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Novel ways to use sensor data to improve mastitis management

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ABSTRACT

Current sensor systems are used to detect cows with clinical mastitis. Although, the systems perform well enough to not negatively affect the adoption of automatic milking systems, the performance is far from perfect. An important advantage of sensor systems is the availability of multiple measurements per day. By clearly defining the need for detection of subclinical mastitis (SCM) and clinical mastitis (CM) from the farmers' management perspective, detection and management of SCM and CM may be improved. Sensor systems may also be used for other aspects of mastitis management. In this paper we have defined 4 mastitis situations that could be managed with the support of sensor systems. Because of differences in the associated management and the epidemiology of these specific mastitis situations, the required demands for performance of the sensor systems do differ. The 4 defined mastitis situations with the requirements of performance are the following: (1) Cows with severe CM needing immediate attention. Sensor systems should have a very high sensitivity (>95% and preferably close to 100%) and specificity (>99%) within a narrow time window (maximum 12 h) to ensure that close to all cows with true cases of severe CM are detected quickly. Although never studied, it is expected that because of the effects of severe CM, such a high detection performance is feasible. (2) Cows with mastitis that do not need immediate attention. Although these cows have a risk of progressing into severe CM or chronic mastitis, they should get the chance to cure spontaneously under close monitoring. Sensor alerts should have a reasonable sensitivity (>80%) and a high specificity (>99.5%). The time window may be around 7 d. (3) Cows needing attention at drying off. For selective dry cow treatment, the absence or presence of an intramammary infection at dry-off needs to be known. To avoid both false-positive and false-negative alerts, sensitivity and specificity can be equally high (>95%). (4) Herd-level udder health. By combining sensor readings from all cows in the herd, novel herd-level key performance indicators can be developed to monitor udder health status and development over time and raise alerts at significant deviances from predefined thresholds; sensitivity should be reasonably high, >80%, and because of the costs for further analysis of false-positive alerts, the specificity should be >99%. The development and validation of sensor-based algorithms specifically for these 4 mastitis situations will encourage situation-specific farmer interventions and operational udder health management.
Key words: mastitis, sensor systems, management

INTRODUCTION

In general, mastitis is regarded as being the most prominent production disease in developed dairy-producing countries, both in terms of incidence as well as in economic consequences (Hogeveen et al., 2019). Mastitis affects 2 milk quality measures used broadly in dairy-producing countries: SCC and, if mastitis is clinical, visibly abnormal milk. On dairy farms working without an automatic milking system (**AMS**), a well-established method to detect clinical mastitis (**CM**) is to strip milk before unit attachment and to check the foremilk for abnormalities (Rasmussen, 2005; Rasmussen and Bjerring, 2005). The development and use of automated mastitis detection systems has received much attention since the proliferation of AMS during the mid-1990s (Frost et al., 1993), and currently AMS are installed on both smaller farms (Jacobs and Siegford, 2012) and an increasing number of larger farms.

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Automated detection of mastitis is an integral part of automatic milking to ensure milk quality and maintain animal welfare through the prompt attention to cows with clinical (painful) mastitis.

The demands for CM detection models have been defined to be 80% sensitivity and 99% specificity (ISO, 2007). There is a large variation in the scope and quality of the scientific literature on the use of sensors and algorithms of CM detection models, but thus far, none of the published CM detection models meets this target (Hogeveen et al., 2010; Miekley et al., 2012, 2013a,b; Jensen et al., 2016; Sorensen et al., 2016; Khatun et al., 2017, 2018). For instance, at a specificity of 90%, the reported sensitivity was 80% (Dalen et al., 2019a) and 91% (Khatun et al., 2018) for the detection of cows with CM.

As a consequence of the suboptimal performance of current CM detection systems, farmers either have to check many cows per day (false-positives, which are a consequence of less than perfect specificity) or have to accept that a lower proportion of cows with CM will be detected in time (false-negatives, which are a consequence of relatively low sensitivity). Regarding the detection of CM, it seems that farmers prefer a lower sensitivity over a lower specificity (Mollenhorst et al., 2012). In a Dutch study on 7 farms, farmers were followed for 3 wk to describe their response to alerts from their CM detection system. These farmers checked only 3% of the alerts, of which 67% had CM (Hogeveen et al., 2013). However, 74% of the CM cases that were associated with the alerts were not detected by the farmers. Although collected on a relatively small number of farms in one specific region, these results do provide an explanation for the lower reported CM incidence on AMS farms compared with farms milking with a conventional milking system (Deng et al., 2019).

Until now, research on automated mastitis detection systems has been aimed at detection of CM, using methods from the visual mastitis detection era as the gold standard. Also, in the advice provided to farmers, the importance of visual confirmation of CM takes a central position. Through the technological progress that is being made, improvements in the development of sensors and algorithms are to be expected (Fadul-Pacheco et al., 2021; Slob et al., 2021). However, due to the nature of mastitis as a complex of different types of infections interacting with the cow and resulting in variable subclinical and clinical effects, the improvement in the overall performance of sensor systems in the detection of CM in general will be challenging. In a sensor-based detection system aimed at CM, a detection alert that is a false-positive may very well be a case of subclinical mastitis (**SCM**), sometimes even with a considerable increase in SCC but without clinical signs.

Given these observations, we can argue that there is a need for a novel approach to the detection and management of mastitis supported by sensor systems. Mastitis situations should be defined from a temporal urgency to intervene rather than to be solely based on their comparability to nonsensor udder health indicators (the old paradigms).

In the context of the preceding argument and reasoning from a farm management perspective, we can define 4 different situations where management action is needed and where sensor systems may support the farmers' management:

1. Cows with severe CM needing immediate attention;
2. Cows with SCM, mild, or moderate CM not needing immediate attention;
3. Cows needing attention at drying off; and
4. Monitoring of udder health at the herd level.

It is our hypothesis that the sensor systems with algorithms developed for specific mastitis situations may be more beneficial for the improvement of udder health than the use of novel sensors or algorithms that indiscriminately try to detect CM, as is the current approach. The redefinition of mastitis situations based on the timing and urgency of potential intervention has consequences for the evaluation and demands on the performance of sensor systems.

This paper aims to define a set of mastitis situations in which automated mastitis detection systems can aide the farmers' management by identifying mastitis cases that require or could benefit from appropriate intervention. First, we will provide a concise overview of the current knowledge on sensor systems and methods used to evaluate the performance of sensor systems. Then, 4 sections will describe the 4 different mastitis situations, including demands for performance of sensor systems and potentially associated management. The paper will conclude with a discussion of the challenges and opportunities as we chart a path forward.

SENSOR SYSTEMS TO SUPPORT MASTITIS MANAGEMENT

Intramammary infections result in decreased milk production and compositional changes in the milk that vary with the intensity and duration of the infection. These changes are associated with the inflammatory response as a result of bacteria entering and multiplying in the udder (Harmon, 1994), leading to compositional changes linked to the production of numerous mediators of inflammation (Wellnitz and Bruckmaier, 2012) and to the change in blood capillary permeability due to mastitis (Kitchen, 1981). An important compositional change consists of the influx of polymorphonuclear neutrophil leukocytes into the mammary tissue, making up a large proportion of the SCC (Kelly et al., 2000; Wickstrom et al., 2009), forming the basis of the use of SCC as a test to monitor udder health (Harmon, 1994; Dufour and Dohoo, 2013; Damm et al., 2017). More recently, these changes in milk composition were used to develop sensors aimed at automated inline or online detection of CM (Hogeveen et al., 2010; Martins et al., 2019).

Commercially Available Sensors

A large number of sensors are currently commercially available. Electrical conductivity (**EC**) is the measure of the resistance of a material to an electric current and is linked to a change in blood capillary permeability due to mastitis. For decades, this change in EC has been used as indicator for CM (e.g., Nielen et al., 1992; Hamann and Zecconi, 1998). Following mastitis enzymatic reactions, L-Lactate dehydrogenase will appear as part of the cow's innate immune response against infection (presence of udder pathogens) and changes in cellular membrane (Chagunda et al., 2006; Friggens et al., 2007), reflecting the host response to an IMI rather than the IMI itself (Jorgensen et al., 2016). A sensor system based on inline measurements of L-Lactate dehydrogenase is commercially available. Sensor systems are also available to measure a change in color, which is a visible aspect of abnormal milk, mostly due to CM. The principle of the color measurement sensor is based on the reflection of light generated by a light-emitting diode (Ouweltjes and Hogeveen, 2001) or light transmission instead of light reflection (Whyte et al., 2004). More recently, 3 sensor systems measuring SCC became commercially available. Two systems are measuring SCC indirectly, either based on gel formation of the milk (comparable to the California Mastitis Test; Deng et al., 2020) or physical measurements in the milk flow. The third SCC sensor is based on staining of a milk sample and optical counting of the number of cells by fluorescence (Dalen et al., 2019a). In addition to sensor systems directly aimed at measuring mastitis indicators, many other sensor systems are on the market that measure one or more aspects that may serve as support to more specific mastitis sensors (Caja et al., 2016), activity monitors or behavior sensors (e.g., Van Hertem et al., 2016), milk production and constituent sensors, such as the commonly available electronic milk meters and fat and protein sensors, location sensors (e.g., Barker et al., 2018), rumination measurement (e.g., Grinter et al., 2019; Hamilton et al., 2019), temperature sensors (e.g., Kim et al., 2019), rumen pH sensors (e.g., Doroodmand et al., 2016), automated body condition scoring systems (e.g., Spoliansky et al., 2016; Mullins et al., 2019), and BW measuring systems (e.g., Maltz et al., 1997).

Sensor Systems

The sensors can be seen as the basic element of sensor systems (Figure 1; Rutten et al., 2013), delivering data regarding the composition of milk or the physiological status of a cow. By using computational algorithms, these data can be connected to events that are of interest to herd managers and thus, can be converted to useful management information. Regarding mastitis management, algorithms are aimed at the identification of a deviation from normality that could be predictive of mastitis. As a further step, diagnosis can be carried out, defined as judgment about the presence of a particular illness after an appropriate diagnostic procedure has been performed.

Algorithms to detect events of interest may use data from one or more sensors, potentially combined with data from other (farm) sources (Dominiak and Kristensen, 2017; Slob et al., 2021). The algorithms are expected to detect deviations from normality that could be predictive of a specific status that is of interest to the decision maker. For most sensor systems this prediction of an abnormal status (alert) needs to be confirmed by either clinical examination or secondary testing (e.g., bacteriological culture or PCR of one or more quarter milk samples). When an abnormal status is confirmed, this would constitute a diagnosis. The diagnosis can be combined with other knowledge (such as economic information), to produce advice for the farmer (decision support). Decision support can be very complex but can be compiled as well into standard operating procedures (**SOP**) on what to do with the diagnosis that has been made. Finally, a decision needs to be made and acted upon by the farmer.

Based on preprocessing of data classification, alerts are generated (van der Voort et al., 2019) that always have a level of uncertainty. Sensor systems may or may not provide a probability of an event interest. The overall performance of a sensor system is dependent on the quality of the sensor(s) in combination with the quality of the algorithm.

To build useful algorithms, it is of high importance to clearly define the events to be detected. The event should be defined in such a way that it can be linked to potential interventions. The developers of an algorithm need data to build it. Such data typically consist of the sensor and other data that are going to be used by the algorithm in combination with measurements of the events (the reference standard). The reference standard is usually measured by nonsensor technologies (e.g., by visual observation, clinical examination, and other diagnostic tests such as bacteriological culture).

Evaluating Sensor Systems

Sensors for detection of mastitis or abnormal milk are considered diagnostic tests, which can be characterized using epidemiological parameters. It is very important that the event of interest is clearly defined; especially because the demands for a test might differ for the event of interest (Kamphuis et al., 2013). For instance, the demands for the detection of visually abnormal milk to fulfill milk quality requirements (Rasmussen, 2005) may differ from the demands for the detection of CM.

Basic evaluation measures of a sensor system are repeatability and reproducibility. Repeatability can be defined as the closeness of the agreement between the results of successive measurements of a sensor in the same sample. The repeated measurements should be done under circumstances as equal as possible. Reproducibility can be defined as the closeness of the agreement between the results of successive measures of the sensors under varying circumstances, using another sensor and measuring under different circumstances.

Evaluating a sensor for its practical use can be done in an experimental setting or based on collection of routine data where the alerts given by the sensor are compared with the occurrence of an event as determined by the reference standard (gold standard; Kamphuis et al., 2016). Because both the start of the gold standard event and the alert are points in time, a time window has to be defined to connect these 2. The length of the time window has an effect on the classification of alerts, as well as on the usefulness of the alerts (Kamphuis et al., 2013). Given a certain predefined time window, the outcomes of an evaluation experiment can be classified as follows (Kamphuis et al., 2013): number of observations in which the event occurs with an alert (*TruePosCount*); number of observations in which the event occurs without an alert (*FalseNegCount*); number of observations in which the event does not occur with an alert (*FalsePosCount*); and number of observations in which the event does not occur without an alert (*TrueNegCount*).

Using the basic classifications, the performance of a sensor for discrete events can be evaluated as follows. Because they are independent of the prevalence of the event (mastitis), the 2 most important parameters to evaluate sensor systems are sensitivity and specificity:

$$\text{Sensitivity (\%)} = 100 \times \mathit{TruePosCount}/(\mathit{TruePosCount} + \mathit{FalseNegCount}), \text{ and}$$

$$\text{Specificity (\%)} = 100 \times \mathit{TrueNegCount}/(\mathit{FalsePosCount} + \mathit{TrueNegCount}).$$

For those such as farmers relying on the sensor, however, the sensitivity and specificity are not notable. A farmer sees alerts and wants to know if the alert is a true positive case or a false-positive case. This inter-

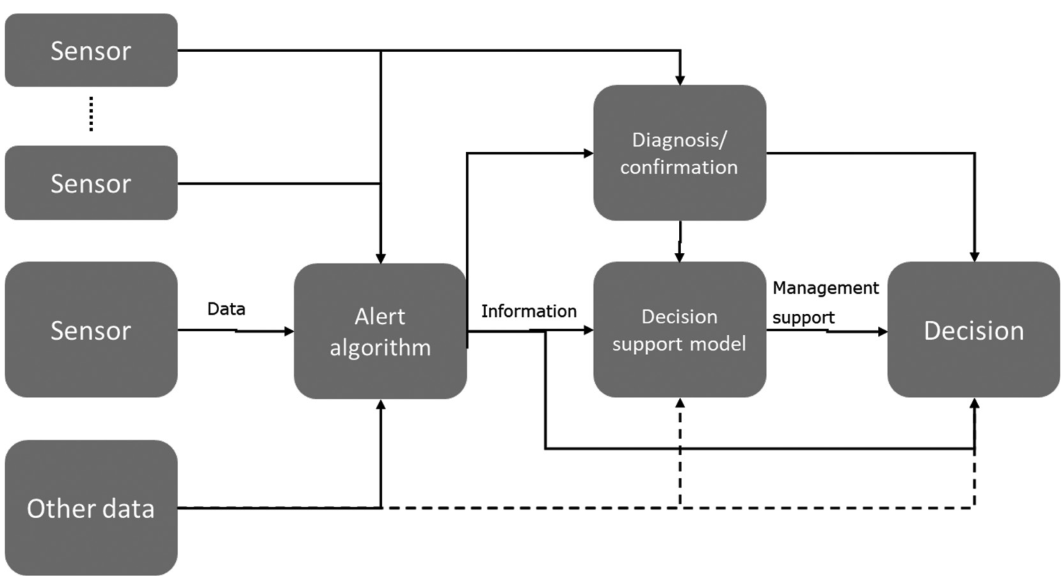

Figure 1. Elements of a sensor system (adapted from Rutten et al., 2013). Several sensor systems providing data may be combined. Data from other sources than sensors, such as DHI data or economic data, may be incorporated to increase accuracy of the algorithm or support decision making.

pretation is influenced by not only the sensitivity and specificity of the test system, but also the underlying prevalence of the event (mastitis). Hence, the following 2 definitions were proposed for a practical evaluation of sensor systems (Sherlock et al., 2008):

$$\text{Success Rate} = \mathit{TruePosCount}/(\mathit{TruePosCount} + \mathit{FalsePosCount}), \text{ and}$$

$$\text{False Alert Rate} = 1{,}000 \times \mathit{FalsePosCount}/\mathit{Total\ Cow\ Milkings}.$$

Success rate (or positive predictive value) varies with the prevalence of the condition being monitored and is dependent on specific farm situations. Therefore, when defining demands for sensor systems that can be objectively evaluated, it is best to use sensitivity and specificity, while keeping the expected range of prevalence of the condition to be monitored in mind (Kamphuis et al., 2013).

COWS WITH SEVERE MASTITIS NEEDING IMMEDIATE ATTENTION

The severity of CM can be classified as mild, moderate, or severe (IDF, 2011), also described as a clinical severity score of 1, 2, or 3 (Pinzon-Sanchez and Ruegg, 2011; Ruegg, 2012). Cows with mild CM have abnormal milk as the only clinical sign. Cows with moderate CM have abnormal milk and changes in the affected udder quarter, but the general condition of the cow is not affected. The affected udder quarter(s) typically show signs of inflammation, such as swelling, redness, pain, or warmth. In contrast to cows with mild or moderate CM, cows with severe CM have a compromised general condition with one or more systemic signs of illness. Typical signs are an abnormally increased or decreased rectal temperature, dehydration or marked depression (inappetence or recumbency). In most herds, a minority (5–14%) of the clinical cases are severe (Ruegg, 2012).

Even though the incidence of severe CM within a herd is usually low, the severe consequences underline the necessity of accurate and early detection for cow welfare, as well as economic reasons. A cow with severe CM needs immediate attention and treatment. The aim of immediate treatment is to save the cow's life, reduce clinical signs and thereby improve the cow's welfare, and increase chances of cure and return to acceptable milk production.

The sudden onset of severe clinical signs (within a few hours) and the severely compromised welfare, with risk of the affected cow being lost if not immediately identified and treated properly, poses high demands on an on-farm sensor system. On dairy farms with a conventional milking system, milkers can detect severe CM when fetching the cow or preparing the cow for milking. In such a system, it is relatively easy to detect severe CM, even with minimal procedures for mastitis detection (e.g., no prestripping). On farms with an AMS, detection of severe CM needs to be done using sensor systems. Sensor systems may also be helpful on large-scale dairy farms with large capacity rotary milking parlors, because in these systems, there is a very short period of time that milkers interact with the cow.

Demands for Sensor Systems

To prevent further animal suffering and potentially the death of the cow, the purpose of a sensor system to detect cows with severe CM is to detect virtually all severe cases of CM within hours after, and definitely not more than 12 h after, the onset of the severe CM. A very high (close to 100%) sensitivity is needed to ensure the trust of farmers in the system to be able to detect cows that would definitely be detected visually. Because of the clear consequences of severe CM (e.g., toxic mastitis) on SCC, EC, and milk production, it is expected that a very high sensitivity is possible. Regarding the short time interval, there is, to our knowledge, no research available that provides insight into the effects of different times to treatment for severe CM. Demands to identify cows with severe CM are the following: (1) A sensitivity of >95% and preferably as close to 100% as possible to ensure that close to all cows with true cases of severe CM are detected; (2) a high specificity to detect a cow with compromised general health condition of >99%, which minimizes the number of false-positive alerts; and (3) a narrow time window (≤12 h).

It should be recognized that with such a high demand in terms of performance (sensitivity >95% and specificity >99%), false-positive alerts will be an issue. Consider a herd of 100 milking cows with an annual incidence of CM of 30%, with 10% of those CM cases being severe CM. Cows are tested (assessed) twice a day for 365 d to identify the 3 severe CM cases. Although the sensitivity is high enough to detect all 3 cases, the success rate would be less than 0.5%. The sensor system would result in, on average, 733 positive alerts/yr, with all but 3 of those being false-positive alerts. This means that, on average 2 false-positive alerts/d are given. It is expected, that a large proportion of these false-positive alerts for severe CM are associated with mild or moderate CM. As a consequence, in practice, these alerts will not be regarded as a false-positive because there is value in examining those cows.

When using an AMS, due to the sudden onset of severe CM, sensor information based on changes in milk and measurements collected solely during milking will not be sufficient for all cases. Due to systemic signs, cows with severe CM may not visit the AMS and sensor data from the previous milking may show little if any deviations. A combination of several sensor-based and AMS-based indicators may therefore have to be combined to reach the necessary demands. Sufficient performance of a sensor-based detection system may also be reached by the combination of sensor-based or automatic milking-based monitoring systems in combination with additional monitoring strategies including visual observations linked to certain events (e.g., a cow that does not visit the AMS spontaneously can be checked for disease symptoms when being fetched). To date, sensitivity and specificity to identify severe CM based solely on sensor data are unknown.

Associated Management

Cows identified as potentially having severe CM require immediate attention by the farm personnel to evaluate the presence and severity of clinical signs, discriminate between moderate and severe cases and to decide how the case should be managed. A clinical examination of milk, udder, and general condition of the cow must be carried out including the following aspects: (1) visual inspection of milk, (2) visual inspection and palpation of the udder, and (3) assessment of general condition (e.g., rectal temperature, dehydration, rumen functioning, attitude and diarrhea). A herd-specific protocol, developed together with the herd veterinarian, should be present on the identification and treatment of severe CM.

COWS WITH SCM OR MILD OR MODERATE CM NOT NEEDING IMMEDIATE ATTENTION

In addition to severe CM, 2 other types of mastitis can be distinguished: SCM and mild or moderate CM. SCM is an inflammation of the mammary gland that is not visible and requires a diagnostic test for detection. The most commonly used diagnostic test to identify SCM is milk SCC. Subclinical mastitis is the most prevalent form of mastitis (IDF, 2011). Mild or moderate CM is an inflammation in the udder characterized by observable abnormalities in milk, such as clots of flakes, with no or moderate signs of swelling of the mammary gland or systemic illness (IDF, 2011).

Research on treatment systems with delayed treatment of mild and moderate CM to allow further on-farm bacteriological diagnosis has shown that it is possible to be judicious with the use of antimicrobials without any negative effects on mastitis cure rate and production (Lago et al., 2011; Pinzon-Sanchez and Ruegg, 2011; McDougall et al., 2018; Vasquez et al., 2018; Bates et al., 2020). Moreover, from an animal welfare point of view, there is no need to treat cows with mild CM immediately. Therefore, reasons to treat mild CM are to prevent the case from developing into a severe CM, to prevent a reduction of milk quality (bulk milk SCC), and to reduce the transmission of mastitis to other cows (Osteras and Solverod, 2009).

Different diagnostic tools and thresholds for diagnosing SCM have been discussed. The basis for such discussions should be repeated sampling and bacteriological culture of quarter milk samples in a herd (Dalen et al., 2019a). Because of the costs, such an approach can be used for research, but it is not rational for routine decision support. Because the definition of SCM is based on detecting signs of inflammation, detection is most commonly through the routine measurement of SCC at the cow level. An elevated SCC is frequently associated with IMI (Reksen et al., 2008). Therefore, traditionally, SCC from DHI systems have been used as a proxy for monitoring IMI status at the cow, herd, and population levels (Schukken et al., 2003).

Similar arguments for treatment of mild CM can be used in the discussion about treatment of SCM. Although in general it is not advised to treat SCM, the arguments that are used in studies on the treatment of SCM are to prevent the progression of the SCM case into (severe) CM, to improve milk quality and to prevent transmission of IMI to other cows (e.g., van den Borne et al., 2010; Leitner et al., 2017; Gussmann et al., 2019; van den Borne et al., 2019).

Due to the costs involved with routine measurement of the cow's SCC, testing is stretched to a 3- to 6-week interval and combined with other milk recording measurements. As a result, the cow's mastitis status is not known at all times and many infections are undetected in between the 2 SCC measurements. Sensor systems have the potential to provide routine monitoring of SCM and mild CM on a daily basis.

Demands for Sensor Systems

The purpose of a sensor system to detect mild or moderate mastitis not needing immediate attention is either to stimulate the application of further management procedures (i.e., diagnostic testing) or to monitor the cow's status, which gives the cow the opportunity to cure spontaneously, reduces the risk that the mastitis case will become chronic, prevents it from developing into severe CM, and avoids unnecessary production losses. The mild and potentially chronic nature of SCM or mild CM, means that immediate intervention with these cases is not necessary. Sensor systems that identify cows with mild CM or SCM should fulfill the following demands:

1. A sensitivity of >80% is needed to ensure that an acceptable number of cows with mild CM or SCM are detected. Although a higher sensitivity is always better because of the relatively mild consequences of these cases, it is not important to have a very high sensitivity.
2. A very high specificity of >99.5% is needed to prevent false-positive alerts.
3. Because there is no need for a quick intervention, a wide time window of approximately 7 d can be allowed, although a shorter time window may also be used.

For this mastitis situation, we consider the same 100 milking cow herd with 30% CM annual incidence and 50% SCM annual incidence. From the CM cases, 90% is mild or moderate. Because interventions do not necessarily have to be carried out immediately, we consider a once-weekly moment to confirm and follow up with cows with mastitis that do not need immediate attention. That means there will be 5,200 tests/yr. A sensitivity of 80% would mean that 62 of the 77 SCM or mild or moderate CM cases would be identified. A specificity of 99.5% would, for this specific herd, lead to a success rate of 70% with 25 false-positive alerts/yr.

Associated Management

Detection of SCM or mild CM during lactation is only relevant if there is any management that is associated with the detection of these cases. As a reaction on the detection of SCM or CM during lactation, a wide range of potential management measures can be considered.

Management can be focused on a reduction of risk factors or a reduction of transmission of udder pathogens between identified cows with SCM or mild CM and susceptible cows. To advocate prudent use of antimicrobials in the context of SCM and mild CM, antimicrobial treatment of cows that will self-cure, that will not cure with treatment, and that are not at risk of transmitting the disease to others should be avoided. Hence, treatment of SCM and mild CM cases can be started with measures to increase the probability of spontaneous cure (Wilson et al., 1999). Also, interventions can be accompanied by the use of (on-farm) diagnostics (e.g., to identify pathogens that caused the SCM or mild CM case) to improve a judicious application of antimicrobials and increase the probability of cure as has been described earlier.

The moment of intervention (in terms of time after onset of the event) will be important, especially when costs are made for the intervention. The costs of intervention (including additional diagnostics and use of antimicrobials) should be weighed against the benefits of a higher probability of cure. Because the probability of self-cure decreases with progressing chronicity, it is expected that with progressing time after onset of the case of SCM or mild CM, intervention will become more cost-effective. Optimal methods of intervention upon the detection of SCM and mild CM cases will be subject to farm-specific circumstances, as well as on country- and area-specific rules and regulations.

COWS NEEDING ATTENTION AT DRYING OFF

Since the 5-point contagious mastitis control plan was developed (Neave et al., 1969), the process of blanket dry cow therapy (**BDCT**), drying off all cows within the herd with antimicrobial treatment, has been a key element in the control of mastitis. Thus, BDCT, was and is in many countries the recommended approach to drying off cows. The use of BDCT serves 2 purposes: (1) to cure existing IMI (Halasa et al., 2009a), and (2) to prevent and control new IMI during the dry period (Halasa et al., 2009b).

Societal concerns about the use of antimicrobials in animal production (e.g., Aarestrup et al., 2008; Tang et al., 2017) stress the need to re-evaluate the recommendations on the use of antimicrobials at dry-off to prevent new infections. Because most cows being dried off do not harbor any major udder pathogens, it is possible to apply selective dry cow treatment (**SDCT**) programs instead of BDCT programs. By implementing SDCT, the use of antimicrobials can be reduced (Rindsig et al., 1978; Berry and Hillerton, 2002; Rajala-Schultz et al., 2011; Scherpenzeel et al., 2016; Zecconi et al., 2020) cost-efficiently (Scherpenzeel et al., 2018) or even with small economic benefit of SDCT over BDCT (Berry et al., 2004; Huijps and Hogeveen, 2007). Selective dry cow treatment consists of identifying cows with (chronic) IMI or SCM that will benefit from treatment with antimicrobials at dry-off and treating these cows with antimicrobials. Cows without IMI should not be treated with antimicrobials (no prophylactic treatment). Although practiced in the Nordic countries since the 1990s, (Osteras and Solverod, 2009), in recent years in a large number of countries, SDCT has become the standard (e.g., Scherpenzeel et al., 2016) or is under study (e.g., Zecconi et al., 2019; Rowe et al., 2020a,b).

In an SDCT system, consistent and approved procedures to identify cows to be selected or not selected for antimicrobial treatment need to be in place to minimize the risk of major pathogen IMI in the subsequent lactation. In addition, the procedures should fulfil requirements of health authorities in the respective countries. Currently, 2 methods are applied to identify cows to not be treated at drying off: (1) the use of SCC measured in a DHI system before drying off (Scherpenzeel et al., 2014; Vasquez et al., 2017; Lipkens et al., 2019; Zecconi et al., 2019), and (2) microbiological analysis of milk, which can be carried out in combination with the use of SCC (Cameron et al., 2014, 2015; Vasquez et al., 2018; Rowe et al., 2020a). Microbiological analysis is relatively easy to perform and interpret but could be expensive. On the other hand, not all farms are enrolled in a DHI program and moreover, the last test-day can be 6 wk or even longer before dry-off. Therefore, DHI SCC measurements may have a relatively small accuracy to predict IMI at drying off. Because of the continuous measurements over the lactation, sensor systems may provide a good method to identify cows that have an IMI at drying off and need to be treated with antimicrobials.

Demands for Sensor Systems

The purpose of a sensor system for cows needing attention at drying off is to identify cows with SCM that will benefit from treatment with antimicrobials at dry-off. A sensor system to support selection of cows for antimicrobial treatment at dry-off is relatively indifferent to false-positive and false-negative alerts. Because of the trade-offs between sensitivity and specificity, a higher sensitivity will be associated with a lower specificity and thus more false-positive alerts and could lead to higher, unnecessary use of antimicrobials. On the other hand, a higher specificity and thus lower sensitivity will lead to more false-negative alerts and a higher number of nontreated IMI with major pathogens at drying off, potentially leading to more cases of mastitis during the dry period and in the next lactation. The aversion of false-positive alerts or false-negative alerts will differ between countries and situations, depending on farmers' goals, herd situation (contagious pathogens), and regulations.

There are no published studies that have examined automatic sensor-based identification of cows with IMI at drying off. Based on our knowledge about the detection of CM and the possibility to create algorithms based on a repeated number of mastitis indicator measurements before drying off in combination with other cow information, we argue that a sensor system to identify cows with SCM at drying off should fulfil the following demands: (1) A high sensitivity of >95% to prevent false-negative alerts; (2) a high specificity of >95% to prevent false-positive alerts; and (3) the definition of an alert time window is not necessary, because the sensor system can provide sufficient data close to the moment of drying off, based on sensor data generated during the days or weeks before the drying off moment.

Because identification of cows without an IMI or with an IMI caused by minor pathogens can be a major strategy for SDCT in herds with contagious mastitis, sensors should have an equally high diagnostic performance for the identification of uninfected cows. For this mastitis situation, we consider the same 100 milking cow herd with a prevalence of IMI caused by major pathogens at drying off of 25%. Based on a yearly culling rate of 30% and a calving interval of 410 d, in this herd, per year, 62 cows are dried off. Because an alert only needs to be provided at the moment of drying off, the yearly number of tests is 62. A sensitivity of 95% would mean that with a success rate of 88%, 15 of the 16 IMI at drying off would be identified. A specificity of 95% would mean that 2 of the 46 cows without IMI would be a false-positive alert.

Associated Management

Drying off is not only about the use of antimicrobials, dry-off management should promote cow welfare, prevent mastitis, and maintain high milk production potential for the next lactation. High milk production levels at drying off (Annen et al., 2004; Steeneveld et al., 2013; Chapinal et al., 2014) are a risk factor for IMI established during the dry period (Klaas et al., 2005; Rajala-Schultz et al., 2005; Gott et al., 2016). When prophylactic treatment with antimicrobials at dry-off is not possible, herd-specific SOP for reduction of feeding and milking frequency need to address mastitis risks and cow welfare during the dry-off process. Depending on the dry cow circumstances, SDCT showed to be associated with no to a little higher frequency of new IMI (Scherpenzeel et al., 2014; Vasquez et al., 2018; Lipkens et al., 2019; Rowe et al., 2020c). Therefore, farm-specific SOP should involve IMI rate after calving.

MONITORING OF UDDER HERD HEALTH AT THE HERD LEVEL

In addition to the 3 individual mastitis situations described so far (operational mastitis management), sensor systems may also be used at the herd level. Data collected by a sensor system can be used to support tactical mastitis management. Sensor systems can be used to monitor udder health by providing a day-to-day overview of the herd-level mastitis situation. Monitoring is an important aspect of dairy herd health management (Green et al., 2012; Figure 2). Either explicitly formulated or implicitly, farmers do have a planned level of udder health (objective) that needs to be managed. Routine monitoring of udder health is needed to identify deviations from the farmers' goals. When deviations occur farmers, together with their herd health advisor(s), will have to act accordingly by re-evaluating their goals (accepting a decreased udder health with all economic and animal welfare damage) or changes in farm management.

To support herd-level monitoring, key performance indicators (**KPI**) can be developed with increased use. Such KPI are used to detect any deviances from the expected or planned level of udder health on a farm (De Vries and Reneau, 2010). Currently several KPI are used to monitor the herd's mastitis situation: incidence rate of CM, bulk milk SCC, average cow milk SCC, and the number of cows with a new high SCC.

Because sensor systems measure every milking and provide information from all cows that are milked, sensor systems offer novel opportunities to monitor the mastitis situation at the herd level. Sensor systems can provide short-term information on a change in the number of cows with increased levels of mastitis indicators (e.g., EC or SCC), as well as in the average or median herd level of these indicators. In this way change in the

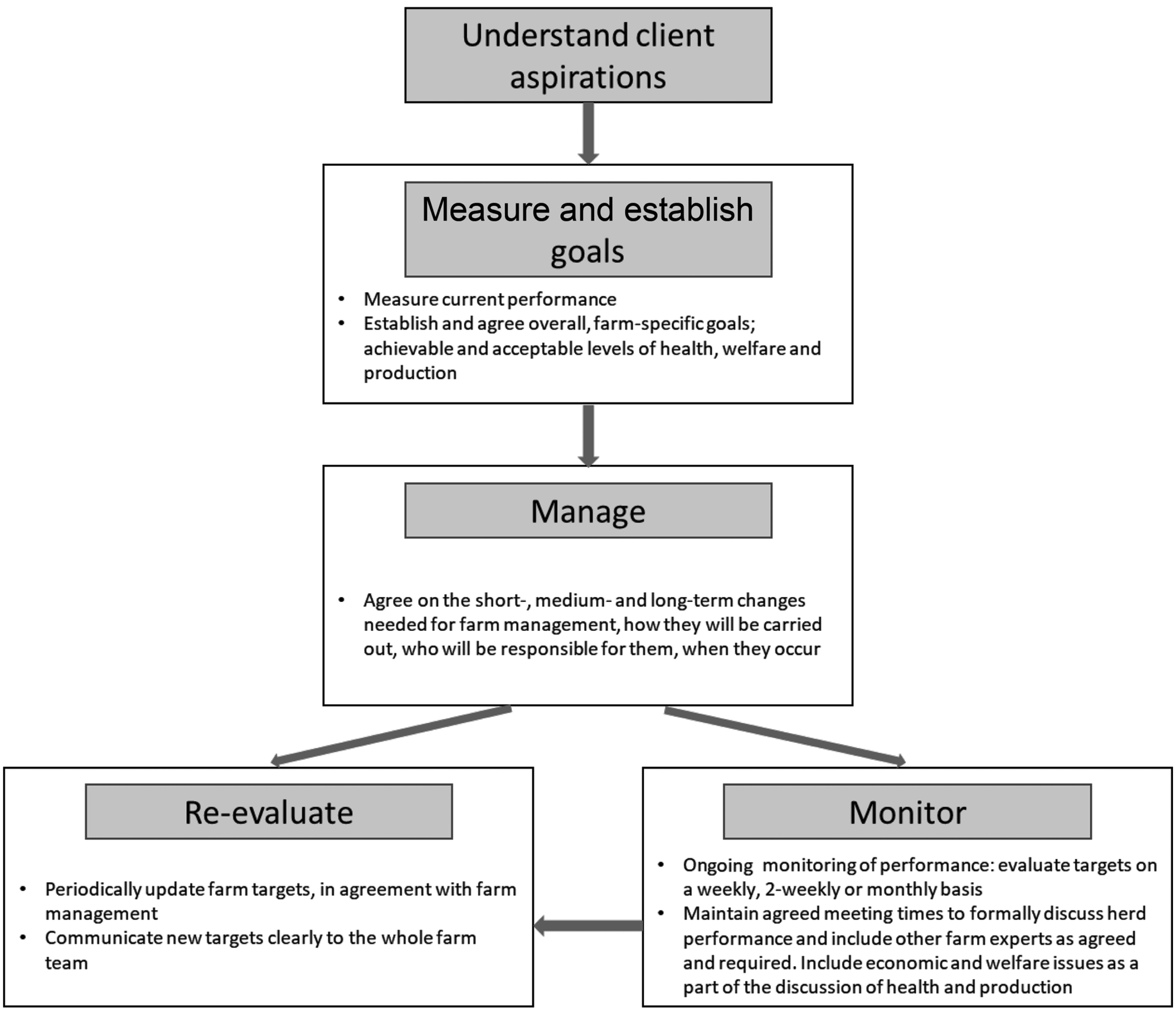

Figure 2. The dairy herd health management cycle. Taken from Dairy Herd Health (Green et al., 2012). Reproduced with permission of CAB International through PLSclear.

herd's mastitis status quo can be quickly detected allowing for rapid interventions. On the other hand, after changes in mastitis management, a potential (positive) effect of these changes can be efficiently monitored.

Demands for Sensor Systems

The purpose of a sensor system to detect herd-level mastitis problems is to identify the moment that a negative change in the herd's mastitis status quo occurs. To be used to monitor the herd's mastitis situation, first some KPI are needed that can be used for sensor systems. The KPI can be aimed at different aspects of the herd's mastitis situation. The most important aspect is the overall mastitis situation of the herd. Potential KPI can be the average level of all cows regarding a sensor system measurement (e.g., based on EC or SCC measurements) or the prevalence of cows with a sensor measurement level above a (farm-) specific threshold (Dalen et al., 2019b). When a sensor system consists of more than one sensor measurement that is combined into alerts, a KPI can be based upon the number of alerts that are given per day. When a sensor system can distinguish episodes of mastitis (inflammation or infection), the incidence of these episodes can be used as KPI. Only little research is done to define KPI based on sensor systems to evaluate the herd-level mastitis situation (Dalen et al., 2019b).

Together with the possibility to create algorithms based on a repeated number of mastitis indicator measurements before drying off in combination with other cow information, we argue that a sensor system to detect herd level mastitis problems should fulfill the following demands:

1. A high sensitivity of >80% is needed to enable a timely detection of herd-level mastitis problems.
2. A high specificity of > 99% is needed because the managerial consequence of an alert will consist of an analysis which is time-consuming and potentially costly. False-positive alerts should therefore be prevented.
3. Herd-level mastitis problems should be identified as quickly as possible, but not at the expense of false-positive alerts. A time window should be measured in weeks rather than in days. By having a larger time window, data of multiple days can be used, increasing the power of the analysis.

To illustrate this mastitis situation, we consider a herd in which every 2 yr the mastitis status quo is negatively disturbed and in need of intervention. We assume that the herd status is evaluated every month, linked to the visit of a veterinarian as part of a herd health and management program (whereas the veterinarian may visit the herd as frequently as every 2 wk, it is unlikely that the udder health is assessed at every visit). That means that in a period of 10 yr, 120 tests are done. A sensitivity of 80% would mean that with a success rate of 80%, one of the 5 mastitis problems will not be detected timely. With a specificity of 99%, in a period of 10 yr, there will be one false-positive alert.

Associated Management

The goal of preventive mastitis management is to prevent new IMI (Ruegg, 2017). From an economic perspective, the level of resources to be used in preventive mastitis management should be weighed against the reduction of losses (Hogeveen et al., 2019). However, the benefits of good udder health go beyond economics. Animal welfare aspects (related to the image of dairy products) are also important benefits of good udder health.

Starting from the 5-point plan (Neave et al., 1969) through the National Mastitis Council 10-point plan (NMC, 2000), for many dairy farming situations, preventive plans have been developed. Because of the multifactorial nature of mastitis and the large differences between farms on structural aspects (barn, field, management capacity of the farmer), number of preventive measures in place and quality of the execution of prevention, it is immensely difficult to define SOP to evaluate the causes of herd-level mastitis problems. Preventive mastitis management may already be different between farms with conventional milking systems and AMS (Hovinen et al., 2009; Dohmen et al., 2010; Deng et al., 2019). In the past, the use of computers to diagnose herd-level mastitis problems has considered, but they were not very accurate (Hogeveen et al., 1995a,b).

DISCUSSION

Since the first peer-reviewed publication about online measurement of EC to detect CM (Yamamoto et al., 1985) in 1985 and follow-up work in the early 1990s (Maatje et al., 1992; Nielen et al., 1995a,b; Woolford et al., 1998), an improved detection performance in online detection of CM was apparent in the first decade of the 21st century (e.g., Kamphuis et al., 2010; Mollenhorst et al., 2010; Steeneveld et al., 2010). These improvements could be attributed to advances in sensor technology and increased computing power in combination with novel machine learning technologies. Although publications since that time do describe their results as promising, few studies report advances in detection performance of sensor systems for CM. In an automatic milking rotary, detection performance for CM achieved a sensitivity of 90% and specificity of 90% (Khatun et al., 2018). In AMS with online SCC measurements, detection performance of CM reached a sensitivity of 80% at a specificity of 90%. When the specificity increased to 99%, sensitivity was 60% (Dalen et al. 2019a). A very large number of potential indicators can be derived from current sensor systems (Kamphuis et al., 2008). Interestingly, in all the analytical approaches that have been tried in the past, only one publication did evaluate the interquarter ratio (Fogsgaard et al., 2015). So, some additional improvement may be gained by exploring that aspect further.

Mastitis is a gradual disease (Friggens et al., 2007) with at any given moment a rather large proportion of cows (10–20%) having mastitis that may vary from a very minor increase in SCC (Dohoo and Morris, 1993; Schepers et al., 1997) to severe CM. Still, when we want to use sensor systems to create alerts for farmers, we have to create thresholds above which we give the farmer an alert. Because of the graduality of mastitis, performance will never be perfect. False-positive alerts often do denote some kind nonperfect udder health situation, but there are no visual symptoms and therefore farmers regard the alert as being false-positive.

It is logical that, in the past, CM was chosen as the reference standard. The current operational mastitis management is aimed at, among others, treatment of lactational cases of CM. However, in this paper, we have made a strong argumentation that we could generate more value from sensor systems by revisiting the mastitis situations we want to detect. We, therefore, distinguish between severe CM and mild mastitis (consisting of SCM and mild or moderate CM). Severe CM needs to be detected as fast and accurate as possible, which is very well possible because of the severe signs of these CM cases. However, the fast progression of clinical signs can hamper timely detection, as affected cows may not attend the milking system and the absence of new data is an indication of a problem and thus valuable information to consider in the sensor alert.

In contrast to cows with severe CM, cows with SCM or mild or moderate CM may be given some time to cure spontaneously. Using that approach, sensor systems can use data of several milkings to generate an alert. Although no research into the number of milkings that are needed for such an alert is carried out, it is expected that data from 4 to 5 d should be sufficient for an alert system for mild mastitis. Farmers may create a routine approach to evaluate these types of cows once every week. In such a routine the actions to carry out when cows show clinical signs may differ from the actions to carry out when cows do not show clinical signs and are most probably having SCM. Detection becomes more important when mild CM or SCM progresses to severe CM or chronic mastitis. By this classification we do skip the CM cases denoted as moderate (Ruegg, 2012) and group these mostly in the mild CM category. In addition, sensor systems aiming to early detection of severe CM will identify some moderate CM cases. Rather than seeing these moderate CM cases as false-positive alerts, they can be treated according to the farm protocol. It is tempting to try to create sensor systems for SCM separately. However, because of the very nature of mastitis indicators, such as SCC, there will be an overlap of cows with mild or moderate CM and SCM. Hence, the accuracy of sensor systems aimed at detection of SCM will most probably be low, leading to farmer frustration and consequently to a situation where such systems are not used. That is the reason we combined SCM and mild or moderate CM into one category. Future research into these ideas should show whether it is possible to use this category in the way we have thought it over.

The performance examples that we provided were based on a binary alert. Another approach toward the detection of herd-level mastitis problems is not to detect problems (a binary yes or no algorithm). For all defined mastitis situations, except severe CM, where we belief it is important that they are treated immediately, it may also be possible to provide a probability that a cow may have mastitis or that the realized udder health situation is above the goal together with a confidence interval how much the realized udder health situation is above the goal, similar to what has been proposed by (Friggens et al., 2007). Such an approach will allow farmers to follow-up on potential problems based on their own preferences and risk attitude.

In addition to operational management regarding lactational treatment, sensor systems can also be used to classify cows for SDCT. Incorporating all available sensor information collected during lactation should improve the distinction between cows that will benefit from antimicrobial treatment at drying off to cure existing infections and cows that will not benefit from antimicrobial treatment at drying off. Because of differences in the underlying prevalence of infected cows and regional differences in attitude toward over-treatment or under-treatment of cows at drying off, there is an opportunity to fine-tune the detection algorithms to suit the needs of the herd and region. It is likely that specific sensitivity and specificity thresholds are not needed, but rather that the algorithm can be changed to minimize the probability of either false-positive or false-negative classification.

A final application of sensor systems is at the herd-level, aimed at tactical decision-making regarding udder health. The day-by-day measurement of udder health, using sensor systems, may enable farmers to identify significant increases as well as decreases in new infection rates, incidence of chronically infected cows, or incidence of CM cases. Changes in sensor-based udder health KPI can be detected earlier in comparison to KPI based on monthly to bimonthly DHI test-day SCC measurements. In addition, sensor-based udder health KPI could be a valuable tool for herds not participating in DHI programs. However, KPI for this type of systems have not yet been developed and tested in practice.

A sensor system identifies cows with or without a certain condition, it does not diagnose a disease. The performance of the system should be documented and continuously validated. Each farmer applying sensor technology to identify cows with IMI with the intention of subsequent antimicrobial treatments, together with a veterinarian, needs to define detection methods, confirmatory procedures, and treatment guidelines that fulfill regulations in their respective country, both for lactational therapy, as well as for dry cow therapy. Several countries have already put rules in place directing the application of antimicrobials based on certain diagnostic results e.g., positive microbiological analysis or higher than a certain SCC threshold at a DHI test-day or on the use of SDCT. To our knowledge, none of these regulations today consider the use of sensor data output as criteria to allow or not allow the use of antimicrobials. This peculiar, but important, aspect should be taken in account when sensors are applied for this specific scope. There are 2 possible ways to address this problem: producing the evidence of a performance comparable to the one observed for any approved method (i.e., microbiological analysis or SCC), or use sensors as a discriminating method to identify cows to be further evaluated by an approved method.

In this paper, we have made a strong argument that we could generate more value from sensor systems by revisiting the mastitis situations we want to detect. We defined 4 novel ways to use sensor systems. We defined demands for sensor system performance for all of these 4 mastitis situations. Because of our experience with CM detection algorithms and the novel machine learning methods that are becoming available (Fadul-Pacheco et al., 2021; Slob et al., 2021), we are confident that these demands can be met in practice. Nonetheless, research needs to be carried out to design and evaluate algorithms specifically for these 4 mastitis situations. Any algorithm defined as proposed in this paper should be tested and the detection performance for the described mastitis situations documented, both on individual cow and herd-level. Ideally, the test performance of the specific sensor systems for the intended mastitis management would be certified (e.g., by ICAR; Rome, Italy). To do so, test protocols need to be developed. Based upon known performance of specific mastitis sensor systems SOP can be developed.

CONCLUSIONS

Sensor systems have a large potential to support mastitis management. Reasoning from the perspective of farm management, 4 separate mastitis situations were identified and defined for which sensor systems can be beneficial: (1) cows needing immediate attention, (2) cows not needing immediate attention, (3) cows needing attention at drying off, and (4) monitoring udder health at the herd level. These 4 situations are of high relevance for dairy farmers in managing mastitis. Each of these 4 mastitis management areas has specific demands for a sensor system. That means that for a full and successful implementation of sensor-based mastitis management, instead of using one alert algorithm, which currently is done, the algorithms of these sensor systems should be aimed to monitor each of these 4 mastitis situations specifically. The performance of the sensor systems should meet the demands as described in this document.

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