 150 cows to 220 cows.
- Reduced labor from 3 full time employees to 1 full time employees.
- Increased profits due to better management tools
- QOL – improved quality of life for the cows and our family

## Essential management practices for success

- Ensure Partial Mixed Ration (PMR) is accurate to support good cow traffic and production
- Equipment Knowledge – Farmer Technical Training from AMS Galaxy USA training center in Kutztown, PA
- Daily observation and inspection of equipment
- Preventative Maintenance Program
- Stall maintenance and utter singeing program
- Heifer Training Protocol
- A breeding program focused on feet and legs, teat placement, and milk speed
- Hoof health

## Troyer Startup

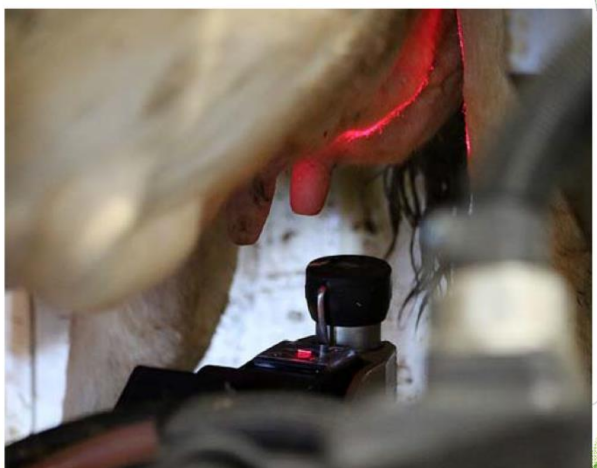
- 2 Galaxy Start-up specialists at the farm 24 hours a day for 10 days.
- Robot ration support for the first 3 months.
- Manually milk cows for the first milking, then start attaching cows with the arm during the second milking.
- Noticeable improvement every day and by the end of the first week many of the cows were entering the robots and attaching.
- Be patient with the cows.
- Having a person in the barn who understands cows, keeps them clean, and can do some maintenance on the robot is essential.
- Be willing to observe and make changes in routine. Always look at ways to improve efficiency.
- Find what works for your operation.

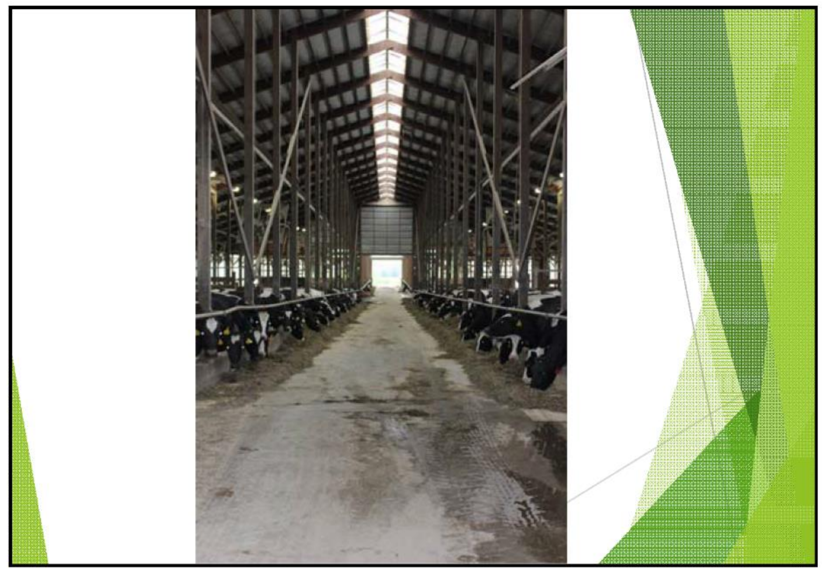
## The benefits of precision dairy for our farm…

- Elimination of hired help for milking
- Improved health of my body
- Less time in the barn and more time with my family
- Improved animal health – more lactations, fewer replacement heifers needed
- Highest annual production in the life of the farm
- Highest dairy profits in the life of the farm
- Low feed costs due to individual feeding in the Astrea and accurate mixing of PMR

## Feeding Calves with an Urban Paula Feeder

- Calves grow very well with putting minimal time feeding calves.
- Software put calves on a feeding curve ramping them up during peak time and wean them off milk at the end of the curve.
- Can medicate calves on an individual basis.
- All self contained unit making it easy for cleaning.








## Thank you

***In communities across our nation, no tradition runs deeper from generation to generation than that of working on a family farm.***

# Automated calf feeder systems: What we learned from farms in the upper Midwest USA

Marcia Endres, PhD
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**miendres@umn.edu**

Individual housing of preweaned calves reduces transmission of infectious diseases as a result of limited physical contact between calves. In addition, individually housed calves are easier to observe which can result in more effective disease treatment. However, individual calf housing results in lack of social contact among calves at an early age and limits their movement. Housing calves in groups allows them to interact with each other and have space to move around and play. In addition, dairy producers are housing calves in groups to facilitate improved labor efficiency and working conditions and to make it easier to deliver higher amounts of milk/milk replacer to young calves.

Feeding calves in groups allows calves to express some natural behaviors that cannot be expressed when they are housed individually, but offers some challenges in relation to maintaining good health, another important aspect of good animal welfare. Good health is achievable in group housed preweaned calves as long as appropriate management and maintenance of equipment are emphasized and implemented.

There has been consistent growth in the upper Midwest US on the number of farms installing automated computerized calf feeders. This paper summarizes some of the findings of a field study we conducted at the University of Minnesota involving 38 farms with automated calf feeding systems. Farms were located in MN, WI, and NW IA. We used the data collected on the farms to identify factors that were associated with successful use of these systems. This methodology does not provide a direct 'cause and effect' connection, but we can identify guidelines and factors that influence success on the farm.

## Some management and housing observations

The average number of calves per group was 17.6, which is less than the maximum suggested by manufacturers or dealers (up to 30), and the space per calf was about 49 square feet. Average peak milk allowance was 8.3 liters per day and start milk 5.4 liters per day with some farms offering 10 or 15 liters per day. Calves were placed on the feeder at 5.2 days of age (range of 0 to 14 days) and about 25% of the farms placed calves in the group at one day of age. Most of the farms (87%) used positive pressure tubes to improve ventilation in the barn.

## Calf health observations

Figure 1 summarizes the calf health scores for the top $10^{th}$ and the bottom $10^{th}$ percentile farms. At each visit, research associate Amber Adams-Progar scored calves (total of 10,185 calves) for health including attitude, eyes, ears, nose, and hide cleanliness (indicator of scours). There was considerable variation among farms, indicating that housing and management factors can definitely influence the success of using these feeding systems.

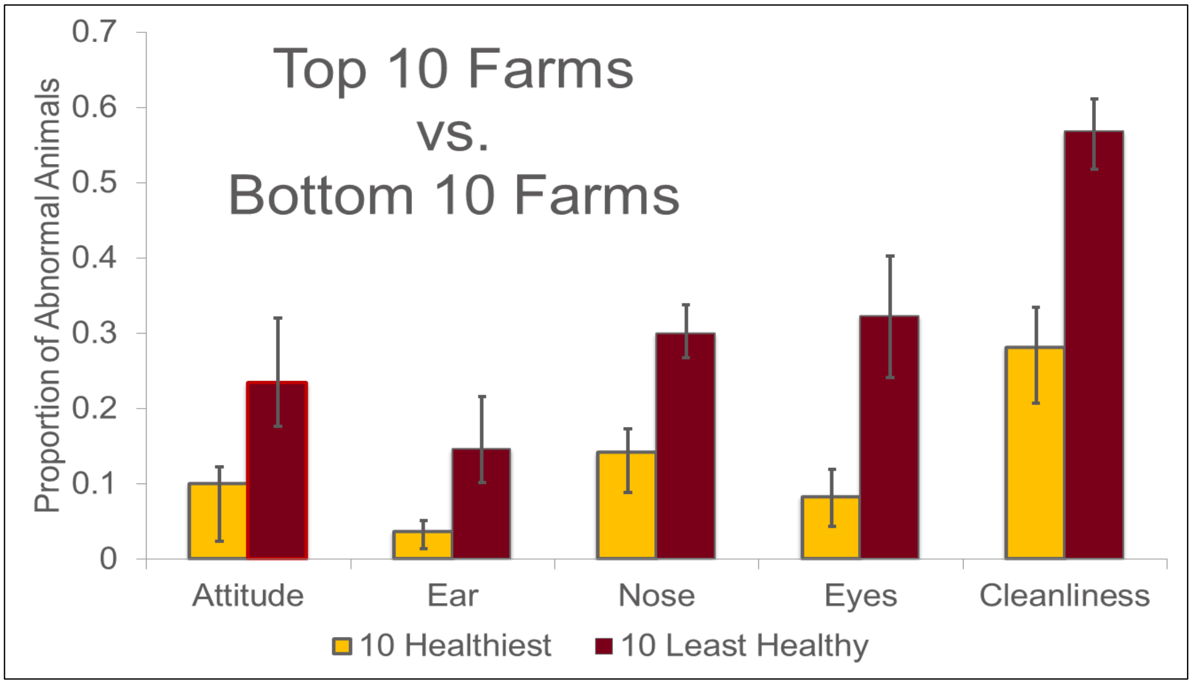



Figure 1. Average proportion of abnormal scores (indicating potential disease presence)

Amber and PhD student Matt Jorgensen also collected blood samples from calves younger than 5 days of age to test for serum protein concentration as an indicator of passive immune transfer (n = 985 calves). Body temperature was measured if a calf had an abnormal health score. Matt also collected milk samples from the mixer and the feeder tube or hose to test for standard plate count (SPC) and coliform count. There was a lot of variation in milk SPC and coliform counts across farms; some very extreme numbers were detected. The milk/milk replacer fed to preweaned calves should have a standard plate count of less than 100,000 CFU/ml and a coliform count of less than 10,000 CFU/ml. Some farms had SPC of over 20,000,000!

**Risk factors for abnormal health scores, mortality or health treatment rates**

Our statistical analysis indicated that the following factors can be important for the successful use of automated calf feeder systems:

- Reduced time to reach peak milk allowance
- Milk/milk replacer with low bacterial counts (cleanliness of equipment is key)
- Use of positive pressure ventilation tubes in the barn
- Sufficient amount of space per calf in the resting area
- Small number of calves per group
- Adequate farm average serum total protein concentration (an indicator of passive immune transfer)
- Use of drinking speed as a warning signal to identify sick calves
- Practicing navel and between group disinfection consistently
- Narrow age range within calf groups

We also observed that winter was the season with worst health scores and highest health treatment rates.
It was interesting to learn that some producers were not very clear about the need for cleaning the equipment on a routine basis, which resulted in a wide distribution for the quality of the milk/milk replacer fed to the calves across farms. It is extremely important to run circuit and mixer cleaning as recommended by the manufacturer, replace feeder hoses and nipples regularly (weekly/biweekly and daily, respectively), use the recommended cleaner to remove biofilms from the surfaces, keep the area around the feeder clean, provide clean and dry bedding to the calves, provide high quality milk, calibrate the equipment to deliver appropriate concentration of nutrients and temperature for the milk, etc. Researchers at Virginia Tech recommended a combination of three times per day mixer/heat exchanger cleaning before major feeding times along with once a day circuit cleaning after major

feeding times to reduce bacterial counts in milk. Circuit cleaning involves hand cleaning of the nipple and machine cleaning of the lines and internal workings of the feeder which must be instituted by the operator. The mixer/heat exchange cleaning is automated and involved cleaning of the element used for heating milk if used and the mixer.

**Suggestions for making automated calf feeders systems work**

Although more research and on farm observations are still needed, here are some general recommendations for using automated calf feeder systems:

- Excellent colostrum management programs are essential!
- Clean, dry, comfortable bedding and minimum of 40-45 square feet per calf.
- Milk/milk replacer with low bacterial count (SPC less than 100,000 CFU/ml).
- Adequate training of calves to use the feeders by gently leading them to the nipple when they are moved into the group housing.
- Stocking rates of no more than 12 to 15 calves per group, although research has shown that 7 to 8 calves per group is best for good health outcomes. A balance between health outcomes and economics needs to be considered. Larger group sizes are more successful when the age range among calves is narrow.
- Milk allowances of minimum 8 L per calf per day as peak amount. Calves will easily drink 10 L per day.
- Meal sizes of 1.8 to 2.5 L each. Meal size recommendations for younger calves tend to be lower and increase to upper limits by 2 to 3 weeks of age. Calves typically consume their daily allocation in 4 to 6 meals per day.
- When milk replacer is used, powder is diluted with water to approximately 13 to 15% solids. It is important that the feeder is calibrated routinely and all parts kept clean so that powder flows properly and dilution is consistent.
- Cleaning of the equipment and its various components is one of the most important keys to making these systems work successfully.

**Conclusions**

Automated calf feeders for raising young calves in groups are growing in popularity as producers want more flexible labor management and consumers want animals to have a more natural life. Feeding calves in groups allows calves to express some natural behaviors that cannot be expressed when housed individually, but offers some challenges in relation to maintaining good health, another important aspect of good animal welfare. Good health is achievable when using automated calf feeders to raise preweaned calves as long as appropriate management and maintenance of equipment are emphasized and implemented.

**Acknowledgments**

- Research personnel – Matt Jorgensen, Amber Adams-Progar, undergraduate students
- Collaborators: Kevin Janni, Anne Marie de Passille, Jeff Rushen, Jim Salfer, Hugh Chester-Jones, Sandra Godden, Bill Lazarus
- Dairy farm cooperators
- USDA-AFRI-NIFA for funding; competitive grant no. 2012-67021-19280



## Our History
## - STENSLAND FAMILY FARMS -

- **1915** STENSLAND FARMS WAS HOMESTEADED BY TOBIAS
- **1952** GRANDPARENTS, ART & ROSIE WERE MARRIED
- **1955** ART & ROSIE BEGAN THEIR FAMILY AND WERE MILKING 12 COWS BY HAND
- **1969** PROGRESSED TO MILKING 60 COWS WITH THE AID OF A PIPELINE
- **1979** STEP-UP PARLOR WAS INSTALLED IN THE ORIGINAL BARN
- **1989** ART RETIRED & SOLD ALL EQUIPMENT THE BARN SAT EMPTY
- **2002** TWINS, JASON & JUSTIN BEGAN WORKING ON OTHER AREA FARMS
- **2003** THE TWINS APPROACHED GRANDPA ART ABOUT RESTARTING THE DAIRY
- **2004** AT 16 YEARS OLD THE TWINS REBUILT THE DAIRY BASED OFF OF OLD FAMILY VIDEOS & BEGAN MILKING 40 COWS
- **2009** TALKS OF A CREAMERY BEGAN AMONGST THE STENSLAND FAMILY
- **2011** THE DAIRY INSTALLED 3 ROBOTIC MILKERS AND INCREASED HERD TO APPROXIMATELY 200
- **2015** THE DREAM OF A CREAMERY WAS REBORN & THE FAMILY BROKE GROUND
- **2016** PRODUCTION BEGAN...

Stensland
• FAMILY FARMS •

- Stensland Family Farms,
- Family owned and operated, multi-generational farm
- Located just outside of Larchwood, Iowa.
- Our dairy herd is 200+ strong
- Farm 1500 acres of organic cropland
- 3 robotic milkers
- Collar identifies each cow and relays weight, temperature, activity, and rumination. Important part of our practice is choosing NOT to use rBST
- Loafing shed contains waterbed with sawdust
- Self grooming station.
- Scraping system in place so the lanes are being cleared 24/7.
- All of these things contribute to the health and well being of our cows.

Collar identifies each cow and relays weight, temperature, activity, and rumination

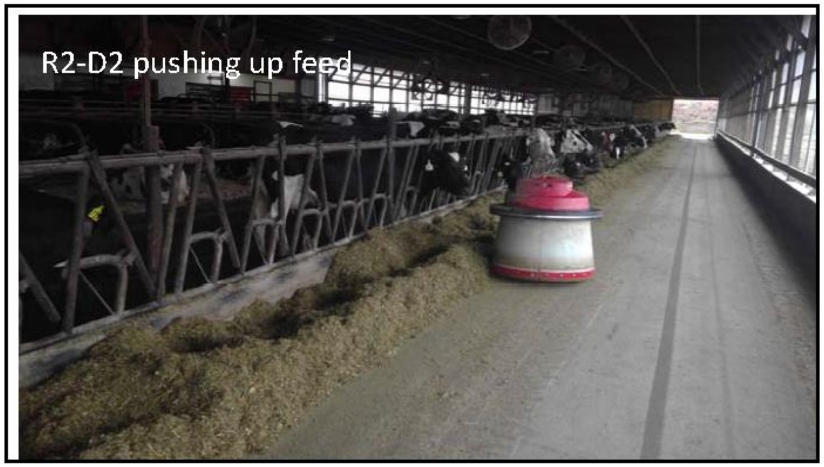
3 robotic milkers

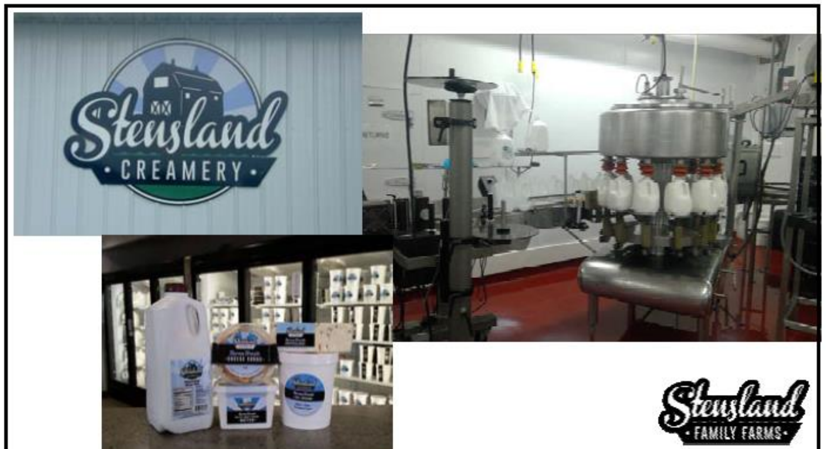
3 robotic milkers


3 robotic milkers

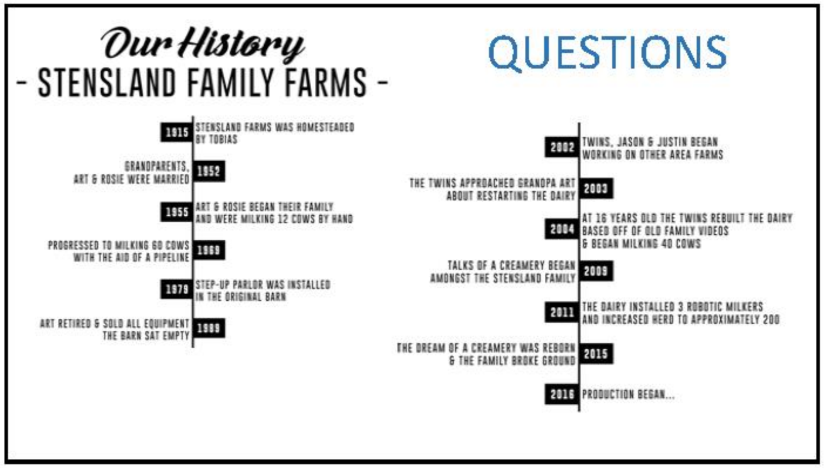

Scraping system in place so the lanes are being cleared 24/7

Stensland FAMILY FARMS




Stensland FAMILY FARMS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2016 PRODUCTION BEGAN...


Stensland
FAMILY FARMS
Thank you
Top: Jason, Leah, Doug, Kyle, Kelton, Justin, Chelsea, Rainalynn

## Activity- based heat detection with the smaXtec intraruminal bolus system

## Introduction of the smaXtec inside monitoring solution for progressive heat detection in dairy herds

Dr. Sina Stein, smaXtec animal care

### Introduction

Dairy farming has undergone significant transformation in the past few years. Against a background of increased global milk demand and aggravated cost pressure, farmers are encouraged to manage their dairy herd as efficiently as possible. They react with intensified production using high-producing animals in large-scale facilities, which often leads to shorter animal productive lifetimes due to reduced fertility and impaired health. The reproductive performance of a dairy herd is one of the major key drivers of a farm´s profitability. Regrettably, the overall fertility status of dairy cows is constantly decreasing and it is therefore becoming increasingly difficult to ensure successful fertilization. Studies, for example, report drops of 1-2 % in the conception rate per year in high performance dairy herds (Sheldon et al. 2006; Norman et al. 2009). In this connection, heat detection remains one of the most important components of a successful reproduction program. Due to changes in animal performance and management, estrus expression has changed dramatically over the past few decades. Estrus duration has decreased and is less pronounced, which complicates heat detection. While studies undertaken in the 1970´s report estrus times of around 17h, authors like Roelofs (2005) and Sveberg (2011) found estrus times of between only 7h to 11h with less mounting events. Another aspect is that cows often tend to show typical signs of being in heat like mounting and standing during the night at times when the herdsman is not observing the animals (Peralta et al. 2005). Farmers pursue a variety of approaches in heat detection like – the historically most common - method of visual observation, tail heat marking, timed breeding programs or automated animal activity monitoring and try to react to the new challenges of heat detection. While timed breeding programs dominate the US market, numerous European dairy herds are successfully monitored and managed with the help of activity monitoring systems. So far, most of the systems used work with collars and pedometers, which are associated with problems due to the device becoming displaced, causing injury or getting lost, while the latter could be more problematic in large-scale herds where individual observation is rare. Such systems take up a significant amount of working time as collars need to be replaced (after being lost) or regularly adapted to animals' weight. The use of pedometers is associated with the same type of problems and veterinarians also report injuries on the legs of heifers when farmers do not adjust the pedometers according as the animals grow.

### Solution: Activity-based heat detection with a bolus system located in the dairy cow's rumen

While heat detection based on activity levels is already accepted as a reliable method to detect cows in heat, there continue to be negative side-effects mostly due to the handling of the devices. The smaXtec inside monitoring solution has none of the reported disadvantages due to its use of another measurement location. The smaXtec solution (Figure 1) consists of a measuring device located in the rumen of the animal (bolus), meaning that additional devices such as pedometers, collars or ear tags are not required. The bolus is administered orally and stays in the rumen for the animal's lifetime without the risk of loss or shifting. It measures rumen temperature and activity (via accelerometer) continuously at 10 min intervals with activity measurement not affected by rumen motility. The recordings are read out by a simple plug& play infrastructure (Base Station and Repeater), which automatically transfers the data to the smaXtec cloud. This online approach means that data is accessible anywhere anytime and is permanently saved. The software (smaXtec Messenger) functions as an online platform for data and alert access, general organization and data sharing with veterinarians, consultants or farm staff. Notifications can be also received on smart devices such as tablets or smartphones (Android, iOS).
Typical increases in activity during heat are detected immediately and lead to the above-mentioned alert notifications being sent to the herdsman. Cow- individual activity levels are considered within the data processing. The heat events are presented to the farmer as graph (Figure 2) or list (Figure 3), where also the status of the event can be noted (e.g. insemination or pregnancy). Thus, the dairy cows' history of previously successfully conducted inseminations can be documented in the software to calculate the expected lactation.

Via the included temperature recording, the system also provides calving management support. About 15h before calving dairy cows show a drop in temperature, which enables onset of calving to be detected by the smaXtec system. Furthermore, continuous temperature measurement provides additional information about drinking behavior, which is relevant in addressing issues relating to health as well as to feeding. The combination of 24/7 activity and temperature measurement enables one-stop health monitoring and early disease detection. In addition, the smaXtec system also offers pH measurement (Premium bolus) enabling the monitoring of rumen conditions relating to health (acidosis detection) and feeding management quality (feed conversion efficiency).

**Performance Testing**

The performance of the smaXtec Heat Detection system has been verified based on data from flagship farms as well as research projects conducted in collaboration with external partners. The latest study, which will be presented in detail, was conducted in cooperation with the University of Goettingen.

The study was conducted on a commercial farm with a herd of 600 Holstein dairy cows in Germany. Data for this investigation originated from 100 cows (primiparous and multiparous) with an average milk yield of 11,200 kg/annum. All dairy cows were housed in a free stall with cubicles and were milked three times a day. They received a TMR mainly based on maize silage. The cows were equipped and monitored with a smaXtec Basic bolus (temperature und activity measurement) 2 weeks prior to expected calving date. Heat detection started 30 days antepartum with daily visual observation, the smaXtec system and blood progesterone, while the latter was used as gold standard. Visual checks were performed on all cows daily in the morning by trained staff independently of the smaXtec data. Blood samples from all cows, which where visually in heat as well as from all cows with a smaXtec alert, were taken to measure blood progesterone levels.

To test the performance of the smaXtec system, heats based on progesterone data were compared with heats detected by smaXtec. To provide quantitative information, the following metrics were used to evaluate all the collected data:

Precision: $\frac{True\ Positives}{True\ Positives+False\ Positives}$

Sensitivity: $\frac{True\ Positives}{True\ Negatives+False\ Negatives}$

The study confirmed the results of previous tests and demonstrated that the smaXtec system is an accurate tool for use in heat detection. With a precision of 93% and a sensitivity of 95% in the described trial, the system is proved to be reliable. With inclusion of the results of previous tests, the overall precision is 89% and sensitivity is 92%.

**Conclusion**

The detection of cows in heat has become more and more difficult over the past decades due to changes in animal behaviour and management. Besides timed breeding programs, which are often costly due to poor conception rates, the use of activity monitoring systems developed into a reliable and accepted method in farms worldwide. While activity was previously only measured by collars, ear tags or pedometers, for the first time the smaXtec system delivers an activity-based heat detection system with data directly from the rumen. Performance tests confirmed the accuracy of the system. Together with its advantages in handling it is shown to be a reliable, innovative alternative for progressive heat detection and general herd monitoring.

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**Figures**

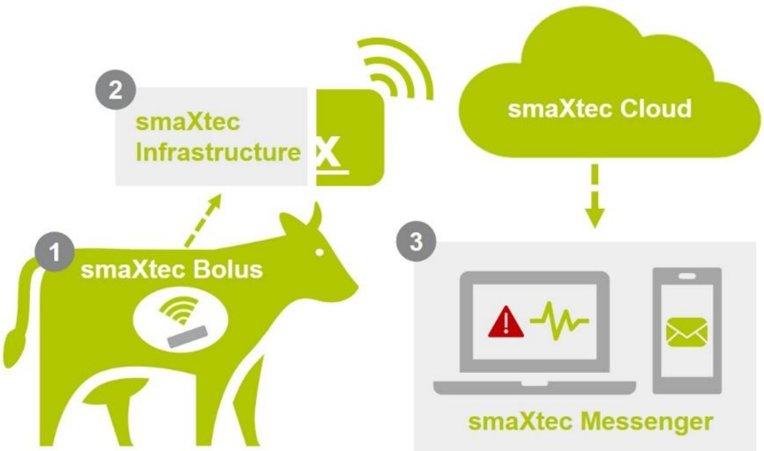



*Figure 1: Components of the smaXtec inside monitoring system.*

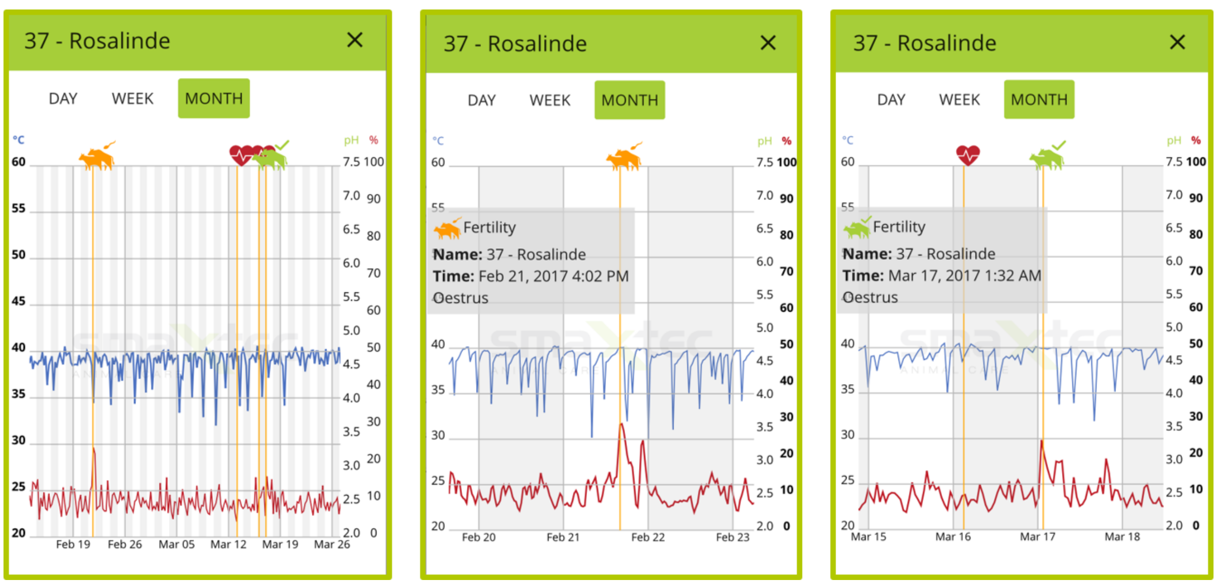



*Figure 2: Graph of two heat events of cow Rosalinde. The first insemination did not lead to pregnancy, while the following was successful.*

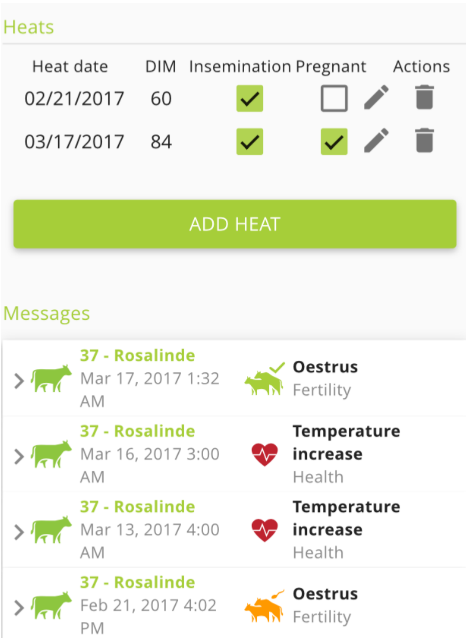



*Figure 3: Heat events and health messages in cow Rosalinde´s profile.*

Edge Computing
**Applications in the Dairy Industry and What It Can Do for You**

In the past 100 years, technology has come from producing the first automobiles to be sold to the public and patenting zippers to 3D printers, drones and self-driving cars. With the incredible progress of technology, never has the ancient occupation of farming had more resources at its disposal to improve production and sustainability.

Agriculture has evolved from primitive irrigation systems employed in ancient societies and automated harvesters developed in the 1800's to the present-day integration of computing, GPS navigation and predictive modeling into the discipline of "Precision Agriculture."

Most "Precision Agriculture" conversations focus on crop applications; using GPS and thermal imaging to detect areas of high pest populations or disease and using aggregated data to determine the best crops to plant in which soil, at what densities and with which protection products to extend the growing season and maximize the yield.

However, the dairy industry is far from being left behind in this technological explosion. With increasing urban populations and land prices, farmers have been increasing production to generate more income. This means larger herds, which results in more time required to properly monitor the cows. Time that most farmers simply don't have.

Edge Computing technologies allow dairy farmers to better monitor their herd's health and production remotely, decreasing labor and treatment costs while increasing yield, quality and animal comfort.

**What is it?**
Edge Computing refers to the aggregation and analysis of data by an individual or group for the purpose of studying that data and using it to improve a system or process. This technology can be differentiated into two subgroups: Cloud Computing when data is aggregated and stored for use by a single network user, or Fog Computing when that data is distributed among many network users.

In both cases data is collected at remote locations, transmitted to a central node to be aggregated and analyzed, then displayed as reports and anonymously shared with others. With data sharing, farmers can make decisions based on more information and data from farms in similar locations, parlor styles and herd size/breed, among other things.

Common devices already in use in the dairy industry for gathering data include pedometers, e-tags, e-collars, e-pills, motion sensors and microphones. Along with reporting of data and drawing global conclusions, a central processor can also be programmed to send email or text notifications to convey time sensitive data, such as a cow in distress. This real time data is important to the farmer and can also be useful for veterinarians, breeders and feed companies.

**General Health Monitoring**

Using E-collars/tags is an optimal way to monitor cows out at pasture. The devices can measure the cows' vitals in addition to activity level and rumination time as well as environmental factors such as ambient temperature and humidity. Built in GPS tracking enables more efficient herding, as well as the ability to see which pasture areas have more traffic. This information can help with pasture rotation, planning water/shade availability to prevent heat stress and monitoring fences or ground for required maintenance.

More detailed internal information can also be gathered. E-pills collect information about rumen func- tion, including pH levels, feed intake and fermentation activity. Having this real time data on site can prevent acidosis and nutritional deficiencies or enable treatment to be started sooner, ultimately increasing the probability of a positive outcome as well as decreasing the treatment costs.

**Milk Production & Mastitis**

With the increasing use of robotic milking systems comes an increase in data. Most robotic parlors include monitors for electrical conductivity and somatic cell counts (SCC). Paired with e-collars/tags the system delivers personalized care to each cow; individual ration sizes, teat scrubbing and foot-baths are common in most models. Sensors monitor changes in teat location and health and meters record the cow's weight, yield and milking frequency.

All of this data can be sent to a central computer to be incorporated into health records which can be monitored for individual or herd health status. Inferior quality milk, such as that from cows with mastitis or recently calved cows can be automatically diverted from the bulk tank, with no human intervention required.

**Reproduction**

Good milk production starts with efficient and healthy breeding. Devices such as e-collars/tags and pedometers can track breeding dates and heat cycles. Cows walk up to 6 times more when they are in heat[1], making pedometers an invaluable tool to utilize that narrow breeding window in each cycle, especially since many cows do not display symptoms such as standing heat. Monitoring the dam's vital signs throughout pregnancy helps prevent many health issues that could lead to abortion or stillbirth. The devices can also be used to smooth the calving process.

Since cows prefer to calve in privacy without human intrusion, the labor can be monitored remotely and intervention only carried out when necessary. Decreasing the stress involved with calving enables a faster recovery, allowing cows to return to heat sooner and in better health. Some farms using this technology have seen breeding rates increase from 44% to 99%[1]. This translates into a significant increase in milk production and calf sales as well as decreased costs of insemination.

## How To Successfully Implement Edge Computing Technology

The best technology in the world will never deliver the full potential benefits if the people using it do not understand why they are using it, its capabilities and limitations and how to regularly review its perfor- mance. The graphic below outlines four steps in successfully implementing Edge Computing technology on the farm.

To some extent, the benefits that will be seen depend on your current level of herd management. If you are already operating at a 99% pregnancy rate with a mastitis incidence under 5%, for example, the system will be more useful as a monitoring tool for prevention than for improving health and production.

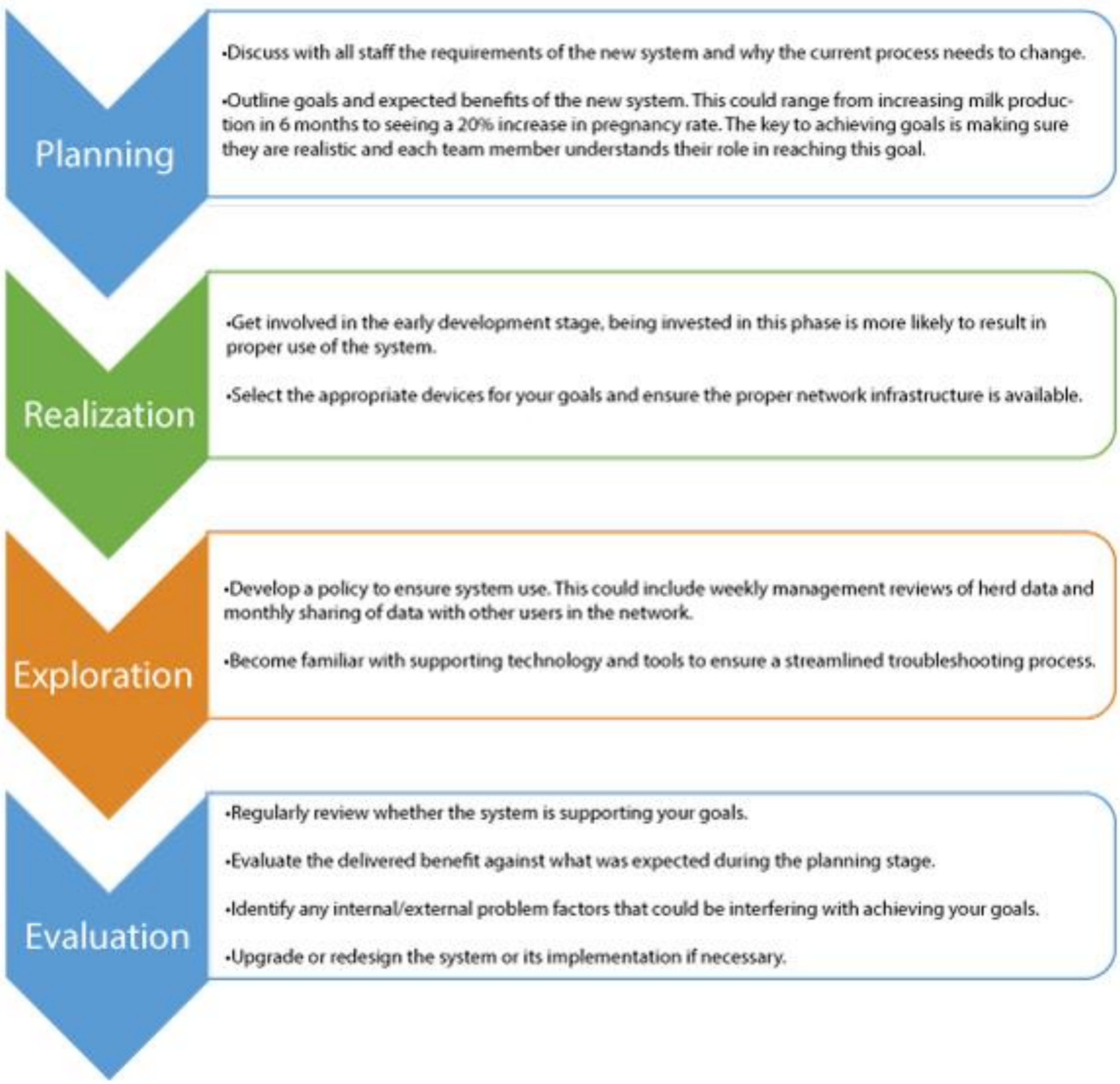



**Figure 1:** Steps to Successfully Implementing Edge Technology on Your Farm. Adapted from: (Khampachua & Wisitpongphan, 2014)[2]

**What Can Edge Technology Do for You?**
The data collected from on-site devices can be vital to your decision making and help in many ways:

- Information collected can be compiled into lists or reports which can then be used to sort cows into groups (based on treatment or nutritional needs for example) to reduce labor, as well as to track individual cow history.

- Data from real time monitoring enables immediate action to be taken based on current information about the situation, not what it was 2 days ago.

- Personalized care can be given to each animal, optimizing cow comfort, health and nutritional programs and subsequently production and profitability

- Treatment can be administered earlier based on changes in vital signs rather than clinical signs that may not appear until 7-10 days later. The decreased time required for treatment, monitoring and manually recording data allows farmers to step back and look at the bigger picture

- Aggregating and anonymously sharing data between farms allows you to benchmark your farm against average figures from similar producers. You can see which treatments work most effectively for which groups of cows, which groups benefit the most from certain feed additives —and much more

Edge Computing is the latest resource available for dairy farmers to manage their herds to be cost effective, healthy, productive and profitable.

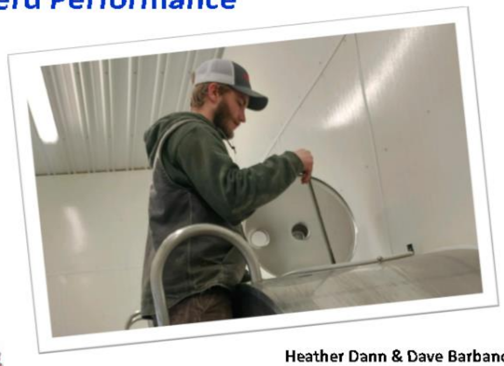
**About the Author**
Anna Schwanke is an undergraduate student at the University of Guelph, Ontario. She is responsible for researching and writing about a wide variety of topics related to dairy cow welfare and manage- ment for Dairy Quality Inc. The 10 years she spent living in Australia, as well as her love of travelling, give her a firsthand viewpoint of issues facing the international dairy community. She plans to gradu- ate from the University's College of Physical & Engineering Science in 2019 and pursue a career in the Life Sciences or Agriculture industry.

**References**

[1]Pretz, K. (2016, May 6). Connected Cattle: Wearables are Changing the Dairy Industry. Retrieved from The Institute: http://theinstitute.ieee.org/technology-topics/life-sciences/connected-cattle-wearables-are-changing-the-dairy-industry

[2]Khampachua, T., & Wisitpongphan, N. (2014). ICT Benefit Realization for Dairy Farm Management: Challenges and Future Direction. 11th International Joint Conference on Computer Science and Software Engineering (JCSSE) (pp. 280-285). Pattaya, Thailand: King Mongkut's University of Technology North Bangkok, Thailand.

## New Milk Analysis Technologies to Monitor Management and Improve Herd Performance



Heather Dann & Dave Barbano

Precision Dairy Farming – May 30 to June 1, 2017

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Used world-wide to measure fat, protein, and lactose for payment and dairy herd improvement programs

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Develop new tools in milk analysis for bulk tank using mid infrared technology to provide information to support decision making for feeding and general management of the herd

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## St. Albans Co-op first in the nation to adopt fatty acid analysis and provide results to farmers on a daily basis



(February 2016)

## Bulk Tank Milk Report for Farmer

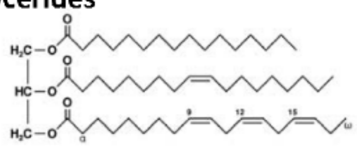
| TRANS_DATE | TANK | POUNDS | BFAT | PROT | LACT | TSOL | SNF | OSOL | CELL | MU | DEN | MIX | PREF | DBOND | RAW | PAST | PI | CRYO |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 07-MAR-2017 | 1 | | 4.13 | 3.17 | 4.86 | 13.05 | 8.92 | 5.75 | 140 | 12.86 | [illegible] | 1.44 | 1.63 | [illegible] | | | | 550 |
| 05-MAR-2017 | 1 | 15480 | 4.17 | 3.19 | 4.85 | 13.12 | 8.95 | 5.76 | 180 | 11.56 | 1.00 | 1.37 | 1.76 | 0.280 | | | | 536 |
| 04-MAR-2017 | 1 | 15674 | 4.27 | 3.19 | 4.88 | 13.25 | 8.98 | 5.79 | 190 | 11.9 | 1.03 | 1.40 | 1.84 | 0.285 | | | | 548 |
| 03-MAR-2017 | 1 | 15932 | 4.19 | 3.19 | 4.85 | 13.13 | 8.94 | 5.75 | 180 | 12.95 | 1.00 | 1.38 | 1.77 | 0.285 | | | | 546 |
| 02-MAR-2017 | 1 | 15846 | 4.04 | 3.15 | 4.88 | 12.97 | 8.93 | 5.78 | 110 | 13.16 | 0.98 | 1.29 | 1.76 | 0.289 | | | | 536 |
| 01-MAR-2017 | 1 | 15824 | | | | | | | | | | | | | 3 | 5 | 15 | |
| 28-FEB-2017 | 1 | 16018 | 4.13 | 3.16 | 4.87 | 13.03 | 8.9 | 5.74 | 110 | 12.85 | 0.96 | 1.44 | 1.58 | 0.282 | | | | 538 |
| 27-FEB-2017 | 1 | 15695 | 4.1 | 3.21 | 4.88 | 13.12 | 9.02 | 5.81 | 100 | 13.28 | 1.04 | 1.33 | 1.79 | 0.268 | | | | 544 |
| 26-FEB-2017 | 1 | 15889 | 4.16 | 3.17 | 4.9 | 13.12 | 8.96 | 5.79 | 140 | 13.04 | 0.97 | 1.49 | 1.58 | 0.285 | | | | 543 |
| 25-FEB-2017 | 1 | 15738 | 4.2 | 3.17 | 4.88 | 13.13 | 8.93 | 5.76 | 120 | 13.17 | 0.94 | 1.54 | 1.55 | 0.283 | | | | 544 |
| 24-FEB-2017 | 1 | 15824 | 4.16 | 3.15 | 4.88 | 13.08 | 8.92 | 5.77 | 130 | 13.9 | 0.94 | 1.53 | 1.51 | 0.293 | | | | 542 |
| 23-FEB-2017 | 1 | 16039 | 4.12 | 3.16 | 4.89 | 13.04 | 8.92 | 5.76 | 120 | 13.04 | 0.92 | 1.54 | 1.46 | 0.292 | | | | 547 |
| 22-FEB-2017 | 1 | 16104 | 4.22 | 3.16 | 4.85 | 13.11 | 8.89 | 5.73 | 90 | 13.09 | 0.92 | 1.52 | 1.55 | 0.295 | | | | 544 |
| 21-FEB-2017 | 1 | 15588 | 4.28 | 3.17 | 4.85 | 13.17 | 8.89 | 5.72 | 120 | 13.95 | 0.94 | 1.61 | 1.47 | 0.284 | | | | 545 |
| 20-FEB-2017 | 1 | 16125 | 4.2 | 3.17 | 4.85 | 13.08 | 8.88 | 5.71 | 110 | 13.42 | 0.92 | 1.56 | 1.49 | 0.291 | | | | 544 |
| 19-FEB-2017 | 1 | 15996 | 4.26 | 3.16 | 4.83 | 13.1 | 8.84 | 5.68 | 150 | 11.61 | 0.92 | 1.64 | 1.46 | 0.277 | | | | 544 |

## What is this information?

## Milk Fat Composition

### Most Variable Component of Milk

- 98% triglycerides

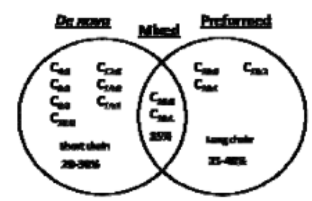


- More than 400 unique fatty acids (FA) in milk
- About 20 FA make up the majority
  - Broadly grouped into 3 subcategories

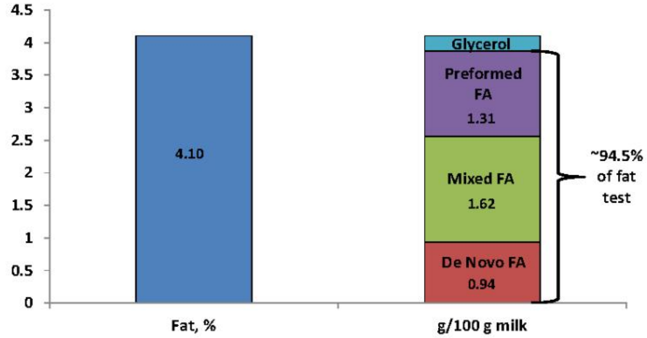
Jensen et al., 2002; Palmquist, 2006; Moate et al., 2007

## Milk Fatty Acid (FA) Groups

- De novo FA - C4 to C14
  - Made in the mammary gland
  - Influenced by rumen fermentation/function
  - 18-30 relative % (21-26)
- Mixed origin FA - C16, C16:1
  - From fat the diet
  - Made in the mammary gland
  - 30-40 relative % (35-42)
- Preformed FA - ≥C18
  - From fat the diet
  - From body fat mobilization
  - 32-42 relative % (35-42)

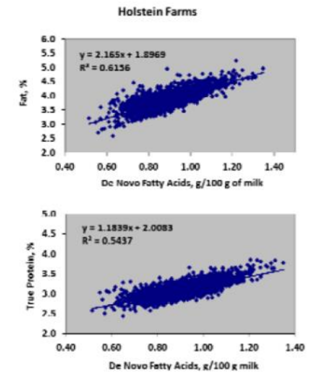


## Fat and Fatty Acid Groups – Relationship in Bulk Tank Milk




## Key Findings from Monitoring 430 Farms over a 15-Month Period

- Milk fat and protein increased when de novo fatty acids in milk increased
- Occurred for both Holstein and Jersey herds



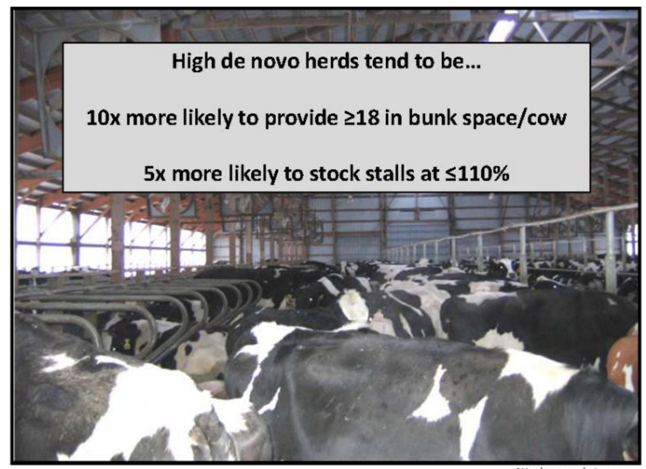

Barbano, 2016

## Surveys Conducted in 2014 and 2015

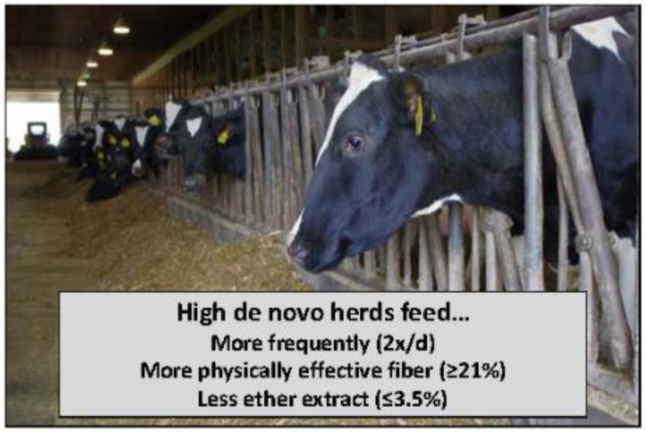
### Better Understand Management and Nutrition Differences between Herds with High and Low De Novo Fatty Acids

| | High | Low |
|---|---|---|
| 2014 | | |
| Fat, % | 4.55 | 3.90 |
| True protein, % | 3.50 | 3.16 |
| De novo FA, g/100 g milk | 1.13 | 0.90 |
| Mixed FA, g/100 g milk | 1.65 | 1.36 |
| Preformed FA, g/100 g milk | 1.52 | 1.43 |
| 2015 – Holstein herds | | |
| Fat, % | 3.96 | 3.75 |
| True protein, % | 3.19 | 3.10 |
| De novo FA, g/100 g milk | 0.92 | 0.81 |
| Mixed FA, g/100 g milk | 1.53 | 1.41 |
| Preformed FA, g/100 g milk | 1.27 | 1.30 |

Woolpert et al., 2016; Woolpert et al., in press




Woolpert et al., in press




Woolpert et al., 2016; Woolpert et al., in press

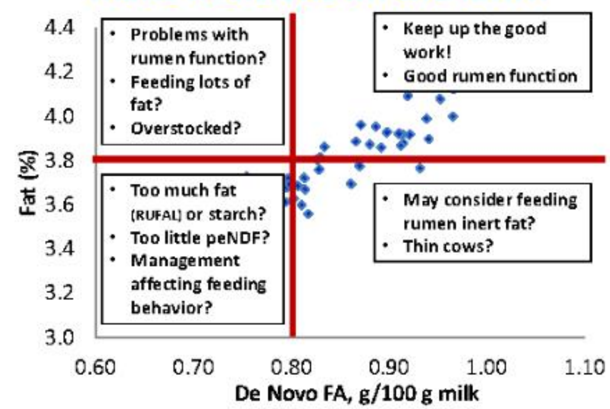
## How Should We Use This Information?

1. Herd "snapshot" and troubleshooting

## Bulk Tank "Alarms" for Holstein Herds

| Milk Component | Units | Alarm Value |
|---|---|---|
| Fat | % | <3.8 |
| De Novo FA | g/100 g milk | <0.8 |
| Mixed FA | g/100 g milk | <1.3 |
| Preformed FA | g/100 g milk | <1.3 |
| FA Unsaturation | double bonds/FA | >0.31 |

## Can we use milk fatty acid data to make decisions on the farm?



## Soybeans, RUFAL, and Low Milk Fat

- **Snapshot: ~3.4 to 3.5% fat**
  - 0.77 g de novo FA/100 g milk
  - 1.09 g mixed FA/100 g milk
  - 1.30 g preformed FA/100 g milk
  - 0.35 double bonds/FA
- **Problem: Diet too high in RUFAL**
  - Use of home grown roasted soybean
  - Ground extremely fine with hammer mill
- **Solution: ↑ grind size**

- **Outcome: ≥ 3.7% fat**
  - 0.94 g de novo FA/100 g milk
  - 1.18 g mixed FA/100 g milk
  - 1.56 g preformed FA/100 g milk
  - 0.31 double bonds/FA

Example courtesy of M. Carabeau

## Factors Associated with Increased Risk of Milk Fat Depression

- **Fats (RUFAL)**
- **Fermentable carbohydrates**
  - Starch, forage fiber, peNDF
- **Yeasts/molds**
- **Management**
  - Stocking density

Jenkins, 2013

2010

## Herd with Low Milk Fat

- **Snapshot: 7 to 10 days, Holstein herd >90 lb milk**
- **What are the diet and management opportunities?**

| | Aug 2016 | Jan 2017 | Comment |
|---|---|---|---|
| Lactose, g/d | 1942 | 1965 | Good, excellent milk yield |
| Fat, %* | 3.37 | 3.68 | Opportunity for improvement |
| True protein, %* | 3.04 | 3.17 | Good, rumen microbial biomass (AA) |
| De novo FA, g/100 g milk | 0.72 | 0.79 | Low, de novo synthesis issue |
| Mixed FA, g/100 g milk | 1.19 | 1.29 | Low, de novo synthesis issue, C16 fat |
| Preformed FA, g/100 g milk | 1.29 | 1.38 | OK |
| Unsaturation, DB/FA | 0.34 | 0.33 | Too high (RUFAL?) |

*Larger than normal variation...changes in time budget of cows (milking, feeding, etc)?

## How Should We Use This Information?

1. Herd "snapshot" and troubleshooting
2. **Evaluating changes over time**

## Monitor Fatty Acid Groups in Bulk Tank Milk for Changes Over Time

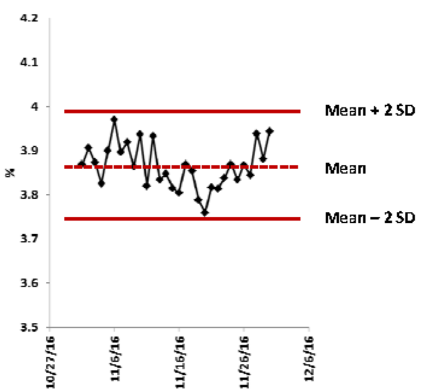
| Fatty Acid Group | Increases | Decreases |
|---|---|---|
| De novo FA | • Positive impact on milk fat and/or protein<br>• Response to improved rumen function and/or feed quality | • Evaluate management and nutrition<br>• Did an unexpected change occur? |
| Mixed FA | • Response to increased dietary fat<br>• Possible response to de novo synthesis | • Evaluate management and nutrition<br>• Did an unexpected change occur? |
| Preformed FA | • Response to more body fat mobilization or increased dietary fat | • Herd BCS too low<br>• Milk fat may decrease<br>• Herd BCS may increase |

## Need to Know the Farm's Typical Variation

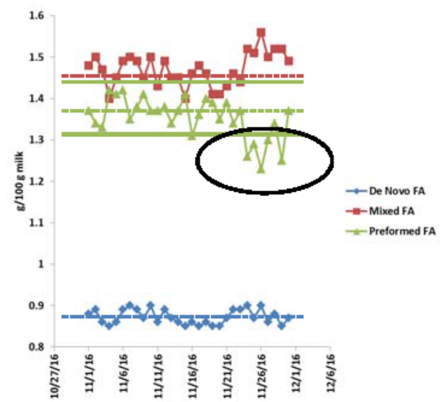
| | Mean | Standard Deviation (SD) | Coefficient of Variation (CV) (SD/mean x 100) |
|---|---|---|---|
| Fat, % | 3.84 | 0.06 | 1.52 |
| FA, g/100 g milk | | | |
| De Novo | 0.86 | 0.02 | 2.19 |
| Mixed | 1.43 | 0.03 | 2.37 |
| Preformed | 1.39 | 0.05 | 3.63 |

1 tank, 305 samples from 13 month period

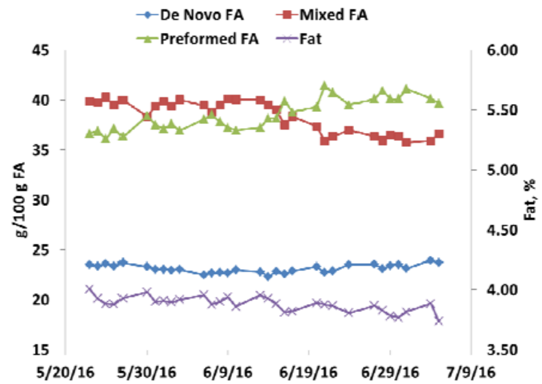
## Fat %




## Variation in November… Something Changed



## Forage Quality Changed




## Factors Affecting Variation

### Within & Between Herds

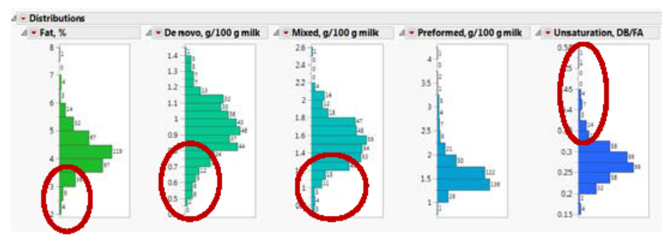
- Management related to feeding, housing, and milking of cows
- Diet and feed quality
- Consistency in day to day routine
  - Affects time budget of cow
- Days off and vacations
- Weather changes
- Filling sequence of multiple tanks

## Bulk Tank Changes Associated with Milk Fat Depression

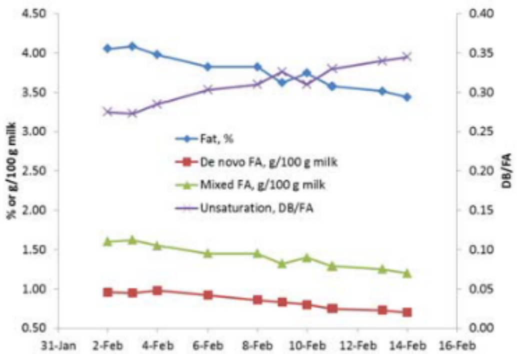
A gradual change in fat % under most situations

1. ↑ in unsaturation index (>0.31 DB/FA)
2. ↓ in mixed FA (g/100 g milk)
3. Continued ↓ in mixed FA and ↓ de novo FA (g/100 g milk)
4. ↓ in true protein (%)

## Herd Distribution



## Herd with Decreasing Milk Fat



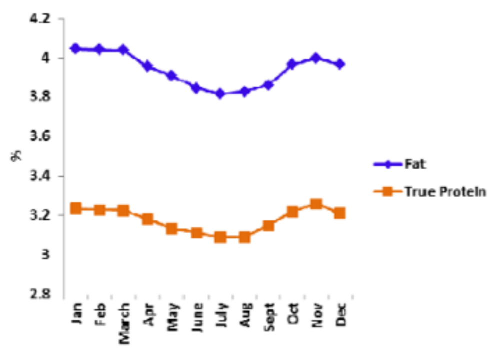

## Recovery from Milk Fat Depression

1. ↑ in mixed FA (g/100 g milk)

2. Continued ↑ in mixed FA and ↑ de novo FA (g/100 g milk)

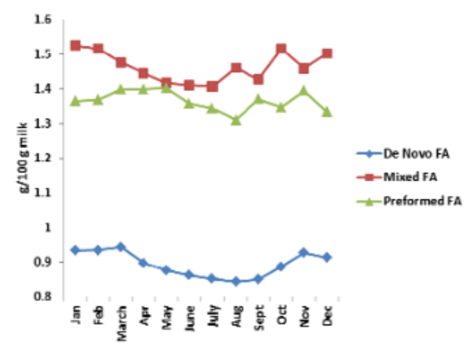
- Monitor milk yield (often no change expected) and milk fat
- Be realistic about time it takes for milk fat to recover (>10 days)


## Seasonal Changes in Milk Composition



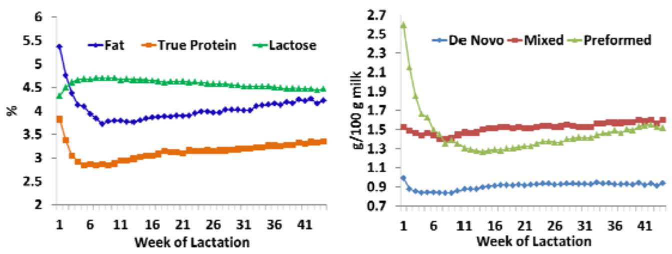

40 St. Albans Coop herds Jan 2014 to Feb 2016

## Seasonal Changes in Milk Composition

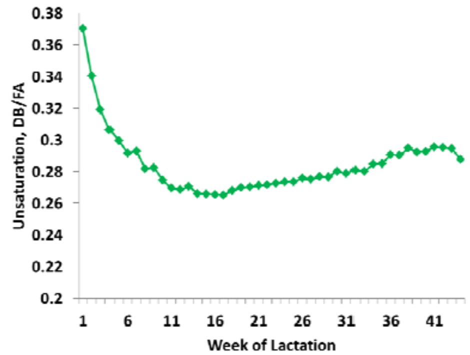



40 St. Albans Coop herds Jan 2014 to Feb 2016

## “Days In Milk” Changes in Milk Composition




## Unsaturation Index Changes Over the Lactation Cycle



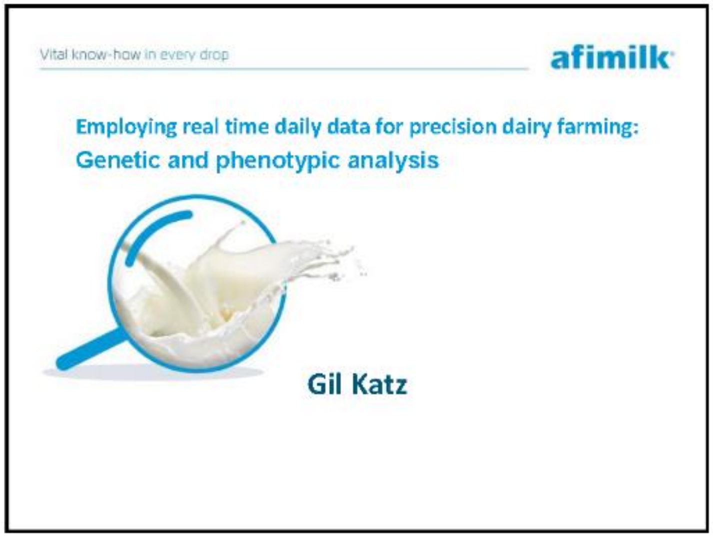

## Take Home Messages

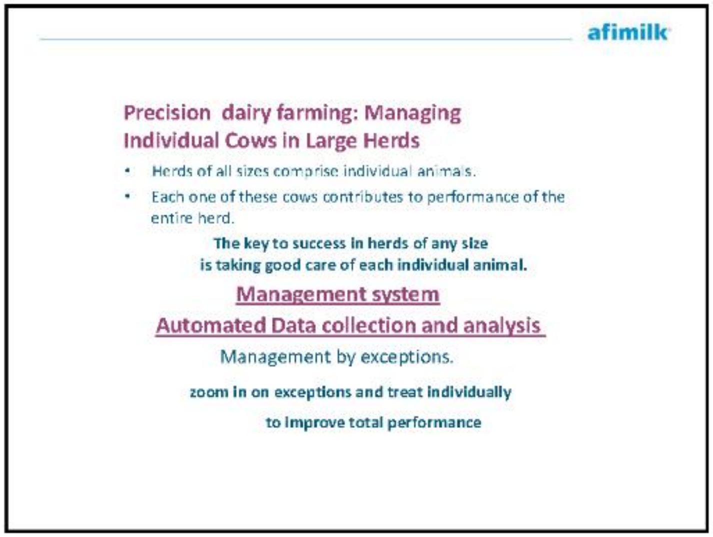
- Bulk tank milk fatty acid metrics are available
- Indication of rumen function, body reserves, risk for milk fat depression
- Make nutrition and management decisions

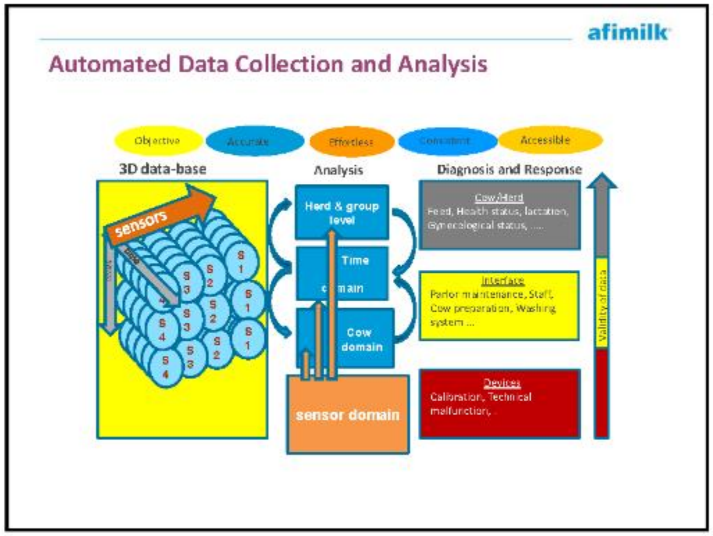
## Take Home Messages

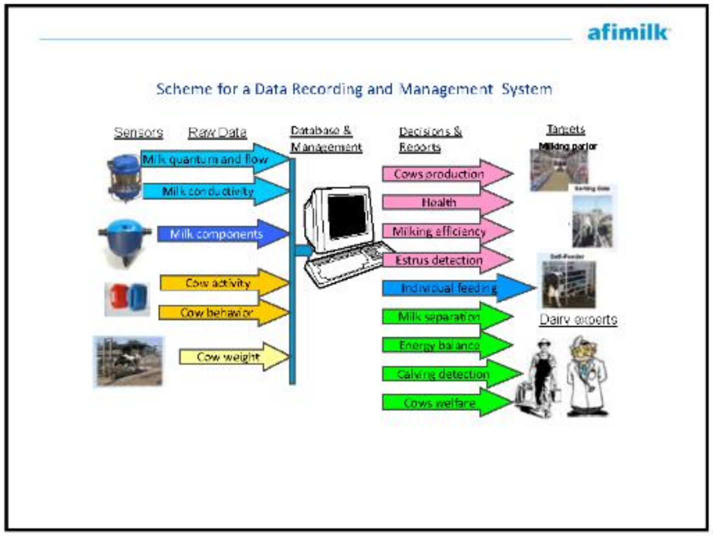
- Herd “snapshot” and troubleshooting
  - Milk fat depression
- Evaluating changes over time
  - Planned and unexpected

**Genetic and Phenotypic Analysis of Milk, Fat, and Protein Production Based on Real Time Daily Milk Analysis**
***Dr. Gil Katz, afimilk***



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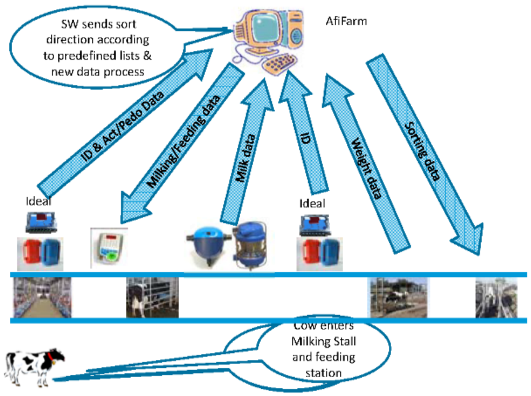


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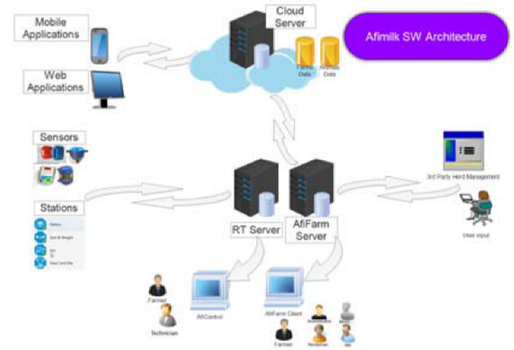


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## Manage and merge different Data types

**Quantitative data (monotonic structure)**
milk yield, milk components, milk flow, weight ….

**Qualitative data (discreet structure)**
gynecological status, health status …

**Behavioral data (pattern based)**
activity pattern, grouping pattern, rest pattern, feed pattern ….

Milking stall sensors – milk yield, milk flow, milk conductivity,
milk fat, protein, lactose, blood, coagulation potential, fatty acids

Cow sensors – activity, lying times, lying bouts, rumination and eating

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## Big Data

Complex biological systems

**Challenge:**
construct data, collect data, mine data, Develop predictive models,
Validate models, construct comparative standards

### Disciplines

| Biology, Chemistry, Physics | Data science, Mathematics, computer science | Health, Fertility, Feed, Genetics, Production |
|---|---|---|

**Challenge: Pattern recognition of subjective multi dimensional data**

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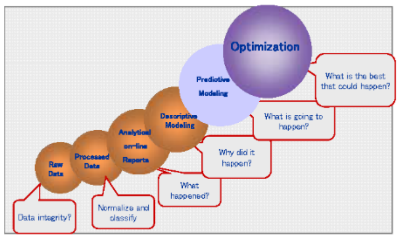
## From Data Collection to Decision Making

Data → Information → Knowledge → Intelligence




Arkadi Slezberg, 2009

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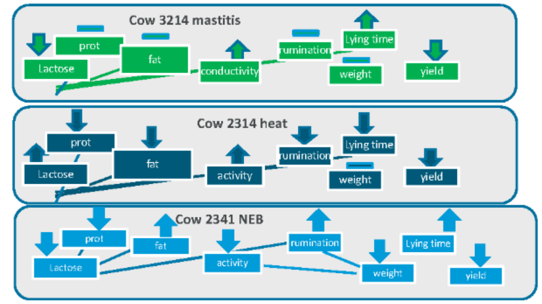
## Descriptive :From highlighting irregularities to diagnostics

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## Can we move on from descriptive to Predictive?

**J. I. Weller and E. Ezra, "*Genetic and phenotypic analysis of daily Israeli Holstein milk, fat, and protein production as determined by a real-time milk analyzer*", JDC, Vol. 99 No. 12, 2016**

- Scope: >37,000 Holstein cows spanning over 2 years
- Finds agreement between Afimilk's inline milk lab real time analysis and between DHIA monthly tests.
- Selected for 'Editor's Choice' of JDSc

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## Objectives

To test the hypothesis that a combination of more frequently but less accurately analyzed milk components should give a more representative measure of a cow's longer-term milk composition than a DHIA sample taken once per month

- Joel Ira Weller and E. Ezra

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## Estimation of milk components on monthly test days

- Daily records from 37,486 cows at 44 large Kibbutz herds in Israel were collected from January 2014 through January 2016.
- Cows were milked three times daily. Each month on the test day the milk inspector collects samples from 2 out of 3 milkings, which are mixed in proportion to the milk produced by the cow in each of the 2 milkings.
- Visits are arranged so that a different milking is missed in each consecutive visit.
- Milk components are determined in the Central Milk Laboratory of Israel Cattle Breeders Association (ICBA) using a CombiFoss™(Foss, Hillerød, Denmark), and a Combi Bentley FTS+FCM (Bentley Instruments, Inc., Chaska, MN).

- Joel Ira Weller and E. Ezra

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## Conclusions with respect to 305 d lactation production

- ICBA mean fat production and percentage were higher than the corresponding AfiLab means in both parities.
- All correlations between the lactations were higher than the correlations between the records for daily production.
- Correlations for first and second parity were nearly identical for all traits.
- As found for the daily records, correlations were higher for fat and protein production, as compared to fat and protein percentage.
- Correlations for fat and protein production were 0.77 and ~0.9 in both lactations.

- Joel Ira Weller and E. Ezra

Heritabilities and genetic and environmental correlations among 7,866 first parity 305 d lactations computed from the ICBA and AfiLab records.

| Trait | Heritabilities | | Correlations | |
|---|---|---|---|---|
| | ICBA | AfiLab | genetic | environmental |
| Milk (kg) | 0.33 | 0.35 | 1.00 | 0.96 |
| Fat (kg) | 0.23 | 0.31 | 0.59 | 0.70 |
| Protein (kg) | 0.27 | 0.32 | 0.86 | 0.87 |
| % fat | 0.48 | 0.57 | 0.70 | 0.66 |
| % protein | 0.55 | 0.46 | 0.56 | 0.52 |

Heritabilities were higher for the AfiLab records for all traits, except for % protein. Both genetic and environmental correlations were relatively low, except for milk.

- Joel Ira Weller and E. Ezra

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Phenotypic correlations among complete and extended 7,892 first parity lactations computed from the last ICBA test day and the last two weeks of AfiLab records.

| Fat(Kg) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Trait | Mean days in milk at truncation | | | | | | | | |
| | 30 | 60 | 90 | 120 | 150 | 180 | 210 | 240 | 270 |
| ICBA | 0.67 | 0.75 | 0.79 | 0.87 | 0.91 | 0.93 | 0.95 | 0.95 | 0.96 |
| Afilab | 0.77 | 0.84 | 0.89 | 0.92 | 0.94 | 0.95 | 0.96 | 0.96 | 0.97 |
| **Protein(Kg)** | | | | | | | | | |
| Trait | Mean days in milk at truncation | | | | | | | | |
| | 30 | 60 | 90 | 120 | 150 | 180 | 210 | 240 | 270 |
| ICBA | 0.70 | 0.76 | 0.78 | 0.87 | 0.90 | 0.92 | 0.94 | 0.94 | 0.95 |
| Afilab | 0.72 | 0.83 | 0.87 | 0.90 | 0.93 | 0.94 | 0.95 | 0.95 | 0.96 |

- Joel Ira Weller and E. Ezra

## Conclusions from extended lactations

- The AfiLab phenotypic correlations are higher than the ICBA correlations for all 3 traits at all 9 truncation points, even though DIM at truncation was lower for the AfiLab records.
- The AfiLab genetic correlations were higher than the phenotypic correlations for all 3 traits at all truncation points (not shown).
- With only 30 DIM genetic correlations ranged from 0.73 to 0.79 for the 3 traits.

- **Joel Ira Weller and E. Ezra**

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Vital know-how in every drop — afimilk

## Prediction of complete lactations

- Our objective: To adapt the **large scale retrospective** study's method to a **prospective prediction** of complete (305_days) lactations in individual herds
  - ✓ For selection
  - ✓ For production planning (quota, summer/winter)
- The operational need: To enable farmers to get the decision as early as possible, **but before breeding**

Oded Nir (Markusfeld)

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Vital know-how in every drop — afimilk

## Waiting Periods

| Herds | Cows/herd | Voluntary waiting period (days) | Days to 1st AI |
|---|---|---|---|
| 13,885 | 158.4 ± 325 SD | 58.4 ± 5.6 SD | 95.2 ± 26.9 SD |

Ferguson J.D. & Skidmore A. (2013). JDS 96 (2) 1269 -1289

| Days to 1st AI | 50 | 51 - 80 | 81 - 110 | 111 - 150 |
|---|---|---|---|---|
| 1st lactation | 0.4% | 41.4% | 45.2% | 13.0% |
| 2nd lactation | 9.7% | 58.4% | 26.9% | 5.1% |

Ezra E. (2013). HerdBook Summary (Hebrew). ICBA

**Our objective is to be able to make the decision at 60 DIM**

Oded Nir (Markusfeld)

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Vital know-how in every drop — afimilk

## Materials & Methods

- Basic Models were computed from all cows calving through a whole year, cows with complete data of milk, fat & protein 305_d yields were included. Data are from 3 Israeli Holstein herds. 663 cows, 937 cows & 298 cows annual calving in herds #1, #2, & #3 respectively
- Data were analyzed by a stepwise multiple regression, estimates of p<0.01 were included in the final models.
- Variables were those of Weller & Ezra's models + length of the dry period, gestational length, twins, stillbirth, uterine diseases & FPR. Effects of parity was included in all models. Predicted Transmitting Ability (PTA) from N.O.A were included in some models.
- Predictions derived from the basic models were applied to cows calving through months following the last month of the basic models.

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### Criteria for Success

- R^2= RSquare of the **summary of fit**
- r = **Correlations** to actual production
- 75% & 90%tiles of **the differences between the predicted & actual estimates** of the various traits **(for planning & selection)**
- **Predictive Values & accuracy** for **selection decisions**
  - ✓ PPR (positive predicting value)=The probability that a cow defined by test as a "low yielder" is truly so
  - ✓ NPR (negative predicting value)=The probability that a cow defined by test as a "high yielder" is truly so

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Vital know-how in every drop — afimilk

### Prediction of complete lactations in Afifarm

- Our objective: To adapt the **large scale retrospective** study's method to a **prospective prediction** of complete (305_days) lactations in individual herds
  - ✓ For selection
  - ✓ For production planning (quota, summer/winter)
- The operational need: To enable farmers to get the decision as early as possible, **but before breeding**

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Vital know-how in every drop — afimilk

### Herd #769

| | Milk, kg/305 days | | | Fat, kg/305days | | | Protein, Kg.305 days | | | ECM, kg 305 days | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 34 | 54 | 84 | 34 | 54 | 84 | 34 | 54 | 84 | 34 | 54 | 84 |
| RSquare | 0.683 | 0.726 | 0.786 | 0.704 | 0.737 | 0.704 | 0.653 | 0.698 | 0.768 | 0.717 | 0.753 | 0.804 |
| Correlations | 0.930 | 0.949 | 0.968 | 0.926 | 0.931 | 0.926 | 0.918 | 0.935 | 0.956 | 0.923 | 0.941 | 0.962 |
| +tive PV | 65.0% | 72.2% | 84.6% | 47.5% | 57.6% | 47.5% | 65.0% | 80.0% | 84.6% | 52.9% | 56.7% | 76.5% |
| -tive PV | 78.6% | 79.3% | 79.0% | 86.1% | 88.4% | 86.1% | 78.6% | 78.7% | 79.0% | 83.3% | 82.6% | 81.0% |
| Accuracy | 75.0% | 77.6% | 80.0% | 65.8% | 75.0% | 65.8% | 75.0% | 78.9% | 80.0% | 69.7% | 72.4% | 80.0% |
| 10%tile to 90%tile | -10.1% to 8.4% | -7.5% to 9.2% | -4.7% to 8.6% | -11.4% to 7.0% | -9.5% to 6.8% | -11.4% to 7.0% | -8.7% to 9.8% | -7.1% to 10.1% | -4.0% to 9.0% | -11.8% to 4.6% | -9.3% to 6.3% | -5.5% to 7.0% |

Herd #3: n for 12/14-11/15=717 (34 DIM); 1,195 (54 DIM); 1,912 (84 DIM); n for 12/14-02/16=76

- Prediction of all the production variables examined improved with time from calving
- The smaller herd behaved similar to the larger one

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### Afilab <=34 DIM vs. 1st ICBA milk test <=34 DIM (All lactations combined)

| | Milk, kg/305 d | | Fat, kg/305 d | | Protein, Kg.305 d | | ECM, kg 305 d | |
|---|---|---|---|---|---|---|---|---|
| Herd #1 | Afi | ICBA | Afi | ICBA | Afi | ICBA | Afi | ICBA |
| RSquare | 0.568 | 0.554 | 0.523 | 0.388 | 0.543 | 0.502 | 0.571 | 0.513 |
| Correlations | 0.858 | 0.800 | 0.866 | 0.727 | 0.845 | 0.784 | 0.860 | 0.777 |
| +ve PV | 75.0% | 54.2% | 60.6% | 40.9% | 71.4% | 66.7% | 75.0% | 57.1% |
| -ve PV | 83.1% | 79.1% | 87.0% | 71.1% | 82.8% | 76.9% | 83.1% | 78.3% |
| Accuracy | 81.0% | 70.1% | 75.9% | 61.2% | 79.7% | 74.6% | 81.0% | 71.6% |
| 10%tile to 90%tile | -9.3% to 10.3% | -10.4% to 10.7% | -10.8% to 6.8% | -14.3% to 9.8% | -9.9% to 8.7% | -12.2% to 11.2% | -9.4% to 9.9% | -9.7% to 12.3% |

Prediction for milk & fat, proved superior to that of ICBA (truncation at 34 DIM)

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## Afimilk; Afilab + Predicted Transmitting Ability (PTA)

| | Milk, kg/305 days | | Fat, kg/305days | | Protein, Kg.305 days | | ECM, Kg/305 days | |
|---|---|---|---|---|---|---|---|---|
| | DIM34 | +PTA | DIM34 | +PTA | DIM34 | +PTA | DIM34 | +PTA |
| R^2 | 0.683 | 0.782 | 0.704 | 0.744 | 0.653 | 0.719 | 0.717 | 0.78 |
| r^2 | 0.93 | 0.942 | 0.926 | 0.927 | 0.918 | 0.935 | 0.923 | 0.929 |
| APD | -2.55% | -2.97% | -3.65% | -3.31% | -0.79% | -1.52% | -4.25% | -4.69% |
| ppv | 60.00% | 52.60% | 54.20% | 50.00% | 81.80% | 71.40% | 45.00% | 45.80% |
| npv | 85.20% | 86.00% | 90.40% | 87.00% | 86.20% | 87.10% | 83.90% | 86.50% |
| accuracy | 80.30% | 77.60% | 78.90% | 76.30% | 85.50% | 84.20% | 73.70% | 73.70% |
| dif+ | 8.40% | 5.20% | 6.96% | 7.00% | 9.82% | 7.14% | 4.58% | 5.23% |
| dif- | -10.06% | -10.20% | -11.43% | -11.12% | -8.74% | -8.09% | -11.78% | -11.42% |

Adding PTA to the 34 DIM models in proved disappointing! improved prediction of milk & protein

Oded Nir (Markusfeld)





## Summary & Conclusions

- ✓ Prospective prediction of complete lactations in individual herds yielded similar results to Weller & Ezra's large retrospective study
- ✓ Results could improve with additional variables
- ✓ Predictions using Afimilk in 34 DIM proved superior to those using the first Milk Test
- ✓ Though prediction improves with time in lactation, the present results allow for "safe" selection, culling & production planning at 54 DIM, and even earlier in lactation.
- ✓ *ECM (economically corrected milk) could be predicted un early lactation*
- ✓ *Results for small & large sized herds were similar*
- ✓ Adding PTA to the models slightly improved prediction of milk & protein in early lactation
- ✓ **Each herd has its own truth, present results should be verified in more herds**

Oded Nir (Markusfeld)





# Thank you

## Economics of precision dairy monitoring techniques[1]

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### Introduction

Precision dairy farming (PDF) refers to the use of technologies that makes farmers less dependent on human labor, that support them in their (daily) management, and that helps them to improve their farm profitability (Bewley, 2010; Kamphuis et al., 2015). These PDF technologies are more than equipment that solely automate (laborious) processes, for example automated mobile barn cleaners.The development of applications for precision dairy farming, PDF started in the 1970s with the development of electronic cow recognition (Kuip, 1987). Besides the development of individual concentrate supplementation, PDF applications were not implemented at a large scale, although in the 1980s and 1990s work was carried out into PDF applications (e.g., Nielen et al., 1992; Thompson et al., 1995). An important aspect of PDF technologies is to monitor health and production and to translate the monitoring results in useful information for the herdsman and preferably tailor-made actions for the herdsman to follow.

Currently, PDF applications are finding their way on dairy farms, although there seem to be differences in the uptake of PDF applications between dairy systems. Despite the growing demand, adoption rates of most commercially available PDF technologies are limited. Farmers have indicated uncertainty regarding investment in PDF technologies (Borchers and Bewley, 2015; Eastwood et al., 2015; Steeneveld and Hogeveen, 2015) and this uncertainty might be due to a lack of information on the added economic value when these PDF technologies are implemented on farm. Reasons not to invest in PDF technologies included farmers' perception that current commercially available PDF technologies have not proven themselves in the field (yet), that they are technically unreliable, and have an uncertain return on investment (Russell

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[1] This paper is for a large part based on Hogeveen et al. (2017): Principles to determine the economic value of sensor technologies used on dairy farms, to be published in Handbook for Large Dairy Herd Management (3rd edition), American Dairy Science Association, in press.

and Bewley, 2013; Borchers and Bewley, 2015; Steeneveld and Hogeveen, 2015). This lack of clear cost benefit information is one of the most limiting factors for commercialization of PDF technologies (Banhazi et al., 2012).

This paper will describe the factors that make PDF monitoring applications work at the farm, with a focus on economics. In the first part, the success factors of adoption of PDF systems will be discussed, including the current adoption rates of PDF. This will be followed by sections that describe the economics and adoption of two important PDF systems: automatic milking systems (AMS) and estrus detection systems. This paper will be finished with some conclusions.

**Success factors to make precision dairy farming work**

Three groups of success factors for PDF applications can be distinguished: System specifications, cost-efficiency and socio-economic factors.

*System specifications.*

Recently, many new initiatives are taken in the development of PDF applications. Some of these new initiatives are associated with the introduction of automatic milking, where detection of abnormal milk and clinical mastitis could not be done by visual inspection of the milk and/or udder anymore. Many new initiatives, e.g., introduction of automated estrus detection equipment, are not necessarily associated with automatic milking. New initiatives (sensors or other hardware) that are potentially interesting for application on dairy farms often started from engineers. The development of hardware is, however, only a first step in the development of a PDF system, which consists of four stages (Rutten et al., 2013): (1) technique, (2) data interpretation, (3) integration of information and (4) decision making.

A first step in development of a PDF system is the development and description of equipment that measures one or more parameters. Data interpretation is the important second step that transforms data, collected by the PDF systems hardware, into usable information. This is a crucial step, because it involves a clear definition of the animal or farm status that needs to be detected and the gold standard associated with that. Algorithms needs to be developed and validated to transform data into information. This data interpretation can be very tedious (Hogeveen et al., 2010). For instance, because of the decisions that have to be made on interpretation of sensor output. It is clear that a PDF alert for estrus 4 days after estrus took place will be too late. However, a PDF alert for mastitis 4 days after onset of clinical signs might be in time (dependent on the severity of the mastitis case).

At the third stage, the information obtained from the hardware can be combined with other on- or off-farm information (e.g., non-sensor cow data and economic data) to support decisions. This third step is not a necessary step in PDF systems, but it will improve the value of a PDF system. Stage four is the actual decision making, either by the herdsman or autonomously by the PDF system. Automated concentrate feeders are, for instance, making decisions autonomously.

For a PDF application it is immensely important that it is clear what the application is doing (the golden standard). Applications should at least go to stage 2, data interpretation (alerts). The alerts that a PDF application give, need to be useful for a farmer. Alerts without any appropriate management action or standard operating procedures associated with it, are not useful at all.

*Cost-efficiency*.

The second success factor for a PDF application is the cost-efficiency of the investment, and this depends on many different aspects of the PDF application. The economic value of a PDF application depends on the type of application. Many new developments are aimed at improved disease situations (e.g., mastitis, metabolic disorders, claw problems). The costs of disease is then an important first element, because in the costs of disease lies the potential economic value of the PDF system. Although for many endemic dairy cattle diseases cost estimates are available (see for instance Hogeveen et al., 2011, Bruijnis et al., 2010 and Ettema et al., 2010), the benefits of the improved management because of PDF applications is often unknown.

Other benefits may be present as well: for example improved production efficiency (e.g., concentrate feeder systems) and reduced labor (e.g., automatic milking). The benefits of improved disease levels, reduced labor, reduced feed costs per kg milk should be weighed against the investment costs of the system. For some PDF systems, economic advantages in the dairy production chain are envisaged. Because the farmer is the one investing, these benefits should be taken out of the equation unless chain partners motivate farmers to invest in PDF systems that benefit the entire chain.

*Non-economic factors.*

Even if a PDF application is cost-effective, adoption of the technology is dependent on other factors. A large heterogeneity exists among farmers (micro-level behavior) with regard to the adoption of technology. Economic factors such as size effects, risk preference and variation in the availability of labor and/or capital are factors for adoption of new technology. Also timing and investment irreversibility are important factors for adoption of new technology (Sauer and Zilberman, 2012).

Goals of farmers differ and has shown to have an effect on the farmers entrepreneurial behavior (Bergevoet et al., 2004). It might be that behavior with regard to PDF applications also differs between farmers. Preferences of the farmer are often overlooked. Especially on farms where the family provides a large proportion of the labor, goals of farmers go wider than only profit maximization. With, for instance, conjoint analysis, farmers preference for systems can very well be studied (e.g., Mollenhorst et al., 2012). For this type of work, it is necessary to have clear (as SMART as possible) descriptions of the potential PDF applications.

*Current use of sensor systems*

Systematic data on the use of sensor systems are scarce. In Kentucky, USA, in an online survey in 2013, the PDF technology adoption of 109 farmers was evaluated. A total of 68.8% of the respondents indicated to use technology on their dairies (Borchers and Bewley, 2015). Daily milk yield (52.3%), cow activity (41.3%), and mastitis (25.7%) were selected most frequently. Producers indicated mastitis detection (a score of 4.77 on a scale of 5), estrus detection (a score of 4.75 on a scale of 5) and and daily milk yield measurement (a score of 4.72 on a scale of 5) to be most useful.

In the same year, a survey was sent to 1,672 Dutch dairy farmers (Steeneveld and Hogeveen, 2015). The final data set consisted of 512 dairy farms (response rate of 30.6%); 202 farms indicated that they had sensor systems and 310 farms indicated that they did not have sensor systems. A wide variety of sensor systems was used on Dutch dairy farms; those for mastitis detection and estrus detection were the most-used sensor systems. The use of sensor systems was different for farms using an automatic milking system (AMS) and a conventional milking system (CMS) (Table 1).

Reasons for investing were different for different sensor systems. For sensor systems attached to the AMS, the farmers made no conscious decision to invest: they answered that the sensors were standard in the AMS or were bought for reduced cost with the AMS. The main reasons for investing in estrus detection sensor systems were improving detection rates, gaining insights into the fertility level of the herd, improving profitability of the farm, and reducing labor. Main reasons for not investing in sensor systems were economically related. It was very difficult to characterize farms with and without sensor systems. Farms with CMS and sensor systems had more cows than CMS farms without sensor systems. Furthermore, farms with sensor systems had fewer labor hours per cow compared with farms without sensor systems. Other farm characteristics (age of the farmer, availability of a successor, growth in herd size, milk production per cow, number of cows per hectare, and milk production per hectare) did not differ for farms with and without sensor systems.

Table 1. Overview of used sensor systems at farms with an automatic milking system (AMS) and a conventional milking system (CMS) (Steeneveld and Hogeveen, 2015)

| Type of sensor system | % of AMS farms (N=121) | % of CMS farms (N=81) |
|---|---|---|
| Color sensor | 60 | 1 |
| SCC sensor | 17 | 1 |
| Electrical conductivity sensor | 93 | 35 |
| Weighing platform | 27 | 5 |
| Rumination activity sensor | 9 | 12 |
| Activity meters and pedometers for young stock | 12 | 28 |
| Activity meters and pedometers for dairy cows | 41 | 70 |
| Fat and protein sensor | 20 | 0 |
| Temperature sensor | 6 | 14 |
| Milk temperature sensor | 46 | 5 |
| Progesterone sensor | 2 | 1 |
| Urea sensor | 2 | 1 |
| Lactate dehydrogenase (LDH) | 3 | 1 |
| B-Hydroxybutyrate (BHB) sensor | 3 | 1 |
| Other sensor systems | 4 | 10 |

**Estrus detection systems**

In the late 1980's and early 1990's, research into the use of pedometers to detect estrus was carried out (e.g., Holdsworth and Markillie, 1982; Redden et al., 1993). More recently, 3D-accelerometers are becoming available and are used to detect estrus (Valenza et al., 2012; Lovendahl and Chagunda, 2010). Besides these activity-based automated estrus detection systems, other systems are also available, for instance a progesterone measuring system (Friggens and Chagunda, 2005).

Automated estrus detection systems do have a clear aim: detection of estrus with as associated action the insemination of a cow in estrus. The detection system may be combined with a system to optimize the time of insemination. For some individual cows it can be economically beneficial to extend the time of insemination (Steeneveld et al., 2012). Because of the necessity of timely insemination, the definition of the gold standard in order to evaluate the performance of estrus detection systems is also quite straightforward. Estrus should be detected in time for insemination.

The benefits of automatic estrus detection are twofold. First, automated estrus detection can save labor. Visual estrus detection requires a lot of labor. Dutch recommendations are three times daily 20 minutes of visual inspection of the cows. When this activity is automated, a large proportion of this time is saved. The second benefit lies in an increase in the estrus detection rate. Especially because most farmers do not reach the recommended time of visual inspection. An average estrus detection rate of 50% was assumed (Inchaisri et al., 2010). So when the sensitivity of an automated estrus detection system reaches, for instance, 80%, this can be seen as an improvement of estrus detection. As a consequence the average number of open days and the calving interval will reduce. One study is known on the economic effects of automated estrus detection (Østergaard et al., 2005). In this normative study it was estimated that the break-even price for an automated estrus detection system, based on in-line progesterone measurements was for an average Danish herd of 120 cows was $CA 66[i] per cow per year. The break-even price depended on the differences in the type of estrus detection system and herd reproduction management and varied between $CA 4 and $CA 118 per cow per year.

Recently the investment in estrus detection equipment was extensively studied for a basic farm of 130 cow places, a conception rate of 50%, an 8 week dry period and an average milk production level of 8,310 kg per cow per 305 days.  Model inputs were derived from real farm data and expertise. For the analysis, visual detection by the farmer was compared to automated detection, in this case activity meters. For visual estrus detection, an estrus detection rate of 50% with an specificity of 100% was assumed. Accordingly, for automated estrus detection, an estrus detection rate of 80% with a specificity of 95% was assumed. The results of the cow simulation model were used to estimate the annual cash flow and the Internal Rate of Return as a profitability indicator (Rutten et al., 2014). Results showed that an estrus detection rate of 50% resulted in an average calving interval of 419 days and an average yearly milk production of 1,032,278 kg. For activity meters, the results showed that an estrus detection rate of 80% resulted in an average calving interval of 403 days, and an average yearly milk production of 1,043,751 kg. It was estimated that for a herd of 130 cows the investment for activity meters would be $CA 25,883[i], with additional costs of $CA 131 per year for replacement of malfunctioning activity meters. The yearly net cash flow was calculated by adding up increased revenues of milk and calves sold, extra costs of increased number of inseminations, number of calvings and feed consumption, and the reduced costs of culling and labor, caused by the difference in detection rate and specificity. In the baseline scenario the increase in yearly net cash flow was $CA 4,600. With this increase in cash flow the Internal Rate of Return, which is a measure for the return on invested capital, was on average 11%. On average investment in activity meters was profitable. The most influential assumption was the share of the culled cows that was culled due to fertility. A practical tool (in Dutch) that can be used to support investment decisions in estrus detection

systems has also been developed and is available on-line
http://www.smartdairyfarming.nl/nl/actueel/detail/12/rekenhulp).

In a another study, herd production and reproduction data as well as accountancy data were compared for farms that did and did not invest in PDF technology. Two groups of investments were distinguished: investment in AMS (at least combined with sensor systems to detect mastitis, but sometimes also combined with other sensor systems), and investments in PDF technology by farmers milking with conventional milking systems. These investments were mostly in estrus detection systems. (Steeneveld et al., 2015a). When comparing the effect of the implementation of estrus detection systems before and after implementation, for both groups of farmers, the days to first service did decrease. The decrease was a little more for farms that were milking with a conventional milking system than for farms that were milking with an automatic milking system (Figure 1).

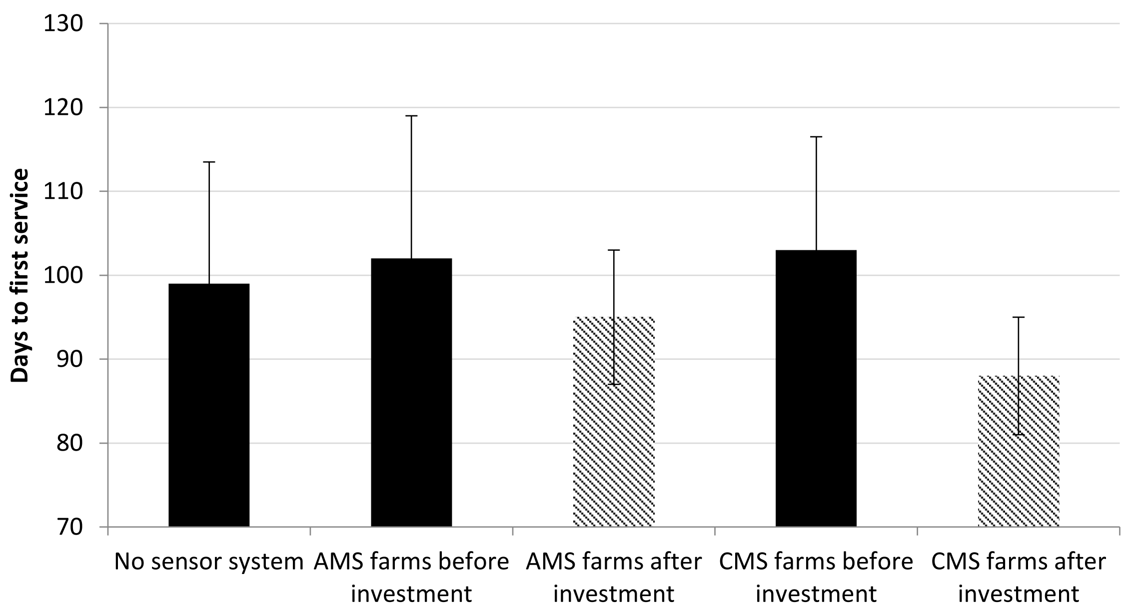


Figure 1. Days to first service of farms with and without an estrus detection system (Steeneveld et al., 2015a).

Further, economic, analyses (Steeneveld et al., 2015b) showed that the profit decreased on farms that invested in an AMS. This decrease was especially caused by an increase in capital costs, that were not sufficiently compensated by increased revenues and decreased labor costs. Farms with a conventional milking system that invested in PDF technology did, on average, have an increased profit, that was, however, not statistically significant (Table 4).

Table 2: Average values (corrected for the year 2008) for the costs, revenues and profit ($US/100 kg milk[1]) over the years 2008 to 2013 for farms without sensor systems, for farms with an automatic milking system (AMS) before and after the investment in sensor systems, and for farms with a conventional milking system (CMS) before and after the investment in sensor systems.

| | No sensor | AMS | | CMS | |
|---|---|---|---|---|---|
| | | Before | After | Before | After |
| Capital costs | 11.45 | 10.72 | 15.41 | 12.22 | 12.69 |
| Labor costs | 13.66 | 12.90 | 12.47 | 12.47 | 11.51 |
| Variable costs | 21.46 | 20.59 | 21.85 | 20.17 | 21.23 |
| Revenues | 51.06 | 48.47 | 51.17 | 50.50 | 52.05 |
| Profit | 4.49 | 4.26 | 1.45 | 5.64 | 6.80 |

[1]The original study was carried out in €. Results were converted to $US using an exchange rate of € 1 = 1.1033 (May 16, 2017).

**Calving detection**

Management during calving is important for the health and survival of dairy cows and born calves. Although the expected calving date is known, this information is imprecise and farmers still have to check a cow regularly to identify when it starts calving. A sensor system that predicts the moment of calving could help farmers efficiently check cows for calving. Observation of a cow prior to calving is important because dystocia can occur, which requires timely intervention to mitigate the adverse effects of dystocia on both cow and calf. Because farmers have less time available per cow, sensors might aide farmers with the detection of the precise moment of calving. Rutten et al. (2017) used data from 400 cows on two Dutch dairy farms equipped with sensors. The sensor was a single device in an ear tag, which synthesized cumulative rumination activity, activity, and temperature on an hourly basis (Agis Herdmanager, Harmelen, the Netherlands). Data were collected during a one-year period. During this period, the exact moment of 417 calvings was recorded using camera images of the calving pen taken every five minutes. In total, 114 calving moments could be linked with sensor data. The moment at which calving started was defined as the first camera snapshot with visible evidence that the cow was having contractions or had started labour. When only the expected calving date was used, a sensitivity of 9.1% was reached. This sensitivity could be improved by sensor data to 36.4%, both with a fixed false positive rate of 1%. Results indicate that the inclusion of sensor data improves the prediction of the start of calving; therefore the sensor data has value for the prediction of the moment of calving. However, the performance (sensitivity) of the sensor-aided detection system decreased when a more precise time window was used. A sensitivity of 21.2% could be reached for a one-hour time window and a sensitivity of 42.4% could be reached for a three-hour time window. This indicates that prediction of the specific hour in which calving started was not possible with a high accuracy. The inclusion of sensor data improves the accuracy of a prediction of the start of calving, compared to a prediction based only on the expected calving date. Farmers can use the alerts of the predictive model as an indication that cows should be supervised more closely in the next hours.

Table 3. Marginal effect of using a sensor system that predicts the start of calving on total profit in $ per calving for dairy farms of 300 cows with 20,000 simulated calvings per farm. Three systems were analyzed, a sensor originally from the equine sector , an activity and rumination activity measuring sensor with a 1 hour time window (TW 1) sensitivity 21.2% and with a 6 hour time window (TW 2) with a sensitivity of 54.4%, the specificity was in both cases 99%.

| | Baseline (equine sensor) | | | TW1 | | | TW2 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Min | Max | Mean | Min | Max | Mean | Min | Max |
| Insemination costs | 0.02 | 0 | 80 | 0.02 | 0 | 64 | 0.02 | 0 | 63 |
| Days open | 0.04 | 0 | 14 | 0.05 | 0 | 14 | 0.05 | 0 | 13 |
| Labor[1] | 5 | -10 | 35 | 4.86 | -9 | 32 | 4.86 | -8 | 31 |
| Costs of metritis[2] | 0.63 | 0 | 345 | 0.65 | 0 | 294 | 0.66 | 0 | 314 |
| Stillbirth | 0.79 | 0 | 495 | 0.12 | 0 | 457 | 0.30 | 0 | 452 |
| Annual costs of Sensor system[3] | -5 | -12 | -5 | 0.00 | 0 | 0 | 0.00 | 0 | 0 |
| TOTAL | 0.97 | -213 | 964 | 5.71 | -9 | 861 | 5.89 | -8 | 873 |

[1] Labor costs included labor for observing cows and assisting cows when *dystocia* is suspected.
[2] Metritis cost included costs for treatment, culling and reduced milk production.
[3] Costs of the sensor system included investment costs, telecommunication subscription and labor to attach sensors to the cows.

Follow-up work was carried out to evaluate the economic efficiency of such a model (Rutten et al., 2017) for a typical mid-sized (100-500 cows) dairy farm in the United States. To do so a specialized calving sensor already used in the equine sector was compared to a estrus detection system with an additional algorithm for calving detection. Dynamic discrete event Monte Carlo simulation was used to estimate the economic benefits. Stochastic information for input variables was derived from scientific literature, survey results, and the authors' expertise. Effects on insemination costs, time spent observing close-up cows, assisting cows during calving, days open, treatment, culling and lost milk production due to metritis, stillbirth rate, and the costs, lifetime, time to apply the sensor, and subscription costs related to the sensor systems were considered. Marginal profit of the equine sensor was on average $0.97 per cow on mid-sized dairy farms with a range from - $22 to $964 (Table 3). This profit mainly consisted of a reduction in labor costs, and a reduction in metritis incidence and stillbirth rates. The alternative sensor was already used for estrus detection, therefore no investment costs were incurred. This caused profit for the estrus sensor the be higher that the profit of the equine sensor. The most influential input was the labor costs regarding calving management.

**Mastitis detection**

Automated detection has been widely studied since the 1980's (Hogeveen et al., 2010) and much work is still carried out to improve the performance of mastitis detection systems by developing novel sensors and/or algorithms (e.g., Ferrero et al., 2014; Jensen et al., 2016; Koop et al., 2015). Until now, mastitis detection sensors are mostly applied in automatic milking systems and hardly in conventional milking parlors. For automatic milking systems there is not much discussion about the value of mastitis detection sensors. It is absolutely necessary to be able to detect mastitis cases to be treated in such a system. However, the focus of mastitis detection is on the detection of clinical mastitis. A task that a human milker can quite easily perform. Therefore the economic value of mastitis detection systems for conventional milking systems seems to be rather limited. On the other hand, the fact that subclinical mastitis can also be detected seems to be valuable. Indeed, the large number of observations by mastitis detection systems provides a great insight in the dynamics of infections in individual cows. The challenge, however, is to work on prediction of events that are useful for farmers to intervene. In other words, to work on the relation between sensor measurement and farm management. Only when we can foresee farmer interventions we will be able to look at the cost-efficiency of mastitis sensor systems in conventional milking systems.

**Conclusions**

In order to be successful, PDF applications need to address a clear problem associated with clear actions or standard operating procedures. Economic advantages of PDF applications either come from reduced (labor) costs (the PDF application replaces something else) or increased returns because of improved herd productivity. For PDF applications the economic advantages are rarely studied. Besides economics, also other aspects may play a role, especially on farms with a large proportion of family labor. These aspects may explain the difference in adoption rate of automatic milking between regions. Automated estrus detection is starting to be adopted rapidly, both in North America as in the Netherlands. Most probably because of clear (monetary) benefits. However, there is quite some difference in the profitability estimated in the model calculations as compared to the increase in profitability found in real farm data. The benefits of improved estrus detection might come from two ways: replacement of labor and improve reproductive performance. It could be that farmers do not utilize the full potential of the estrus detection systems. By using the information collected by PDF systems, the production performance of the cattle can be improved, making these systems more cost-efficient.

As a general rule, PDF technology should pay for itself in order to get adopted by dairy farmers. At the moment there are not very many economic calculations available to evaluate the cost-effectivity of current PDF technology. Only for estrus detection decent economic calculations are available and they show that estrus detection systems do pay for themselves. Recently calculations for calving detection have been made and they show a (small) positive effect of the use of sensors, as long as the marginal costs of the sensors is zero (i.e., the sensors are purchased for another goal).

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Precision Dairy Conference Presentation

# Farm Decision Making: Unlocking the Power of Data and Analytics

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Cargill Animal Nutrition

The dairy industry today has become very efficient at turning forage, grain, and co-products into milk. We are constantly looking for ways to optimize every part of the business to improve animal productivity and our return on investment. One output of this activity is the creation of mountains of data on everything from the minute details of each animal's life to the financial results of the business. Often this data is collected on a form with pen and paper, typed into spreadsheets, spread across multiple software platforms on farm computers, and in today's world synced to mobile devices for better access to the data.

The challenge is to take these mountains of data and turn them into valuable information to run the business. Before we go any further let's look at the two key terms I would like to discuss today as we explore unlocking the power of data and analytics.

- Data
  - Factual information (as measurements or statistics) used as a basis for reasoning, discussion, or calculation
  - Information output by a sensing device or organ that includes both useful and irrelevant or redundant information and must be processed to be meaningful
  - Information in numerical form that can be digitally transmitted or processed
  - *Merriam-Webster.com*

- Analytics… or Data Analytics
  - Data analytics (DA) is the process of examining data sets in order to draw conclusions about the information they contain, increasingly with the aid of specialized systems and software
  - *TechTarget.com*

Our challenge in the dairy industry today is that the modern dairy operation is **full of data that complicates timely and precise decision making,** and forces our dairy owners and their advisors to work with multiple unconnected data sources, reports and analytical tools. The system is not effective nor efficient. The data tends to be used more for daily activities leaving the vast majority of the data underutilized.

This creates opportunity for us to **use analytics to turn data into information for decision making.** The challenge is to consolidate data from multiple systems and turn it into relevant and actionable information helping dairy owners and their advisors to anticipate problems and plan a brighter future.

Ultimately our goal must be to have 24/7 access to seamless, structured, and actionable information that can be used for long term decision making, data driven decisions and risk mitigation.

It's easy to say that we should just do a better job of using all of the data on the farm more effectively but there are many barriers and roadblocks to this, including time and expertise. This is where the farm advisor role comes into play. Most farms rely on trusted advisors to manage their nutrition programs and provide production management and business insights. Today this already requires an advisor that has basic skills in data analytics. Our future farm advisors must be data analytics experts to create data driven solutions and track results. We need to be data driven… not just providing "gut feel" recommendations. We need to be more proactive in all of our day to day work… not reactive and chasing our tail. We need to be more strategic in our decision making… not just opportunistic when we stumble across something.

***The Current State***

Figure 1. Current Farm / Advisor Model

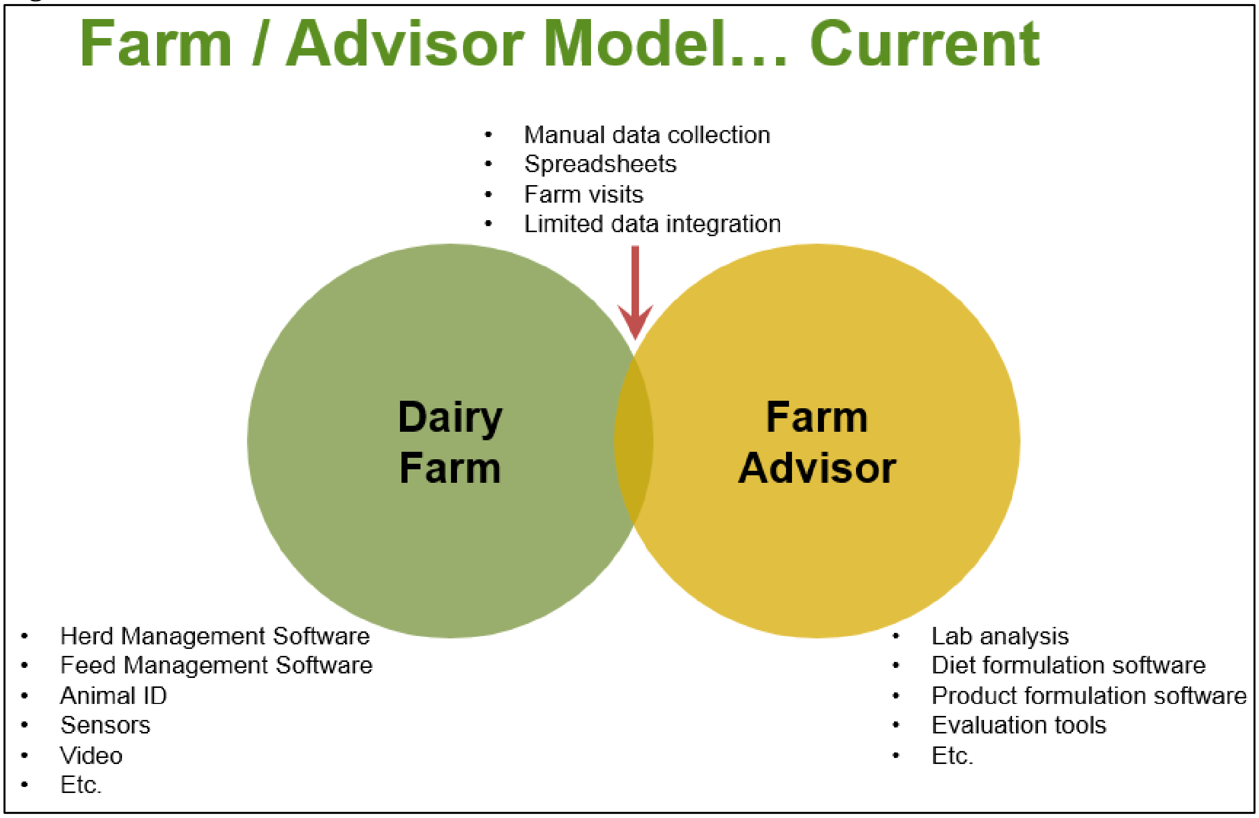



Figure 1 shows the current farm advisor / dairy farm model. We certainly use data and analytics today but there are major barriers with real-time access, data platforms, and data organization that create a lot of inefficiency in this model. Let's take a deeper dive into this current state.

Let's start with the dairy farm data. Typically the on-farm data is scattered across multiple platforms with limited connectivity. The information is used mainly for daily management work like breeding and treatment lists, and basic performance monitoring. Farm advisors often access this data to support their work but the lack of integrated systems and data sources make it difficult to stitch together the pieces of data they need to make better recommendations. There is also a need to learn multiple software platforms. This often leads to more “gut feel” recommendations vs. data driven decisions. When we want to run any type of comparison across farm peer groups this mix of multiple herd management, feed management, and sensor systems make it difficult to understand if differences are truly there or are simply differences in the way the data is collected or how software runs calculations.

Moving to the advisor side of the model there are three key data / analytics areas that I would like to discuss:

1) Lab analysis
2) Product formulation
3) Diet formulation

Lab Analysis

When working on a nutrition program one of the first key pieces of data is the lab analysis to understand the nutrient content of the on-farm and manufacturing plant ingredients. The lab is all about managing big sets of data and using analytics to constantly monitor data quality and develop new nutrient measures. Data is often integrated from multiple data sources and platforms, including other labs. Reporting often incorporates market comparison data to benchmark current forage quality with others in the local market. At Cargill we also provide our dairy consultants with analytical tools to do time trend analysis or comparisons for a single farm or across a region.

Product Formulation

Lab data is also connected real-time with product formulation. All of our formulation systems require the most up-to-date data about the ingredients we use in our products. Analytics tools are used to evaluate the highest nutrient value sources across multiple ingredient suppliers to optimize the nutritional value at the best cost. Other tools allow us to constantly monitor existing products to assure consistent nutrient content based on ingredient supplier or source changes.

Diet Formulation

This is the key area where all of the information comes together on farm. For Cargill dairy consultant’s, data from production plants is synchronized to our on-farm ration balancing software, the MAX™ system. This ensures up-to-date ingredient prices and nutrient content. The software itself contains analytic tools to do diet level ingredient valuation comparisons to aid the farm with purchasing decisions around the right ingredients from the right supplier to maximize farm returns.

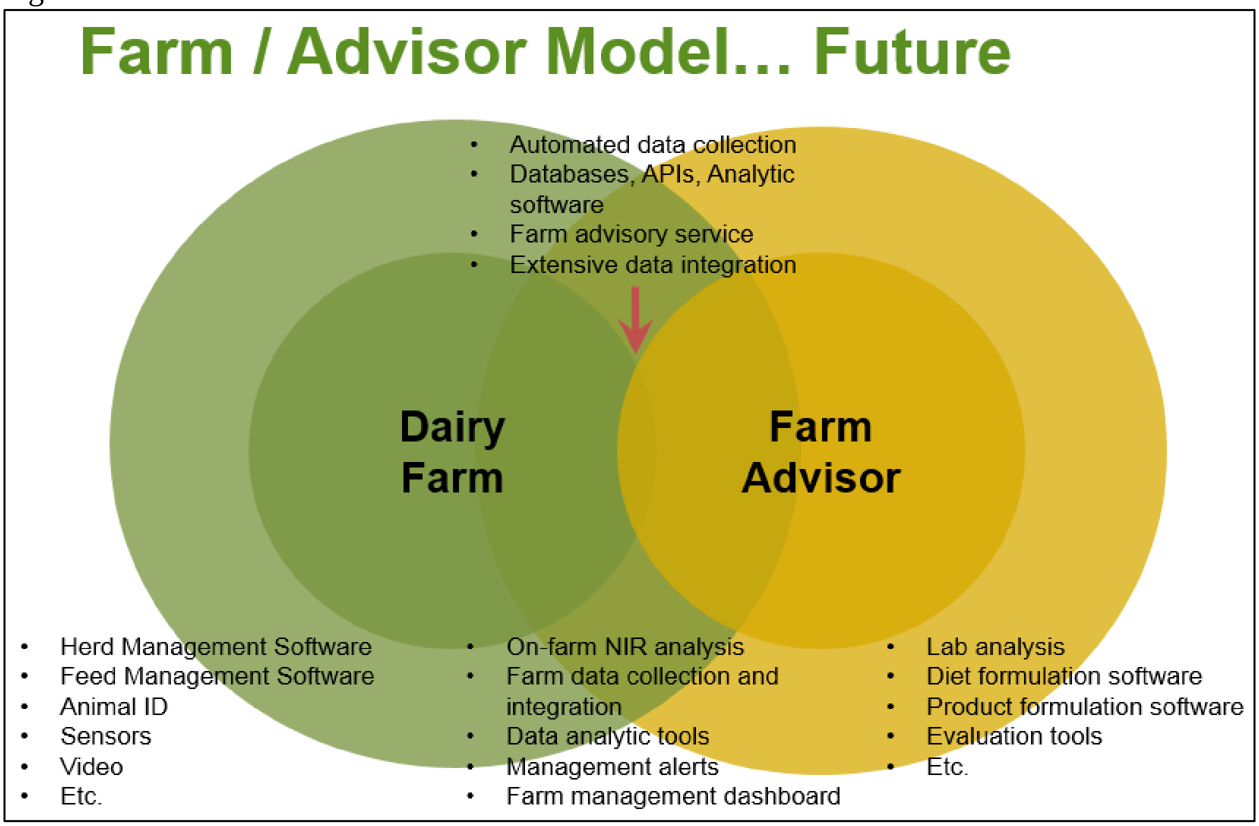
In summary, the current model does include some powerful data management and analytic tools but they tend to be more limited to either the farm or advisor side of the model independently. The Cargill analytic tools are mainly focused on integrating nutrition information from the lab analysis data through the diet and product formulation. Farm information is often collected manually and keyed into systems as needed. There is limited integration between on-farm software systems. This creates a number of barriers to unlock the opportunity to fully utilize farm data.

*The Future State… Cargill Dairy Enteligen™*

As we look to the future we see a world that is moving fast, ever changing and evolving. We can't understand a complex dairy farm system by looking at individual, or a reduced set of, data points. The challenge is to consolidate data from multiple systems and turn it into relevant and actionable information to anticipate problems. The integration of data from multiple data sources will enhance management decisions and lead to more strategic decision making.

To achieve this future vision Cargill is working with a new data management platform called Dairy Enteligen™. The ultimate goal is to provide a much more integrated and efficient data platform that allows the dairy farm and the farm advisor to make decisions that are better founded, more direct, and substantiated with proof.

Figure 2. Future Farm / Advisor Model




Let's take a deeper look at what this future dairy farm / farm advisor model can look like. From the farm side data is brought into a system that runs data validations and standardization to enable cross platform comparison and monitoring. Farm data access is provided to key advisors to enhance their ability to make more data driven recommendations and more precisely monitor the results of those recommendations. The farm data is also integrated with the manual data and observations collected by the farm advisor. Once running, the system can provide full farm performance monitoring through consolidated farm management dashboards and alert systems allowing much more proactive management of the operation. Farm data can also be integrated with other public data sources to enhance management decisions. This can include things like ingredient and dairy market data where insights can help develop longer term risk management and farm investment strategies.

The advisor side of the model also becomes more integrated with the dairy farm. Part of our platform development includes the evaluation of new cutting edge sensors that we can integrate into the system to collect critical data points. One example of this links directly into the lab analysis component. NIR technology is evolving rapidly. Portable NIR machines have been in the market for many years but size, cost and management of calibrations restricted their use. The Cargill lab team is evaluating a new NIR tool that breaks through these barriers. In addition to the lab sensors we are working to improve farm access to lab analysis results and integrate them with on-farm systems.

Another exciting area for this platform will be in the diet formulation space. It will allow on-farm ingredient and diet information to be integrated with farm production and feeding management data. This will allow more direct evaluation of the impact of diet changes directly on animal performance. As we build on this farm data it will allow us to more precisely adjust animal nutrition requirements at the individual farm level based on animal response. We can also integrate diet information with farm management dashboards for real time access to current diet information.

As we look to the future we need to continue evaluating ways to unlock the power of farm data. How do we move from effectively using only 10-15 percent of the farm data today for daily management to fully utilizing all of the data for more strategic management decisions? As we improve the integration and access to the data we can start to use analytic tools that will drive more proactive management decisions. We will also be able to empower the dairy farm and the farm advisor with real-time data to improve the quality and timeliness of management decisions along with the tools needed to monitor the results.

# Maximizing Returns from Technology Investments

## Interfaces Provide a Single Management Information Access Point for Producers

Since 1988, DRMS has developed interfaces between PCDART, its on-farm management software, and Automated Milk Recording systems to ensure accurate and thorough data transfer while saving time for the dairy producer. For all AMR systems, once the data transfers to PCDART, it is ready to be integrated with other PCDART information in screen displays, management reports, and analysis to provide a single management information access point for the producer.

For most AMR systems, all of the usual daily inputs such as calvings, dry, left-herd, breedings, lot changes, and pregnancies should be entered into PCDART. In turn, PCDART will prepare a file of these entries to send to the AMR system. The producer can manually initiate the delivery to the AMR or the delivery process can be automated.

In all cases, PCDART uses the interface developed by the AMR company that is already in place, so no changes in the interface are required by the AMR company to operate with PCDART. Additionally, this approach enables the AMR company to completely control all the data allowed into its database to avoid database corruption. Likewise, milk weights and other data recorded in the AMR are routinely transferred from the AMR to PCDART. In this case, the PCDART interface will accept the data as presented by AMR company.

## Current PCDART Interfaces

As of May 1, 2017, over 800 herds use PCDART to transfer data with the following systems:

Automatic Milk Recording: *AfiFarm, AIC, Boumatic SmartDairy /2050, Delaval Alpro and Delpro, DairyMaster, FullWood, GEA Dairyplan, Jantec, and SCR DataFlow II.*
*Robotic: Delaval Delpro, Galaxy, GEA DairyPlan and Lely.*
Heat Monitoring: *Agis CowManager, Afimilk AFIAct, Boumatic HeatSeeker II/Realtime Activity, DairyMaster Moo Monitor+, Delaval Heat Monitoring, ENGS Track A Cow, NEDAP CowWatch, SCR Dataflow II /Heatime Pro /Heatime HR, Select Detect, and Semex ai24.*
Feed: *Digistar TMR Tracker, EZ Feed, and Feed Supervisor .*
Hoof Trimming: *AccuTrim and Hoof Supervisor*

## Additional Technologies To Enhance Management Potential and Protect Valuable Data

The **PocketDairy** app enhances management potential by enabling cowside or "anytime, anywhere" record access and input. When inputs are made on an Android phone or tablet, PocketDairy will sync the data with PCDART either by Wi-Fi or USB cable to update the database. Since many producers do not have access to a reliable internet connection, PocketDairy syncs to the farm's computer rather than to the "cloud." Also, an internet connection is not required for producers to access data on their computer, phone or tablet.

The **Vet Check Maxx** feature of PocketDairy is designed to maximize everyone's time during a herd or vet check. Filters help find cows to check. Data needed cowside is organized on one screen. If cows have RFID tags, wanding the tag will pull up her data. Input findings and treatments as cows are checked, and the next sync will update PCDART.

The **DART Safe** feature of PCDART enables producers to protect their data with daily offsite backups to DRMS. With more and more data being collected on the farm, it's no longer sufficient to have a backup from the last DHI test. DART Safe ensures data can be recovered since the last backup. Another advantage of DART Safe backups is they can be accessed by the producer's consultant (with permission). This enables analysis of the most up-to-date data possible, which is especially beneficial to herds using AMRs or receiving genomic test results.

Technologies like **PocketDairy** and **DART Safe** enable dairy producers to save time, increase accuracy, secure data and make timely information easily accessible to all decision makers.

## Feedback Affirms the Value of Interfacing On-Farm Technology

Dairy producers verify how interfaces, mobile technology and backups enable data to be protected, current as well as easily integrated, accessed and utilized for management decisions. Investing in precision dairy technology is an investment in improving productivity and enabling sound, data-driven management decisions.

*"PCDART really brings it all together in one spot. I do all the data entry in PCDART and then it communicates to my other software [DairyPlan and NEDAP] and allows me to get all the information needed to make decisions. It's a lot easier to use when one program brings it all together."* *Fred Rowe, KY*

*"We love the PCDART interface with our Lely system. DRMS worked with us to make sure transponder numbers and breeding dates were accurately syncing between the systems. It works really, really well!"* *Parker Hardy, MI*

*"I think it [the PCDART / AfiFarm interface] is excellent. On this size herd, I would not want to rely on once-a -month testing for cow information. Larger herds need daily data collection!"*
*Dick James, NE*

*"I am pleased with the interface between the two programs. Our main use is to get milk production data to PCDART and repro data back to DairyPlan. The process is automatic … works great!"*
*Russell Jungemann, SD*

*"One reason we like PCDART is because it has adapted to our needs. I get the impression that the PCDART people are very responsive to equipment changes and in how we analyze our cows."*
*Steve Harnish, PA*

*"We're beginning to wonder how we managed before PocketDairy. Having the information on the phone has tremendous value. I'm continually amazed with what the program can do. It benefits what we do every day."* *Joe Shockey, DVM, WV*

*"Readily available information is a big time saver. You never forget cows or have to run to the computer to check something. It's all right at your fingertips!"* *Lynae VanBronkhorst, MI*

*"I think DART Safe is an excellent idea because I highly doubt anyone backs up as often as they should. My consultant recommended it because he can get more information from this backup."*
*Rick Pausma, IA*

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# Hyatt Regency Floor Plan