# Automated detection of oestrus and mastitis in dairy cows

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Proefschrift
ter verkrijging van de graad van doctor
op gezag van de rector magnificus
van Wageningen Universiteit,
dr. C.M. Karssen,
in het openbaar te verdedigen
op maandag 5 juni 2000
des namiddags te vier uur in de Aula.

The research described in this thesis was carried out at the Institute of Agricultural and Environmental Engineering (IMAG) in Wageningen, in co-operation with Wageningen University, the Institute for Animal Science and Health in Lelystad (ID-Lelystad) and the Research Station for Cattle, Sheep and Horse Husbandry (PR) in Lelystad. Financial support by Alfa Laval Agri (Tumba, Sweden) and the Dutch Ministry of Agriculture, Nature Management and Fisheries (Research programme 258, Integration of innovative technological principles into dairy farming) is gratefully acknowledged.

de Mol, R.M.
Automated detection of oestrus and mastitis in dairy cows
Thesis Wageningen University - With ref. - With summaries in English and Dutch
ISBN 90-5808-229-6

IMAG

This thesis is also available as publication No. 2000-05 (ISBN 90-5406-182-0) of the Institute of Agricultural and Environmental Engineering, P.O. Box 43, 6700 AA Wageningen, the Netherlands



Printed in the Netherlands, by Ponsen & Looijen bv, Wageningen

Cover design: Elly Smits
Cover photography and realisation: Mario van Zeeland

# *Abstract*


de Mol, R.M., 2000. Automated detection of oestrus and mastitis in dairy cows. PhD thesis, Wageningen University, Wageningen, The Netherlands (177 pp., with summaries in English and Dutch).



Keywords: dairy cows, monitoring, management, oestrus detection, mastitis detection, time series, Kalman filter, fuzzy logic, automatic milking systems



Detection models for oestrus and mastitis in dairy cows were developed, based on sensors for milk yield, milk temperature, electrical conductivity of milk, cow's activity and concentrate intake, and on combined processing of the sensor data. The detection model generated alerts for cows, that need the farmer's attention, because of a possible case of oestrus or mastitis. A first detection model for cows, milked twice a day, was based on time series models for the sensor variables, where the parameters were fitted on-line for each cow after each milking by a Kalman filter. This model was tested during two years on two experimental farms, and under field conditions on four farms during several years. A second detection model, for cows milked in an automatic milking system (AMS), was based on a generalisation of the first model. Two data sets (one small, one large) were used for testing. The results of both models for oestrus detection were good, for mastitis varying. Fuzzy logic was used for the classification of mastitis and oestrus alerts with both detection models, to reduce the number of false positive alerts. Input for the fuzzy logic model were alerts from the detection models and additional information. The number of false positive alerts decreased considerably, while keeping the number of detected cases at the same level. The models make automated detection possible in practice.

# *Voorwoord*

Dit is het proefschrift van Rudi en dit gaat over koeien en zo.

Dat was de werktitel van Mario bij de eerste probeersels voor het ontwerp van de omslag. Deze werktitel was op zich een goede beschrijving van dit boekwerk, maar was niet helemaal volledig. Zoals de omslag duidelijk maakt, gaat het met name over de wisselwerking tussen de koe en de computer. Hoe je de computer kunt gebruiken als hulpmiddel voor de melkveehouder. In dit boek wordt duidelijk gemaakt dat de computer goed bruikbaar is als instrument bij de bedrijfsvoering. De rol van de mens is daarmee niet uitgespeeld. Zoals mijn nichtje Pim op de omslag symboliseert, blijft de mens belangrijk. De melkveehouder blijft het laatste woord houden bij beslissingen over zijn dieren.

De werktitel was ook niet helemaal correct, omdat deze suggereert dat het onderzoek een éénmansactie is geweest. Integendeel, dit onderzoek zou niet mogelijk zijn geweest zonder de medewerking van heel veel mensen:

- De promotoren, prof. dr. ir. A.J. Udink ten Cate en prof. dr. ir. A. A. Dijkhuizen, die het onderzoek stuurden en de druk op de ketel hielden. Voor allebei werd dat steeds moeilijker nadat zij van de Wageningen Universiteit waren vertrokken, Alexander Udink ten Cate werkt nu bij de Hogeschool van Utrecht en Aalt Dijkhuizen bij Nutreco in Boxmeer. Bedankt dat jullie er, ondanks de verandering van baan, toch in slaagden om tijd vrij te maken voor de begeleiding.
- De co-promotor, dr. ir. C.E. van 't Klooster, die het onderzoek vanuit het IMAG begeleidde. Bedankt Kees, ook omdat je er voor zorgde dat het onderzoek nooit in de verdrukking kwam, zelfs toen de financiering moeilijker werd.
- De overige leden van de begeleidingscommissie, Jan Achten, Arie Brand en Henk Hogeveen. Bedankt voor jullie zinvolle aanvullingen en sturing van het onderzoek.
- Hans Breteler, die in de laatste maanden een essentiële rol vervulde. Bedankt. Door jouw positief-kritische beoordeling van mijn concepten is het proefschrift een completer en beter leesbaar geheel geworden. Als buitenstaander in dit vakgebied heb je toch erg veel bijgedragen aan dit proefschrift en een stimulerende rol gespeeld bij de laatste loodjes.

- De collega's binnen IMAG, ID-Lelystad en PR die aan dit onderzoek hebben meegewerkt. De bijdrage van Jan Achten, Margriet Hendriks, Bertus Keen, Gerrit Kroeze, Klaas Maatje, Wijbrand Ouweltjes en Wim Rossing blijkt uit het co-auteurschap van één of meer artikelen. Bertus Keen is op 7 november 1996 overleden. Zijn ideeën hebben dit onderzoek in de beginfase op het juiste spoor gezet. Ook andere collega's, zoals Reina Ferwerda-van Zonneveld, Pieter Hogewerf en Bert Ipema, hebben veel bijgedragen aan dit onderzoek. Allemaal bedankt, omdat jullie dit Wageningen-UR-onderzoek *avant la lettre*, mogelijk hebben gemaakt.
- De medewerkers van de proefbedrijven: De Vijf Roeden van IMAG in Duiven; De Bunzing in Zeist en Vestiging Runderweg in Lelystad, van ID-Lelystad (v.h. IVO); Cranendonck, Bosma Zathe, De Marke en De Waiboerhoeve (Melkvee 4 en het hig-techbedrijf) van het PR. Bedankt, jullie hebben het uitgangsmateriaal voor dit onderzoek geleverd.
- De stagiair(e)s en afstudeerders: Erik Blumink, Marc van Boeckel, Olav Dijst, André ten Dolle, Maurice van Erp, Fenna Feenstra, Geert de Graaf, Helmut Kuipers, Bert Pakkert, Hans Peeters, Wouter Wagenvoort. Bedankt voor jullie inzet en inbreng vanuit de praktijk.
- Collega's van de ondersteunende afdelingen van het IMAG: I&S, Bibliotheek, FBMZ, OCM en P&O. Bedankt, zonder jullie ondersteuning was dit onderzoek niet mogelijk geweest. Peet Jansen, bedankt voor de ondersteuning in alle etappes van deze promotie-Tour.
- Collega's van de clusters Systeemkunde en 'Arbeid en Veiligheid', binnen de afdeling Technologie Open Teelten van het IMAG. Bedankt voor de plezierige werksfeer, die erg stimulerend was.
- De directie van IMAG, bedankt voor de verleende faciliteiten.
- De leden van de leerstoelgroep Agrarische Bedrijfseconomie van Wageningen Universiteit, bedankt voor de plezierige samenwerking in de AIO-bijeenkomsten.
- Wayne Woldt, thanks for the support in the fuzzy logic part, it was an inspiring and pleasant co-operation.
- De bridgers en de fietsers, bedankt dat jullie er voor zorgden dat ik ook nog tijd besteedde aan mijn andere hobby's.
- Mario van Zeeland maakte de omslagfoto's, en samen met Elly Smits maakte hij de omslag. De foto's zijn gemaakt op het melkveebedrijf van Peter en Neeltje van de Laar in Nistelrode. Pim de Mol speelt de hoofdrol op de foto's. Bedankt voor jullie hulp bij het maken van de omslag. Het boek is er aantrekkelijker door geworden.
- Tenslotte wil ik mijn ouders bedanken, die de basis hebben gelegd voor dit werk. Ons pap mag het helaas niet meemaken, maar ik weet zeker dat hij net zo trots op dit boekje zou zijn, als ons mam nu is.

## Account

The chapters 2, 3, 4, 5 and 6 are based on articles for scientific journals as mentioned at the bottom of the opening page of these chapters. Reference should be made to the original articles.

The contents of these chapters have not changed, but minor typographical changes were made for this thesis:

– the lay-out of all chapters was standardised;
– American English (Chapters 4 and 6) was transformed into British English (e.g. oestrus instead of estrus);
– all numbers use a dot as decimal separator and a colon as thousand separator;
– all numbering of sections, tables and figures includes the number of the chapter;
– the notation of references was standardised.

# *Contents*

# *Chapter 1*

# A framework for automated dairy cow status monitoring

## 1.1 Introduction

One of the main functions of farm management is control, defined as "measuring performance and correcting deviations from expected behaviour to assure the accomplishment of plans" (Boehlje and Eidman, 1984). The control function is a combination of monitoring and making decisions to take appropriate actions. Boehlje and Eidman define six steps in the development of a control system:

1. break the enterprise into subsystems;
2. list the inputs and outputs to monitor for each subsystem;
3. specify the monitoring interval for each input and output selected;
4. identify the appropriate means of monitoring each item selected;
5. specify the standard and the "in-control" range for each variable being monitored;
6. establish rules of action to apply when the observed variable is outside of the in-control range.

Monitoring, keeping track of a process, is involved in four out of six steps. Only the first and the last step do not include monitoring.

Monitoring the production process is necessary to control dairy farming. Due to the increase in herd size, a decrease in labour potential and the introduction of automated milking systems, monitoring by visual observation is getting more difficult. Moreover, a high animal performance and a high milk quality, together with sufficient animal welfare, are required. All developments mentioned, urge optimal management by adequate control of the entire production process. Automated monitoring is a way to improve control (Schlünsen et al., 1987; Frost et al., 1997; Geers et al., 1997 and Mottram, 1997). Generally, monitoring in dairy farming concerns methods to monitor farm processes (like mineral flow) and the cow status (health and reproduction). Both farm processes and cow status are related to milk yield and milk composition. Analysing the milk composition and assessing the presence of contaminants (e.g. residues of antibiotics), also gives an opportunity to determine the quality of the milk for further processing in the dairy factory. A monitoring system, based on milk composition and other quantities, is therefore essential for an optimal management of dairy farms.

## 1.2 Framework for dairy cow status monitoring

Dairy cow status monitoring is a broad term and includes many aspects. In this section, a framework is given to structure the field of interest. The objectives of the present research within this field are defined in Section 1.3.

### *1.2.1 Application areas*

A modern dairy farmer may apply automated monitoring systems to different areas of the operational management of his herd. Some application areas are given hereafter.

- **Health control**: mastitis (clinical or subclinical), lameness and other diseases.
  Mastitis is an important health disorder on dairy farms. Costs of mastitis include milk production losses, treatment costs and culling due to mastitis. Clinical mastitis is defined (Brand et al., 1996) as "a farmer observed abnormality on either the milk and/or the udder". Subclinical mastitis is defined as "the presence of a micro-organism in combination with an elevated somatic cell count of the milk". Mastitis has a negative influence on the milk quality by an increased somatic cell count and the (possible) occurrence of antibiotics in the milk.
  Lameness reduces animal productivity and animal welfare, and results in costs for treatment and extra labour, reduced milk yield, loss of body condition, a prolonged calving interval (suboptimal oestrous expression), increased risk of teat lesions and a higher culling risk (Brand et al., 1996).
  Other diseases like metabolic disorders and infectious diseases, other than mastitis, have similar negative consequences.

- **Reproduction control**: oestrus detection, timing of insemination and pregnancy checking.
  Dairy farmers, striving for economically optimal calving intervals (365 days or less; Dijkhuizen et al., 1985), can only reach their goal with effective oestrus detection. The most common way for oestrus detection is by visual observation (Van Eerdenburg et al., 1997); cows in oestrus behave differently (more restless, stand to be mounted). Visual observation is time-consuming and difficult in larger herds. Oestrus can also be detected by changes in milk progesterone level or in behaviour.
  Once oestrus has been detected, the farmer has to decide whether he wants to inseminate the cow. If so, insemination must be done timely (Dransfield et al., 1998). A pregnancy check is needed to see whether an insemination was successful.

- **Quality control**: coping with imposed requirements.
  The value of milk is positively related to its contents of protein and fat, and is negatively related to cell counts and residues, including antibiotics. The dairy factory imposes requirements for the milk. These requirements will be strengthened further in the future, because of the stronger consumer's demand for safe products. On-line measurements of the cell counts and residues are not yet possible, which makes an efficient quality management difficult.

Other application areas, like management of minerals, nutrition and breeding, are outside the scope of this thesis (see Section 1.3). The application areas correspond with functions in the operational management of a dairy farm, as described in the information model for dairy farms by Brand et al. (1995).

The monitoring process is divided into three stages:
1. measurement of relevant variables;
2. determination of standards;
3. comparison of measured values with the standards.

These stages are based on the steps in the development of a control system (explained in Section 1.1), as defined by Boehlje and Eidman (1984). The three stages are described in the next sections.

### *1.2.2 Measurement methods*

Most monitoring methods for dairy cows are based on measurements in milk. The measurement location can vary, as well as the measurement time and the aggregation level. Some variables are measured on-line during milking per quarter of the udder, while other variables are measured later on a herd level in external laboratories. Variables, other than milk variables, are the cow's activity and other behavioural characteristics (like visiting patterns and intake of feed and water), and other quantities like animal weight.

Eight measurement levels for variables were distinguished (Table 1.1), varying from external processing of milk tank samples to on-line measurements on a quarter level. A survey of variables is given in Table 1.2, in which for each variable the application areas as well as the level that is currently reached in practice, and the desired level per application area, are given.

***Table 1.1***

*Levels of measurement of monitored variables (used in Table 1.2).*

| level | location | time | aggregation level |
|---|---|---|---|
| | on farm or external | on-line or off-line, during or after milking (hours/days) | herd, animal or quarter |
| 1 | external | off-line, days after milking | herd |
| 2 | external | off-line, days after milking | animal |
| 3 | farm | off-line, hours after milking | herd |
| 4 | farm | off-line, hours after milking | animal |
| 5 | farm | off-line, during milking | herd |
| 6 | farm | off-line, during milking | animal |
| 7 | farm | on-line | animal |
| 8 | farm | on-line | quarter |

***Table 1.2***

*Measurement level (defined in Table 1.1) for a number of measured variables. First column: the level reached in practice. Other columns: the desired level per application area. ? = possibilities not clear/new technique; . = not applicable.*

| measured variable [1] | level reached in practice | desired measurement level per application area | | |
|---|---|---|---|---|
| | | health control | reproduction control | quality control |
| milk yield | 7 | 8 | 7 | 3 |
| duration of milk flow | 7 | 8 | 7 | . |
| milk temperature | 7 | 8 | 7 | . |
| electrical conductivity of milk [2] | 8 | 8 | . | . |
| cell count | 2 | 6/8 | . | 7 |
| residues of antibiotics | 1 | . | . | 6 |
| milk progesterone level [3] | 2 | . | 4/6 | . |
| fat content of milk | 1 | . | . | 6 |
| protein content of milk | 1 | . | . | 6 |
| bacteriological examination of milk | 2 | 4/6 | . | . |
| animal's activity [4] | 7 | 6/7 | 7/8[11] | . |
| behaviour [5] | ? | 4 | 4/6 | . |
| feed intake | 6 | 6 | . | . |
| water intake | 6 | 6 | . | . |
| body weight [7] | 7 | 7 | . | . |
| body temperature [8] | 4 | 7 | 7 | . |
| blood composition | 2 | 6 | . | 6 |
| vaginal mucus resistance [6] | 6 | . | 4 | . |
| breath [9] | ? | 6 | . | . |
| noise [10] | ? | 6 | 6 | . |

[1] A description of most variables (physiological background, implementation) can be found in Brand et al., 1996, Frost et al., 1997, Mottram, 1997 and Geers et al., 1997

[2] Hamann and Zecconi, 1998; Milner et al., 1996; Maatje et al., 1992; Nielen, 1994

[3] Rajamahendran et al., 1989; Delwiche and Claycomb, 1997; Tang et al., 1998

[4] Kiddy, 1977; Koelsch et al., 1994; Thompson et al., 1995

[5] Behavioural characteristics like visiting patterns as described in Horrell et al., 1984

[6] Schofield et al., 1991, Scipioni and Foote, 1999

[7] Maltz and Metz, 1994

[8] Redden et al., 1993; Gil et al., 1998

[9] Mottram et al., 1999

[10] Jahns et al., 1998

[11] Level 8 for animal's activity means higher data frequency than for milking, e.g. each hour

Table 1.2 shows which variables may be used to develop an automated monitoring system for a certain application area. One has to keep in mind, however, the technical limitations, which are not given in this table. The objective, within an area of application, should be the goal and a measured variable a means to reach that goal. If a certain variable appears to be difficult to measure, it may be better to focus on other variables. The choice of variables depends further on the friendliness for the user and for the animal. The requirements for the performance level can vary. Sometimes exact values need to be known, e.g. milk yield, contents of fat and protein. In that case, exact measurements are needed, that can be calibrated and are fraud-proof. In other cases, only relative changes are important, e.g. activity and behaviour. Then only changes in level must be detectable.

In practice, variables based on milk quantities or behavioural measurements will be easiest to implement, especially when they can be measured in the milking parlour. Milk yield, temperature and the like can be measured during milking. Behavioural variables, like animal's activity, may be recorded when the cow visits the milking parlour.

### *1.2.3 Determination of standards*

Measurement of variables is not enough for detection. It should be decided whether measured values are deviating, relatively or absolutely, from a standard. A deviating value should be interpreted to give a plausible cause and a suggested action. Table 1.3 shows how a standard can be determined for some variables. The standard can be based on relative or absolute levels. The complexity of the calculations differs per variable (Table 1.3) and depends on the farming system: conventional with milking two or three times a day at more or less fixed intervals, or with an automatic milking system (AMS) with variable milking frequencies and intervals (Rossing et al., 1997; Artmann, 1997).

The application area determines whether an absolute or relative level is needed for milk yield. For health and reproduction control, the relative level may be sufficient. For quality control, the absolute level may be better suited. The same holds for cell counts. For health control, a relative level will do. For quality control, an absolute level is needed.

***Table 1.3***
*Characterisation of methods to determine standards for a number of variables. First column shows whether the standard is based on an absolute value or a relative value. Second column: the complexity of the calculation model depending on the farming system, conventional (milking two or three times a day) or with an automatic milking system (AMS); simple = based on measurement value; transformation = measurement value needs to be transformed; complex = complex algorithms necessary.*

| measurement variable | standard based on | complexity of calculation | |
|---|---|---|---|
| | absolute or relative value | conventional | AMS |
| milk yield | absolute/relative | transformation | complex |
| milk temperature | relative | transformation | complex |
| electrical conductivity of milk | relative | complex | complex |
| cell count | absolute/relative | transformation | transformation |
| residues of antibiotics | absolute | simple | simple |
| milk progesterone level | absolute | transformation | transformation |
| fat content of milk | absolute | simple | simple |
| protein content of milk | absolute | simple | simple |
| bacteriological examination of milk | absolute | simple | simple |
| animal's activity | relative | transformation | complex |
| behaviour | relative | transformation | complex |
| feed intake | absolute/relative | transformation | transformation |

Some variables are easy to interpret. For residues, for example, only the check whether a threshold is exceeded is relevant. Other variables need a more or less complex transformation before interpretation, e.g. milk yield per milking is easier interpreted after transformation to milk yield per unit of time, e.g. to a 24 hours yield. Conductivity measurements ask for complex transformations, while the interrelationships between quarters must be taken into consideration. Determination of standards is more complex for AMS farms (Table 1.3). The development of monitoring systems for these farms needs special attention.

### *1.2.4 Comparison of measured and standard levels*

For detection of deviations it does not suffice to take the difference between the measured value and the standard. The variance needs to be taken into account to interpret the deviation. A method to determine this variance must be used. For a better interpretation, it may be better to consider a combination of variables. For example, for oestrus detection one should not only regard the activity but also the milk yield and the milk temperature.

Therefore, a detection model should include a method to determine the variance and should take combinations into account.

A detection model for automated dairy cow status monitoring generates alerts in case of deviating measurements. These alerts do not automatically imply an action of the farmer. An alert can be false positive, or no action is needed while the deviation may vanish automatically. A detection model must be integrated into a monitoring system. Support is needed in the use of a monitoring system by the farmer (Brand et al., 1996, Pietersma et al., 1998). A user-friendly implementation is not enough, a good introductory course and support by advisers are needed. Monitoring should be coupled with appropriate decision-making to perform the control function in farm management in an adequate way.

Monitoring systems that are currently used in practice, are mostly based on detection models with a simple structure, e.g. moving average or exponential smoothing of variables. The application of monitoring systems is not widespread and detection results can be disappointing (ATC, 1999; Brand et al., 1996; Hamann and Zecconi, 1998). The development of more advanced detection models is a first step for a successful introduction of automated dairy cow status monitoring.

## 1.3 Scope of this thesis

The research, described in this thesis, addresses some elements of the framework for dairy cow status monitoring. The application areas of monitoring, and monitoring methods are defined by the research objectives (Section 1.3.1). The working methods to reach these objectives are given in the outline of the thesis (Section 1.3.2).

### *1.3.1 Research objectives*

The objectives of the research were twofold:

1. The development of a detection model for oestrus and mastitis in dairy cows, applicable on farms with a conventional milking system (twice a day with fixed intervals) and on farms with an AMS. This detection model should be applicable, as a part of a monitoring system, for the dairy farmer to support his operational management. The model is based on:
   - the application of commercially available sensors for measuring the milk yield, milk temperature, electrical conductivity of milk, cow's activity and concentrate intake;
   - a combined processing of the variables by applying advanced data processing techniques, selected after a structural analysis of the data characteristics.
2. A test of the detection model under practical conditions, with the following performance goals:
   - for oestrus detection: detection level at least as high as the current level reached in practice, and meanwhile keeping the number of false alarms in practice at an acceptable level (see Section 7.6);
   - for mastitis detection: all cases of clinical mastitis should be detected timely (preferably before clinical signs are observable), cows suspicious of subclinical mastitis should be identified, and the number of false alarms should be acceptable in practice;
   - the detection model should outperform the farmer (detection based on visual observation) as well as commercially available detection models (not based on combined data processing).

The focus in this thesis is on oestrus and mastitis, which are major aspects in reproduction and health control. Dijkhuizen and Morris (1997) defined mastitis and subfertility as the two most important disease categories at the herd level in dairy cattle. Automated detection of mastitis and oestrus may yield a management tool to limit the financial losses owing to reproductive failure and mastitis.

This thesis deals with cow status monitoring only, i.e. signalling deviating variables, by a detection model, that may indicate an oestrus or mastitis case. For the completion of the control function, also rules of action have to be established (Boehlje and Eidman, 1984; see Section 1.1). Planning of actions is outside the scope. Examples of actions are the diagnosis of mastitis problems (Hogeveen, 1994) and the timing of insemination (Maatje et al., 1997).

A restriction has been made to variables for which sensor systems are available for practical application. A lot of variables (Table 1.2) is thus far only used in experiments, and not yet ready for field use. Sensors for milk yield, milk temperature, electrical conductivity, animal's activity and concentrate intake are used in practice. Commercial systems for mastitis detection are based mostly on a simple transformation of conductivity data. Oestrus detection is mostly based on activity measurements. It was assumed, however, that the detection results with commercially available sensors could be improved by applying a more sophisticated data-processing method. A new methodology, based on advanced statistical techniques combined with fuzzy logic, was developed in the present research, as will be described in Chapters 2, 5 and 6.

Commercially available sensors were the starting point for the research. Optimal detection results with these sensors were sought by application of advanced data processing techniques. Further development of the sensors was beyond the scope of the present work.

### *1.3.2 Outline of the thesis*

A detection model for cows milked conventionally (twice a day), described in Chapter 2, was developed in a co-operative research of IMAG [1)], Alfa Laval [2)] and ID-Lelystad [3)]. The first results on the experimental farms are presented in Chapter 3. These results may be different under field conditions, therefore a field test on four additional farms of PR [4)] was performed, the outcome of which is given in Chapter 4. The detection model was adapted for conventional systems with more frequent milkings and for an AMS (Chapter 5). The number of false-positive alerts appeared to be a possible obstacle for introduction in practice. Therefore a refinement step for the classification of alerts was developed (Chapter 6). This thesis concludes with a general discussion and the main conclusions (Chapter 7).

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# *Chapter 2*

# Description of a detection model for oestrus and diseases in dairy cattle based on time series analysis combined with a Kalman filter

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Computers and Electronics in Agriculture, 22 (1999) 171-185

**Abstract**
Sensor measurements can be used in dairy farming for the detection of oestrus and diseases. A new model has been developed to process the measured variables in a combined way. It is based on time series models for milk yield, milk temperature, electrical conductivity of quarter milk and the cow's activity, and a probability distribution for the concentrate leftovers. The parameters of the time series models and the probabilities are fitted on-line for each cow after each milking by Kalman filters. This makes it possible to combine the variables and to generate cow-specific alerts. Global results on the detection of oestrus, mastitis and other diseases are given.

*Keywords:* dairy cattle, oestrus detection, health monitoring, time series, Kalman filter, management information systems

## 2.1 Introduction

Timely recognition of oestrus and diseases is very important in dairy farming. Oestrus detection is important because it determines the insemination time and as a derivative of this also the interval between two successive calvings (calving interval). It is traditionally done by visual observations by the farmer. Cows in oestrus behave differently, they are more active and stand to be mounted. Visual observation has become more difficult as the average herd size has increased. Therefore alternative methods have been developed that may be automated (De Mol et al., 1993).

Detection of diseases is also important, not only because an ill cow produces less milk but also because a disease can have harmful consequences; it may be a reason for culling animals. Especially mastitis (udder inflammation) is a frequently occurring disease that can lead to considerable yield reductions (Houben, 1995). Automated methods have also been developed for detection of diseases.

Several methods for automated detection of oestrus and diseases that can already be used in practice are based on measurement of variables with sensors. Sensors are available for measuring milk yield, milk temperature, electrical conductivity of the milk, animal activity (with step counters) and concentrate intake.

The qualitative relationships between the measured variables and the occurrence of oestrus and diseases are shown in Table 2.1. This shows that temperature and activity are increased in case of oestrus, yield and feed intake may be decreased and conductivity is unchanged. The conductivity increases in case of mastitis.

Information from a management information system (MIS), such as the number of days in lactation, previous cases of oestrus and diseases, is useful for the interpretation of the measurements.

Models based on one variable have been developed in previous research for the detection of oestrus and diseases: for example the activity for oestrus (Eradus et al., 1992) or the conductivity for mastitis. Different variables have also been taken into account separately (Maatje et al., 1992).

***Table 2.1***
*The relations between measured variables and the occurrence of oestrus and diseases[a].*

| | yield | temperature | conductivity | activity | feed intake |
|---|---|---|---|---|---|
| oestrus | neg/– | pos | – | pos | neg/– |
| mastitis | neg | pos | pos | – | neg/– |
| other infective diseases | neg | pos | – | neg | neg/– |
| metabolic diseases | neg | – | – | neg | neg |
| lameness | neg | – | – | neg | neg |

[a] neg, significant negative influence, pos, a significant positive influence, –, no influence (after Hogewerf et al., 1992)

It is clear from Table 2.1 that there is a significant potential for improvement by considering the combination of variables for the interpretation of the measurements. An increased temperature can have different causes, but when coupled with an increased activity, oestrus will be an obvious explanation; when it coincides with an increased conductivity, mastitis might be the reason. Therefore a research has been carried out in which sensor measurements from the different variables and information from the MIS are processed in a combined way. This leads to a detection model for oestrus and diseases that can be a part of a MIS (De Mol et al., 1992).

## 2.2 The structure of the model

The detection model should generate alerts for oestrus and diseases (especially mastitis) based on sensor measurements and information from the MIS. These alerts are meant for the farmer to draw his attention to a cow that may be in oestrus or ill so that he can undertake appropriate action. For each cow and each milking, measurement data are available for:

- milk yield,
- milk temperature,
- electrical conductivity of the milk for each quarter of the udder, and
- activity based on the counter values of the step counter,

  and for each cow and each day:
- the concentrate intake and the ration.

Measurements are available from the experimental farms of IMAG-DLO in Duiven and from ID-DLO in Lelystad obtained in 1993 and 1994. The cows were milked twice a day. Maatje et al. (1992) describe the measuring methods. Reference data are available for testing: progesterone, somatic cell counts and others from laboratory analyses, veterinary treatments, and so on.

Several processing techniques are suitable for the development of such a model. In the past simple statistical techniques were used, such as the moving average. A structure that is based on more advanced statistical techniques, namely time series analysis combined with a Kalman filter, is used in this paper. Time series analysis has already been used for milk yield in Deluyker et al. (1990) where a generally applicable model has been proposed. A cow-dependent, but generally applicable, model is described here. The Kalman filter has also been used in a somewhat comparable research (Thysen, 1992), but the approach in this paper is fundamentally different.

The detection model uses underlying models that describe the 'normal' behaviour of the measured variables. These underlying models are cow-specific and estimates of parameters are updated after each milking. For each cow and each milking the following steps are taken:

1 use of the underlying model to calculate predictions for the measurements with standard errors;
2 reading of the actual new measurements;
3 comparison of the actual and the predicted values and generation of an alert if the combination of variables is aberrant; and
4 use of the new information from the measurements to update the parameter estimates in the underlying models.

In this way each cow gets her own model describing her characteristics. This makes it possible to generate cow-specific alerts in case of abnormal behaviour, possibly due to oestrus or illness. The underlying models for yield, temperature, conductivity and activity are time series models (described in Section 2.3), for the concentrate intake a probability distribution is used (Section 2.4). Kalman filters are used to update the parameters in these models (Section 2.5).

This approach has not been used before for the development of detection models. Similar approaches can be found in other fields: e.g. for condition monitoring in an industrial plant in Christer et al. (1997), for a river-flow forecasting model in Awwad et al. (1994) and Bidwell and Griffiths (1994), for estimating dynamic tree ring climate relationships in Van Deusen (1990), for gas transport processes in Federspiel (1997) and for groundwater monitoring networks in Van Geer (1987).

## 2.3 Time series models for cow variables

Time series, like the sensor measurements, are observations of a phenomenon made sequentially in time (Chatfield, 1989). Consequently, the measurements of the cow variables are time series. A characteristic of time series is the fact that in general the successive observations are not independent. This relationship is made explicit in a time series model, which is used to forecast the measurement values for a next milking. The new measurements can then be compared with these forecasts. It is assumed that the model is valid for healthy cows that are not in oestrus. Too great deviations indicate that this assumption is no longer valid.

The usability of time series models for the measured cow variables has been examined. A model has been searched for each variable by following the standard procedure: plot the data, examine the correlograms of the autocorrelations and partial autocorrelations, select an appropriate ARIMA model (AutoRegressive Integrated Moving Average model) and fit the chosen model. This procedure has been applied for the cow variables. Appropriate time series models have been found for the cow variables milk yield, milk temperature, electrical conductivity of the milk and the cow's activity.

### *2.3.1 Yield*

The measured yield is influenced by the length of the interval since the previous milking and the diurnal rhythm. A farmer is mostly concerned with the daily milk yield. An approximation of the daily milk yield based on the two latest milkings is used:

$$Y_{D,n} = (Y_{M,n} + Y_{M,n-1}) \cdot \frac{24}{24 + M_n - M_{n-2}} \tag{2.1}$$

with:

$n$ = latest milking, $n\text{-}1$ = previous milking, ... ;
$Y_{D,n}$ = daily yield at milking $n$;
$Y_{M,n}$ = yield at milking $n$; and
$M_n$ = decimal time of milking $n$ (between 0 and 24 h).

For the differences of successive daily yields, the following moving average (MA) model is used:

$$\nabla Y_{D,n} = Y_{D,n} - Y_{D,n-1} = Z_{Y,n} - \alpha_Y \cdot Z_{Y,n-2} \tag{2.2}$$

with:
$\nabla Y_{D,n}$ = difference of daily milk yield at milking $n$;
$Z_{Y,n}$ = random disturbance on yield at milking $n$;
$\alpha_Y$ = parameter of yield model.

The disturbances $Z_{Y,n}$ (zero means, normally distributed) are calculated recursively, the parameter $\alpha_Y$ must be estimated. The last term in Eq. (2.2) is needed to compensate for the artificial autocorrelations introduced by Eq. (2.1).

### *2.3.2 Temperature*

The temperature fluctuates during the day. Therefore comparison with the previous milking is not useful. An MA model for the differences of the milk temperature with two milkings ago is used:

$$\nabla T_n = T_n - T_{n-2} = Z_{T,n} - \alpha_T \cdot Z_{T,n-2} \tag{2.3}$$

with:
$\nabla T_n$ = difference of milk temperature with lag 2 at milking $n$;
$T_n$ = milk temperature at milking $n$;
$Z_{T,n}$ = random disturbance on temperature at milking $n$;
$\alpha_T$ = parameter of temperature model.

### *2.3.3 Activity*

The activity depends on the diurnal rhythm of the cow. To compensate for this diurnal effect, the hourly activity for each milking is calculated, based on the difference of the two counter values (cumulatives ranging from 0 to 999) and the interval:

$$A_{H,n} = \frac{V_n - V_{n-1}}{M_n - M_{n-1}} \tag{2.4}$$

with:

$A_{H,n}$ = hourly activity at milking *n;*
$V_n$ = counter value at milking *n* (differences are taken modulo 1000);
$M_n$ = decimal time of activity measurement (differences are taken modulo 24.0).

For the differences in hourly activity an MA model is used:

$$\nabla A_{H,n} = A_{H,n} - A_{H,n-2} = Z_{A,n} - \alpha_A \cdot Z_{A,n-2} \tag{2.5}$$

with:

$\nabla A_{H,n}$ = difference of hourly activity with lag 2 at milking *n;*
$Z_{A,n}$ = random disturbance on activity at milking *n;*
$\alpha_A$ = parameter of activity model.

As with the yield model, the last term in Eq. (2.5) is introduced to compensate for the artificial autocorrelations introduced by Eq. (2.4).

### *2.3.4 Conductivity*

The electrical conductivity of the quarter milk depends mostly on the conductivity at the preceding milkings. Therefore an autoregressive (AR) model is used for the conductivity:

$$E_{q,n} - \mu_C = \alpha_C \cdot (E_{q,n-1} - \mu_C) + \beta_C \cdot (E_{q,n-2} - \mu_C) + Z_{Cq,n} \tag{2.6}$$

with:

$E_{q,n}$ = electrical conductivity of quarter *q* at milking *n;*
$\mu_C$ = the average conductivity of each quarter (parameter of conductivity model);

$\alpha_C$ = parameter of conductivity model;
$\beta_C$ = parameter of conductivity model;
$Z_{Cq,n}$ = random influence on conductivity of quarter q at milking $n$.

The same parameters, $\mu_C$, $\alpha_C$ and $\beta_C$, are assumed to be valid for each quarter.

It is possible to forecast new measurement values if the values of the parameters are known. However, after fitting the models, these parameters appeared to be different for each cow and also different for successive lactations of the same cow. Therefore the parameter values should be calculated for each cow and each lactation separately. With standard techniques this is only possible at the end of a lactation, which is undesirable for practical application because results are needed during the current lactation. Application of a Kalman filter can relieve this problem (Section 2.5.2).

## 2.4 A stochastic model for the concentrate leftovers

The concentrate leftovers are not included in the detection model by a time series model. This variable has a different behaviour; it mostly equals zero and is sometimes higher. Therefore a different approach is used. It is assumed that successive leftovers are independent and there is a probability distribution for $L$, the percentage of the leftover of the concentrate ration, defined by:
$p_0$ = P($L$ = 0%),
$p_1$ = P(0% < $L \leq$ 10%),
$p_2$ = P(10% < $L \leq$ 30%),
$p_3$ = P(30% < $L \leq$ 50%),
$p_4$ = P(50% < $L \leq$ 100%).

This distribution can be used to calculate the probability P($L \geq L_n$) of the actual leftovers $L_n$ at a certain milking $n$. An alert for low concentrate intake will be given when this probability is low.

This distribution is, however cow-dependent. For some cows the leftovers are zero at most times, for other cows the leftovers are quite often greater than zero. A Kalman filter is used to fit the distribution for each individual cow ( Section 2.5.3).

## 2.5 The Kalman filter

### *2.5.1 General description*

A Kalman filter is applied because the parameters in the models for the different variables are cow-dependent and a model for the dependency between the variables is wanted. It is a method to estimate the state of a system on-line. The state is a quantity that determines the coming behaviour of the system. The estimate of the state is adjusted after each new observation by using the new information. First, a general description is given and later two applications where:

1. the state consists of the parameters in the time series models (Section 2.5.2);
2. the state consists of the probability distribution of the percentage of the concentrate leftover (Section 2.5.3).

The system must be described with state-space equations to apply the Kalman filter, consisting of observation equation:

$$y_n = C_n \cdot x_{n-1} + v_n \tag{2.7}$$

and a system equation:

$$x_n = A_n \cdot x_{n-1} + w_n \tag{2.8}$$

In these equations $x_n$ is the state vector, $y_n$ the observation vector, $C_n$ and $A_n$ are system matrices, $v_n$ is the random observation error and $w_n$ is the random system error. The observation equation (2.7) describes the relationship between the measurements and the state, the state itself is not directly measurable in general. The system equation (2.8) gives the relation between the states at successive times. The distribution of $v_n$ is $N(0, V_n)$ and of $w_n$ is $N(0, W_n)$.

In general the estimate of the state $x_n$ at time $n$ using the observations $y_1, \ldots, y_{n-1}$ is desired. The Kalman filter can be applied when a system is described with state equations (Harrison and Stevens, 1976; Harvey, 1989). It gives a new estimate of the state $x_n$ after each observation and furthermore a variance-covariance matrix $P_n$ for the state estimate.

The Kalman filter is an estimation procedure with two stages:
Stage 1 (prediction stage) is an estimate of the state based at the previous state:

$$\hat{x}_{n/n-1} = A_n \cdot \hat{x}_{n-1} \tag{2.9}$$

with variance-covariance matrix:

$$P_{n/n-1} = A_n \cdot P_{n-1} \cdot A_n^T + W_n \tag{2.10}$$

where:

$\hat{x}_{n/n-1}$ = estimate of state *x* at time *n* using all information up to time *n-1*;

$\hat{x}_{n-1}$ = estimate of state *x* at time *n-1* using all information up to time *n-1*;

$P_{n/n-1}$ = estimate of the variance-covariance matrix *P* at time *n* using all information up to time *n-1*;

$P_{n-1}$ = estimate of the variance-covariance matrix *P* at time *n-1* using all information up to time *n-1*.

Stage 2 (updating stage) updates the estimate with the observation $y_n$, the estimation error is:

$$e_n = y_n - C_n \cdot \hat{x}_{n/n-1} \tag{2.11}$$

where:

$e_n$ = the estimation error at time *n*.

This gives an improved estimate of the state:

$$\hat{x}_n = \hat{x}_{n/n-1} + K_n \cdot e_n \tag{2.12}$$

with variance-covariance matrix:

$$P_n = P_{n/n-1} - K_n \cdot C_n \cdot P_{n/n-1} \tag{2.13}$$

where:

$$K_n = P_{n/n-1} \cdot C_n^T \cdot [C_n \cdot P_{n/n-1} \cdot C_n^T + V_n]^{-1} \tag{2.14}$$

The resulting estimates can be used in the next time step. The matrix $K_n$ is called the Kalman gain; it gives the influence of the error at time $n$ on the state estimate, see Eq. (2.12). This is also the influence of the current observation, as can be derived from Eqs. (2.11) and (2.12):

$$\hat{x}_n = K_n \cdot y_n + (I - K_n \cdot C_n) \cdot \hat{x}_{n/n-1} \tag{2.15}$$

where $I$ is the identity matrix.

Harvey (1989) proves that the Kalman filter gives the minimum mean square linear estimator (MMSLE) of $x_n$, $P_n$ is the unconditional variance-covariance matrix of the estimation error when estimating $x_n$. The variance-covariance matrix, $\Sigma_n$, of $e_n$ is given by:

$$\Sigma_n = C_n \cdot P_{n/n-1} \cdot C_n^T + V_n \tag{2.16}$$

when the system matrices are fixed and known. Duncan and Horn (1972) show that even if the error vectors are not normally distributed, the Kalman filter estimator will still be the MMSLE provided the $v_n$ and $w_n$ are independent vectors with mean zero.

### *2.5.2 Fitting the parameters of the time series models*

In standard usage of the Kalman filter the state is used to model the measured variables, e.g. the level and trend of a variable. In that case the level and trend are included in the state vector. The Kalman filter is here used to estimate the parameters of the time series models of the cow variables, therefore the state consists of these parameters. The Kalman filter gives a new estimate of the state after each milking, which means new estimates of the parameters of the time series models. With these parameters new measurement values are forecasted so that highly deviant measurements can be signalised. Also the variance-covariance matrix of the estimated state is given, this is used to relate the variables mutually. We apply the following definitions:

$$x_n = \begin{bmatrix} -\alpha_Y \\ -\alpha_T \\ -\alpha_A \\ \mu_C(1-\alpha_C-\beta_C) \\ \alpha_C \\ \beta_C \end{bmatrix}, \quad y_n = \begin{bmatrix} \nabla Y_{D,n} \\ \nabla T_n \\ \nabla A_{H,n} \\ E_{rh,n} \\ E_{rf,n} \\ E_{lf,n} \\ E_{lh,n} \end{bmatrix}, \quad z_n = \begin{bmatrix} Z_{Y,n} \\ Z_{T,n} \\ Z_{A,n} \\ Z_{Crh,n} \\ Z_{Crf,n} \\ Z_{Clf,n} \\ Z_{Clh,n} \end{bmatrix}, \tag{2.17a}$$

$$C_n = \begin{bmatrix} Z_{Y,n-2} & 0 & 0 & 0 & 0 & 0 \\ 0 & Z_{T,n-2} & 0 & 0 & 0 & 0 \\ 0 & 0 & Z_{A,n-2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & E_{rh,n-1} & E_{rh,n-2} \\ 0 & 0 & 0 & 1 & E_{rf,n-1} & E_{rf,n-2} \\ 0 & 0 & 0 & 1 & E_{lf,n-1} & E_{lf,n-2} \\ 0 & 0 & 0 & 1 & E_{lh,n-1} & E_{lh,n-2} \end{bmatrix} \tag{2.17b}$$

$$A_n = I, v_n = z_n, w_n = 0 \tag{2.17c}$$

where the abbreviations rh (right hind), rf (right front), lf (left front) and lh (left hind) are used for the four quarters.

Using this definition, the state space equations Eqs. (2.7) and (2.8) are in fact a reformulation of the time series models as defined in Eqs. (2.2), (2.3), (2.5) and (2.6), which makes it possible to apply the Kalman filter. The matrix $W_n$ is taken equal to the zero matrix, as we suppose that the parameters are fixed but unknown for an individual cow (Eq. (2.8)). The matrix $V_n$ (the variance of the observation errors, needed in Eq. (2.14)) is calculated by exponential smoothing using actual values of $v_n$ as defined in Eq. (2.17). Elements of $V_n$ are also taken as zero if interrelationships between measurements of variables are not plausible. For example there is no reason to suppose a relationship between measurement of yield and activity. Only influences between the measurements of the conductivity of different quarters seem possible. This means $V_n$ has the following form:

$$V_n = \begin{bmatrix} v_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & v_{22} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & v_{33} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & v_{44} & v_{45} & v_{46} & v_{47} \\ 0 & 0 & 0 & v_{54} & v_{55} & v_{56} & v_{57} \\ 0 & 0 & 0 & v_{64} & v_{65} & v_{66} & v_{67} \\ 0 & 0 & 0 & v_{74} & v_{75} & v_{76} & v_{77} \end{bmatrix} \tag{2.18}$$

### *2.5.3 Fitting the probability distribution in the concentrate leftover model*

Again, a Kalman filter is applied. A description with state space equations Eq. (2.7) and Eq. (2.8) is needed for this. In this case the following definitions apply:

$$x_n = [p_0 \quad p_1 \quad p_2 \quad p_3 \quad p_4]^T,\ y_n = [r_0 \quad r_1 \quad r_2 \quad r_3 \quad r_4]^T,\ A_n = I,\ C_n = I \tag{2.19}$$

The vector $x_n$ is the state, here the probability distribution (Section 2.3), $y_n$ is the observation with $r_i$ defined as:

if $L_n = 0\%$ $\quad r_0 = 1$, $r_i = 0$ if $i \neq 0$,
if $0\% > L_n \leq 10\%$ $\quad r_1 = 1$, $r_i = 0$ if $i \neq 1$,
if $10\% > L_n \leq 30\%$ $\quad r_2 = 1$, $r_i = 0$ if $i \neq 2$,
if $30\% > L_n \leq 50\%$ $\quad r_3 = 1$, $r_i = 0$ if $i \neq 3$,
if $50\% > L_n \leq 100\%$ $\quad r_4 = 1$, $r_i = 0$ if $i \neq 4$.

The matrices $A_n$ and $C_n$ are equal to the identity matrix $I$, $V_n = I$ and $W_n = 0.01 \cdot I$.

With this definitions the estimation error is:

$$e_n = [r_0 - p_0 \quad r_1 - p_1 \quad r_2 - p_2 \quad r_3 - p_3 \quad r_4 - p_4]^T \tag{2.20}$$

A component of $e_n$ is positive when $r_i = 1$ and negative when $r_i = 0$. Starting values for the probability distribution are based on observed distributions, the starting value for $P_0$ is taken $0.1 \cdot I$.

In this case the Kalman filter can be rewritten as:

$$\hat{x}_n = \hat{x}_{n-1} + K_n \cdot e_n, \quad P_n = (I - K_n) \cdot (P_{n-1} + 0.01 \cdot I), \quad K_n = f_n \cdot I \tag{2.21}$$

where the factor $f_n$ can be calculated recursively:

$$f_n = \frac{f_{n-1} + 0.01}{f_{n-1} + 1.01}, \quad f_0 = 0.1$$

## 2.6 Detection method

The detection model is meant to draw the attention of the farmer to possible deviations in his cows, the model should generate alerts for that purpose. Alerts can be generated based on yield, temperature, conductivity and activity with the time series models for these variables. With the help of the time series models together with a Kalman filter for each milking, an estimate of the observation is available following the observation equation Eq. (2.7). The estimate is compared with the real measurement to get the error vector $e_n$. The estimate of the state based on the measurements up to the preceding milking, is used for this. A normal distribution is assumed for $e_n$. The variance-covariance matrix of $e_n$ can also be calculated (Eq. (2.16)). This matrix is used to standardise $e_n$. The stochastic model together with the Kalman filter gives the probability of the actual concentrate leftover.

There are two methods to generate alerts:

1) Single alerts: each component of the standardised error vector has a standard-normal distribution. Observations outside some confidence intervals result in an alert. An alert can correspond with: errors outside the 95% confidence interval, errors outside the 99% interval and errors outside the 99.9% interval. A single alert for the concentrate leftover can be given when the calculated probability is below 5, 1 or 0.1%.

2) Combined alerts: the components of the standardised error vector are mutually comparable, due to the special form chosen for $V_n$ (Eq. (2.18)). This makes it possible to consider combinations of the elements. Alerts correspond with combinations falling outside a 95%, a 99% and a 99.9% confidence region. An oestrus alert is given when the activity is rather high and the sum of standardised errors of activity, yield and temperature falls outside a certain confidence interval. A mastitis alert is given when the conductivity error is rather high and the sum of standardised errors of conductivity, yield and temperature falls outside a certain confidence interval. An illness alert is based on the sum of standardised errors of yield, temperature, activity and concentrate intake.

## 2.7 Adjustments for practical implementation

The Kalman filter as described in the previous section is adjusted in the practical implementation:

– The update of the state as defined in the updating stage, Eq. (2.12), is limited to prevent unwanted effects caused by start-up effects or strong deviating measurements. The updating stage is modified such that limits can be set. In practical applications the absolute change in Eq. (2.12) is limited to 0.1.

– The update of the matrix $V_n$ is also limited to prevent too great changes in one step. A value of $v_n$ outside the 99% confidence interval is replaced by the value on the border of this confidence interval.

– There are also several possibilities for applying the Kalman filter. The Kalman filter may be used only when measurements of all variables are available or used when at least one variable is measured correctly. In the latter case it is used to improve only the parameters of the ARIMA models of the right variables. Furthermore, the Kalman filter may be used only when no alerts are given or used also when there are alerts on some variables. The ARIMA model is suitable for healthy cows. A cow may be sick (or in oestrus) in case of alerts, so applying the Kalman filter may lead to wrong parameters. In both applications a Kalman filter is used when at least one variables is measured correctly and in all cases, with or without alerts. In this way all information is used as much as possible and the model adapts if the circumstances changes, e.g. when the cows go the pasture in spring.

– Measurement errors can give problems, not only for the current milking but also for following milkings, as follows from Eqs. (2.1), (2.3), (2.4) and (2.6). For example, for the calculation of the daily milk yield two successive measurements are needed (Eq. (2.1)). To prevent consequences of measurement errors for the next milking the expected value of $y_n$ is calculated and used as a substitute value for the missing measurement. These substitute values are used in cases with only one successive missing measurement. No substitute values are used when there are more missing measurements in a row.

– Measurement errors for the activity can result in false counter values and thus in great differences in Eq. (2.4) and wrong alerts. It is possible to neglect counter values, which are apparently coupled with a wrong cow number.

– A combined alert is based on a combination of errors of different variables. The detection method is adapted if some variables are missing. An alert is also given when a combination of some variables minus one exceeds a similar threshold: e.g. an oestrus alert in case of increased activity and decreased yield but also a lower temperature.

## 2.8 Illustration of outcomes

The described model has been implemented and tested on two experimental farms (of IMAG-DLO and ID-DLO). Cases of oestrus or disease that were signalled by the model are true positive (TP), not signalled cases are false negative (FN). Milkings outside an oestrus or illness period are true negative (TN) if there is no alert from the model, otherwise they are false positive (FP). The model performance was expressed in the sensitivity and the specificity.

The sensitivity is the percentage of truly signalled cases: (TP/(TP+FN))·100%.

The specificity is the percentage of truly not signalled milkings outside oestrus or disease periods: (TN/(FP+TN))·100%. The specificity for mastitis is calculated by regarding cows without any mastitis case during the test period.

Some results are given in Table 2.2, 2.3 and 2.4; more results can be found in De Mol et al. (1997). The results depend on the chosen confidence interval. Tightening the criterion leads to a lower sensitivity and higher specificity, and vice versa. Results for oestrus are satisfying, as well as the sensitivity for mastitis. The number of false positives (as implied by the specificity) may be too high for practical implementation. The results for diseases are promising but further research is needed.

***Table 2.2***

*The sensitivity and specificity for oestrus based on 537 oestrus cases and 41,803 milkings outside oestrus periods.*

| alerts (confidence interval, %) | sensitivity (%) | specificity (%) |
|---|---|---|
| 95 | 94.2 | 94.5 |
| 99 | 86.5 | 96.9 |
| 99.9 | 82.5 | 98.1 |

***Table 2.3***

*The sensitivity for clinical and subclinical mastitis and the specificity for mastitis.*

| alerts (confidence interval, %) | sensitivity clinical mastitis (52 cases) (%) | sensitivity subclinical mastitis (21 cases) (%) | specificity (6,495 milkings) (%) |
|---|---|---|---|
| 95 | 96 | 100 | 95.3 |
| 99 | 90 | 76 | 98.2 |
| 99.9 | 65 | 57 | 99.4 |

***Table 2.4***

*The sensitivity for diseases (mastitis excluded) and specificity of the detection model, based on 263 cases and 40,286 milkings outside illness periods.*

| alerts (confidence interval, %) | sensitivity (%) | specificity (%) |
|---|---|---|
| 95 | 99.6 | 86.0 |
| 99 | 90.5 | 93.5 |
| 99.9 | 76.8 | 96.7 |

## 2.9 Discussion

The detection model is based on cow-specific time series models. Specific time series models (moving average, exponential smoothing) have been used more in detection models. Here a selection was made by a systematic search within the class of ARIMA models, resulting in a suitable MA or AR model for each variable. A general model that can be used for each cow as in Deluyker et al. (1990) was not searched for here. The use of the Kalman filter makes it possible to work with cow-specific parameters for the time series models. The filter gives for each cow after each milking an estimate of the parameters that describe the normal behaviour of the cow. The model is no longer valid if new measurements widely deviate from the forecast because the cow is in oestrus or ill. An alert is given in that case.

A Kalman filter is also applied by Thysen (1992) to model the somatic cell count of milk. He has a general model for all cows and uses a 'multi-state' model in which a cow can have three possible states: normal level, an outlier or a change of level. A normal behaviour is assumed here and deviant measurements do not fit in our model. The application of time series analysis with a Kalman filter is new for a detection model. A similar approach in other fields to the use of a Kalman filter can be found in the literature as described in Section 2.2.

The model is developed to detect short-term changes in cow variables. After a few days the model will be adapted to the new situation. This feature will be in general advantageous because changes in grazing system, lactation stage and the like, should not result in alerts. Slow changes will be adapted by the model without generating alerts. This means that the model may not detect some diseases because the symptoms appear slowly.

A combined alert is given when the error for activity (for oestrus) or conductivity (mastitis) is high and the sum of standardised errors is outside a confidence interval. Other possibilities may lead to improved detection results: changing the threshold for the error for activity or conductivity, or changing the relative weight of variables in the sum, or excluding a variable or including new variables in the sum.

The detection model gives each cow has her own model, independent of other cows. Group effects are not taken into account. The number of FP alerts can be reduced be looking at the group effects. Oestrus might not be the reason if all cows have an increased activity, so no oestrus alerts should be given in that case.

The model is based on a milking frequency of twice a day. This is used in the time series model to include diurnal effects. Adaptation for a milking frequency of three times a day is straightforward. Adaptation to a variable milking frequency (in systems with a milking robot) is less apparent.

## 2.10 Conclusions

The existing detection models are mostly based on a moving average or exponential smoothing; these can be considered as specific time series models. The described detection model is for most variables based on time series models combined with a Kalman filter to estimate the parameters on-line and to be able to consider the mutual connection. The application of time series models gives more selection possibilities and can thus lead to better models. The distribution of the concentrate leftovers is an appropriate model for this variable. The Kalman filters make it possible to adapt the model on-line.

The results of the detection model are based on a comparison with reference data. The sensitivity is high (but depending on the chosen criterion). The specificity seems also high but may be too low for practical application, therefore additional research is directed to a reduction of the number of false positive alerts.

Further research is directed to an adaptation of the detection model for other milking frequencies (in case of an automatic milking system) and reducing the number of false positive alerts by a further processing of the standardised errors.

**Acknowledgements**

- This paper is dedicated to co-author A. Keen, who passed away on November 7th, 1996. Bertus Keen came up with to idea to apply a Kalman filter for this purpose.

- This study was a co-operation among Alfa Laval Agri in Sweden, IMAG-DLO and DLO Research Institute for Animal Husbandry and Animal Health (ID-DLO) in The Netherlands.

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# *Chapter 3*

# Results of a multivariate approach to automated oestrus and mastitis detection

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Livestock Production Science, 48 (1997) 219-227

**Abstract**
In modern dairy farming sensors can be used to measure on-line milk yield, milk temperature, electrical conductivity of quarter milk, concentrate intake and the cow's activity. Together with information from the management information system (MIS), the sensor data can be used for the automated detection of oestrus and diseases. A model has been developed to process the measured variables in a multivariate way. This model is based on time series analysis combined with a Kalman filter. Sensor data, MIS information and reference data of two experimental farms (approx. 90 cows for two years) were available to test the model. The test results were expressed in sensitivity, the percentage of True Positive alerts, and specificity, the percentage of True Negative alerts. For oestrus, it resulted in a sensitivity ranging from 94% to 83% (with the level of significance ranging from 95% to 99.9%), coupled with a specificity from 95% to 98%. For clinical mastitis a sensitivity ranging from 96% to 65% was found, for subclinical mastitis it was ranging from 100% to 57%; the coupled specificity for mastitis (clinical and subclinical) was ranging from 95.3% to 99.4%. For other diseases, a sensitivity ranging from 99.6% to 76.8% with a specificity from 86% to 97% was found. Some possibilities to improve these results are discussed.

*Keywords:* dairy cows, oestrus detection, mastitis detection, time series analysis, Kalman filter

## 3.1 Introduction

Early detection of oestrus and diseases is important in dairy husbandry. A proper detection of oestrus leads to a higher success rate for inseminations and to preset calving intervals. Diseases should be detected early to minimize the production losses and other adverse consequences, especially mastitis is a frequently occurring disease with negative effects. The losses caused by fertility problems are estimated at Dfl. 80 per cow per year (Dijkhuizen et al., 1985), and the losses caused by mastitis at US$ 83 (approx. Dfl. 140) per cow per year (Houben et al., 1994).

Some developments augment the need of improved and automated detection of oestrus and diseases. First, there is a tendency to larger herds in dairy practice. In The Netherlands the percentage of farms with more than 100 cows increased from 0.7% in 1975 to 4.5% in 1995 (LEI-DLO and CBS, 1996). The classical detection method of visual observations is more difficult and time-consuming in larger herds. Second, the introduction of robotic milking makes milking possible in the absence of the farmer. Visual observations of abnormalities of cows during milking are not possible in that case. Therefore, visual observations of the farmer in the cowhouse are supported by automated detection in the milking parlour. Furthermore, the importance of mastitis detection will increase in the near future, due to increasing milk quality demands. For example, the requirements as regards the somatic cell counts in the milk will be strengthened.

Automated detection is possible using sensor measurements and information from a Management Information System (MIS) as described in Schlünsen et al., 1987; Hogewerf et al., 1992; De Mol et al., 1993. The sensors measure variables such as milk yield, milk temperature, feed intake, electrical conductivity of the milk and activity of the cow. These variables are more or less aberrant due to oestrus or a disease. Information from the MIS is useful for the judgement of the causes of aberrations. An occurrence of oestrus is more likely when the last known oestrus case was about three weeks ago. Occurrences of a disease may be more likely if previous occurrences of the same disease were recorded.

A model which combines all available data and transforms it into useful information to the farmer is the missing link for automated detection. The output of a detection model should consist of alerts to the farmer (warning him that certain cows are likely to be diseased or in heat). The farmer can then take appropriate action for these cows.

Much research has been done on the development of sensors and appropriate models to detect oestrus and diseases. Milk temperature can be used to detect oestrus (Maatje and Rossing, 1976; McArthur et al., 1992). The activity of cows (usually measured by pedometers) is also used for oestrus detection (Rossing et al., 1983; Lehrer et al., 1992, Koelsch et al., 1994; Scholten et al., 1995). Sensors for mastitis detection are often based on measurements of the electrical conductivity of quarter milk (Rossing et al., 1987; Maatje et al, 1992; Nielen, 1994). The milk yield may be used for the detection of clinical diseases (Distl et al., 1989; Deluyker et al., 1991). Only single variables are considered in the described models or different variables are considered successively. The occurrence of oestrus however, may lead not only to increased cow activity but also to increased milk temperature and decreased milk yield. Mastitis may lead to increased milk conductivity and milk temperature as well as decreased milk yield. A disease may influence the milk yield, milk temperature, cow activity and feed intake. This suggests that the results of a detection model may be improved by combining the variables.

MIS's have been created for dairy farming and other branches of agriculture (Kroeze, 1990; Kroeze and Oving, 1987). An extension to these management information systems is the addition of decision support systems (DSS), which shifts the emphasis from recording to the use of recorded data in decision support models. A detection model is an example of such a DSS. The use of data from the MIS can improve the performance of the detection model (Hogeveen et al., 1991).

Results from a newly developed model for oestrus and diseases detection in dairy cows are described in this paper. This model is different from previous developed models in the multivariate approach and in the possibility of an integrated use of MIS information.

## 3.2 Material and methods

### *3.2.1 Sensor data*

Sensor data were recorded on two locations for two years: 36 lactating cows on the experimental farm of IMAG-DLO in Duiven from January 1993 till December 1994, and 60 cows on the experimental farm of ID-DLO in Lelystad during the same period (with intermissions during the summer holidays). The cows were housed in a cubicle house with slatted floor. Individual concentrate rations were provided by automated concentrate dispensers. The cows were milked two times a day, the complete data set contained 75,077 milkings.

Individual cows were identified automatically, and the following data were recorded automatically with sensors in the milking parlour (Maatje et al., 1992):
- milk yield;
- milk temperature, the maximum temperature during a milking;
- activity, the counter value of an activity tag attached to the right foreleg;
- electrical conductivity of the milk, measured for each quarter seven times per second and averaged over 5 s, the average of the 20 highest values being recorded.

The concentrates rations were determined by the MIS per cow and per day, the leftovers were recorded each morning.

The sensor data were stored in a database, which was part of the MIS of the experimental farms. Sensor data together with additional information from the MIS (the cow status) are input for the detection model. The milk temperature and conductivity are corrected for sensor influences in a similar way as indicated by Hogewerf et al. (1992).

### *3.2.2 Reference data*

Reference data, consisting of laboratory examinations of milk samples and observations by herdsman and veterinarian, are necessary to be able to evaluate the output of the detection model.

Reference data for oestrus detection are progesterone concentrations in mixed milk samples, visual observations by the herdsman and rectal palpations of the ovary and reproductive tract by the veterinarian. Reference data for mastitis detection are mixed milk somatic cell counts twice weekly, bacteriological examinations of quarter milk samples every two months, quarter milk somatic cell counts every two months and clinical observations. Veterinary inspections were carried out periodically (once or twice a week) and after consultation.

A cow is in oestrus, according to the reference data, if the progesterone level in milk is low (≤ 7 ng/ml) and a low progesterone level is preceded and followed by a high level. Visual observations, recorded in the MIS, are only used if available to confirm the date of oestrus. The date is assessed in the centre of the period of low progesterone, if there is no observation available. A cow is also considered to be in oestrus if the first increase in progesterone level after calving can be coupled with a visual heat observation.

A cow is suffering from clinical mastitis if clinical signs (clots in the milk or swollen quarters) are present; and from subclinical mastitis if, for one or more quarters, the cell count exceeds 500,000/ml and mastitis pathogens are established.

Occurrences of other diseases were indicated by the veterinarian or herdsman. These were divided into five categories: locomotion, digestive upsets, reproduction, udder health and others.

### *3.2.3 Model description*

The input of the detection model is built up from the sensor data and MIS information (calving date, date of last observed oestrus date, status of cow). The main output consists of alerts for oestrus and diseases, especially mastitis. These alerts indicate cows that need the farmer's attention ('management by exception').

The model is based on time series analysis combined with a Kalman filter approach, as depicted in Figure 3.1 (De Mol et al., 1996). Time series models have been derived for milk yield, milk temperature, cow activity and milk conductivity. The parameters of these models appeared to be cow-dependent. A multivariate approach is not possible with time series models for single variables. A Kalman filter is a method to estimate the state of a system on-line. By defining the state as the parameters of the time series models, the application of a Kalman filter makes it possible to estimate for each cow after each milking:

– updated parameter values;
– the multivariate distribution of the parameters (and of the multivariate error).

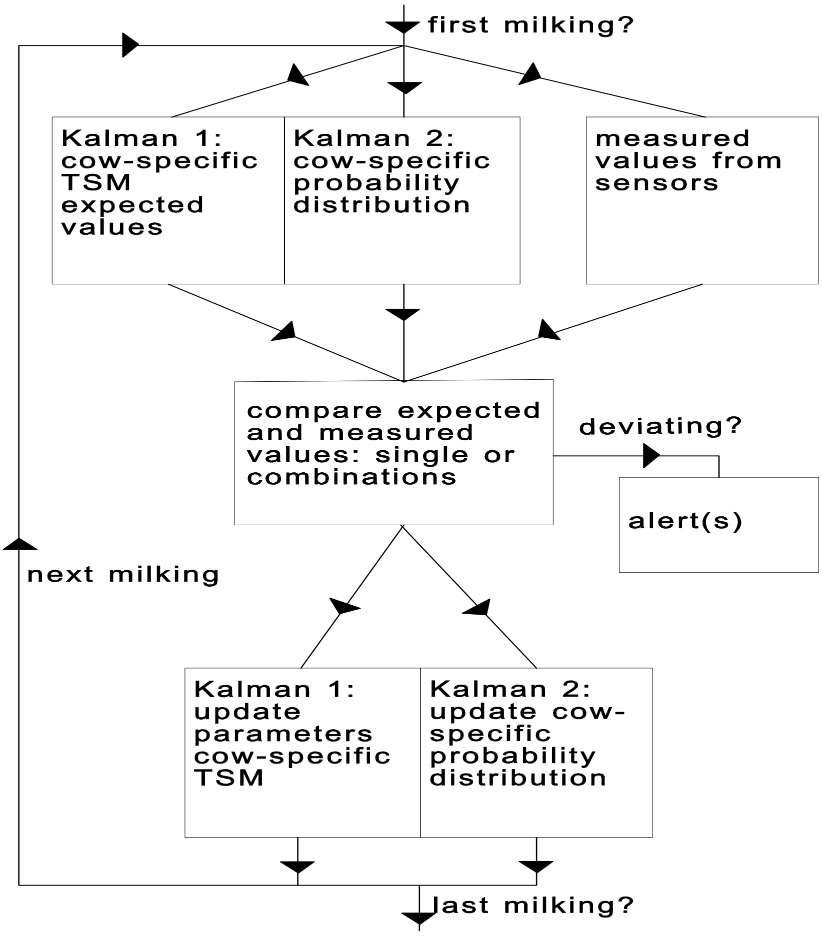


***Figure 3.1*** *Flow-chart of the detection model with the interaction between the underlying time series models (TSM) and the probability distribution with the Kalman filters.*

This approach provides each cow with her own model, which describes the characteristics and variability of that individual cow. An alert is given when the measurements fall outside the normal pattern for the particular cow.

Concentrate intake is not modelled by time series. A probability distribution for the leftover as a percentage of the ration is used. This probability distribution also appeared to be cow-dependent. Therefore, this distribution is fitted for each cow every day with a second Kalman filter, where the probability distribution is regarded as the state, to get cow-specific distributions.

An alert is given when a single variable or a combination of variables is deviant. Such combinations are:

- for oestrus: increased activity, increased milk temperature and decreased milk yield;
- for mastitis: increased conductivity of quarter milk, increased milk temperature and decreased milk yield;
- for other diseases: increased milk temperature, decreased milk yield, decreased activity and increased concentrates leftovers.

Alerts can be given at various levels: they are given for single variables or combinations of variables falling outside a 95%, a 99% or a 99.9% confidence interval. MIS information can additionally be used to establish alerts. In the current version of the model, this is only done for oestrus: an oestrus case is more likely if a previous observed oestrus was about three weeks ago.

### *3.2.4 Implementation of the detection model*

The detection model has been designed as a black box to be independent of the MIS used and to be able to compare the time series model with other detection models. The black box does not have a memory, all information needed is passed to the black box by an input file (with cow data, sensor data and model-oriented data). The black box delivers an output file with alerts and updated model-oriented data. Any cow, that is new for the model, starts with average model parameters and an average multivariate distribution; these give reasonable results but the results improve as more information of that cow (data of more milkings) becomes available.

The MIS software was originally developed by IMAG-DLO but has been commercialized by Argos/Uniform (Kroeze, 1990). The communication with the black box has been made independent of the MIS by applying the ADIS protocol (ISO, 1995).

### *3.2.5 Test protocol*

The alerts of the detection model were evaluated by using the reference data. Test results are available for two data sets: Duiven and Lelystad, where data have been collected in 1993 and 1994. Each case of oestrus, mastitis or disease is classified as True Positive (TP) if one or more alerts are given or as False Negative (FN) if no alerts are given. The TP alerts must fall within a certain period around the date established. The length of the periods is given in Table 3.1. Periods round a case of disease can overlap, two mastitis cases with an overlap in the periods are taken as two cases, two cases of another illness with an overlap are taken as one case (with a longer period). The sensitivity is the percentage of TP cases:

$$\text{sensitivity} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \cdot 100\%$$

A milking outside an oestrus, mastitis or disease period is True Negative (TN) if no alert is given or False Positive (FP) if an alert is given. The specificity is the percentage of TN milkings:

$$\text{specificity} = \frac{\text{TN}}{(\text{TN}+\text{FP})} \cdot 100\%$$

***Table 3.1***
*The length of the period around the date established for a case of oestrus, mastitis and other diseases.*

| type | length of period |
|---|---|
| oestrus | from 2 days before till 1 day afterwards |
| clinical mastitis | from 10 days before till 7 days afterwards |
| subclinical mastitis | from 14 days before till 14 days afterwards |
| other diseases | from 7 days before till 7 days afterwards |

This test protocol is illustrated for oestrus in Figure 3.2, where two oestrus dates are established. The first case is TP, because alerts are given within the oestrus period, the second case is FN because no alert is given. Alerts outside the oestrus periods are FP, milkings outside these periods without an alert are TN.

Alerts for oestrus can only be generated if activity measurements are available. Sometimes, measurement errors occurred during the test period, these were caused by missing or erroneous pedometers, or by errors in reading the step counter values. A question mark is given for such a milking to note the impossibility of making a judgement. The missing value is replaced with the expected value for successive milkings to prevent a chain reaction of one disturbance leading to a series of question marks. An oestrus period with question marks is still TP when one or more alerts are given, it is not considered FN when there are no alerts.

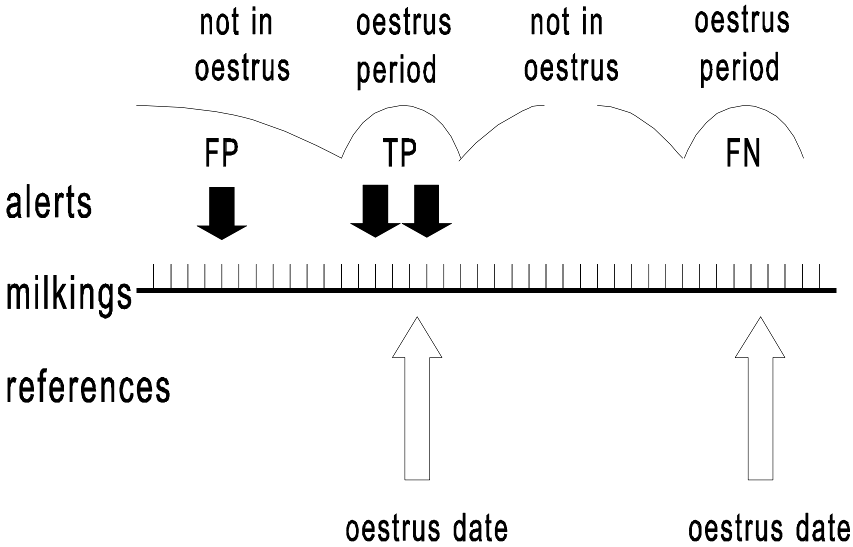


***Figure 3.2*** *Illustration of the test protocol for oestrus for a cow with two oestrus dates (one case TP, the other FN) and an FP milking outside the oestrus periods.*

## 3.3 Results

### *3.3.1 Detection of oestrus*

The evaluation of single (based only on activity) and combined alerts (based on a combination of variables) for oestrus are given in Table 3.2 (sensitivity) and Table 3.3 (specificity). The cow status, as known by the MIS, is used to exclude oestrus alerts for cows that are in calf or dry.

The results depend on the chosen confidence interval for the alerts. Tightening the criterion leads to a lower sensitivity and higher specificity, and vice versa. A logistic regression model have been used to test the significance of the differences between single and combined alerts and of the differences between Duiven and Lelystad. The combined alerts give a significantly higher sensitivity and specificity when a 95% confidence interval is used. The sensitivity results for Lelystad are better in some cases, the higher specificity for Duiven is significant in all cases.

***Table 3.2***

*Classification of oestrus cases (TP, FN or ?) and sensitivity of single (based only on activity) and combined alerts for different confidence intervals; for the complete data set and both farms separately.*

| alerts | | total: 537 cases | | | | Duiven: 179 cases | | | | Lelystad: 358 cases | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | TP | FN | ? | sensitivity | TP | FN | ? | sensitivity | TP | FN | ? | sensitivity |
| single | 95% | 435 | 42 | 60 | 91.2%[a] | 135 | 17 | 27 | 88.8% | 300 | 25 | 33 | 92.3% |
| | 99% | 411 | 64 | 62 | 86.5% | 123 | 29 | 27 | 80.9%[b] | 288 | 35 | 35 | 89.2%[b] |
| | 99.9% | 378 | 89 | 70 | 80.9% | 111 | 38 | 30 | 74.5%[b] | 267 | 51 | 40 | 84.0%[b] |
| combined | 95% | 451 | 28 | 58 | 94.2%[a] | 141 | 12 | 26 | 92.2% | 310 | 16 | 32 | 95.1% |
| | 99% | 411 | 64 | 62 | 86.5% | 127 | 25 | 27 | 83.6% | 284 | 39 | 35 | 87.9% |
| | 99.9% | 387 | 82 | 68 | 82.5% | 117 | 34 | 28 | 77.5%[b] | 270 | 48 | 40 | 84.9%[b] |

[a] significant difference between single and combined alerts at $P<0.05$

[b] significant difference between Duiven and Lelystad at $P<0.05$

***Table 3.3***

*Classification of milkings (FP, TN or ?) outside oestrus periods (cows in calf or dry excluded) and specificity of single (based on activity only) and combined alerts for different confidence intervals; for the complete data set and both farms separately.*

| alerts | | total: 41,803 milkings | | | | Duiven: 12,935 milkings | | | | Lelystad: 28,868 milkings | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | TN | FP | ? | specificity | TN | FP | ? | specificity | TN | FP | ? | specificity |
| single | 95% | 34,863 | 1,619 | 5,321 | 95.6%[a] | 10,358 | 417 | 2,160 | 96.1%[b] | 24,505 | 1,202 | 3,161 | 95.3%[b] |
| | 99% | 35,418 | 1,064 | 5,321 | 97.1% | 10,512 | 263 | 2,160 | 97.6%[b] | 24,906 | 801 | 3,161 | 96.9%[b] |
| | 99.9% | 35,755 | 727 | 5,321 | 98.0% | 10,610 | 165 | 2,160 | 98.5%[b] | 25,145 | 562 | 3,161 | 97.8%[b] |
| combined | 95% | 34,462 | 2,020 | 5,321 | 94.5%[a] | 10,243 | 532 | 2,160 | 95.1%[b] | 24,219 | 1,488 | 3,161 | 94.2%[b] |
| | 99% | 35,363 | 1,119 | 5,321 | 96.9% | 10,505 | 270 | 2,160 | 97.5%[b] | 24,858 | 849 | 3,161 | 96.7%[b] |
| | 99.9% | 35,802 | 680 | 5,321 | 98.1% | 10,620 | 155 | 2,160 | 98.6%[b] | 25,182 | 525 | 3,161 | 98.0%[b] |

[a] significant difference between single and combined alerts at $P<0.05$

[b] significant difference between Duiven and Lelystad at $P<0.05$

The sensitivity of farm observations appeared to be 72% (386 cases were notified). This figure should be handled with care because alert lists of prototypes of the model were available and may have influenced the visual observations. Some further analysis has been done for Duiven. The FP alerts have been examined, most were during summer and probably caused by weather circumstances, other FP alerts may be caused by other cows being in oestrus.

### *3.3.2 Detection of mastitis*

The sensitivity for mastitis detection has been calculated for clinical and subclinical mastitis. The results are given in Table 3.4. The sensitivity of combined alerts is significantly higher for clinical mastitis, for subclinical mastitis only in case of the 99% confidence interval.

***Table 3.4***

*Classification of mastitis cases (TP or FN) and sensitivity of single (based on conductivity only) and combined alerts for different confidence intervals; for the complete data set; for clinical and subclinical mastitis.*

| alerts | | clinical mastitis: 52 cases | | | subclinical mastitis: 21 cases | | |
|---|---|---|---|---|---|---|---|
| | | TP | FN | sensitivity | TP | FN | sensitivity |
| single | 95% | 26 | 26 | 50%[a] | 16 | 5 | 76% |
| | 99% | 25 | 27 | 48%[a] | 10 | 11 | 48%[a] |
| | 99.9% | 19 | 33 | 37%[a] | 5 | 16 | 24% |
| combined | 95% | 50 | 2 | 96%[a] | 21 | 0 | 100% |
| | 99% | 47 | 5 | 90%[a] | 16 | 5 | 76%[a] |
| | 99.9% | 34 | 18 | 65%[a] | 12 | 9 | 57% |

[a] significant difference between single and combined alerts at $P<0.05$

***Table 3.5***

*Classification of milkings (FP or TN) and specificity of single and combined alerts for cows without mastitis and different confidence intervals; in total and for each farm separately.*

| alerts | | total: 16 cows, 6,495 milkings | | | Duiven: 5 cows, 2,432 milkings | | | Lelystad: 11 cows, 4,063 milkings | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | FP | TN | specificity | FP | TN | specificity | FP | TN | specificity |
| single | 95% | 257 | 6,238 | 96.0% | 61 | 2,371 | 97.5%[b] | 196 | 3,867 | 95.2%[b] |
| | 99% | 78 | 6,417 | 98.8% | 13 | 2,419 | 99.5%[b] | 65 | 3,998 | 98.4%[b] |
| | 99.9% | 37 | 6,458 | 99.4% | 3 | 2,429 | 99.9%[b] | 34 | 4,029 | 99.2%[b] |
| combined | 95% | 303 | 6,192 | 95.3% | 88 | 2,344 | 96.4%[b] | 215 | 3,848 | 94.7%[b] |
| | 99% | 117 | 6,378 | 98.2% | 24 | 2,408 | 99.0%[b] | 93 | 3,970 | 97.7%[b] |
| | 99.9% | 40 | 6,455 | 99.4% | 8 | 2,424 | 99.7%[b] | 32 | 4,031 | 99.2%[b] |

[b] significant difference between Duiven and Lelystad at $P<0.05$

The specificity for mastitis is more difficult to determine since the mastitis status is not known in periods between two sampling dates. Quarter milk samples were collected every two months, a mastitis alert halfway through this interval may be FP as well as TP. Therefore, the specificity for mastitis is determined in another way. Cows were selected, for which mastitis pathogens were never established and for which the cell count of the quarter milk or the mixed milk never exceeded 500,000/ml. Alerts for these cows without mastitis were classified as FP and used to calculate the specificity. The results are given in Table 3.5. This has been done for both single and combined alerts, the differences are not significant. The specificity for Duiven is significantly higher than for Lelystad in all cases.

### *3.3.3 Detection of other diseases*

Single alerts for other diseases are difficult to define since it is difficult to couple a single variable to a every kind of disease. Only combined alerts are used for other diseases. The results are presented in Table 3.6 (sensitivity) and Table 3.7 (specificity).

The differences in sensitivity between Duiven and Lelystad are not significant; the specificity for Lelystad is significantly higher than for Duiven in case of a 95% or 99% confidence interval.

The sensitivity and specificity for diseases depends strongly on the chosen confidence interval. A very high sensitivity is coupled with a low specificity. The detection results were mostly in proportion to the known influence of diseases to the measured variables. For example, fever was detected well and results for acetonaemia were worse.

***Table 3.6***

*Classification of cases of disease (TP or FN) and sensitivity of combined alerts for different confidence intervals; for the complete data set and both farms separately.*

| alerts | | total: 263 cases | | | Duiven: 61 cases | | | Lelystad: 202 cases | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | TP | FN | sensitivity | TP | FN | sensitivity | TP | FN | sensitivity |
| combined | 95% | 262 | 1 | 99.6% | 61 | - | 100.0% | 201 | 1 | 99.5% |
| | 99% | 238 | 25 | 90.5% | 54 | 7 | 88.5% | 184 | 18 | 91.1% |
| | 99.9% | 202 | 61 | 76.8% | 45 | 16 | 73.8% | 157 | 45 | 77.7% |

***Table 3.7***

*Classification of milkings outside disease periods (TN or FP) and specificity of combined alerts for different confidence intervals; for the complete data set and both farms separately.*

| alerts | | total: 40,286 milkings | | | Duiven: 12,526 milkings | | | Lelystad: 27,760 milkings | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | TN | FP | specificity | TN | FP | specificity | TN | FP | specificity |
| combined | 95% | 34,630 | 5,656 | 86.0% | 10,628 | 1,898 | 84.8%[a] | 24,002 | 3,758 | 86.5%[a] |
| | 99% | 37,674 | 2,612 | 93.5% | 11,666 | 860 | 93.1%[a] | 26,008 | 1,752 | 93.7%[a] |
| | 99.9% | 38,940 | 1,346 | 96.7% | 12,104 | 422 | 96.6% | 26,836 | 924 | 96.7% |

[a] significant difference between Duiven and Lelystad at $P<0.05$

## 3.4 Discussion

The detection model has been tested as regards the data from two experimental farms in Duiven and Lelystad. The data from Duiven became available during the model development period. These data have partly been used to determine the model structure; the data of Duiven have also been used for testing. The data from Lelystad have only been used for testing. The results are farm-dependent, but there is no structural difference, the results of Lelystad are sometimes better and sometimes worse than the results of Duiven. This may indicate that the model is generally applicable but further testing is needed to prove this fact. A general applicability may be expected since the model structure gives each cow an individual model, which is updated after each milking.

The data collection period is very long for such research. As much as possible the recorded data are used. No cows or periods are excluded from testing. Measurement errors are taken into account. Their occurrence may also be expected in practical farming situations. These features make it difficult to compare our results with other research results; overviews can be found in Lehrer et al., 1992 for oestrus and in Nielen et al., 1992 for mastitis. In practice, the sensitivity and specificity will depend on the farmer's attitude but they may reach the same level as in the present research. Testing on other farms, however, is recommended.

The definition of the periods as mentioned in Table 3.1 is not a matter of course. These were chosen with the available reference data taken into account. In a follow-up research other definitions and the timeliness of alerts will be examined.

The sensitivity and specificity are mutually dependent. Increasing the sensitivity by choosing another alert level leads to a decreased specificity, and vice versa. A high sensitivity is preferred when no cases should be missed and when false positive alerts are no problem. A high specificity is better when false positive alerts should be avoided. An optimum level may be determined by minimizing the sum of the costs of FP alerts and FN alerts.

The results for oestrus detection are influenced by measurement errors, which is indicated by the number of cases and milkings with question marks in Tables 3.2 and 3.3. The increase in activity due to oestrus is temporary and can easily be missed if the sensors should fail in the oestrus period. This stresses the need of adequate data management and reliable sensors. The influence of measurement errors is less important in case of mastitis and diseases. This is because the periods considered for these cases are longer (Table 3.1).

The sensitivity is fairly high for oestrus detection. It may be difficult to improve these results by applying sensor measurements only. Some cases will never be detected, because the variables hardly change during oestrus (e.g. in case of a silent heat). The specificity may be improved. This could be done by applying more of the MIS information (it is hardly used in the current model) and by taking group influences into account for the generation of alerts (this is not yet included in the model).

The results for mastitis with single alerts are much worse than with combined alerts, which shows the relevance of a multivariate approach. The sensitivity for mastitis is rather high for combined alerts with a low or medium level. A high alert level leads to a sharp decrease in sensitivity. The underlying alert rules may be improved. The specificity seems reasonable but the number of FP alerts may still be too high for practical application. Further research to sensor improvements may be worthwhile. The sensitivity may also be improved by taking group influences into account, regarding the number of previous alerts for the same cow and previous occurrences of mastitis.

A multivariate approach seems the best one for to the detection of diseases. The sensitivity can be high, but the specificity is (too) low. The detection of other diseases was not one of the main goals of this research. The results may be improved by changing the alert rules and taking other factors, like occurrences of oestrus or previous diseases, into account.

## 3.5 Conclusion

The detection model gives promising results. Automated detection of oestrus gives a higher sensitivity than the classical method of observation by the herdsman. The specificity for oestrus detection is encouraging, but may be improved by model adaptations. For oestrus detection a combination of variables gives a slightly higher sensitivity than a single variable approach, with the same specificity.

The results for mastitis are quite good but may not be good enough for practical implementation. Further research seems worthwhile to improve the results, especially the specificity. The results with combined alerts are much better than the results with single alerts. A multivariate approach proves to be very useful for mastitis detection.

The detection results for other diseases are promising. They show that a multivariate approach is valuable for the detection of diseases.

## Acknowledgements

This research has been supported by Alfa Laval Agri, Tumba, Sweden

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*Chapter 4*

# Detection of oestrus and mastitis: field performance of a model

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**Abstract**

A new detection model ('IMAG model') for oestrus and mastitis in dairy cows was tested on four farms during several years. Such a test is necessary because information is lacking about the performance of detection models under field conditions. The test gave insight into the field performance of the IMAG model and the results were compared with the results of older models and with the results predicted by experts. Sensor data of milk yield, milk temperature, electrical conductivity of milk and animal activity were the inputs for the IMAG model. The IMAG model is based on time series analysis combined with a Kalman filter. This structure yields cow-dependent model parameters and combines data of different sensors. Results were compared with the manufacturer's model (supplied with the sensors), based only on exponential smoothing on data from one sensor. The sensor equipment differed between farms. The sensitivity (percentage of oestruses detected) for oestrus varied from 80 to 63%, depending on the threshold used. Specificity (non-oestruses not detected as oestrus) varied from 94 to 98%. The sensitivity for clinical mastitis varied from 79 to 54%, depending on the threshold used. The specificity for mastitis varied from 94 to 99%. There were great differences between farms, in sensitivity for oestrus and mastitis. The applied equipment could only partly explain the differences in oestrus and mastitis detection results between farms. No relation between stage of lactation and activity level was found, although a lower activity level in the first period of lactation might be expected. The main conclusion is that a detection model can give good results, but only if the equipment is working properly. The new model outperformed the manufacturer's model.

*Keywords:* detection, oestrus, mastitis, models

## 4.1 Introduction

Sensors can be used for livestock monitoring (Frost et al., 1997; Geers, 1994; Schlünsen et al., 1987). The sensor data are input for detection models for oestrus and mastitis. Sensor systems (sensors and detection model) for the detection of oestrus and mastitis are commercially available. The sensors measure activity (for oestrus), electrical conductivity (for mastitis), or yield and temperature of milk (for both). Activity is measured by a pedometer attached to a collar around the neck or to the leg of the cow. Electrical conductivity is measured in the milk flow during milking; either in mixed milk or in quarter milk. Milkmeters record the yield. Milk temperature is related to body temperature and is measured in the milk flow. Some data from experiments with sensor systems are available now. Gil et al. (1997) detected 79% out of 38 oestrus cases by temperature increase. Koelsch et al. (1994) detected ca 70% out of 29 oestrus cases by three activity-comparison procedures. In a literature review Lehrer et al. (1992) reported a success rate of oestrus detection in the range 60 to 100%. Mastitis in 22 cows in first lactation was clearly identifiable by conductivity and yield changes (Graupner and Barth, 1994). Maatje et al. (1992) detected 100% of 25 clinical mastitis cases by increased conductivity. Milner et al. (1996) detected 100% of 12 clinical mastitis cases after experimental infection with *Streptococcus uberis* by changes in the conductivity, and likewise 95% of 19 cases after infection with *Staphylococcus aureus*. Hamann and Zecconi (1998), concluded in their evaluation that the published information on electrical conductivity in milk, as a mastitis indicator, comprises very variable results; the published information is too varied to justify the claim that mastitis can be detected, under field conditions, by electrical conductivity measurements.

Detection results under field conditions are not available. There might be a great discrepancy between experimental detection results and results in the field. A lower sensitivity was found in experiments with a low clinical mastitis prevalence, as in the field, than in experiments with a high prevalence, as in experimental circumstances (Hamann and Zecconi, 1998). The implication of research results for use in the field was evaluated by consultation of experts, using conjoint analysis to elicit the opinion of experts on the effect of combinations of sensors on the sensitivity and specificity of the detection of oestrus and mastitis (Van Asseldonk et al., 1998). The results of this consultation can be compared with the performance in the field, on a farm equipped with activity meters, milk-yield sensors, conductivity sensors and milk-temperature sensors. In the opinion of the experts (Van Asseldonk et al., 1998), the sensitivity (percentage of all cases detected), on a farm equipped with these sensors would be 81% for oestrus detection; the specificity (percentage of non-oestrus detected as non-oestrus) 90%. The sensitivity for mastitis would be 71% and the specificity 86%.

The expected performance in the field of existing sensor systems hampers their rapid introduction as a management tool. A new detection model for oestrus and diseases in dairy cattle was developed by IMAG (De Mol et al., 1999) to process the measured variables in a combined way. Other models use only single variables for the detection: mostly activity for oestrus and conductivity for mastitis. The *IMAG model* is based on time series models for yield, temperature and electrical conductivity of milk, and for the cow's activity. The parameters of the time series models are fitted on-line by a Kalman filter for each cow after each milking. The IMAG model combines the variables and generates cow-specific alerts. The model calculates the deviation between the expected values and measured values of the sensor measurements, for each cow and each milking. An alert is given when a combination of deviations falls outside a certain confidence interval, which can be 95, 99 or 99.9%. In a previous research the IMAG model was tested on two experimental farms (De Mol et al., 1997; overall results in Table 4.1). For example, with the 99% confidence interval, 79% of the oestrus cases is detected (one or more alerts are given) and there is no alert for 96.4% of the milkings outside oestrus periods.

***Table 4.1***

*Sensitivity and specificity for oestrus and mastitis by the IMAG model, on two experimental farms and with three confidence intervals. The figures are based on data by De Mol et al. (1997) using different methods for sensitivity and specificity (see text).*

| confidence interval (%) | oestrus sensitivity [a] (%) (537 cases) | oestrus specificity [b] (%) (60,665 milkings) | clinical mastitis sensitivity [a] (%) (53 cases) | mastitis specificity [b] (%) (6,495 milkings) |
|---|---|---|---|---|
| 95 | 87 | 93.7 | 76 | 95.2 |
| 99 | 79 | 96.4 | 59 | 98.1 |
| 99.9 | 74 | 97.8 | 36 | 99.4 |

[a] proportion of positive cases with one or more alerts

[b] proportion of negative milkings without an alert

The detection methods and the equipment used may influence the results. For example, activity can be measured by pedometers attached to the leg or to the neck, and conductivity can be measured for the milk of each quarter of the udder or for mixed milk. The activity of cows, which is used for oestrus detection, may be influenced by the lactation phase. A test in the field may indicate the prospects of the application of sensors and detection models in dairy husbandry. Therefore testing was done at four farms for which sensor data as well as reference data were available. The sensor data have been used as input for the detection model. The results will be compared with the results for the same data of the manufacturer's model (supplied with the sensors), and with the results of the IMAG model for different data in the previous research (De Mol et al., 1997).

The objectives of this research were to get insight into the performance of the IMAG model in the field and to compare the results with those of the manufacturer's model, and with the prediction of the experts (Van Asseldonk et al., 1998).

## 4.2 Materials and Methods

### *4.2.1 Data collection*

Data were collected on four farms equipped with commercially available sensors. These farms, unlike the farms used by De Mol et al. (1997), are managed like commercial farms but they are also used for extension purposes and practical research. All farms had loose housing systems, and the cows were milked twice a day. The farm names are based on the equipment (Table 4.2). On farm ALCQ, Activity was measured by Leg transponders and Conductivity was measured in Quarter milk. On farm ANCQ1, as well as ANCQ2, Activity was measured by Neck transponders and Conductivity was measured in Quarter milk. On farm ALCM, Activity was measured by Leg transponders and Conductivity was measured in Mixed milk.

***Table 4.2***

*Sensor equipment on the four farms: manufacturers (X, Y, Z) and sensor types used to assess the cow's activity and the electrical conductivity of milk.*

| farm | milk yield | milk temperature | cow's activity | conductivity of milk |
|---|---|---|---|---|
| ALCQ | X | X | X: leg transponder | X: quarter milk |
| ANCQ1 | X | X | X: neck transponder | X: quarter milk |
| ANCQ2 | X | X | X: neck transponder | X: quarter milk |
| ALCM | Y | not present | Z: leg transponder | Z: mixed milk |

The periods of data collection and the average number of cows milked are given for each farm in Table 4.3. The dates, but not the time of the day, of observed cases of oestrus and of clinical mastitis were recorded. Milk samples for cell counts were taken once in three weeks on ANCQ1, ANCQ2 and ALCM; and once a week on ALCQ.

***Table 4.3***
*Description of the size of the data sets of the four farms.*

| farm | from | till | number of milkings | number of cows milked | average number of cows per milking |
|---|---|---|---|---|---|
| ALCQ | 16 Nov. ’95 | 6 Apr. ’97 | 1,015 | 41,949 | 41 |
| ANCQ1 | 4 Oct. ’94 | 30 Mar. ’97 | 1,816 | 124,919 | 69 |
| ANCQ2 | 1 Feb. ’96 | 27 Mar. ’97 | 839 | 55,914 | 67 |
| ALCM | 4 July ’95 | 20 May ’97 | 1,350 | 157,755 | 117 |

The farms differed not only in data collection period (Table 4.3) and equipment (Table 4.2), but also in housing system, management practice, geographical location and breed of cows. The cows went to pasture during the summer period on ANCQ1, ANCQ2 and ALCM; cows were kept indoors the whole year round on ALCQ. The frequency of oestrus and clinical mastitis in the data collection period is given in Table 4.4 for all farms. Oestrus and clinical mastitis cases were based on visual detection. Clinical mastitis was treated after observation. The observed oestrus frequency depends on the quality of oestrus detection, the insemination success rate and possibly on other farm-dependent factors. The observed mastitis frequency is also farm-dependent; the mean mastitis frequency in practice is approximately 1 case in 2,000 to 2,400 milkings (Brand et al., 1996). On ALCQ and ANCQ1, the mastitis frequency was above the normal level. Other farm characteristics, such as the attitude towards sensor usage and management goals, may also be important but these are difficult to quantify.

***Table 4.4***
*Observed frequency of cases of oestrus and clinical mastitis on the four farms.*

| farm | oestrus frequency (1/milkings) | clinical mastitis frequency (1/milkings) |
|---:|:---:|:---:|
| ALCQ | 1/236 | 1/999 |
| ANCQ1 | 1/234 | 1/1,288 |
| ANCQ2 | 1/206 | 1/2,542 |
| ALCM | 1/336 | 1/3,093 |

*4.2.2 Detection model*

Sensor measurements and other cow information (such as calving dates) of all four farms were stored in the database of the IMAG model, using the same format as in De Mol et al. (1999). These data were inputs for the detection model. Alerts for oestrus and mastitis are the main outputs of the model. The structure of the model is depicted in Figure 4.1.

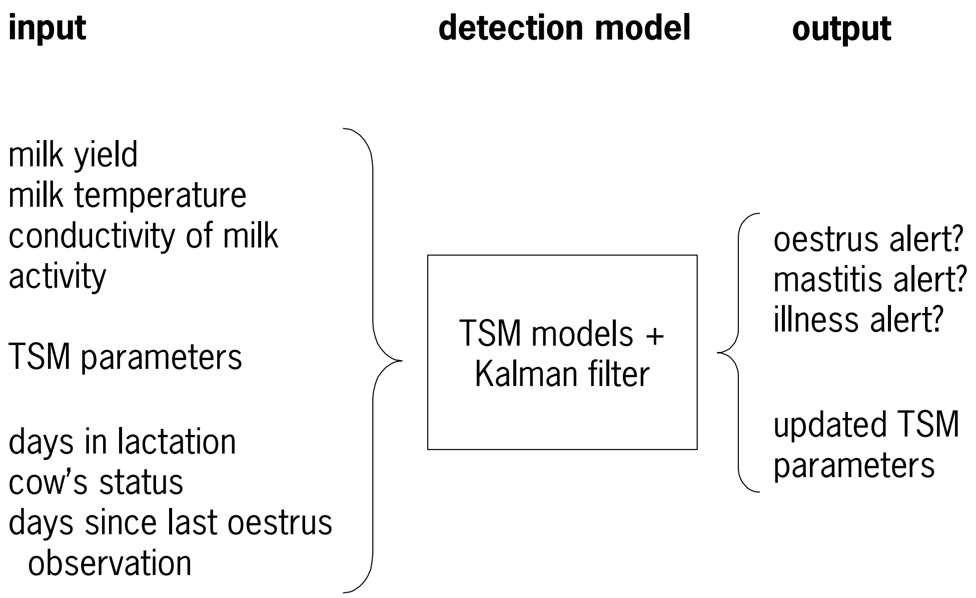


***Figure 4.1*** *The structure of the detection model, based on time series models (TSM) and a Kalman filter with a description of input and output. See text for explanation.*

After each milking an input file is built with for each cow:
– sensor measurements (yield, temperature, conductivity, activity and concentrate intake) for the actual milking and some (depending on the variable, 2-4) previous milkings;
– cow-dependent parameters of the time series model (TSM) for each variable, and the cow-dependent variance-covariance of these parameters;
– cow information: days in lactation, the cow's status (calved, in oestrus, inseminated or in calf), days since last oestrus observation.

For each variable (yield, temperature, conductivity and activity) the parameter values and some previous sensor measurements are used to calculate the expected sensor measurement value for a specific cow and a specific milking. These results are compared with the actual sensor measurements. An alert is given when a combination of deviations falls outside a confidence interval, using the variance-covariance of the TSM parameters. Thresholds for alerts correspond with the chosen confidence interval: 95, 99 or 99.9%. The following combinations are used to generate alerts:
– for oestrus: a combination of increased activity, decreased yield and increased temperature;
– for mastitis: a combination of increased conductivity, decreased yield and increased temperature;
– for illness: a combination of decreased yield, increased temperature and decreased activity.

The Kalman filter is a statistical technique to estimate the state of a system on-line. In the IMAG model, the filter is used to update the parameter values and variance-covariance matrix, which are used for the next milking. For the first milking in a lactation of a cow, average values for the parameters and variance-covariance are used. The model output consists of the alerts (if any) and the updated parameters and variance-covariance values. These are contained in an output file, that is transferred back to the database of the farm. More details, including formulas, are given by De Mol et al. (1999).

The IMAG model is flexible in the number of variables used and in the input settings, therefore only minor adaptations were needed for application in the present research. Milk temperature was not recorded on ALCM. Thus oestrus alerts for ALCM were only based on activity and yield, whereas mastitis alerts were only based on conductivity and yield. When conductivity of mixed milk was recorded, only one variable for conductivity was used in the model (instead of four). Parameter values were updated per cow and per milking by the Kalman filter, so there were no farm-dependent parameter settings needed. Starting values for the parameter values were needed for the first milking in a lactation of a cow. The same starting parameter values were used for all farms. These parameter values were adapted to a cow-specific level after the first few milkings in lactation.

The comparison of the detection performance on the four experimental farms was based on:
- sensitivity to oestrus: the proportion of all oestrus cases observed, with one or more oestrus alerts;
- specificity to oestrus, the proportion of all milkings of cows that are not in oestrus, without an oestrus alert;
- sensitivity to clinical mastitis: the proportion of all cases of clinical mastitis observed, with one or more mastitis alerts;
- specificity to mastitis: the proportion of all milkings of cows that never showed mastitis in the experimental period, without mastitis alert.

For three farms the results based on oestrus and mastitis alerts of the IMAG model were compared with the results of the *manufacturer's model*, that is supplied with the equipment. The manufacturer's model is based on exponential smoothing on single variables: for oestrus on activity, for mastitis on conductivity. Details of the manufacturer's model are not available for commercial reasons.

Comparison of the results on the four farms, with the previous results on two experimental farms was not straightforward because in the previous test more reference data were available; samples of progesterone levels in milk, and bacteriological examinations of milk, were taken. Moreover, milk samples for cell counts were taken more frequently in the previous test.

Alerts are based on the deviation between actual and expected values of a variable. A variable is considered *indeterminable* when:
- the actual value is missing, due to measurement errors (no measurement data available or outlying values considered as measurement errors; see Table 4.5), or

– the expected value of the yield, temperature or activity is undefined, due to start-up effects (first two milkings in a new lactation or after a sequence of measurement errors); the expected value of conductivity is based on average values if data of one of the two previous milkings are missing.

***Table 4.5***
*Acceptable ranges for the milk variables.*

| variable | lower limit | upper limit |
|---|---|---|
| yield (liter) | 0 | 99.99 |
| temperature (°C) | 30 | 45 |
| conductivity (mS/cm) | 3 | 12 |

Indeterminable variables of the manufacturer's model are indicated by the absence of output of the model. The detection results were influenced by the measurement errors indicated as indeterminable variables. Oestrus and mastitis cases associated with measurement errors were difficult to classify. Therefore, sensitivity and specificity for oestrus were based only on cases without indeterminable activity; sensitivity and specificity for mastitis were based only on cases without indeterminable conductivity. Cases with indeterminable yield or temperature were still used in the tests.

### *4.2.3 Oestrus detection*

Results were based on dates of recorded cases of oestrus (dates of observed oestrus or insemination) on the farms with some restrictions:

– dates were used only if sensor measurements of the cow were available for the specific period;
– insemination dates were discarded if oestrus was observed the previous day;
– oestrus and insemination dates were discarded if they did not comply with the oestrus cycle of 3 weeks. Dates were sometimes discarded in retrospect by assessing the oestrus cycle of a cow. E.g. an oestrus case within one week before a next oestrus date, was not used in the tests.

An oestrus case was considered true positive (TP) if one or more oestrus alerts were given in a period of five milkings: two milkings on the day of oestrus, two milkings on the previous day and the morning milking on the next day. Alerts on the oestrus day were TP, alerts on the previous day were TP because oestrus signs might already be present, and alerts on the morning milking of the next day were TP because the oestrus may have started (and been observed) during the evening on the oestrus date. An oestrus case without oestrus alerts in this five-milkings period was classified as False Negative (FN). Milkings outside oestrus periods were False Positive (FP) if an oestrus alert was given, otherwise they were True Negative (TN).

Oestrus detection results may depend on the stage of lactation. Cows in early lactation often have a negative energy balance and this may influence the cow's activity as well as the oestrus detection results (Brand et al., 1996). The hypothesis of a relation between stage of lactation and activity level was tested by dividing the lactation into three periods. Period 1: from the calving day up to day 30, period 2: day 31 up to day 75 and period 3: day 76 and further. A generalized linear mixed model, fitted by iterative re–weighted residual maximum likelihood algorithm (Engel and Keen, 1994), was imposed to analyse the influence of the lactation period and other factors on the activity level (change in activity/hour):

$$y_{dglpcn} = \exp(m + d_d + g_g + i_{dg} + l_l + p_p + j_{lp} + c_{lc}) + \varepsilon_{dglpcn} \qquad (1)$$

with

$\exp(x) = e^x$;

- $y_{dglpcn}$ the $n$-th observation of the activity level of cow $c$ with part of day $d$, with grazing system $g$, in lactation $l$ and lactation period $p$;
- $m$ the overall mean;
- $d_d$ fixed effect of part of day $d$, $d = 1$ (nighttime) or 2 (daytime);
- $g_g$ fixed effect of grazing system $g$, $g = 0$ (in stall) or 1 (in pasture);
- $i_{dg}$ interaction effect between part of day $d$ and grazing system $g$;
- $l_l$ fixed effect of lactation number $l$, $l = 1$ (first lactation), 2 (second) or 3 (third or higher);
- $p_p$ fixed effect of lactation period $p$, $p = 1$, 2 or 3;
- $j_{lp}$ interaction effect between lactation number $l$ and lactation period $p$;
- $c_{lc}$ random effect of cow $c$ in lactation $l$;
- $\varepsilon_{dglpcn}$ random error.

These factors were chosen to clarify the effect of the lactation period separate from other factors that may influence the cow's activity.

### *4.2.4 Mastitis detection*

Automated detection of mastitis has two applications: detection of subclinical mastitis and early detection of clinical cases. In our study, the first application was not examined because appropriate reference data were not available.

Each observed case of clinical mastitis was TP or FN. In a TP case one or more mastitis alerts were given on one of the eight milkings up to the day mastitis was observed (the two milkings on the mastitis day and all milkings on the three preceding days). Three preceding days were included because mastitis signs might already be present. Alerts given earlier (more than three days before the observation) might not be related with the actual case. Cases without any mastitis alert were classified as FN.

The IMAG model also generates illness alerts. These illness alerts were based on yield, temperature and activity, and indicate that the cow might suffer from illness (not necessarily mastitis). Also the sensitivity for mastitis based on these illness alerts was calculated, taking a mastitis case as TP when one or more illness alerts were given in the mastitis period, otherwise FN. The illness alerts in this case were used as mastitis alerts, however they were not based on conductivity.

Calculating the specificity for mastitis was complicated because the real mastitis status of a cow was not always known. A cow without clinical mastitis might suffer from subclinical mastitis. The specificity was determined only with non-mastitis cows, i.e.:

- no case of clinical mastitis in the data collection period;
- cell counts always below 500,000 cells/$cm^3$;
- cow milked at least 300 times;
- number of samples of cell counts at least 10.

Mastitis alerts for non-mastitis cows were considered FP and were used to calculate the specificity.

## 4.3 Results

### *4.3.1 Indeterminable variables*

Figure 4.2 gives the variables that were classified as indeterminable by the IMAG model, as a percentage of the number of cows milked, for each farm and each variable. The indeterminable variables were mostly caused by the absence of measurement values. A minor part (less than 5% of the indeterminable variables) was due to values observed outside the ranges defined in Table 4.5. Exceptions to this rule were the milk temperature for ALCQ and ANCQ1, and conductivity (all quarters) for ANCQ1.

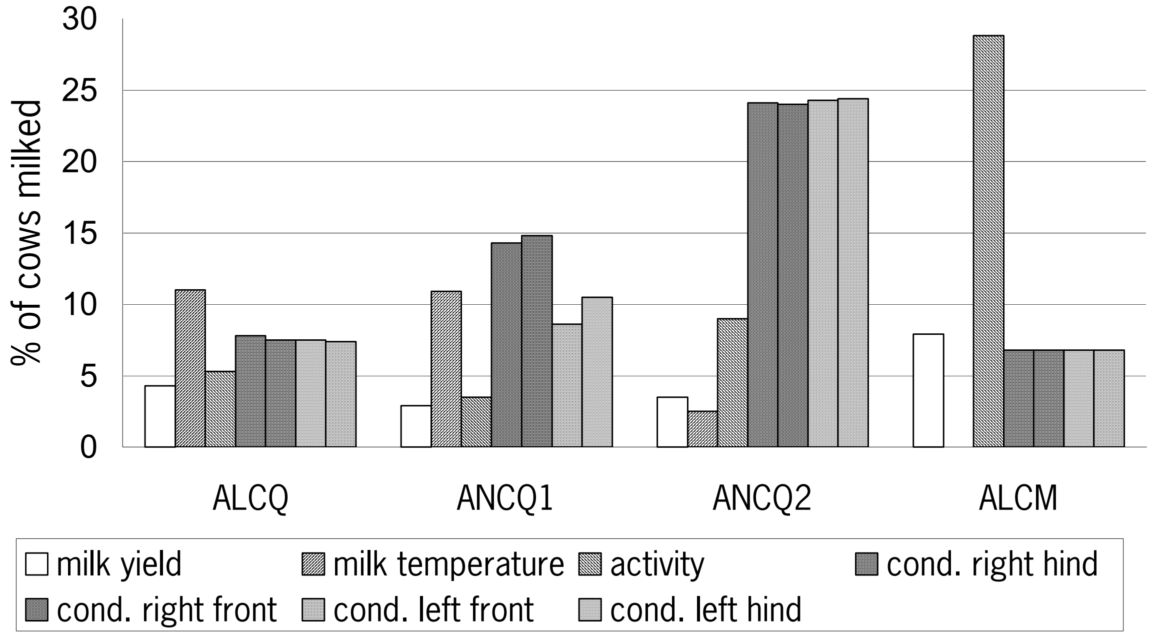


***Figure 4.2*** *Indeterminable variables as a percentage of the number of cows milked, for each farm and each variable (cond. = conductivity).*

Indeterminable variables were found over the whole data collection period. The percentage of milkings without any indeterminable variable differed between farms: 82 for ALCQ, 72 for ANCQ1, 68 for ANCQ2, and 67 for ALCM. For milkings with indeterminable variables, the number of indeterminable variables varied (Figure 4.3). This number varied between 1 and 7 on ALCQ, ANCQ1 and ANCQ2, but 3 was the maximum on ALCM because only three variables were recorded (yield, activity and conductivity of mixed milk). For milkings with one or more indeterminable variables, the occurrence of one indeterminable variable was predominant, with ANCQ2 as an exception. In indeterminable variables of ANCQ2, there were mostly four conductivity measurements missing (one for each quarter).

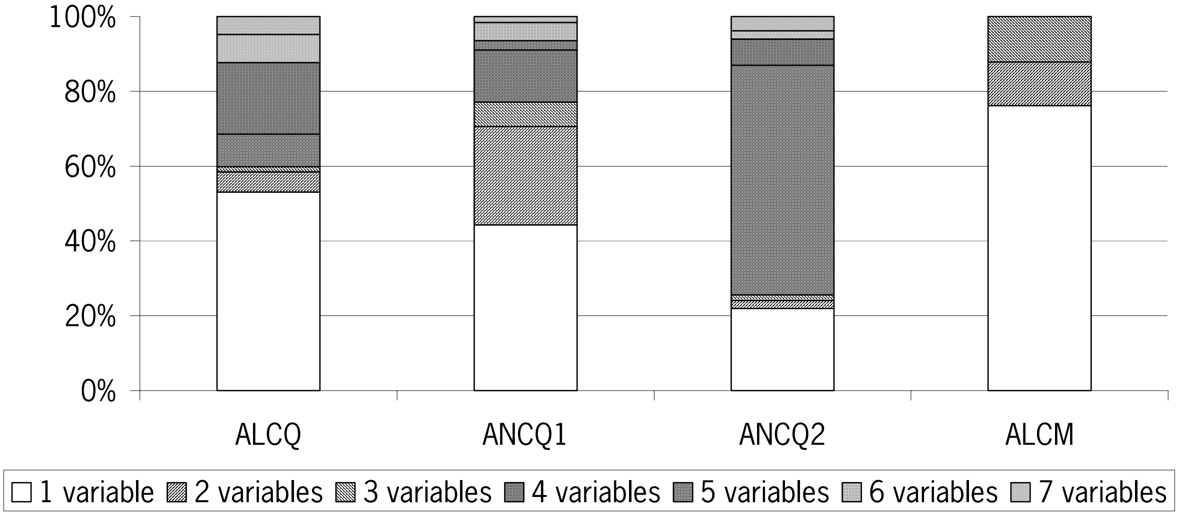


***Figure 4.3*** *The distribution of the milkings with one or more indeterminable variables over the number of indeterminable variables per milking, for each farm.*

*4.3.2 Oestrus*

Oestrus detection results depended on the model used and the farm (Table 4.6 and 4.7). Choosing a higher threshold in the IMAG model (a higher confidence interval) gave a lower sensitivity but a higher specificity, and vice versa.

***Table 4.6***

*Number of true positive oestrus cases (TP), number of false negative cases (FN), number of TP and FN cases with indeterminable activity (?/TP and ?/FN, resp.), and sensitivity (TP/TP+FN), found with the IMAG model (with three confidence intervals, % in brackets) and the manufacturer's model (not available for ALCM) for all farms together and each farm separately.*

| farm | (# cases) | model | TP | FN | ?/TP | ?/FN | sensitivity (%) |
|---|---|---|---|---|---|---|---|
| all farms | (1,452) | IMAG (95) | 919 | 236 | 98 | 199 | 80 [a] |
| | | IMAG (99) | 820 | 335 | 83 | 214 | 71 [a] |
| | | IMAG (99.9) | 726 | 429 | 67 | 230 | 63 [a] |
| | (982) | manufacturer | 567 | 326 | 26 | 63 | 63 [a] |
| ALCQ | (178) | IMAG (95) | 138 | 11 | 25 | 4 | 93 |
| | | IMAG (99) | 134 | 15 | 25 | 4 | 90 |
| | | IMAG (99.9) | 129 | 20 | 25 | 4 | 87 |
| | | manufacturer | 132 | 21 | 16 | 9 | 86 |
| ANCQ1 | (533) | IMAG (95) | 395 | 110 | 11 | 17 | 78 |
| | | IMAG (99) | 350 | 155 | 8 | 20 | 69 |
| | | IMAG (99.9) | 313 | 192 | 5 | 23 | 62 |
| | | manufacturer | 324 | 187 | 3 | 19 | 63 |
| ANCQ2 | (271) | IMAG (95) | 152 | 66 | 25 | 28 | 70 |
| | | IMAG (99) | 127 | 91 | 21 | 32 | 58 |
| | | IMAG (99.9) | 101 | 117 | 15 | 38 | 46 |
| | | manufacturer | 111 | 118 | 7 | 35 | 48 |
| ALCM | (470) | IMAG (95) | 234 | 49 | 37 | 150 | 83 |
| | | IMAG (99) | 209 | 74 | 29 | 158 | 74 |
| | | IMAG (99.9) | 183 | 100 | 22 | 165 | 65 |

[a] farm effect significant at $P < 0.05$

***Table 4.7***
*Number of true negative milkings (TN) for oestrus, number of false positive milkings (FP), number of milkings with indeterminable activity (?), and specificity (TN/TN+FP), found with the IMAG model (with three confidence intervals, % in brackets) and the manufacturer's model (not available for ALCM) for all farms together and each farm separately.*

| farm | (# milkings) | model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|---|---|
| all farms | (354,674) | IMAG (95) | 280,704 | 19,138 | 54,832 | 93.6 [a] |
| | | IMAG (99) | 289,866 | 9,976 | 54,832 | 96.7 [a] |
| | | IMAG (99.9) | 294,292 | 5,550 | 54,832 | 98.1 [a] |
| | (206,907) | manufacturer | 196,626 | 4,576 | 5,705 | 97.7 [b] |
| ALCQ | (37,270) | IMAG (95) | 33,230 | 2,129 | 1,911 | 94.0 |
| | | IMAG (99) | 34,227 | 1,132 | 1,911 | 96.8 |
| | | IMAG (99.9) | 34,756 | 603 | 1,911 | 98.3 |
| | | manufacturer | 35,591 | 424 | 1,255 | 98.8 |
| ANCQ1 | (118,762) | IMAG (95) | 107,998 | 6,620 | 4,144 | 94.2 |
| | | IMAG (99) | 111,632 | 2,986 | 4,144 | 97.4 |
| | | IMAG (99.9) | 113,211 | 1,407 | 4,144 | 98.8 |
| | | manufacturer | 113,771 | 2,977 | 2,014 | 97.5 |
| ANCQ2 | (50,875) | IMAG (95) | 43,622 | 2,696 | 4,557 | 94.2 |
| | | IMAG (99) | 45,001 | 1,317 | 4,557 | 97.2 |
| | | IMAG (99.9) | 45,661 | 657 | 4,557 | 98.6 |
| | | manufacturer | 47,264 | 1,175 | 2,436 | 97.6 |
| ALCM | (147,767) | IMAG (95) | 95,854 | 7,693 | 44,220 | 92.6 |
| | | IMAG (99) | 99,006 | 4,541 | 44,220 | 95.6 |
| | | IMAG (99.9) | 100,664 | 2,883 | 44,220 | 97.2 |

[a] farm effect significant at P < 0.05
[b] significance of farm effect not determined

There were numerical differences in detection results between farms. The statistical significance of the differences between farms was tested with a logistic regression model (Genstat, 1993). The differences between farms in sensitivity and specificity of the IMAG model were all significant. The difference in sensitivity was also significant for the manufacturer's model. It was not possible to test the significance of the differences in specificity of the manufacturer's model with the logistic regression model, because the major part of the deviance was caused by a cow effect (a few cows had a high number of FP alerts). For farms ANCQ1 and ANCQ2, having the same sensor equipment, the pairwise differences in sensitivity and specificity were all significant, except specificity in case of the 95% confidence interval. The sensitivity on ALCQ was significantly higher than the sensitivity on the other three farms; and the sensitivity on ANCQ2 was significantly lower.

The oestrus sensitivity, as given in Table 4.6, is based only on cases without indeterminable activity. Sensitivity based on all cases, with or without indeterminable activity, can also be calculated from the figures in Table 4.6: [(TP+?/TP)/ (number of cases)]×100. The sensitivity based on all cases on all farms varied between 70% for the IMAG model with a 95% confidence interval (919 + 98 out of 1,452 cases) and 55% for a 99.9% confidence interval. These lower percentages express the oestrus sensitivity presented to the farmer by the sensor system. The percentages in Table 4.6 express the sensitivity found by the IMAG model.

Fitting the generalized linear mixed model for the activity level, Eq. (1), showed that the activity level is not always lower in the first lactation period than in the next periods (Table 4.8), as might be expected due to a negative energy balance in early lactation. The predicted mean activity level was lower for the first lactation period on farms ANCQ1, ANCQ2 and ALCM, but the differences were relatively small. The predicted mean activity level was even higher in the first lactation period for farm ALCQ. The predicted mean activity level generally decreased as the lactation number increased (data not shown).

***Table 4.8***

*Predicted mean activity level (change in activity/hour) for each lactation period and for each farm.*

| farm | days in lactation | | |
|---|---|---|---|
| | ≤ 30 | > 30 and ≤75 | > 75 |
| ALCQ | 4.03 | 3.81 | 3.62 |
| ANCQ1 | 1.44 | 1.63 | 1.68 |
| ANCQ2 | 1.99 | 2.21 | 2.30 |
| ALCM | 1.16 | 1.24 | 1.45 |

### *4.3.3 Mastitis*

Results for clinical mastitis detection were calculated, based on mastitis alerts (Table 4.9) and based on illness alerts (Table 4.10). Mastitis specificity results were only based on mastitis alerts (Table 4.11).

**Table 4.9**

*Number of true positive clinical mastitis cases (TP), number of false negative cases (FN), number of TP and FN cases with indeterminable conductivity (?/TP and ?/FN, resp.), and sensitivity (TP/TP+FN), found with mastitis alerts of the IMAG model (with three confidence intervals, % in brackets) and with mastitis alerts of the manufacturer's model (not available for ALCM) for all farms together and each farm separately.*

| farm | (# cases) | model | TP | FN | ?/TP | ?/FN | sensitivity (%) |
|---|---|---|---|---|---|---|---|
| all farms | (212) | IMAG (95) | 75 | 20 | 77 | 40 | 79 [a] |
| | | IMAG (99) | 64 | 31 | 66 | 51 | 67 [a] |
| | | IMAG (99.9) | 51 | 44 | 56 | 61 | 54 [a] |
| | (161) | manufacturer | 47 | 97 | 5 | 12 | 33 |
| ALCQ | (42) | IMAG (95) | 21 | 4 | 12 | 5 | 84 |
| | | IMAG (99) | 20 | 5 | 10 | 7 | 80 |
| | | IMAG (99.9) | 18 | 7 | 10 | 7 | 72 |
| | | manufacturer | 11 | 23 | 2 | 6 | 32 |
| ANCQ1 | (97) | IMAG (95) | 48 | 6 | 37 | 6 | 89 |
| | | IMAG (99) | 40 | 14 | 35 | 8 | 74 |
| | | IMAG (99.9) | 31 | 23 | 31 | 12 | 57 |
| | | manufacturer | 32 | 57 | 3 | 5 | 36 |
| ANCQ2 | (22) | IMAG (95) | 2 | 1 | 12 | 7 | 67 |
| | | IMAG (99) | 2 | 1 | 8 | 11 | 67 |
| | | IMAG (99.9) | 1 | 2 | 5 | 14 | 33 |
| | | manufacturer | 4 | 17 | 0 | 1 | 19 |
| ALCM | (51) | IMAG (95) | 4 | 9 | 16 | 22 | 31 |
| | | IMAG (99) | 2 | 11 | 13 | 25 | 15 |
| | | IMAG (99.9) | 1 | 12 | 10 | 28 | 8 |

[a] farm effect significant at $P < 0.05$

***Table 4.10***
*Number of true positive clinical mastitis cases (TP), number of false negative cases (FN) and sensitivity (TP/TP+FN), found with illness alerts of the IMAG model (with three confidence intervals, % in brackets) for all farms together and each farm separately.*

| farm (# cases) | model | TP | FN | sensitivity (%) |
|---|---|---|---|---|
| all farms( 212) | IMAG (95) | 174 | 38 | 82 |
| | IMAG (99) | 159 | 53 | 75 |
| | IMAG (99.9) | 132 | 80 | 62 |
| ALCQ (42) | IMAG (95) | 37 | 5 | 88 |
| | IMAG (99) | 33 | 9 | 79 |
| | IMAG (99.9) | 25 | 17 | 60 |
| ANCQ1 (97) | IMAG (95) | 80 | 17 | 82 |
| | IMAG (99) | 76 | 21 | 78 |
| | IMAG (99.9) | 60 | 37 | 62 |
| ANCQ2 (22) | IMAG (95) | 17 | 5 | 77 |
| | IMAG (99) | 14 | 8 | 64 |
| | IMAG (99.9) | 14 | 8 | 64 |
| ALCM (51) | IMAG (95) | 40 | 11 | 78 |
| | IMAG (99) | 36 | 15 | 71 |
| | IMAG (99.9) | 33 | 18 | 65 |

***Table 4.11***

*Number of true negative milkings (TN) for mastitis, number of false positive milkings (FP), number of milkings with indeterminable conductivity (?), and specificity (TN/TN+FP), found with mastitis alerts of the IMAG model (with three confidence intervals, % in brackets) and the manufacturer's model (not available for ALCM) for all farms together and each farm separately.*

| farm (# cows; # milkings) | model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|---|
| all farms (164; 140,269) | IMAG (95) | 119,576 | 8,011 | 12,682 | 93.7 [a] |
| | IMAG (99) | 124,847 | 2,740 | 12,682 | 97.9 [a] |
| | IMAG (99.9) | 126,696 | 891 | 12,682 | 99.3 [a] |
| (105; 85,983) | manufacturer | 82,364 | 1,189 | 2,430 | 98.6 [b] |
| ALCQ (20; 14,749) | IMAG (95) | 12,669 | 1,342 | 738 | 90.4 |
| | IMAG (99) | 13,543 | 468 | 738 | 96.6 |
| | IMAG (99.9) | 13,893 | 118 | 738 | 99.2 |
| | manufacturer | 14,160 | 212 | 377 | 98.5 |
| ANCQ1 (47; 44,609) | IMAG (95) | 39,137 | 2,688 | 2,784 | 93.5 |
| | IMAG (99) | 40,833 | 992 | 2,784 | 97.6 |
| | IMAG (99.9) | 41,388 | 437 | 2,784 | 98.9 |
| | manufacturer | 42,204 | 826 | 1,579 | 98.1 |
| ANCQ2 38; 26,625) | IMAG (95) | 19,388 | 1,433 | 5,804 | 93.0 |
| | IMAG (99) | 20,338 | 483 | 5,804 | 97.7 |
| | IMAG (99.9) | 20,678 | 143 | 5,804 | 99.3 |
| | manufacturer | 26,000 | 151 | 474 | 99.3 |
| ALCM (59; 54,286) | IMAG (95) | 48,382 | 2,548 | 3,356 | 94.8 |
| | IMAG (99) | 50,133 | 797 | 3,356 | 98.4 |
| | IMAG (99.9) | 50,737 | 193 | 3,356 | 99.6 |

[a] farm effect significant at $P < 0.05$

[b] significance of farm effect not determined

A logistic regression model was used to test for statistical significance of the differences between farms. The differences in sensitivity (Table 4.9) of mastitis alerts produced by the IMAG model were all significant. The differences in sensitivity between farms of the manufacturer's alerts (Table 4.9) and illness alerts by the IMAG model (Table 4.10) were not significant. The differences in specificity between farms (Table 4.11) were significant for the mastitis alerts by the IMAG model. It was not possible to test for the significance of the difference in specificity of the manufacturer's model with the logistic regression model, because the major part of the deviance was caused by a cow effect (a few cows had a high number of FP alerts). Three farms (ALCQ, ANCQ1 and ANCQ2) used the same equipment for mastitis detection. The pairwise differences in sensitivity between these farms were not significant, while the significance of the pairwise differences in specificity depended on the confidence interval chosen.

The sensitivity (Table 4.9) is based only on cases without indeterminable conductivity. Sensitivity based on all cases, with or without indeterminable conductivity, on all farms was lower and varied between 73% (IMAG 95%) and 50% (IMAG 99.9%). These lower percentages express the mastitis sensitivity presented to the farmer by the sensor system, the percentages in Table 4.9 express the sensitivity of the detection model.

## 4.4 Discussion

### *4.4.1 Indeterminable variables*

There were many indeterminable variables, mostly caused by measurement errors, with great differences between farms (Figure 4.2). A level of 5% indeterminable variables of the number of cows milked appeared to be normal. A high number of indeterminable variables was found for conductivity on ANCQ2 (almost 25%), but also on ANCQ1 (10-15%); and for activity on ALCM (30%). These high values indicate hardware problems. On ALCM the pedometer tightening strips often went loose, and many cows had lost their transponders. The problems causing the conductivity measurement errors were more difficult to explain because there were great deviations between the three farms using the same equipment (ALCQ, ANCQ1 and ANCQ2). Measurement errors seem inevitable, but the high percentages of milkings with measurement errors should have called earlier for attention on the farm. A monitoring system to check the functioning of the sensor equipment, and immediate servicing at problems are recommended.

Sensitivity for oestrus and mastitis based on all cases is lower than sensitivity based only on cases without indeterminable variables. The occurrence of indeterminable variables (e.g. due to measurement errors) thus devaluates the practical applicability of the detection model.

### *4.4.2 Oestrus*

The oestrus detection results of the previous research (Table 4.1) differ from the results reported by De Mol et al. (1997), although they are based on the same data set. The differences are caused by:

- The length of the oestrus period: Oestrus cases reported by De Mol et al. (1997) were based on progesterone samples. Visual observations were not available for all oestrus cases. Therefore, exact dates were not always known and a period of four days (eight milkings) was used to calculate the sensitivity. In the present report, a period of five milkings was used, which might be too short in cases based only on progesterone without visual observation. The influence of the use of oestrus cases without visual observations, is illustrated by the higher oestrus frequency measured in the former study (1 case in 172 milkings, and 1 in 129) compared with the present results (Table 4.4). In the former study, many cases were based only on progesterone with an assessed oestrus date.
- Oestrus cases with indeterminable activity: De Mol et al. (1997) reported that all TP cases with or without indeterminable activity were used for calculating the sensitivity. In the present paper, only TP cases, without any indeterminable activity in the oestrus period, were used.

The sensitivity for oestrus calculated on all farms in the present research (Table 4.6) was lower than the sensitivity calculated in the previous research (Table 4.1). There were significant farm effects. Farm ALCQ had the same equipment as the farms of the experiments reported in De Mol et al. (1997), but outperformed the results presented in Table 4.1. This may be because only observed oestrus cases were taken into account in the present study. The changes in activity might be greater in observed cases compared with cases based on progesterone samples only. The poor results of ANCQ1 and ANCQ2 might partly be caused by the use of neck transponders, which give worse results then leg transponders (Koelsch et al., 1994). However, the equipment used was not the only cause of farm differences, as indicated by differences between ANCQ1 and ANCQ2 (same equipment, significant differences in results).

Furthermore, the results of ALCQ might be influenced by the housing system: the cows of ALCQ were kept inside all year, while the cows of the other farms were out in the pasture during the summer period. The results of ALCM were influenced by the absence of milk temperature sensors. Alerts for oestrus on this farm were based on activity and yield and not on a combination of activity, yield and milk temperature, as on the other farms.

The sensitivity results obtained with the manufacturer’s model were comparable with the results of the IMAG model with a confidence interval of 99.9% (Table 4.6), as witnessed by the number of TP cases (without or with indeterminable activity). However, the number of FP milkings from the manufacturer’s model (Table 4.7) was much higher on some farms (doubled for ANCQ1 and ANCQ2). Therefore, the performance of the IMAG model was better than that of the manufacturer’s model: less FP milkings and the same sensitivity.

Our results are in accordance with oestrus detection results from experimental farms found in literature. Comparing these results with the performance predicted in Van Asseldonk et al. (1998), makes clear that only the IMAG model with the 95% confidence interval met the expectations (81% sensitivity and 90% specificity). In practice the 99.9% confidence interval might be preferred because of the lower number of FP alerts. The number of FP alerts should not be much higher than the number of TP alerts, otherwise only a minority of the alerts has a practical value for the farmer.

A part of the FP milkings was due to true oestrus cases that were detected by the model but not observed on the farm. This means that the actual specificity might be higher than given here. It was difficult to quantify the effect of inadequate farm observations. Some of these FP oestrus alerts might be classified as TP looking at the oestrus cycle, but such a classification is subjective. However, the specificity of all farms together (Table 4.7) was already higher than the specificity on the farms used in De Mol et al. (1997), as given in Table 4.1.

Although the lactation period was a significant factor in the generalized mixed linear model for the activity level, the predicted means did not always show a decreased activity level in early lactation (Table 4.8). The activity of cows in the first period of lactation was mostly at a lower level than the activity of cows in the second or third period of lactation. However, the differences were small and farm ALCQ showed the opposite trend. A negative energy balance in the first period of lactation (Brand et al., 1996) had no effect on the cow's activity.

*4.4.3 Mastitis*

The mastitis detection results in Table 4.1 differ from the results reported by De Mol et al. (1997), although they are based on the same data set. These differences are caused by:

- The length of the mastitis period: De Mol et al. (1997), reported that a mastitis period of 18 days (36 milkings) was used (from 10 days before till 7 days after the mastitis date). In the present study, a shorter period of only eight milkings was used.
- De Mol et al. (1997), reported that all TP cases with or without indeterminable conductivity were used to calculate sensitivity. In the present paper, only TP cases without indeterminable conductivity were used.

There were significant differences in sensitivity and specificity of mastitis alerts between the farms (Tables 9 and 11). The sensitivity on ALCM was significantly lower than on the other three farms. This is an indication that conductivity of quarter milk gives better detection results than when the conductivity of mixed milk is used as a variable. The increase in conductivity in case of mastitis may be lower and more difficult to detect when the milk of four quarters is mixed.

The sensitivity on ALCQ and ANCQ1 was higher than the sensitivity on the farms used in De Mol et al. (1997) and presented in Table 4.1. There were differences in specificity between farms; the specificity on ALCM was significantly higher than on other farms. There were no differences in specificity between the other farms.

The sensitivity of the IMAG model was much higher than the sensitivity of the manufacturer's model (Table 4.9); the differences in specificity were less (Table 4.11). Many FP alerts given by the manufacturer's model were caused by a small number of cows. This observation made it useless to test for the significance of farm effects with a logistic regression model because the cow effects were greater than the farm effects.

The mastitis sensitivity of all farms based on illness alerts (Table 4.10) was higher than the sensitivity based on mastitis alerts (Table 4.9). This difference was highest on ALCM. Illness alerts were based on deviating yield, temperature and activity. Mastitis alerts were based on conductivity, yield and temperature. The higher sensitivity for illness alerts indicates that deviations in yield and temperature were clearer than deviations in conductivity. Deviations in conductivity were not detectable or their detection might be too late. When a milker notified mastitis, the milk was separated (so no conductivity was recorded) and the cow was treated for mastitis. It was not possible to calculate the specificity of illness alerts with the information available, the occurrence of diseases other than mastitis was not known.

The results for mastitis detection in our experiments were worse than those found in literature. The differences might be explained by the circumstances. Literature data usually refer to more controlled conditions, while in our study field data were used. Hamann and Zecconi (1998) also indicate that sensitivity is much lower in experiments with a low prevalence (as in the present situation). However the results, 71% sensitivity with 86% specificity for the IMAG model with the 95% confidence interval, are within the range expected by experts (Van Asseldonk et al., 1998). The specificity should be high for practical application, taken into account the low prevalence of mastitis in practice. The number of FP alerts is much higher than the number of TP alerts even when the specificity is 99% (IMAG model with 99.9% confidence interval).

## 4.5 Conclusions

- The detection results predicted by an expert panel (Van Asseldonk et al., 1998), are achievable in the field. The results may attain the same level as found under experimental conditions by De Mol et al. (1997), which implies that oestrus detection has been developed far enough for practical usage. Mastitis detection results show that practical usage is difficult with the available sensors. Both sensitivity and specificity are not high enough, and better detection results are attained by using only yield, temperature and activity sensors (no conductivity sensors). The applicability for mastitis detection may be improved by a further development of sensors.

- Good detection results are only possible when the data collection equipment is functioning well. The farmer should monitor his equipment at regular intervals, otherwise detection based on sensor measurements will not yield acceptable results. Thus, implementation of a detection model will only add value to a farm, when accompanied by good management. Data collection might be improved by the use of autocalibration software.

- The IMAG model performs better than the manufacturer's model. Combined processing of the variables based on a more complex algorithm appears to be worthwhile. The advanced software used in the IMAG model gives promising results compared with currently available software.

- The sensor equipment used might explain some differences found between the farms. The results indicate that activity measured by neck transponders may result in lower oestrus sensitivity and that conductivity data of mixed milk may give lower mastitis sensitivity than data of quarter milk.

Further research is directed towards reducing the number of false positive alerts by taking into account other influences, like group influences or the status of the cow. A manual for practical usage of sensors and a detection model, describing and explaining what the farmer should do in case of alerts, may be needed to make these systems ready for introduction in practice.

## Acknowledgements

We wish to thank the farm managers and researchers of the four experimental farms of the Research Station for Cattle, Sheep and Horse Husbandry (PR): Bosma Zathe, Cranendonck, De Marke and Waiboerhoeve, for their co-operation in this research.

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*Chapter 5*

# Detection model for oestrus and mastitis in cows milked in an automatic milking system

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**Abstract**

Automated detection of oestrus and diseases, such as mastitis, in dairy cows can be a good alternative for detection by observation during milking, especially in case of an Automatic Milking System (AMS). An outline of a detection model is given, based on a generalisation of a detection model for cows milked twice a day. Firstly, a model is described for cows milked three or more times a day, at regular intervals. Secondly, a model is described for cows milked at variable times a day, at irregular intervals. The second model is appropriate for farms with an AMS and includes time series models for four variables (milk yield, milk temperature, activity and electrical conductivity of milk), with interpolation on previous values. Parameter values and the residual variances are updated by linear regression after each milking. Alerts for oestrus or mastitis are given when the residuals fall outside given confidence intervals. Two data sets were used: Data set 1 (complete and relatively small) and Data set 2 (only useful for mastitis detection, large). Data set 1 was used to develop the model for cows milked in an AMS and comprised 20 cows during 2.5 months; measurements of all four variables were available. The test of the model on this data set showed good results: all cases of oestrus and mastitis were detected, the number of false positive alerts depended on the chosen confidence interval. Data set 2, only used to test the model, comprised 111 cows during 16 months; only measurements of milk yield and electrical conductivity were available. The test of the model was only possible for mastitis detection: 42 to 44 (depending on the chosen confidence interval) out of 48 cases of clinical mastitis were detected; the remaining cases were not detected because not all data needed were available. These results were better than the results obtained with the model normally used on the farm. The number of false positive alerts depended on the chosen confidence interval and was higher than the number found with the normally used model. The results on both data sets indicate that automated detection on farms with an AMS gives appropriate results.

*Keywords:* detection, oestrus, mastitis, automatic milking systems

## 5.1 Introduction

Detection of oestrus and diseases in dairy cows is important. Proper oestrus detection is needed to plan calving intervals. Early detection of diseases, such as mastitis, may restrict harmful consequences for the cow and yield losses. Higher demands on the quality of milk also make detection more important. The economic consequences of an inadequate detection can be considerably. An improvement in oestrus detection from 50 to 90%, by application of information technology, can increase the gross margin per year per 100 kg fat and protein corrected milk by Dfl 1.28 (ca. $ 0.62) (Van Asseldonk et al., 1999). The total losses by clinical mastitis were found to be $ 83 per cow per year in a herd with average risk, and $ 206 in a herd with twice the average risk (Houben, 1995). Hitherto, detection is mostly done by visual observation of the cows in the milking barn during milkings (2-3 times a day).

Milking can be fully automated by installing an automatic milking system (AMS), which enables an increased milking frequency and milk yield per cow, and a reduced work investment and work load (Artmann, 1997 and Rossing et al., 1997). A further growth of the number of farms with an AMS may therefore be expected, although investment costs are still high. In case of an AMS the observations of the milker during milking are no longer available, which renders an adequate detection by observation more difficult.

Detection of oestrus and mastitis can be automated by using sensor measurements (Frost et al., 1997 and Geers, 1994). Cows in oestrus show different behaviour, resulting in an increased activity level. Furthermore the milk yield may be lower and the body temperature may be higher. Automated oestrus detection is based on activity measurements by pedometers and measurements of the milk yield and the milk temperature (which is correlated with the body temperature). Mastitis influences the milk composition, resulting in an increased electrical conductivity. Furthermore, the body temperature may be higher (due to fever) and the milk yield will be lower in case of mastitis. Automated mastitis detection is based on conductivity measurements combined with measurements of the yield and the temperature of the milk. A detection model generates alerts for cows that may be in oestrus or may suffer from mastitis. These alerts can be used for management to replace the observations in the milking barn in conventional milking systems. Automated detection is therefore particularly suited for cows milked in an AMS.

A detection model for cows, milked twice a day, was developed in an earlier research (De Mol et al., 1999). This model uses activity, yield and temperature measurements to generate oestrus alerts, while mastitis alerts use conductivity, yield and temperature measurements. For the variables yield, temperature, activity and conductivity a time series model is used to calculate the expected value. An alert is given when a combination of deviations between expected and actual values is outside a chosen confidence interval. The detection model was tested on two experimental farms (De Mol et al., 1997) and in a field test on four farms (De Mol et al., 2000). The model proved to be a valuable tool for the detection of oestrus and mastitis, provided that the sensor equipment functions properly.

Normally, cows can visit an AMS more or less voluntarily. Cows are milked when the interval between subsequent milkings exceeds a chosen threshold (e.g. 6 h), otherwise they are rejected by the AMS. Thus, the situation on farms with an AMS, relative to farms without AMS, is different in two ways:

1. The milking frequency is variable. Cows in an AMS may be milked more frequently, and more than twice a day. The actual frequency depends on the capacity of the AMS and the system settings.
2. The milking intervals are more variable. The length of the interval is in between a lower limit and an upper limit. The lower limit depends on the system threshold for acceptance by the AMS. Cows are taken to the AMS by the farmer when the upper limit is exceeded (e.g. when the previous milking is more than 24 h ago).

These aspects of farms with an AMS have consequences for the variables used in a detection model for oestrus and mastitis. The detection model for cows milked twice a day cannot be used, because a fixed milking frequency and a, more or less, fixed milking interval are absent. After each milking, the expected value of each variable is calculated and an alert is generated by the detection model when a combination of deviations exceeds a chosen value. The expected yield is based on the daily yield, estimated by the sum of the two last yields. In case of an AMS, it is generally not possible to estimate the daily yield this way. The temperature has a diurnal rhythm (higher in the afternoon). So the current temperature is best compared with the temperature 24 hours (two milkings) ago, but in general, this comparison is not possible in case of an AMS. The activity also shows a diurnal rhythm, because of the behavioural pattern of the cows. The conductivity may also be subject to a diurnal rhythm. When the cows are milked at variable frequencies and intervals in an AMS, diurnal patterns cannot be used straightforwardly.

In the current research a detection model for cows milked in an AMS was developed and tested. This model was based on a generalisation of a detection model for cows milked twice a day. Firstly, a model was developed for cows milked three or more times a day, at regular intervals. Secondly, a model was developed for cows milked with variable frequencies, at irregular intervals. The latter models describe the normal behaviour of the cows when they are not in oestrus and do not suffer from mastitis. Deviations between the actual and expected pattern result in alerts for oestrus and mastitis. The objectives of this research were to develop an adequate detection model for cows milked in an AMS and to test the model with the available data sets. The test results were compared with other detection results found with other data sets, and with another detection model for the same data set.

## 5.2 Material and methods

In this paper, a detection model for cows milked twice or more a day, at regular intervals, is described first, e.g. for cows milked three times a day: in the morning, around noon and in the evening. Some characteristics of this model were used for a second model for cows milked in an AMS, where the number of milkings per day could vary and the milking intervals were irregular. Both models used sensor data of the milk yield, milk temperature, cow activity and electrical conductivity of the milk, to generate alerts for oestrus and mastitis. Two data sets were used in the current research (Table 5.1). Data set 1 was used for model development and testing. Data set 2 was only used for testing. Data set 1 included measurements of all four variables. Data set 2 included only measurements of milk yield and electrical conductivity. More details are given in Section 5.2.1.

***Table 5.1***

*Measurement period, number of cows, milkings and milkings per cow per day for Data set 1 and Data set 2.*

| data set | from | till | number of cows | number of milkings | average number of milkings per cow per day |
|---|---|---|---|---|---|
| 1 | 8 Jan. '97 | 16 March '97 | 20 | 3,351 | 2.5 |
| 2 | 14 Sep. '97 | 21 March '99 | 111 | 83,918 | 2.6 |

For Data set 2, also alerts from an older model were available. The latter model was based on exponential smoothing; mastitis alerts were based on deviating conductivity values. This model was used by default on farms with this type of AMS. It was delivered by the manufacturer; details of this model were not available. A survey of the detection models in this paper is given in Table 5.2. The new models, *TSMn* and *TSMx* are described in Section 5.2.2.

***Table 5.2***

*Four detection models used in this paper.*

| model name | based on | new [a] or old [b] model | milking frequency | milking intervals |
|---|---|---|---|---|
| *TSM2* | time series models | old | 2 times a day | fixed |
| *TSMn* | time series models | new | *n* times a day | fixed |
| *TSMx* | time series model | new | variable | variable |
| *ESx* | exponential smoothing | old | variable | variable |

[a] developed in research described in this paper
[b] available from earlier research

### *5.2.1 Data collection*

#### *5.2.1.1 Data set 1*

An AMS with two milking stands was installed on the experimental farm in Duiven, the Netherlands of the Institute of Agricultural and Environmental Engineering (IMAG). Data set 1 (Table 5.1) was collected during an experiment in January till March 1997, from 20 cows (9 heifers and 11 second or higher parity) of the HFxFH breed. This experiment was set up to study the effect of the concentrate feeding regime on cow behaviour (number of visits to the AMS, time spent in feeding and lying area), see Ketelaar-de Lauwere et al. (1999) for details. The cows could change freely from lying to feeding (forage and water) area and vice versa, but they could only reach the concentrate feeder by passing the selection unit of the AMS. Cows were selected for milking in the AMS when the last milking was at least 6 hours ago. Cows that did not visit the AMS voluntarily during an interval of 18 hours where fetched for milking, just before the daily cleaning periods (7.30 and 19.30 h). The cows visited the AMS on average 6 times a day, from which they were selected ca. 2.5 times for milking.

The AMS was equipped with a milk yield recording system and sensors for electrical conductivity in milk of 4 quarters. Temperature sensors were added for this research. Activity was measured by neck transponders.

Oestrus and clinical mastitis were recorded after visual inspection at the farm. Progesterone samples of milk were taken twice a week to assess the actual oestrous state. In the first week of the experiment, samples of quarter milk were collected for bacteriological examination and somatic cell counts.

Data set 1 was used to develop the detection model for cows milked in an AMS (*TSMx*). Test results for oestrus detection and mastitis detection for this data set should be taken with some precaution because the validity for other farms might be restricted.

*5.2.1.2 Data set 2*

Data set 2 was collected on a research farm of the Research Station for Cattle, Sheep and Horse Husbandry (PR) in Lelystad, the Netherlands, equipped with an AMS (Table 5.1). The purpose of this farm was to produce 800,000 kg of milk with one milking unit and one labour force. Mastitis detection was based on visual inspection of cows (three times a day), after alerts were given for electrical conductivity, milk yield or milk temperature. Cows were also inspected when they didn't show up voluntary in time at the AMS. Also the milk filter was inspected. The AMS was equipped with a milk yield recording system and sensors for conductivity and milk temperature, but the milk temperature measurements were not stored and thus not available in Data set 2. Measurements of the cow's activity were not available, while pedometers were not applied. The absence of activity measurements made testing of oestrus detection impossible. Testing of mastitis detection, based on yield and conductivity, was possible.

Farm observations of clinical mastitis were recorded. Milk samples of mixed milk to determine somatic cell counts were collected every three weeks. Some bacteriological examinations of milk were available of cows suffering from or suspected of mastitis.

Data set 2 was used to test the detection model for cows milked in an AMS (*TSMx*) and the old model *ESx* for mastitis detection.

### *5.2.2 Model description*

The detection model for cows milked in an AMS was developed in two steps. First the existing model (De Mol et al., 1999) for cows milked twice a day was generalised to the detection model *TSMn* for cows milked more frequently, say *n* times a day, at (more or less) regular intervals. Second, the detection model *TSMx* was developed for cows milked in an AMS, using some characteristics of the model *TSMn*.

#### *5.2.2.1 TSMn: a detection model for cows milked n times a day at regular intervals*

The existing model for cows milked two times a day at fixed intervals (De Mol et al., 1999) was generalised to a model for cows milked *n* times a day (variable frequency and fixed intervals). The value of *n* can for example be 3 or 4. For $n = 2$, the model *TSMn* is the same as *TSM2* (Table 5.2). The existing model was based on the time series models (TSM) for each variable (yield, temperature, activity and conductivity) measured during milking. For *TSMn*, the time series models were adapted for the different frequency.

*Yield*

The TSM of the milk yield was based on the daily yield, the yield during the last 24 hours. The daily yield was approximated by the sum of the yield at the last *n* milkings, this sum was corrected for the time difference between the time of the actual milking and the time *n* milkings earlier:

$$Y_{D,m} = \left(\sum_{i=1}^{n} Y_{M,m-(i-1)}\right) \cdot \frac{24}{24 + (M_m - M_{m-n})} \tag{5.1}$$

with:

$Y_{D,m}$ = daily yield at milking $m$,

$m$ = last milking, $m$–1 = previous milking, ...

$n$ = number of milkings per day,

$Y_{M,m}$ = yield at milking $m$,

$M_m$ = decimal time within the day of milking $m$ (between 0 and 24 hours).

The daily yield was modelled by a TSM to be able to detect deviating milk yields. For the difference of two successive daily yields $\nabla Y_{D,m}$ the following moving average (MA) model was used:

$$\nabla Y_{D,m} = Y_{D,m} - Y_{D,m-1} = Z_{Y,m} - \alpha_Y \cdot Z_{Y,m-n} \tag{5.2}$$

with:
$\nabla Y_{D,m}$ = difference of two successive daily yields at milking $m$,
$Z_{Y,m}$ = random disturbance on yield at milking $m$,
$\alpha_Y$ = parameter of yield model.
The disturbances $Z_{Y,m}$ (with mean = zero) were calculated recursively. The parameter $\alpha_Y$ had to be estimated.

*Temperature*
The milk temperature could best be compared with the temperature approximately 24 hours before, to avoid influences of the diurnal rhythm. Therefore, an MA model for the difference $\nabla T_m$ of the current temperature and that of $n$ milkings ago was used:

$$\nabla T_m = T_m - T_{m-n} = Z_{T,m} - \alpha_T \cdot Z_{T,m-n} \tag{5.3}$$

with:
$\nabla T_m$ = difference of milk temperature with lag $n$ at milking $m$,
$T_m$ = milk temperature at milking $m$,
$Z_{T,m}$ = random disturbance on temperature at milking $m$,
$\alpha_T$ = parameter of temperature model.

*Activity*
The activity depended on the diurnal rhythm of the cow. To compensate for this diurnal effect, the hourly activity prior to each milking based on the difference of the two counter values (cumulatives ranging from 0 to 999), in the hours since the previous milking, was calculated:

$$A_{H,m} = \frac{V_m - V_{m-1}}{M_m - M_{m-1}} \tag{5.4}$$

with:
$A_{H,m}$ = hourly activity at milking $m$,
$V_m$ = counter value at milking $m$ (differences are taken modulo 1,000),

$M_m$ = decimal time of activity measurement at milking $m$ (differences are taken modulo 24.0).

For the difference in hourly activity $\nabla A_{H,m}$ an MA model was used:

$$\nabla A_{H,m} = A_{H,m} - A_{H,m-n} = Z_{A,m} - \alpha_A \cdot Z_{A,m-n} \tag{5.5}$$

with:
$\nabla A_{H,m}$ = difference of hourly activity with lag $n$ at milking $m$,
$Z_{A,m}$ = random disturbance on activity at milking $m$,
$\alpha_A$ = parameter of activity model.

*Conductivity*
An autoregressive model with lag $n$, AR($n$) was used for the electrical conductivity of a quarter:

$$E_{q,m} - \mu_C = \sum_{i=1}^{i=n} \alpha_{Ci} \cdot (E_{q,m-i} - \mu_C) + Z_{Cq,m} \tag{5.6}$$

with:
$E_{q,m}$ = electrical conductivity of quarter $q$ at milking $m$,
$\mu_C$ = the average conductivity of each quarter (parameter of conductivity model),
$\alpha_{Ci}$ = parameters of conductivity model describing the dependency of the current value on the preceding values,
$Z_{Cq,m}$ = random influence on conductivity of quarter $q$ at milking $m$.
It was assumed that the parameters, $\mu_C$ and $\alpha_{Ci}$, had the same value for each quarter.

*Parameter fitting*
The parameters of the time series models could have been fitted on-line with a Kalman filter, in the same way as in the model *TSM2*. For each cow new values of the parameters of the time series models were calculated after each milking, based on all milkings thus far. See De Mol et al., 1999 for details.

Model *TSMn* was based on the assumption that the cows were milked with fixed frequencies so that the milking with lag *n* was ca. 24 hours ago. This assumption was not valid in case of an AMS, so the described model could not be used. However, this model for cows milked *n* times a day, built up from time series models for each variable and combined with the Kalman filter, was used as a basis for model *TSMx*, for cows milked in an AMS.

#### *5.2.2.2 TSMx: a detection model for cows milked in an AMS*

The milking intervals were no longer fixed if the cows were milked in an AMS. The number of milkings per day, as well as the length of the intervals, varied. Therefore the model *TSMn* (Section 5.2.2.1) could not be used. The outline of model *TSMx* was the same as for *TSMn:* use time series model to describe the behaviour of the variables and update the parameters in these models after each milking. The statistical analysis was performed using Genstat (Genstat, 1993).

Each time series model in Section 5.2.2.1 included the value of the variable at some given time earlier, e.g. the milk temperature 24 hours ago ($T_{m-n}$) in Eq. (5.3). These values could only be approximated by interpolation in case of an AMS. For each variable an interpolation method and some time series model were used. The interpolation method is explained for the variable yield.

*Yield*

The expected yield was based on the daily yield (in the last 24 h), that could not be straightforwardly calculated in case of an AMS. Therefore, a linear function was used to model the cumulative yield in between two successive milkings. Interpolation of this piece-wise linear cumulative yield was used to calculate the yield during the last 24 hours. An example is given in Figure 5.1, where four milkings of a cow are given: the current milking at 18.00 h (yield 10 kg), at 8.00 h (8 kg), at 23.00 h the previous day (8 kg) and at 15.00 h the previous day (7.5 kg). These yields were used to construct a piecewise linear function for the cumulative yield. The interpolated daily yield for the current milking was based on this piecewise linear function. The value of this function at 18.00 h at the previous day is 10.5 kg, so the interpolated daily yield for the current milking is 23.0 kg (33.5 – 10.5).

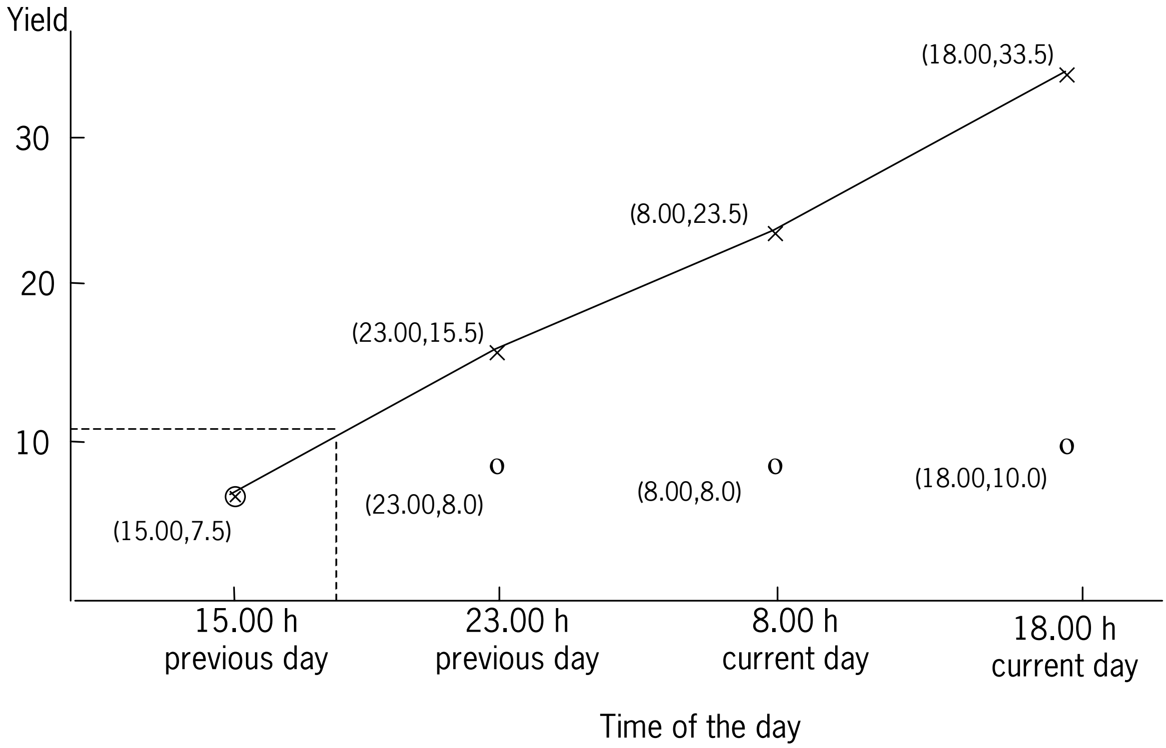


***Figure 5.1*** *Example of the piecewise linear cumulative yield function (×) built up from the yield (o) at various milkings of a cow.*

The interpolated daily yield was fitted by a local linear trend model:

$$\bar{Y}_D(t) = \mu_Y(t) + \alpha_Y(t) \cdot t + Z_Y(t) \tag{5.7}$$

with:

$\bar{Y}_D(t)$ = daily yield at time $t$, calculated by linear interpolation on the cumulative yield,

$t$ = time of milking in decimal number of days (e.g. 3.25 is 6.00 h at the third day),

$\mu_Y(t)$ = current level of daily yield at time $t$,

$\alpha_Y(t)$ = local trend of daily yield at time $t$,

$Z_Y(t)$ = random disturbance at time $t$.

Hidden periodicities in a given time series could be found by plotting periodograms (Chatfield, 1989). Analysis with periodograms showed no major periodicities in the residuals. In most cases only a peak at a low frequency, indicating a long-term pattern, was observed. The time since last milking did explain a part of the noise, because some cases with a long interval (more than 12 h) resulted in a lower yield. It was known from literature that the yield could be lower in case of longer milking intervals (Ouweltjes, 1998). Apparently, fitting for mean and trend was enough to remove any patterns, the remaining residuals could be considered as noise.

*Temperature*

The temperature 24 hours prior to the milking examined, was estimated by linear interpolation on the temperature measured at two milkings, one before and one after that time.

A model similar to Eq. (5.3) was used to model the temperature:

$$T(t) - \bar{T}(t-1) = Z_T(t) - \alpha_T(t) \cdot (\bar{T}(t-1) - \bar{T}(t-2)) \tag{5.8}$$

with:

$T(t)$ = milk temperature at milking at time $t$,
$\bar{T}(t-1)$ = milk temperature 24 hours ago, calculated by linear interpolation,
$Z_T(t)$ = random disturbance at time $t$,
$\alpha_T(t)$ = parameter of temperature model at time $t$,
$\bar{T}(t-2)$ = milk temperature 48 hours ago, calculated by linear interpolation.

There were many temperature measurement errors in Data set 1, so a thorough analysis was not possible, but this temperature model appeared to be appropriate.

*Activity*

The expected activity was based on the daily activity during the last 24 hours. A linear function was used to model the step counter value in between two successive milkings. Interpolation on this piecewise linear step counter function was used to calculate the activity (difference in step counter values) during the last 24 hours.

The interpolated daily activity was fitted by a local linear trend model in the same way as daily yield (Eq. (5.7)):

$$\bar{A}_D(t) = \mu_A(t) + \alpha_A(t) \cdot t + Z_A(t) \tag{5.9}$$

with:

$\bar{A}_D(t)$ = daily activity at time $t$ calculated by linear interpolation on the cumulative activity,
$\mu_A(t)$ = current activity level at time $t$,
$\alpha_A(t)$ = local trend of activity at time $t$,
$Z_A(t)$ = random disturbance on activity at time $t$.

The periodograms of the residuals showed no regular patterns. In some case there were some periodicities with a longer period (e.g. 20 days or a multiple thereof) that might be caused by oestrous cycles.

*Conductivity*
The expected conductivity was based on the values half a day and one day earlier, as in Eq. (5.6). The conductivity 12 and 24 hours prior to milking was estimated by linear interpolation on the measurements before and after these times.

The conductivity was modelled on the interpolated values by an AR(2) model:

$$E_q(t) - \mu_{Cq}(t) = \alpha_{Cq}(t) \cdot (\bar{E}_q(t - \tfrac{1}{2}) - \mu_{Cq}(t)) + \beta_{Cq}(t) \cdot (\bar{E}_q(t-1) - \mu_{Cq}(t)) + Z_{Cq}(t) \qquad (5.10)$$

with:
$E_q(t)$ = conductivity of quarter $q$ for milking at time $t$,
$\mu_{Cq}(t)$ = average conductivity of quarter $q$ at time $t$,
$\alpha_{Cq}(t)$, = parameter of the conductivity model for quarter $q$ at time $t$,
$\bar{E}_q(t-\frac{1}{2})$ = conductivity of quarter $q$, 12 hours ago, calculated by linear interpolation,
$\beta_{Cq}(t)$ = parameter of the conductivity model for quarter $q$ at time $t$,
$\bar{E}_q(t-1)$ = conductivity of quarter $q$, 24 hours ago, calculated by linear interpolation,
$Z_{Cq}(t)$ = random disturbance on conductivity of quarter q at time $t$.

Periodograms of the residuals after fitting did not show structural periodicities, so the conductivity model appeared to be appropriate.

*Parameter fitting*

The parameters in the time series models for the variables of cows milked in an AMS model [Eqs. (5.7) - (5.10)] were not known at forehand. They might be cow-dependent and might change in time (as in model *TSM2*). In the model *TSMx*, the parameters were fitted by an iterative regression procedure: after each milking the parameters were fitted by linear regression on the milkings up to the latest milking. This type of fitting was only possible when enough measurements were available. A steady state model was used if the number of measurements was less than 25. In that case, only the average value was fitted. The yield model was fitted on the measurements during the preceding 30 days, because it is known that the level and trend of yield change during lactation.

Once parameter values and the variance of the residuals were known, alerts could be calculated. An alert was given when the combination of the actual residual fell outside a given confidence interval. For oestrus a combination of activity, yield and temperature; for mastitis a combination of conductivity, yield and temperature was used (as in De Mol et al., 1999). Three confidence intervals were used: 95%, 99% and 99.9%.

So in model *TSMx*, after each milking the following steps were taken:

1. Calculate the interpolated values of each variable needed in the time series models, Eqs. (5.7) - (5.10) for yield, temperature, activity and conductivity, by linear interpolation;
2. Calculate the residual of each variable using the parameters based on the measurements up to the latest milking;
3. Generate combined alerts if the values are outside the 95, 99 or 99.9% confidence interval, using the calculated variance based on the residuals up to the latest milking;
4. Calculate updated parameter values by linear regression on each variable, including the latest measurements;
5. Calculate the residual variance including the actual residuals.

### *5.2.3 Test procedure*

The model outcomes, alerts for oestrus and mastitis, were compared with actual occurrences of oestrus and mastitis. A case of oestrus or mastitis was classified as True Positive (TP) if one or more alerts were given in a period around the recorded date, otherwise the case was False Negative (FN). For oestrus, this period was the day when oestrus was recorded, the previous day and the first 12 hours of the next day. For mastitis, the period comprised the day mastitis was recorded plus the preceding 6 days. Milkings outside these periods were True Negative (TN) if no alert was given, otherwise a milking was False Positive (FP).

The number of TP and FN cases was used to calculate the sensitivity, defined as the percentage of TP cases: $[TP/(TP+FN)]\times100\%$.

The number of TN and FP milkings was used to calculate the specificity, defined as the percentage of TN milkings: $[TN/(TN+FP)]\times100\%$.

The milkings outside periods of clinical mastitis cases were not always TN, because the cow might suffer from subclinical mastitis. Milkings were only classified as TN when the occurrence of subclinical mastitis was very unlikely. For this purpose, cows were selected without any case of clinical mastitis, with samples of cell counts never exceeding 500,000 cells/ml and no positive results of bacteriological examinations (if any).

Sometimes the models could not draw conclusions from the sensor measurements. These "indeterminable" variables could be caused by measurement errors. For yield, temperature and activity indeterminable variables could also be caused by start-up effects (e.g. first milkings in a new lactation). The detection results were influenced by the measurement errors indicated as indeterminable variables. Oestrus and mastitis cases with measurement errors were difficult to classify. Therefore, sensitivity and specificity for oestrus were based only on cases without indeterminable activity. Sensitivity and specificity for mastitis were based only on cases without indeterminable conductivity. Cases with indeterminable values of yield or temperature were still used in the tests.

## 5.3 Results

The model *TSMx* generated oestrus and mastitis alerts after each milking in the data collection period of Data set 1 and 2. By comparing these alerts with the actual cases of oestrus and mastitis the model performance could be assessed.

### *5.3.1 Data set 1*

#### *5.3.1.1 Oestrus*

Based on progesterone profiles and farm observations, eight cases of oestrus were confirmed during the experiment. In all cases one or more oestrus alerts were given on the oestrus day, on the previous day or in the morning of the next day. These alerts corresponded with residual combinations outside the 99.9% confidence interval. The sensitivity was 100% (8 TP cases out of 8). Alerts at milkings outside these oestrus periods were considered FP. The number of FP alerts varied between 40 and 186 (depending on the chosen confidence interval), corresponding with specificity 98.3 and 92.0%, respectively (Table 5.3).

***Table 5.3***

*Oestrus detection for Data set 1 found with alerts of model TSMx with three confidence intervals (% in brackets) based on 2,557 milkings of 21 cows outside oestrus periods. Number of True Negative milkings (TN), number of False Positive milkings (FP), number of milkings with indeterminable activity (?), and specificity, defined as [TN/(TN+FP)]×100%.*

| model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|
| *TSMx* (95) | 2,134 | 186 | 237 | 92.0 |
| *TSMx* (99) | 2,246 | 74 | 237 | 96.8 |
| *TSMx* (99.9) | 2,280 | 40 | 237 | 98.3 |

#### *5.3.1.2 Mastitis*

Two cases of clinical mastitis were recorded during the experimental period. In both cases one or more mastitis alerts (residual combinations outside the 99.9% confidence interval) were generated in the preceding week. So, both cases were TP. Alerts for mastitis for eleven other cows with cell counts of each quarter below 500,000 cells/ml, and negative results of bacteriological examination of milk, were considered FP. The 1,869 milkings of these eleven cows resulted in 231 FP alerts (specificity 86.6%) in case of the 95% confidence interval, and in 41 FP alerts (specificity 97.6%) with the 99.9% confidence interval (Table 5.4).

***Table 5.4***

*Mastitis detection for Data set 1 found with alerts of model TSMx with three confidence intervals (% in brackets) based on 1,869 milkings of 11 cows without mastitis signs. Number of True Negative milkings (TN), number of False Positive milkings (FP), number of milkings with indeterminable conductivity (?), and specificity, defined as [TN/(TN+FP)]×100%.*

| model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|
| *TSMx* (95) | 1,487 | 231 | 151 | 86.6 |
| *TSMx* (99) | 1,623 | 95 | 151 | 94.5 |
| *TSMx* (99.9) | 1,677 | 41 | 151 | 97.6 |

*5.3.2 Data set 2*

The test with Data set 2 gave a good impression of the practical value of the model because Data set 2 was much larger than set 1, and Data set 2 was not used for model development. The test of Data set 2 was limited to mastitis detection, because only yield and conductivity measurements were included.

***Table 5.5***

*Clinical mastitis detection by model TSMx (99.9% confidence interval) and model ESx, per case of clinical mastitis in Data set 2. The classification of cases is True Positive (TP), False Negative (FN), True Positive with indeterminable conductivity (?/TP) or False Negative with indeterminable conductivity (?/FN). For the TP cases also the number of alerts (#) and the moment of the first alert is given (number of days prior to the case).*

| clinical mastitis case | | | model *TSMx* | | | model *ESx* | | |
|---|---|---|---|---|---|---|---|---|
| cow | date (dd/mm/yy) | days in lactation | classification | # of alerts | first alert | classification | # of alerts | first alert |
| 82 | 12/12/97 | 62 | ?/TP | 3 | 2 | ?/TP | 1 | 0 |
| 139 | 16/7/98 | 189 | TP | 1 | 0 | FN | - | - |
| 139 | 23/7/98 | 196 | ?/FN | - | - | ?/FN | - | - |
| 156 | 2/6/98 | 71 | TP | 6 | 2 | TP | 2 | 0 |
| 178 | 9/10/97 | 191 | ?/TP | 1 | 3 | TP | 1 | 0 |
| 235 | 30/6/98 | 111 | ?/TP | 5 | 4 | FN | - | - |
| 235 | 13/7/98 | 124 | TP | 3 | 6 | TP | 7 | 4 |
| 235 | 25/7/98 | 136 | ?/TP | 6 | 6 | TP | 5 | 5 |
| 277 | 9/10/97 | 61 | ?/TP | 1 | 2 | TP | 19 | 6 |
| 378 | 6/2/98 | 118 | ?/TP | 1 | 4 | ?/TP | 4 | 6 |
| 422 | 9/4/98 | 155 | ?/TP | 1 | 0 | FN | - | - |
| 427 | 6/5/98 | 166 | ?/TP | 2 | 0 | ?/FN | - | - |

**Table 5.5** Continued from previous page

| clinical mastitis case | | | model *TSMx* | | | model *ESx* | | |
|---|---|---|---|---|---|---|---|---|
| cow | date (dd/mm/yy) | days in lactation | classification | # of alerts | first alert | classification | # of alerts | first alert |
| 430 | 9/4/98 | 129 | ?/TP | 4 | 6 | TP | 5 | 5 |
| 430 | 14/5/98 | 164 | ?/TP | 4 | 6 | ?/TP | 9 | 6 |
| 448 | 13/1/99 | 1 | ?/FN | - | - | FN | - | - |
| 495 | 16/3/99 | 73 | ?/TP | 3 | 3 | ?/TP | 15 | 6 |
| 645 | 6/4/98 | 136 | ?/TP | 3 | 1 | ?/TP | 1 | 0 |
| 645 | 5/6/98 | 196 | ?/TP | 3 | 0 | FN | - | - |
| 645 | 7/7/98 | 228 | ?/TP | 2 | 5 | TP | 12 | 6 |
| 674 | 29/11/97 | 64 | TP | 3 | 4 | TP | 2 | 2 |
| 727 | 25/10/98 | 2 [a] | ?/TP | 2 | 5 | FN | - | - |
| 816 | 11/2/99 | 266 | TP | 3 | 2 | TP | 1 | 1 |
| 863 | 24/1/98 | 2 | TP | 1 | 0 | FN | - | - |
| 931 | 3/8/98 | 71 | TP | 4 | 4 | TP | 7 | 5 |
| 931 | 21/8/98 | 89 | TP | 5 | 4 | TP | 11 | 6 |
| 931 | 1/10/98 | 130 | ?/TP [b] | 1 | 0 | TP | 9 | 6 |
| 1006 | 14/8/98 | 15 | TP | 3 | 2 | TP | 2 | 0 |
| 1021 | 24/8/98 | 7 | TP | 1 | 5 | FN | - | - |
| 1025 | 1/9/98 | 5 | TP | 2 | 1 | FN | - | - |
| 1078 | 23/10/98 | 3 | ?/TP | 1 | 1 | ?/FN | - | - |
| 1098 | 5/12/98 | 3 | ?/TP | 6 | 1 | FN | - | - |
| 5297 | 3/2/98 | 70 | ?/TP | 1 | 2 | ?/TP | 9 | 6 |
| 5297 | 19/4/98 | 145 | ?/TP | 3 | 6 | TP | 7 | 6 |
| 5297 | 29/4/98 | 155 | ?/TP | 2 | 6 | TP | 3 | 4 |
| 5297 | 16/5/98 | 172 | ?/TP | 2 | 4 | TP | 5 | 6 |
| 5492 | 20/9/97 | 12 | ?/FN | - | - | ?/FN | - | - |
| 5492 | 31/12/97 | 114 | TP | 3 | 2 | TP | 3 | 4 |
| 5492 | 1/2/98 | 146 | TP | 1 | 5 | FN | - | - |
| 5492 | 26/3/98 | 199 | TP | 2 | 0 | TP | 1 | 0 |
| 5507 | 1/10/97 | 253 | TP | 6 | 5 | TP | 6 | 6 |
| 5532 | 25/1/98 | 1 | ?/FN | - | - | FN | - | - |
| 5542 | 6/1/98 | 47 | TP | 4 | 4 | TP | 6 | 3 |
| 5542 | 27/1/98 | 68 | TP | 3 | 6 | TP | 8 | 5 |
| 5568 | 18/10/98 | 18 | ?/TP | 3 | 3 | ?/TP | 2 | 2 |
| 5598 | 21/5/98 | 114 | TP | 2 | 0 | TP | 1 | 0 |
| 5600 | 5/10/97 | 158 | ?/TP | 2 | 4 | ?/TP | 1 | 0 |
| 5665 | 10/11/98 | 75 | ?/TP [c] | 1 | 0 | ?/TP | 1 | 0 |
| 5750 | 30/9/97 | 382 | TP | 2 | 2 | TP | 6 | 2 |

[a] this cow had a dry period of only 1 day

[b] only TP in case of a 99% confidence interval

[c] only TP in case of a 95% confidence interval

For each case of clinical mastitis a classification with models *TSMx* and *ESx* is determined (Table 5.5). Some cases are TP, both for model *TSMx* as and model *ESx* (e.g. cow 156 on June 2, 1998). Other cases are only TP for model *TSMx* (e.g. cow 139 on July 17, 1998). All clinical mastitis cases without indeterminable conductivity were detected with model *TSMx* (Table 5.6), resulting in 100% sensitivity. The sensitivity was 66% with model *ESx*.

***Table 5.6***

*Clinical mastitis detection for Data set 2, found with alerts of the model TSMx with three confidence intervals (% in brackets) and with alerts of the model ESx, based on results in Table 5.5. Number of True Positive cases (TP), number of False Negative cases (FN), number of TP and FN cases with indeterminable conductivity (?/TP and ?/FN, resp.), and sensitivity, defined as [TP/(TP+FN)]×100%.*

| model | TP | FN | ?/TP | ?/FN | sensitivity (%) |
|---|---|---|---|---|---|
| *TSMx* (95) | 19 | 0 | 25 | 4 | 100 |
| *TSMx* (99) | 19 | 0 | 24 | 5 | 100 |
| *TSMx* (99.9) | 19 | 0 | 23 | 6 | 100 |
| *ESx* | 23 | 12 | 9 | 4 | 66 |

Twenty-five cows were selected as cows that never suffered from mastitis, based on observed cases of clinical mastitis and sampling results of cell counts and bacteriological samples. Mastitis alerts for these cows were classified as FP. All 25 cows had some FP alerts with model *TSMx* (Table 5.7); some cows had FP alerts with model *ESx* (e.g. cow 164), while other cows had none (e.g. cow 51). The specificity was 99.3% with model *ESx*, with model *TSMx* the specificity varied between 87.4 and 97.6%, depending on the chosen confidence interval (Table 5.8).

***Table 5.7***
*Number of milkings for each non-mastitis cow and number of milkings with a FP alert or indeterminable conductivity (?) for cows in Data set 2 that never suffered from mastitis, for model TSMx (with three confidence intervals) and model ESx.*

| | | model *TSMx* | | | | model *ESx* | |
|---|---|---|---|---|---|---|---|
| | number of | FP alerts | | | | | |
| cow | milkings | 95% | 99% | 99.9% | ? | FP alerts | ? |
| 51 | 1,689 | 220 | 73 | 39 | 274 | 0 | 81 |
| 164 | 1,018 | 102 | 47 | 30 | 202 | 17 | 72 |
| 174 | 1,276 | 191 | 74 | 25 | 117 | 5 | 41 |
| 301 | 1,122 | 167 | 68 | 26 | 80 | 1 | 31 |
| 534 | 1,345 | 192 | 69 | 25 | 75 | 1 | 38 |
| 544 | 1,431 | 220 | 89 | 36 | 76 | 1 | 31 |
| 566 | 1,290 | 140 | 53 | 24 | 133 | 0 | 43 |
| 663 | 1,390 | 212 | 74 | 36 | 68 | 0 | 14 |
| 665 | 1,335 | 111 | 50 | 24 | 110 | 0 | 27 |
| 666 | 1,460 | 152 | 53 | 14 | 143 | 0 | 56 |
| 701 | 1,064 | 62 | 27 | 14 | 211 | 0 | 48 |
| 723 | 1,576 | 196 | 54 | 17 | 67 | 0 | 14 |
| 773 | 1,353 | 137 | 31 | 8 | 87 | 0 | 26 |
| 803 | 1,614 | 128 | 45 | 17 | 432 | 0 | 97 |
| 827 | 830 | 33 | 15 | 5 | 20 | 1 | 7 |
| 829 | 1,115 | 99 | 42 | 18 | 53 | 0 | 15 |
| 877 | 912 | 77 | 31 | 11 | 31 | 1 | 9 |
| 929 | 907 | 72 | 23 | 6 | 245 | 0 | 83 |
| 997 | 612 | 38 | 11 | 3 | 47 | 0 | 13 |
| 1000 | 580 | 38 | 19 | 5 | 63 | 5 | 19 |
| 4143 | 1,326 | 134 | 54 | 15 | 193 | 31 | 64 |
| 5225 | 999 | 113 | 46 | 23 | 74 | 22 | 31 |
| 5698 | 1,086 | 157 | 79 | 39 | 69 | 0 | 35 |
| 5804 | 1,202 | 244 | 121 | 53 | 77 | 118 | 36 |
| 9318 | 501 | 42 | 17 | 6 | 79 | 0 | 38 |
| total | 29,033 | 3,278 | 1,266 | 520 | 3,026 | 203 | 969 |

***Table 5.8***

*Mastitis detection for Data set 2, found with alerts of the model TSMx with three confidence intervals (% in brackets), and the model ESx, based on 29,033 milkings of 25 cows without mastitis signs, based on results in Table 5.7. Number of True Negative milkings (TN), number of False Positive milkings (FP), number of milkings with indeterminable conductivity (?), and specificity, defined as [TN/(TN+FP)]×100%.*

| model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|
| *TSMx* (95) | 25,755 | 3,278 | 3,036 | 87.4 |
| *TSMx* (99) | 27,767 | 1,266 | 3,036 | 95.1 |
| *TSMx* (99.9) | 28,415 | 618 | 3,026 | 97.6 |
| *ESx* | 28,830 | 203 | 969 | 99.3 |

## 5.4 Discussion

### *5.4.1 Detection models*

Four models were used in this research: two new models and two old models for comparisons (Table 5.2). Model *TSM2* was meant for cows milked twice a day, and therefore not applicable for cows milked more times a day or in an AMS.

Model *TSMn* was a generalisation of model *TSM2* for cows milked more than 2 times a day. *TSMn* was not tested in this research, because no data set was available. The *TSMn* characteristics were similar to those of model *TSM2*, e.g. the application of the diurnal rhythm of variables.

Model *TSMx* was especially developed for cows milked in an AMS with variable frequency and intervals of milking. Some aspects of *TSMx* were similar to *TSM2* and *TSMn*. The time series models for temperature: Eqs. (5.3) and (5.8), as well as the time series models for conductivity: Eqs. (5.6) and (5.10), were similar in *TSM2* and *TSMx*, if n equals 2. Other aspects of *TSMx* were modelled differently. Model *TSMn* used only sensor measurements of previous milkings. Model *TSMx* was based on interpolated values on previous measurements. The time series models for yield and activity were different; an MA model, as in Eqs. (5.2) and (5.5), was not suited in case of an AMS. A local linear trend model was used instead in Eqs. (5.7) and (5.9).

Model *ESx* was used by default for Data set 2. Clinical mastitis sensitivity results with model *ESx* were worse than results with model *TSMx*, while mastitis specificity was better with *ESx* than with *TSMx*. On farms with an AMS, detection of all cases of clinical mastitis will have priority. A high sensitivity will be preferred even if a higher number of false positive milkings is entailed. Because more cases of clinical mastitis were detected, model *TSMx* will be preferred over *ESx*. The model *ESx* also generated alerts for yield and temperature, which might also be FP. The model *TSMx* only yielded combined alerts for mastitis. So the actual difference in the number of FP alerts by *ESx* and *TSMx* was smaller than presented in Table 5.8.

### *5.4.2 Mastitis*

The detailed mastitis results (Table 5.5) lead to some general indications of the usability of automated mastitis detection.

The detection results, especially for *ESx*, appeared to be depending on the stage of lactation (Figures 5.2 and 5.3). Clinical mastitis cases in the first days of lactation were the most difficult to detect, especially for model *ESx*. FN cases for model *ESx*, later in lactation, were mostly caused by a *E. coli* infection.

For most clinical mastitis cases, the first alert was a few days before the farm observations. A detection model thus might give a timely alert for mastitis.

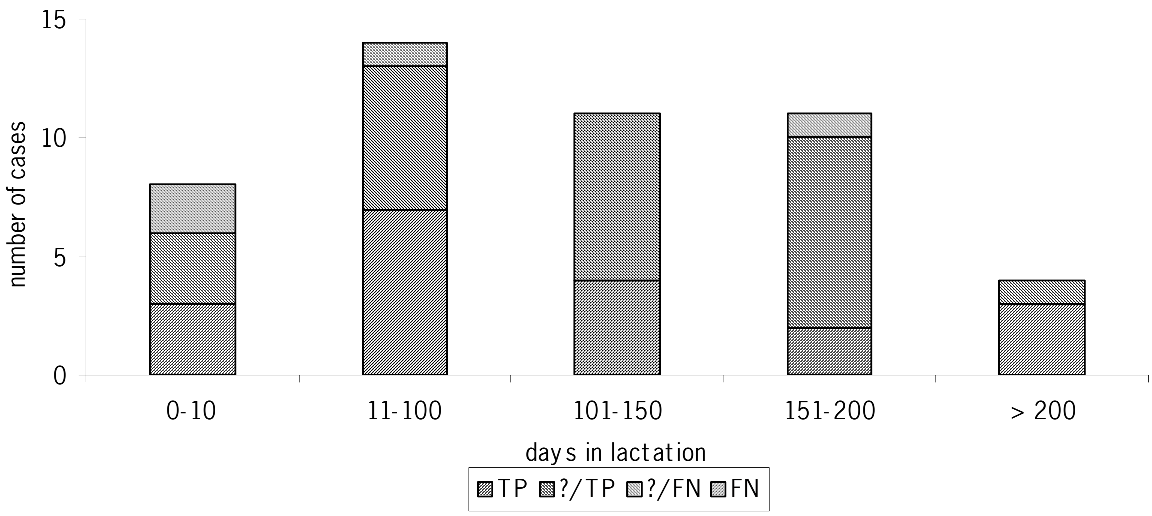


***Figure 5.2*** *Histogram of the classification of mastitis cases of model TSMx (95% confidence interval) in various phases of the lactation period (based on results in Table 5.5).*

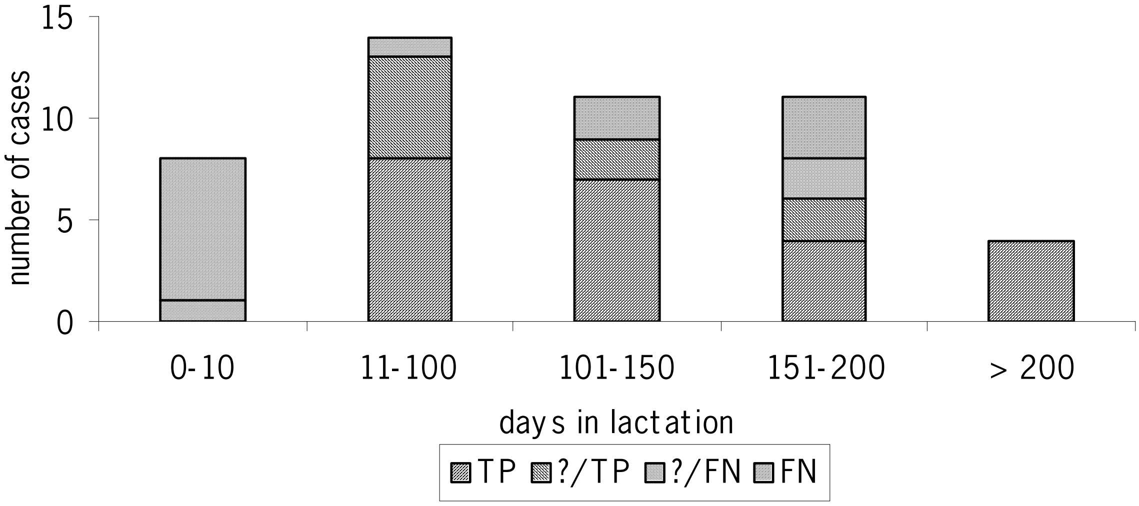


***Figure 5.3*** *Histogram of the classification of mastitis cases of model ESx in various phases of the lactation period (based on results in Table 5.5).*

The model *ESx* gave more alerts in a TP case than the model *TSMx*, e.g. the last case in Table 5.5 gave 2 alerts with *TSMx*, and 5 with *ESx*. This was due to the model structure of *TSMx*, the update of parameters after each milking would lead to an integration of the different conductivity level and a larger variance.

The detailed results for the cows that never suffered from mastitis (Table 5.7), led to the following indications for the occurrence of FP alerts.
The model *TSMx* gave more FP alerts than the model *ESx* and the difference is very large in case of the 95 and 99% confidence interval.
Fourteen cows had none FP alerts with the *ESx* model. All cows had FP alerts with the *TSMx* model, this was inherent in this model as it was based on confidence intervals. Some cows had a relatively large number of FP alerts with the *ESx* model, especially cow 5804. The number of FP alerts with the *ESx* model was cow-dependent.
Indeterminable milkings for model *ESx* (969 out of 29,033) were only caused by measurement errors. The number of indeterminable milkings for model *TSMx* was 3,036; caused by measurement errors and start-up effects. For model *TSMx*, indeterminable milkings were caused by measurement errors or start-up effects. The percentage of milkings with measurement errors was 3.3%, which was low compared with results from an earlier research (de Mol et al, 2000). An adequate automated detection on a farm with an AMS will only be possible when the number of measurement errors is low.

### *5.4.3 Perspectives for practical application*

Detection results found with Data set 1 and Data set 2 appeared to be at the same level, indicating the general applicability of model *TSMx*. The mastitis detection results of the current research were comparable to those obtained with model *TSM2* found in earlier research on farms where cows were milked twice a day (De Mol et al., 1997 and 2000). The sensitivity in the current research was higher and the specificity was lower. A comparable sensitivity might be expected while the same conductivity sensors were used, but the different implementation of the sensors in the AMS might be the cause for the improved detection. The difference in specificity might be explained by the difference in model structure. The goal of automated detection on farms equipped with an AMS is different from farms where cows are milked in a milking barn. In the latter case, a detection model gives additional information, besides the visual observations. No observations during milking may be available on a farm with an AMS, so the detection model might be the only way to signalise deviating cows.

The detection results for Data set 2 might be influenced by the absence of temperature measurements. Inclusion of temperature sensors would lead the improved mastitis detection results, as indicated by the study of De Mol et al. (1997), in which alerts based only on conductivity were compared with alerts based on conductivity, yield and temperature.

Sensitivity and specificity found in the current research, were better than the estimated sensitivity and specificity found by consultation of experts (Van Asseldonk, 1998). The estimated sensitivity and specificity, found in that consultation, on a farm with conductivity, yield and temperature sensors, was 71% and 86%, respectively. It appeared that these experts were too pessimistic.

Clinical mastitis results were based on farm observations. However observations from the milking parlour were not available in case of an AMS. Therefore, these farm observations might be partly based on conductivity measurements, because other information was not always available. The results of Data set 2 showed that farm observations were not only based on alerts from the model *ESx*. Sixteen out of 48 mastitis cases were observed on the farm but not detected by *ESx* (Table 5.5). The farm observations were adequate as shown by a comparison of average cell counts of the farm of Data 2 with eight other farms of PR (Figure 5.4). The level of cell counts of the AMS farm was comparable with the level of the other farms where mastitis observations could be based on observations in the milking parlour. The average cell count values of the AMS farm would be higher if clinical mastitis observations were not adequate.

The mastitis frequency on the AMS farm was comparable with the frequency on other farms (data not shown).

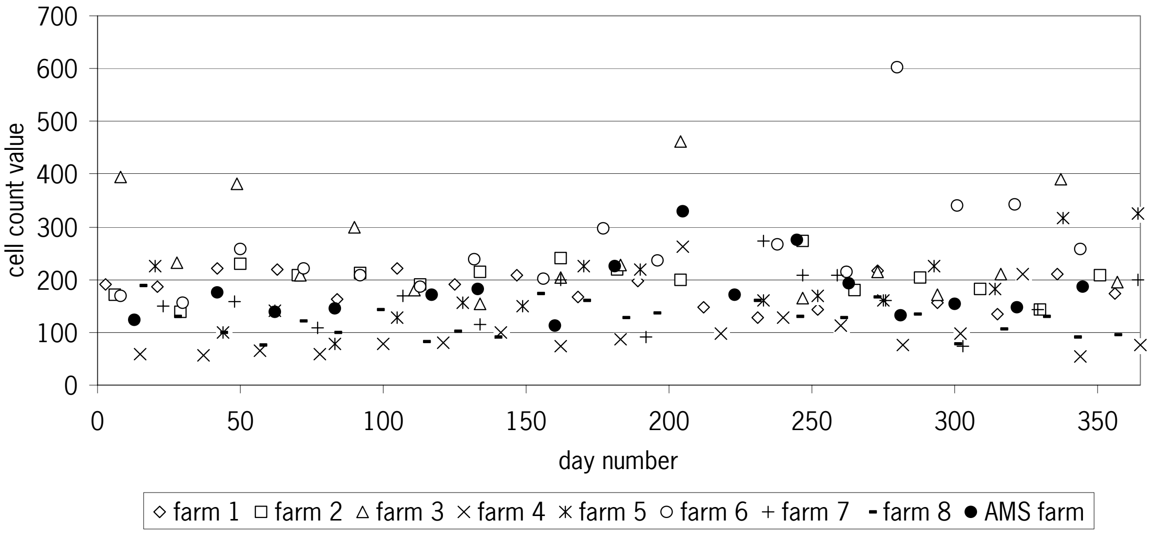


**Figure 5.4** The average value of cell counts samples (1,000 cells/ml) against day number (within the experimental period), on nine farms of PR.

The detection model *TSMx* for cows in an AMS, as described in Section 5.2.2.2, was based on an iterative regression procedure. It took a few days on a Pentium PC to process Data set 2. This procedure might be too time-consuming for practical application. The procedure could be improved by a more efficient programming, so that only a few seconds computer time after a milking would be enough. The same performance might be reached by using a Kalman filter (as in De Mol et al., 1999). A Kalman filter is an efficient alternative for the iterative use of linear regression, but a proper working was not guaranteed while interpolated values on previous variable values were used instead of actual values.

Data set 1 was limited (20 cows during 3 months). This data set was used both for model development and testing, so the results should be considered only as a preliminary indication. Further testing for mastitis detection was possible with Data set 2. Further testing for oestrus detection on a greater scale is recommended.

The number of FP alerts might be too high for practical application. According to the herdsman of the AMS farm, a detection model is only useful when the number of FP alerts is low compared with the number of TP alert (high predicting value positive). This number might be reduced by taking other influences into account. For example, changes in the feeding or disturbances in the barn might lead to alerts for all cows. These alerts were FP, but might be filtered easily. This modification is currently investigated.
Additional information that can also be used for detection purposes (but not used in the presented models) is the number of visits to the AMS and the concentrate feeder, the recorded concentrate leftovers and the occurrences of previous cases of clinical mastitis.

The absence of visual observations during milking on an AMS farm may lead to a worse detection performance, if no additional steps are taken. The economical consequences of changes in detection level, as mentioned in the introduction, were derived for farms where the cows were milked twice a day. But it might be expected that the consequences will be comparable for an AMS farm. In that case, an AMS farm with 100 cows could reduce the losses caused by clinical mastitis cases by more than $10,000 if the detection model reduces the mastitis level from twice the average level to the average level.

It appears to be impossible to reach a sensitivity and specificity level of both 100%. This means that there will remain a task for the herdsman in oestrus and mastitis detection.

## 5.5 Conclusions

Detection of oestrus and mastitis on farms with an AMS can be automated and present an adequate alternative for detection by visual observation in the milking barn. A detection model (*TSMx*) for cows milked with a variable frequency and intervals of milkings, as described in Section 5.2 can be used. The results are good: a high sensitivity: 100% (all cases are detected, if enough measurements are available) and a rather high specificity, 98%, in case of a confidence interval of 99.9%. Increasing the specificity is the subject of further research. The number of FP alerts may be reduced by monitoring the sensor performance or taking group effects or other influences into account.

The sensitivity found with model *TSMx* is higher than the sensitivity found with the model *ESx*, that is normally used on AMS farms. Therefore the model *TSMx* will be preferred over model *ESx*, although the specificity is lower because automated detection of all cases is the first priority on AMS farms.

The economic consequences from changes in detection level after the introduction of the AMS can be considerably. Automated detection of oestrus and mastitis can help to prevent these negative economic consequences.
Computer models can help in the detection of oestrus and mastitis, but they cannot take over completely the role of the herdsman.

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# *Chapter 6*

# Application of fuzzy logic in automated cow status monitoring

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**Abstract**

Sensors for measuring yield, temperature and electrical conductivity of milk, and for animal activity can be used for automated cow status monitoring. The occurrence of false positive alerts, generated by a detection model, creates problems in practice. Fuzzy logic was used for the classification of mastitis and oestrus alerts with the objective to reduce the number of false positive alerts, while keeping the level of detected cases of mastitis and oestrus at the same level. Input for the fuzzy logic model were alerts from the detection model and additional information, like the cow's status. The output was a classification, true or false, of each alert. Only alerts that were classified true should be presented to the herd manager. The additional information was used to check whether deviating sensor measurements where caused by mastitis or oestrus, or by other influences. A fuzzy logic model for the classification of mastitis alerts was tested on a data set from cows milked in an automatic milking system. All clinical cases without measurement errors were classified correctly. The number of false positive alerts from a subset of 25 cows was reduced from 1,266 to 64, by applying the fuzzy logic model. A fuzzy logic model for the classification of oestrus alerts was tested on two data sets. The number of detected cases decreased slightly after classification, and the number of false positive alerts decreased considerably. Classification by a fuzzy logic model proved to be very useful to increase the applicability of automated cow status monitoring.

*Keywords:* fuzzy logic, monitoring, oestrus, mastitis

Abbreviation key:

AMS = automatic milking system
FN = false negative
FP = false positive
$FP^+$ = false positive and classified as true
$FP^-$ = false positive and classified as false
TN = true negative
TP = true positive
$TP^+$ = true positive and classified as true
$TP^-$ = true positive and classified as false

## 6.1 Introduction

Automated cow status monitoring is possible by implementing sensors that measure milk yield, milk temperature, electrical conductivity of milk and the cow's activity (Frost et al., 1997; Geers et al., 1999). The sensor measurements are input data for a detection model, with alerts for oestrus, mastitis and other diseases as output data. A detection model for oestrus and mastitis has been developed in previous research (De Mol et al., 1999). The results from this statistical model can be satisfactory if the sensor equipment performs well (De Mol et al., 1997; De Mol et al., 2000). After a milking of a cow, an alert for oestrus or mastitis is given by the model if the combination of sensor measurements deviates from the normal cow pattern. The model in (De Mol et al., 1999) is applicable when the cows are milked twice a day at (more or less) fixed intervals. A detection model for cows milked in an Automatic Milking System (AMS) is described in (De Mol and Ouweltjes, 2000).

A problem for practical application of the detection model is the generation of false positive alerts. An alert is false positive if the cow with the alert is not in oestrus or does not suffer from mastitis. These false positive alerts are triggered by deviating measurements, caused by influences such as changes in feeding or outdoor temperature, and not necessarily associated with the presence of oestrus or mastitis. A method to classify alerts of the detection model as true or false is necessary.

Fuzzy sets are used to describe uncertainty, imprecision and vagueness in a non-probabilistic framework (Klir and Yuan, 1995; Zimmerman, 1996). This goal is largely accomplished through extension of traditional, binary set theory, to a transitional set theory in which the degree to which an element belongs to a set is defined by the level of membership. Fuzzy logic, also termed fuzzy inference systems, may be considered as a subset of fuzzy set theory. Typical applications include control, analysis of images and patterns, and datamining. Additional applications include decision support systems and modelling and simulation of natural and engineered systems. Fuzzy logic attempts to capture imprecise relations, and then use these relations to make inferences about system behaviour using if/then rules. This procedure can be described as mapping an input space to an output space, in which the mapping is one-to-one, many-to-one, or many-to-many.

The fuzzy logic model in the present research is to be used for the classification of mastitis and oestrus alerts from the detection model, which is based on a statistical analysis of sensor measurements. Only alerts that are classified as true should be presented to the herd manager. This fuzzy logic model is a formalisation of the reasoning of the herd manager when he is judging alerts. Alerts are classified as true or false by taking into account both the sensor measurements and other information explaining the cow's situation.

The aim of this research was to develop and test a fuzzy logic model for the classification of mastitis and oestrus alerts. The goal was to keep the same level of detected cases, and to substantially reduce the number of false positive alerts. A fuzzy logic model for the classification of mastitis alerts was tested on a data set originating from cows milked in an AMS. A more complex fuzzy logic model for the classification of oestrus alerts was tested on a data set originating from cows milked twice a day. The data sets used for the development and testing of the fuzzy logic models have been selected on basis of their success rate, i.e. the proportion of detected cases was high. However, the number of false positive alerts might be too high for implementation in practice.

## 6.2 Material and methods

The detection models developed in earlier research (De Mol et al., 1999; De Mol and Ouweltjes, 2000) were developed by application of sensor data and reference data, combined with a thorough data analysis. Sensor data were measurements of yield, temperature and electrical conductivity of milk, and the activity of each cow, for each milking during the experimental period. In the same period reference data, observations and milk samples, were collected, which made it possible to asses cases of oestrus and mastitis during this period. The sensor data were input for the detection model. The detection model processes these data, which can result in alerts for oestrus and mastitis in case of deviating measurements. The reference data were used to test the alerts.

### *6.2.1 Classification of milkings and cases*

After each milking of a cow, the detection model could give an alert for mastitis or oestrus. Thus a milking of a cow, not suffering from mastitis, or not in oestrus, was classified (see Table 6.1):

– *true negative* (TN) if there was no alert;
– *false positive* (FP) if there was an alert.

***Table 6.1***
*Classification of milkings into four categories of mastitis alerts: true positive (TP), false positive (FP), false negative (FN) and true negative (TN).*

| | alert | no alert |
|---|---|---|
| milking in mastitis period | TP | FN |
| milking outside mastitis period | FP | TN |

The *specificity* was defined as the percentage of TN milkings over all milkings outside mastitis periods:

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \cdot 100\%$$

For each case of mastitis or oestrus there was a certain period when alerts were to be expected from a detection model. For mastitis, this period was defined as a seven-day period prior to the day mastitis was observed. The preceding days were included because mastitis signs might already be noticeable. For oestrus, this period was a combination of the day oestrus was recorded, the previous day and the morning of the next day. Because oestrus signs might already be observed after the last milking of the day and will be detected at the first milking of the next day, the next morning was included. The previous day was included in this period because oestrus signs might already be present and detected by the model.

The definition of mastitis and oestrus periods implies that each case of mastitis or oestrus was (see oestrus example in Figure 6.1):
– *true positive* (TP) if one or more alerts were generated in the defined period each alert in this period was TP, therefore one case could have more than one TP milking;
– *false negative* (FN) if no alert was generated in the defined period.

The *sensitivity* was defined as the percentage of TP cases over all cases:

$$\text{sensitivity} = \frac{TP}{\text{TP} + \text{FN}} \cdot 100\,\%$$

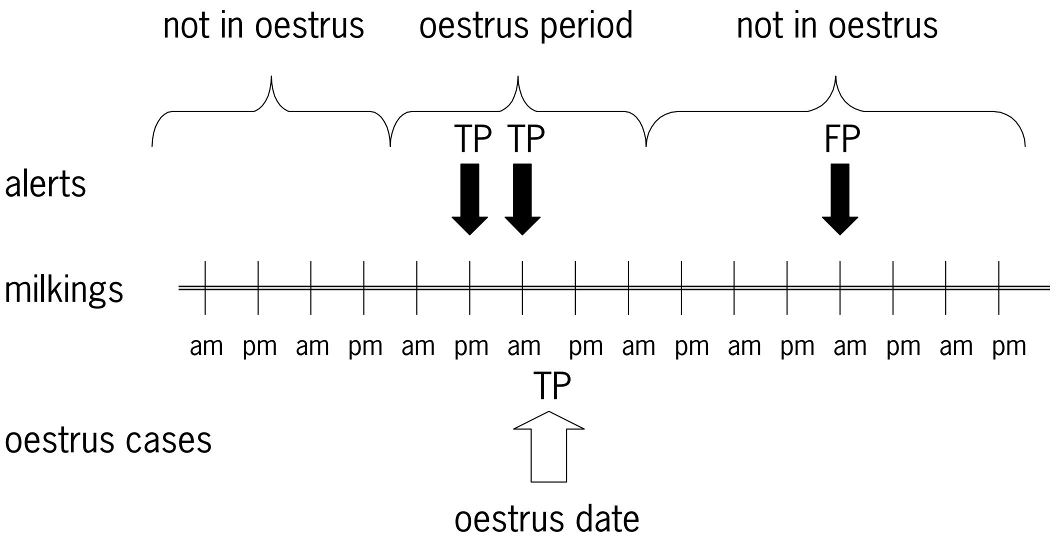


***Figure 6.1*** *Example of classification of oestrus alerts and an oestrus case: 16 milkings with one true positive (TP) oestrus case with two TP alerts in the oestrus period and one false positive (FP) alert outside the oestrus period.*

Sometimes, the detection model classification was complicated by measurement errors and start-up effects in the beginning of the lactation of a cow. These problems caused milkings to be *indeterminable*. If indeterminable milkings occurred in the defined period around a case of mastitis or oestrus, then:

– the case was still TP, if one or more alerts were given at other milkings within the same period;
– the case was FN if no alerts were given, but the absence of alerts might be caused by the measurement errors or start-up effects, resulting in indeterminable milkings.

To prevent a false measure of detection results, the specificity was calculated excluding the indeterminable milkings, and the sensitivity was based only on cases without indeterminable milkings.

A correct classification was not always possible for mastitis alerts, due to occasional lack of reference data. Reference data were observed cases of clinical mastitis, results of cell count samples, and results of bacteriological examinations. For the data set used (De Mol and Ouweltjes, 2000), a correct classification was only possible in the following cases:
– alerts in the defined mastitis period were TP for observed cases of clinical mastitis;
– alerts were FP for cows without any mastitis signs (no clinical cases, cell counts always below 500,000 cells/cc) throughout the experimental period (18 months).

A correct classification was not possible for alerts from cows with one or more cases of clinical mastitis outside the defined periods, or without clinical mastitis but with one or more samples with a high number of cell counts or a positive result from a bacteriological examination. These alerts were not taken into account for the analysis.

*6.2.2 Alerts from the statistical model*

Alerts from the statistical models (De Mol et al., 1999; De Mol and Ouweltjes, 2000) were based on a combination of deviations between expected and actual values of the sensor measurements. The probability of the observed deviations was determined by taking the variance of the deviations into account. A combination of variables was used instead of single variables, because a combination of deviations added credibility to the alert. For example:
– a cow in oestrus might have an increased activity along with a decreased milk yield and an increased temperature;
– a cow with mastitis might show an increased milk conductivity in addition to a decreased milk yield and an increased temperature.

An alert was given when the combination of deviations fell outside a given confidence interval: 95, 99 or 99.9%. Results depended on the selected confidence interval. Increasing the threshold of the confidence interval decreased the sensitivity but increased the specificity, and vice versa (De Mol et al., 1997; De Mol et al., 2000; De Mol and Ouweltjes, 2000).

### *6.2.3 Fuzzy logic*

In the current application, fuzzy logic is applied to classify alerts for mastitis and oestrus. Mastitis alerts are based on relative deviations in measured variables, and they can be evaluated by taking the value of the measured conductivity into account. An alert may be false if the conductivity value for the current milking is higher than the value for the previous milking, but still not exceeding the average level. This reasoning, based on relative and absolute values, is implemented in a fuzzy logic model.

A fuzzy logic system contains three steps (fuzzyTECH, 1999; Klir and Yuan, 1995; Zimmerman, 1996):

1. Fuzzification: Real variables are transformed to linguistic variables with several terms, each with a membership function with a range of [0,1]. For example, the real variable milk yield is transformed to a linguistic variable milk yield with the terms "low", "moderate" and "high". For a particular cow, the real yield value of 25 kg may be transformed to membership 0.0 of "low", membership 0.5 of "moderate" and membership 0.9 of "high", indicating that the yield is certainly not low, rather high and also somewhat moderate.

2. Fuzzy inference: The terms of the linguistic variables are applied in IF…THEN rules, where combinations of conditions lead to conclusions. For example: "IF yield is low AND milk temperature is high THEN health status is bad". Given these conditions, the health status is considered bad. Rules are grouped in rule boxes.

3. Defuzzification: The conclusions of the rules relate to terms of linguistic variables which have to be transformed back to real variables, e.g. a cow is yes or no healthy.

There is a mixture of qualitative and quantitative factors in oestrus detection, so an approach with analytical models may not be sufficient to produce results, that are applicable in practice. The use of fuzzy logic might be useful, because a fuzzy logic representation of knowledge can be applied. The classification of alerts was based on approximate reasoning (Klir and Yuan, 1995; Zimmerman, 1996). For example, if the activity is high and the cow's status is "in heat" then the oestrus alert is 'likely' to be true. Otherwise, if the activity is high, many cows show an increased activity and the cow's status is "in calf", the credibility of the oestrus alert is significantly reduced. Some conditions are crisp (high activity) but others are fuzzy (many cows). A crisp proposition is either true or false; a fuzzy proposition can be both true and false in some degrees of membership. A crisp proposition is either 0 or 1. The degree of membership for the proposition "many cows show an increased activity" can be 0.7 in some situation. Each factor will correspond with a fuzzy variable with a membership function that is used in IF...THEN rules. Fuzzy interference then leads to the classification true or false. Only alerts that are classified as true are presented to the herd manager.

### *6.2.4 Alerts from the fuzzy logic model*

A general scheme for the current application is given in Figure 6.2. The input of the fuzzy logic model was a combination of the alerts of the statistical model and additional information, that might help to exclude other causes of incorrect alert status. Additional information comprised the average and variance of sensor measurements in case of mastitis detection. In case of oestrus detection, the percentage of other cows with deviations, and information on the cow's status, were used as additional information. Automated cow status monitoring was thus realised in two steps: first alerts were calculated by the statistical model, and output of the statistical model was then input for the fuzzy logic model, where alerts were classified as true or false.

The resulting alerts from the statistical model were analysed and compared with the true cases, and the alerts were divided into TP alerts and FP alerts. The correct classification is known when reference data are available. The final results from the fuzzy logic model were analysed and compared with the confirmed true cases, which yielded four categories (see Table 6.2). The TP alerts are divided into $TP^+$ alerts (classified true) and $TP^-$ alerts (classified false); the FP alerts are divided into $FP^+$ alerts and $FP^-$ alerts. The main goal of this research was to develop a fuzzy logic model to maximise the number of $FP^-$ alerts, while at the same time minimising the number of $TP^-$ alerts.

***Table 6.2***

*Division of alerts by the fuzzy logic model.*

| | classified true | classified false |
|---|---|---|
| indeed TP | $TP^+$ | $TP^-$ |
| found FP | $FP^+$ | $FP^-$ |

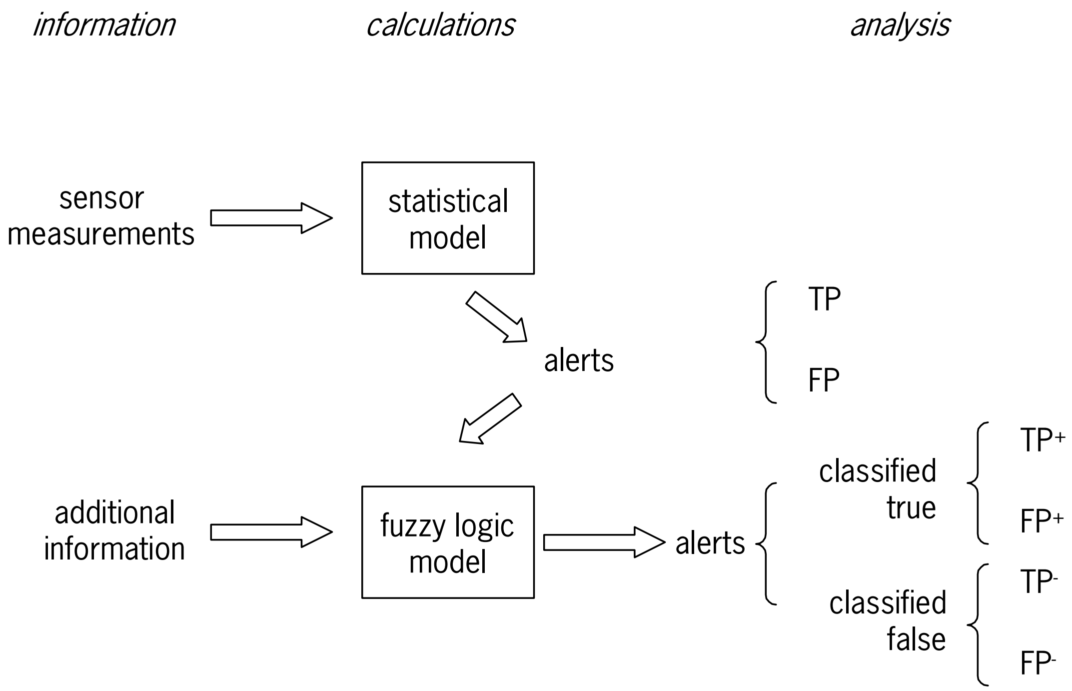


***Figure 6.2*** *Scheme for automated cow status monitoring based on a combination of calculations of the statistical model and the fuzzy logic model. See Table 6.2 for a description of variables.*

*6.2.5 Fuzzy logic model for the classification of mastitis alerts*

Automated mastitis detection, based on sensor measurements of the electrical conductivity of milk, shows varying results (Hamann and Zecconi, 1998). This is also true for the statistical model for cows milked twice a day (De Mol et al., 2000). The performance of the statistical model for cows milked in an AMS was good, all cases of mastitis without indeterminable milkings were detected (De Mol and Ouweltjes, 2000). The relatively high number of FP milkings in (De Mol and Ouweltjes, 2000) might be a problem for practical application. Therefore, this data set was selected to develop and test a fuzzy logic model for the classification of mastitis alerts.

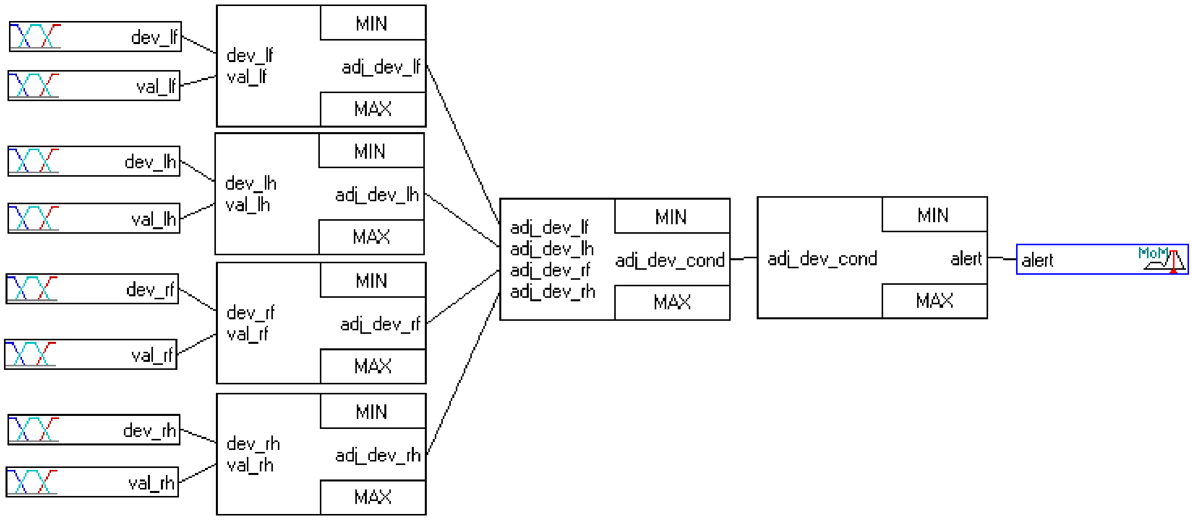


***Figure 6.3*** *Scheme for the fuzzy logic model for classification of mastitis alerts. For explanation, see Tables 6.4 and 6.5, and text.*

A fuzzy logic model was developed using the fuzzyTECH software (fuzzyTECH, 1999). The scheme for the mastitis alerts classification model is given in Figure 6.3. This scheme is divided into five sections (or columns):
1: interfaces for input variables;
2 and 3: rule blocks for the composition of intermediate variables;
4: rule block for the composition of the output variable;
5: interface for output variable.

The electrical conductivity of the milk was measured for each quarter of the udder. For each milking with a mastitis alert, input variables for the fuzzy logic model were:

– Standardised deviation in conductivity of each quarter: left fore (dev_lf, Figure 6.3), left hind (dev_lh), right fore (dev_rf), right hind (dev_rh). These variables were also applied to determine the alerts of the statistical model.

– Measured conductivity value of each quarter: (val_lf, val_lh, val_rf and val_rh; Figure 6.3). These values were additional information for the fuzzy logic model, and were only indirectly used in the statistical model.

It was found that FP alerts were generated when all quarters were aberrant. Therefore, these input variables were preprocessed:

– If, for a combination of a cow and a milking, all quarters showed a positive standardised deviation, then the standardised deviations of all quarters were decreased by the standardised deviation of the quarter with the minimal standardised deviation.

– If, for a cow and a milking, measured conductivity of all quarters was greater than the overall average value, then the measured values of all quarters were decreased by the difference between the value of the quarter with minimal value and the overall average.

The overall average and variance for the data set are given in Table 6.3.

***Table 6.3***
*Overall average value, variance and threshold for confidence intervals (assuming a normal distribution) of all electrical conductivity measurements (mS/cm) in the data set used for the classification of mastitis alerts.*

| quarter | average | variance | threshold for confidence intervals (%) | |
|---|---|---|---|---|
| | | | 95 | 99.9 |
| right hind | 4.719 | 0.2289 | 5.51 | 6.20 |
| right front | 4.705 | 0.2368 | 5.51 | 6.21 |
| left front | 4.712 | 0.2683 | 5.56 | 6.31 |
| left hind | 4.723 | 0.2514 | 5.55 | 6.27 |
| mean | 4.715 | 0.2464 | 5.53 | 6.25 |

The input variables were expressed in a linguistic form, in which their values were translated into terms like "increased" or "high". The definition of the membership functions for the standardised deviation was based on the one-sided confidence interval border of a normally-distributed variable. The membership functions for the measured value were based on the overall average and variance given in Table 6.3. The membership functions for the right hind quarter are given in Figure 6.4. The membership functions for other quarters were similar. If, for example, the standardised deviation is 2.5, the membership value for "increased" and the membership for "high", are both 0.7, and the membership value for the other two membership functions is zero. This indicates that the standardised deviation of 2.5 is both rather increased and rather high, to the same extent, but not very high.

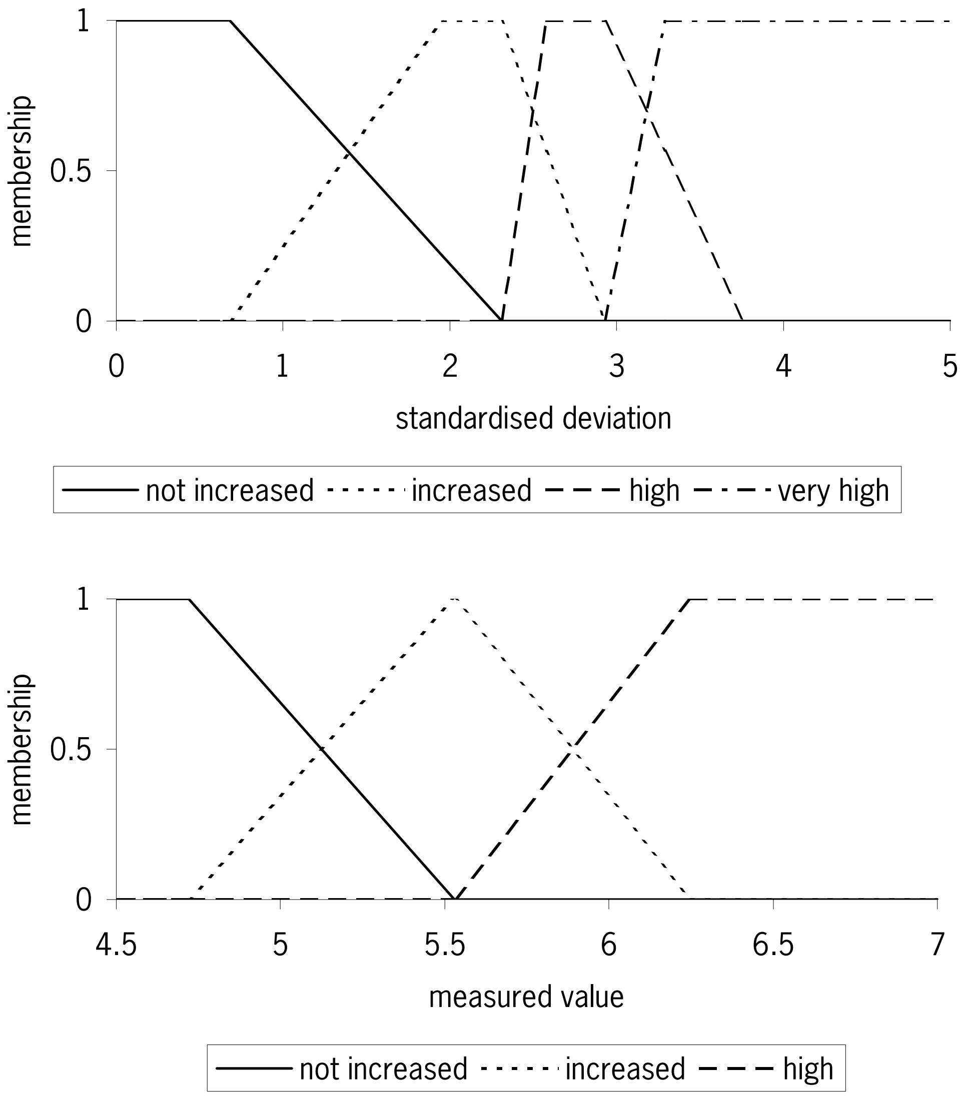


***Figure 6.4*** *Fuzzification of input variables of the right hind quarter as applied in Figure 6.3 for mastitis alerts: standardised deviation of electrical conductivity (top) and measured value (mS/cm, bottom).*

The fuzzy logic model contained six rule blocks: Four rule blocks in the second column in the scheme of Figure 6.3 were used to combine the standardised deviation and the measured value, which resulted in one intermediate variable per rule block (adjusted deviation in conductivity per quarter). One rule block combined the adjusted deviation per quarter into an overall adjusted deviation. The final rule block transformed the overall adjusted deviation into a classification of the alert: "true" or "false". For each alert of the statistical model, the input variables were first transformed into fuzzy expressions, using the membership functions described above. These fuzzy variables were inputs for the subsequent rule blocks and the final variable was defuzzified into a 'crisp' value: true or false.

The rule block for adjusting the standardised deviation of the right hind quarter is contained in Table 6.4. For example, in the last row this rule block states that IF the deviation is "very high" and the value is "high", THEN the adjusted deviation is also "very high". The adjusted deviation was based on the standardised deviation, but adapted if the conductivity value was "not increased" or "increased".

***Table 6.4***
*Rule block for the determination of the intermediate variable 'adjusted deviation right hind' (adj_dev_rh in Figure 6.3), based on the deviation and value of the conductivity of the right hind quarter (dev_rh and val_rh in Figure 6.3).*

| IF | | THEN |
|---|---|---|
| deviation right hind | value right hind | adjusted deviation right hind |
| not increased | not increased | not increased |
| not increased | increased | not increased |
| not increased | high | not increased |
| increased | not increased | not increased |
| increased | increased | not increased |
| increased | high | increased |
| high | not increased | not increased |
| high | increased | not increased |
| high | high | high |
| very high | not increased | not increased |
| very high | increased | increased |
| very high | high | very high |

In the subsequent rule block (column 3 in Figure 6.3), the adjusted deviations per quarter were integrated into an overall adjusted deviation, by taking the maximum value per term ("not increased", "increased", "high" or "very high") over all quarters.

In the final rule block, the adjusted overall conductivity is transformed into an alert classification (Table 6.5). This block indicates that an alert is true if the adjusted deviation of conductivity is "high" or "very high"; otherwise the alert is false. In applications, all terms of the adjusted deviation will be more or less true, the fuzzy value of alert is defuzzified by taking the maximum membership value of the terms "true" and "false".

***Table 6.5***
*Rule block for transforming the 'adjusted deviation conductivity' (adj_dev_cond, see Figure 6.3) to an alert classification.*

| IF | THEN |
|---|---|
| adjusted deviation conductivity | alert |
| not increased | false |
| increased | false |
| high | true |
| very high | true |

*6.2.6 Fuzzy logic model for the classification of oestrus alerts*

The fuzzy logic model for the oestrus alerts classification was developed using data from the experimental farm of IMAG-DLO in Duiven in 1993 and 1994 (De Mol et al., 1997). Data from a similar experiment were also available from the experimental farm of ID-DLO in Lelystad from 1993 and 1994. The Lelystad data were not used for fuzzy logic model development and were used as a test case. Data from cows that had never been in oestrus, and never been inseminated were excluded from testing.

The relation between the statistical model and the fuzzy logic model is depicted in Figure 6.2. The statistical model calculates oestrus alerts, which were input for the fuzzy logic model, in which they are classified true or false. The statistical model generated an alert when the combination of sensor measurements fell outside a confidence interval: 95, 99 or 99.9% (De Mol et al., 1999).

Factors that were used as additional information to evaluate oestrus alerts after a milking were:

– Cow status: calved, in heat, inseminated or in calf. Oestrus was not expected for cows in calf or in the first days after calving. Oestrus might be expected for cows in heat or inseminated, especially around three weeks after the last recorded case of oestrus (or insemination).

– Number of cows with alerts (including TP cows). If, for a specific milking, many cows showed an increased activity, then this increase was probably not caused by oestrus but by some other influence: rumour in the barn, change of grazing system, change in the weather during grazing.

– Strength of alert: combined and single. The larger the deviation, the more likely that there was really something happening with the cow.

The fuzzy logic model for the classification of oestrus alerts is depicted in Figure 6.5. This scheme is divided into four sections, or columns: the first column interfaces with the input variables, the second column includes rule blocks for the composition of intermediate variables, the third column with a rule block for the composition of the output variable, and the fourth column is an interface for defuzzification of the output variable.

The structure of the fuzzy logic model for the classification of oestrus alerts was comparable with the model for the classification of mastitis alerts, described in the previous section.

The input variables were:

– The standardised deviation in activity (dev_activ, Figure 6.5), standardised deviation in temperature (dev_temp) and standardised deviation in yield (dev_yield); these deviations were also used for the calculation of the alerts from the statistical model.

– The weighed percentage of cows with a deviating activity (perc_activ), deviating temperature (perc_temp) and deviating yield (perc_yield) for the actual milking. Cows with deviations outside the 99.9% confidence interval counted fully, cows with a deviation beyond the 95 or 99% confidence interval counted partly. The weighed percentage is in between 0% (no cows with a significant deviation) and 100% (all cows with a deviation outside the 99.9% confidence interval). These variables contained information about the behaviour of other cows.

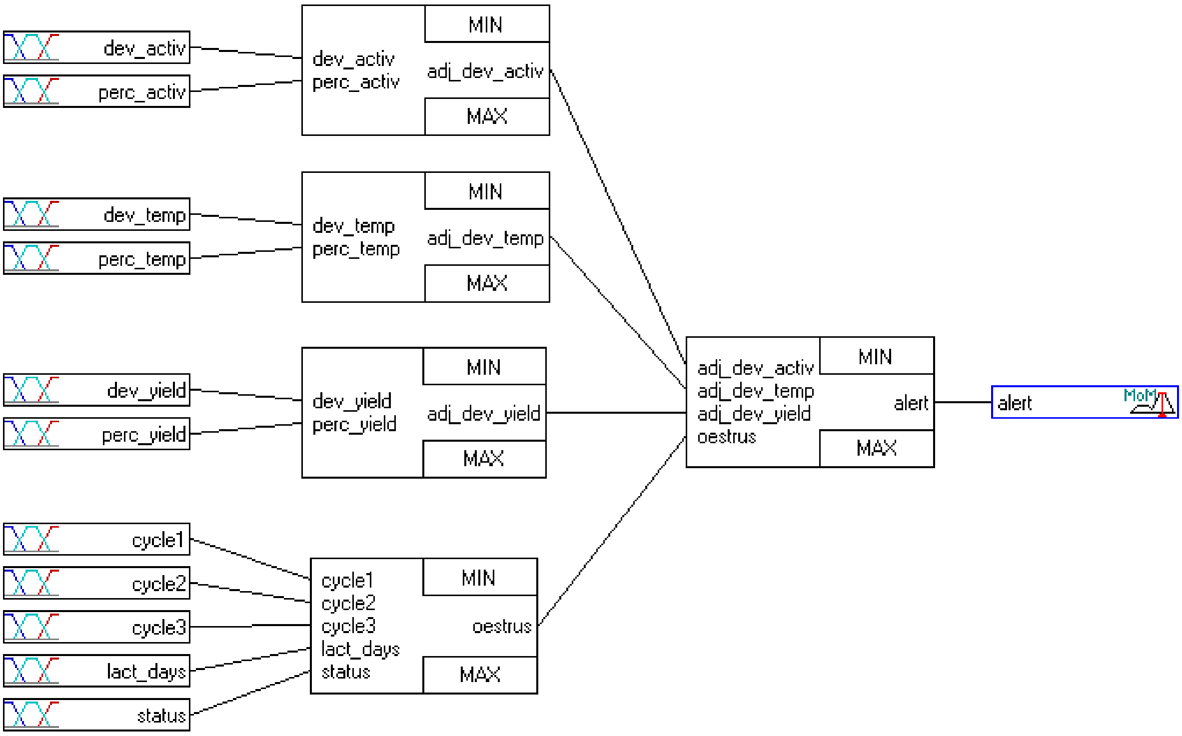


***Figure 6.5*** *Scheme of the fuzzy logic model for the classification of oestrus alerts. For explanation, see Table 6.6 and text.*

The cow status was used for the classification of oestrus alerts with the following input variables:

– A status code (status in Figure 6.5): "calved", "in heat" (but not yet inseminated), "inseminated" (but not yet confirmed in calf) or "in calf".

– The number of days in the actual lactation (lact_days).

Oestrus normally shows a cycle of about three weeks, so information about previous oestrus cases was useful in the classification. The following input variables represented this oestrous information:

– The number of 21-day cycles since last recorded case of oestrus (cycle1, Figure 6.5); used for cows with status in heat, oestrus might be expected if this number approached an integer value.

- The number of days since last insemination date, divided by 21 (cycle2, Figure 6.5); used for cows with status inseminated, oestrus might be expected if this number was close to 1 (and the insemination appeared to be not successful).

- The number of days since the oestrus alert which was closest to day 21 before the actual day (cycle3, Figure 6.5); used for cows with status in heat or inseminated to take oestrus cases into account that haven been detected by the statistical model but haven't been recorded on the farm.

The first three rule blocks in the second column of Figure 6.5 were used to determine the adjusted deviation of activity, temperature and yield, taking into account the behaviour of the other cows. The rule block for the adjusted deviation in activity is given in Table 6.6 as an example. The last rule of this block implies that IF activity is "very high" and "all" cows show an increased activity THEN the adjusted deviation is "increased".

The fourth rule block in the second column (Figure 6.5) was used to determine whether or not oestrus was to be expected, given the cycle and status information of the cow. The intermediate variable oestrus had two terms: "expected" and "not expected".

All intermediate variables were used in the rule block in the third column of Figure 6.5 where the fuzzy classification was determined, given all information on the activity, temperature, yield and the cow's cycle and status. The combination of intermediate variables was given a classification: true or false.

The last column in the scheme of Figure 6.5 is the defuzzification of the fuzzy variable 'alert'. This was done by taking the maximum membership value over the terms "true" and "false".

***Table 6.6***
*Example of a rule base from the scheme in Figure 6.5, used to adjust the deviation in activity (dev_activ) for the percentage of cows with an increased activity (perc_activ), into the adjusted deviation in activity (adj_dev_act).*

| IF | | THEN |
|---|---|---|
| deviation activity | percentage activity | adjusted deviation activity |
| not increased | none | not increased |
| not increased | minor part | not increased |
| not increased | half | not increased |
| not increased | major part | not increased |
| not increased | all | not increased |
| increased | none | increased |
| increased | minor part | not increased |
| increased | half | not increased |
| increased | major part | not increased |
| increased | all | not increased |
| high | none | high |
| high | minor part | increased |
| high | half | increased |
| high | major part | not increased |
| high | all | not increased |
| very high | none | very high |
| very high | minor part | high |
| very high | half | high |
| very high | major part | increased |
| very high | all | increased |

The classification model for oestrus alerts was based on the experiences with the statistical model in previous research (De Mol et al., 1997; De Mol et al., 2000). Attempts were made to further improve this model in two ways:

1. Optimisation by hand using a subset of the data set from the experimental farm in Duiven.
2. Optimisation by applying neural networks using the NeuroFuzzy option in fuzzyTECH (fuzzyTECH, 1999).

## 6.3 Results

### *6.3.1 Classification of mastitis alerts*

The data set used to develop and test the fuzzy logic model for the classification of mastitis alerts contained 48 observed cases of clinical mastitis of lactating cows. In Table 6.7 detection results are given for the statistical model and for the fuzzy logic model, based on alerts of the statistical model, using the 99% confidence interval.

***Table 6.7***

*Cases of clinical mastitis detected by the statistical model, as in De Mol et al., 2000, and by the fuzzy logic model: true positive (TP) cases, false negative (FN) cases, TP cases with indeterminable conductivity in mastitis period (TP/?) and FN cases with indeterminable conductivity in mastitis period (FN/?). Sensitivity defined as [TP/(TP+FN)]·100%.*

| | TP | FN | TP/? | FN/? | sensitivity (%) |
|---|---|---|---|---|---|
| statistical model | 19 | 0 | 24 | 5 | 100 |
| fuzzy logic model | 19 | 0 | 22 | 7 | 100 |

The fuzzy logic model only affected two TP cases with indeterminable milkings in the mastitis period. As these cases were excluded in the calculation of the sensitivity, the performance of the fuzzy logic model was comparable to that of the statistical model.

For the given data set, 25 cows didn't show any signs of mastitis, alerts of these cows were considered FP (Table 6.8). The total number of FP alerts was reduced from 1,266 to 64, by adding the fuzzy logic model. The specificity of the statistical model was 95.1%, the specificity of the fuzzy logic model was 99.75%.

The statistical model with a confidence interval of 99.9% gave 618 FP alerts (De Mol and Ouweltjes, 2000). Compared with these results, the fuzzy logic model also resulted in a considerable decrease in FP alerts (data not shown).

***Table 6.8***
*Number of milkings, indeterminable milkings, false positive (FP) alerts with the statistical model with the 99% confidence interval, as in De Mol et al., 2000, and false positive alerts classified true (FP⁺) by the fuzzy logic model, for 25 cows without any mastitis signs.*

| cow number | number of milkings | number of indeterminable milkings | number of FP alerts | |
|---|---|---|---|---|
| | | | statistical model (FP) | fuzzy logic model ($FP^+$) |
| 51 | 1,689 | 274 | 73 | 1 |
| 164 | 1,018 | 202 | 47 | 9 |
| 174 | 1,276 | 117 | 74 | 2 |
| 301 | 1,122 | 80 | 68 | 1 |
| 534 | 1,345 | 75 | 69 | 0 |
| 544 | 1,431 | 76 | 89 | 6 |
| 566 | 1,290 | 133 | 53 | 0 |
| 663 | 1,390 | 68 | 74 | 0 |
| 665 | 1,335 | 110 | 50 | 4 |
| 666 | 1,460 | 143 | 53 | 0 |
| 701 | 1,064 | 211 | 27 | 2 |
| 723 | 1,576 | 67 | 54 | 0 |
| 773 | 1,353 | 87 | 31 | 0 |
| 803 | 1,614 | 432 | 45 | 0 |
| 827 | 830 | 20 | 15 | 1 |
| 829 | 1,115 | 53 | 42 | 0 |
| 877 | 912 | 31 | 31 | 0 |
| 929 | 907 | 245 | 23 | 1 |
| 997 | 612 | 47 | 11 | 1 |
| 1000 | 580 | 63 | 19 | 0 |
| 4143 | 1,326 | 193 | 54 | 5 |
| 5225 | 999 | 74 | 46 | 5 |
| 5698 | 1,086 | 69 | 79 | 0 |
| 5804 | 1,202 | 77 | 121 | 26 |
| 9318 | 501 | 79 | 17 | 0 |
| total | 29,033 | 3,026 | 1,265 | 64 |

### *6.3.2 Classification of oestrus alerts*

#### *6.3.2.1 Duiven*

The classification of the oestrus alerts in Duiven, using the fuzzy logic model is given in Tables 6.9 and 6.10. The application of the fuzzy logic model reduced the number of FP alerts (only the alerts in category $FP^+$ are to be presented to the herd manager). In the case of a 99.9% confidence interval, 123 $FP^+$ alerts were given instead of 384 FP alerts, 6 $TP^-$ alerts were classified false and there were 3 TP oestrus cases less, resulting in a small decrease in sensitivity. The latter three cases related to:

1. Cow 732 (with status calved) for the afternoon milking of February 18, 1993. There were many cows with an increased activity, so the deviated activity was adjusted from increased to increased (with membership value 0.50) and not increased (0.72).

2. Cow 815 (with status inseminated) for the afternoon milking of January 16, 1993. In the beginning of the experimental period, so there was no information available on previous oestrus cases and alerts.

3. Cow 825 (with status in heat) for the afternoon milking of February 16, 1994. This cow was seen in heat only 7 seven days after calving on February 12, 1994. On February 16, she was thus 11 days in lactation with status in heat, but an oestrus was not yet expected, because the last one was three days earlier.

***Table 6.9***

*Number of oestrus alerts in the Duiven data set, classified by the fuzzy logic model into four categories: true positive classified true ($TP^+$), true positive classified false ($TP^-$), false positive classified true ($FP^+$), false positive classified false ($FP^-$), for three confidence intervals of the statistical model.*

| confidence interval (%) | $TP^+$ | $TP^-$ | $FP^+$ | $FP^-$ | total |
|---|---|---|---|---|---|
| 95 | 159 | 40 | 220 | 958 | 1,377 |
| 99 | 152 | 16 | 176 | 482 | 826 |
| 99.9 | 138 | 6 | 123 | 261 | 528 |

***Table 6.10***

*Number of true positive (TP) oestrus cases, sensitivity (percentage of all oestrus cases detected) and specificity (percentage of non-oestrus milkings without an alert), in the Duiven data set detected by the fuzzy logic model, for three confidence intervals of the statistical model.*

| confidence interval (%) | number of TP cases | sensitivity (%) (based on 179 cases) | specificity (%) (based on 23,381 milkings) |
|---|---|---|---|
| 95 | 115 | 71 | 98.8 |
| 99 | 113 | 70 | 99.1 |
| 99.9 | 107 | 67 | 99.3 |

Alerts were classified true, when the value of the fuzzy output variable exceeded 0.5. For the fuzzy output variables that were classified true (a value between 0.5 and 1.0), there was a clear difference between TP alerts and the FP alerts (Figure 6.6). The higher the value of the fuzzy output variable, the more likely the alert was TP.

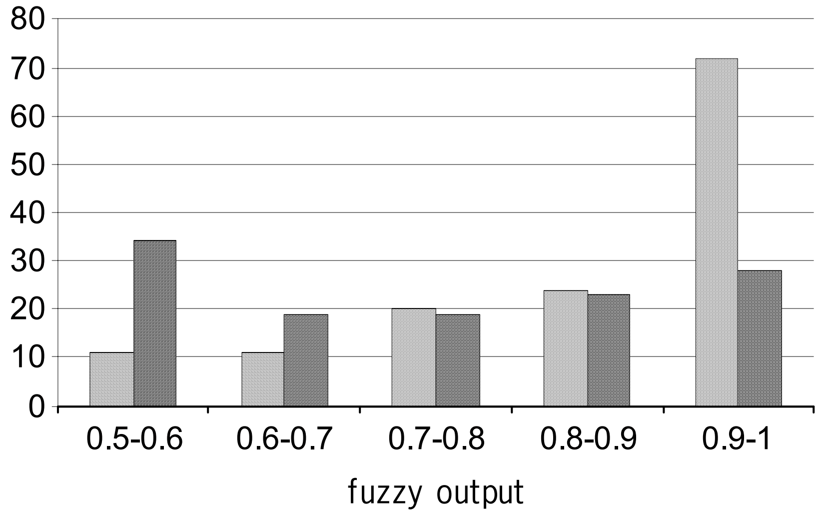


***Figure 6.6*** *Histogram of the fuzzy output variables classified as true oestrus alerts (number of alerts on the ordinate, 99.9% confidence interval), divided into 138 true positive alerts (light bars) and 123 false positive alerts (dark bars).*

*6.3.2.2 Lelystad*

The results of the classification of the oestrus alerts in Lelystad by the fuzzy logic model are given in Tables 6.11 and 6.12. Also in this case, the sensitivity decreased slightly and the specificity increased considerably (decreased number of false positive alerts).

***Table 6.11***

*Number of oestrus alerts in the Lelystad data set, classified by the fuzzy logic model into four categories: true positive classified true ($TP^{+}$), true positive classified false ($TP^{-}$), false positive classified true ($FP^{+}$), false positive classified false ($FP^{-}$), for three confidence intervals of the statistical model.*

| confidence interval (%) | $TP^{+}$ | $TP^{-}$ | $FP^{+}$ | $FP^{-}$ | total |
|---|---|---|---|---|---|
| 95 | 413 | 82 | 638 | 1,461 | 2,594 |
| 99 | 397 | 31 | 545 | 663 | 1,636 |
| 99.9 | 368 | 18 | 395 | 355 | 1,136 |

***Table 6.12***

*Number of true positive (TP) oestrus cases, sensitivity (percentage of all oestrus cases detected) and specificity (percentage of non-oestrus milkings without an alert), in the Lelystad data set detected by the fuzzy logic model, for three confidence intervals of the statistical model.*

| confidence interval (%) | number of TP cases | sensitivity (%) (based on 358 cases) | specificity (%) (based on 38,389 milkings) |
|---|---|---|---|
| 95 | 264 | 79 | 98.1 |
| 99 | 258 | 78 | 98.4 |
| 99.9 | 243 | 73 | 98.8 |

*6.3.2.3 The oestrus classification results after optimisation*

The classification model for oestrus alerts has been optimised manually firstly, by analysing the fuzzy inference for alerts in a subset. This subset contained 66 alerts. Selection was based on the results of Table 6.9 with the 99.9% confidence interval: all 6 $TP^{-}$ alerts, 20 $TP^{+}$ alerts, 20 $FP^{-}$ alerts and 20 $FP^{-}$ alerts (data within the latter three categories were randomly selected). The oestrus detection results after manual optimisation are given in Tables 6.13 and 6.14.

***Table 6.13***

*Number of oestrus alerts in the Duiven data set, classified by the fuzzy logic model after manual optimisation into four categories: true positive classified true ($TP^+$), true positive classified false ($TP^-$), false positive classified true ($FP^+$), false positive classified false ($FP^-$), for three confidence intervals of the statistical model.*

| confidence interval (%) | $TP^+$ | $TP^-$ | $FP^+$ | $FP^-$ | total |
|---|---|---|---|---|---|
| 95 | 161 | 38 | 212 | 966 | 1,377 |
| 99 | 152 | 16 | 156 | 502 | 826 |
| 99.9 | 137 | 7 | 106 | 278 | 528 |

***Table 6.14***

*Number of true positive (TP) oestrus cases, sensitivity (percentage of all oestrus cases detected) and specificity (percentage of non-oestrus milkings without an alert), in the Duiven data set detected by the fuzzy logic model after manual optimisation, for three confidence intervals of the statistical model.*

| confidence interval (%) | number of TP cases | sensitivity | specificity |
|---|---|---|---|
| 95 | 116 | 72 | 98.9 |
| 99 | 113 | 70 | 99.1 |
| 99.9 | 106 | 66 | 99.4 |

Secondly, optimisation of the classification model has been done by applying 'neurofuzzy' technologies. NeuroFuzzy is a combination of fuzzy logic and neural networks (fuzzyTECH, 1999). A rule base, represented as a neural network, can be optimised if an appropriate training set is given. The same subset as for the manual optimisation was used as training set for the neurofuzzy approach. It appeared that this approach was not worthwhile in our situation, since the classification results did not improve after the neurofuzzy training.

## 6.4 Discussion

### *6.4.1 Fuzzy logic*

Fuzzy logic has been used to classify alerts originating from a statistical detection model. This two-step approach (Figure 6.2) gives satisfactory results. The fuzzy logic analysis could have been implemented with comparable results into an analytical model. The application of fuzzy logic, however, gives a model that is easy to interpret (Figures 6.3 and 6.5) and easy to adapt, by changing the membership functions and the rule bases. Such modifications could be implemented by a specialist in detection (herdsman or veterinarian) and not necessarily by a modelling expert.

Classification is a well-known application field of fuzzy logic (Zimmerman, 1996). Fuzzy logic applications of classification in dairy farming are not known. The combination of a statistical model to detect relative changes and a fuzzy logic system to interpret the deviations turned out to be very valuable, because the number of FP alerts decreased considerably while the number of TP cases remained at the same level.

### *6.4.2 Classification of mastitis alerts*

The fuzzy logic model for the classification of mastitis alerts is simple in its nature. Only the deviations and measured values of conductivity are used. The results should be regarded with some care, because the same data set was used for the development of the model and for testing. The simplicity of the model suggests a broader application range. No optimisation steps for this model were taken, but improvements may be possible, e.g. changing model settings or by including other measured variables like milk yield and milk temperature.

A prerequisite for a good performance of the fuzzy logic model is a high sensitivity level. Increasing the specificity, while keeping the sensitivity at the same level, may be cumbersome. The sensitivity level for the given data set is not common, since results from other field-scale experiments showed (much) lower detection levels (De Mol et al., 2000).

The inclusion of other variables, like milk yield and temperature, can improve the fuzzy logic model. Unfortunately, in this data set, milk temperature recordings were not available.

A correct classification of the mastitis alerts was only possible around cases of clinical mastitis and for cows without any signs of mastitis during the experimental period. Alerts outside mastitis periods or for cows with an increased cell count were not taken into account in this research. In practice, most alerts will fall into this category, because most alerts are for mastitis cows or for cows that are suspected from mastitis.

Although the fuzzy logic model had a simple structure, the results were good: the sensitivity was 100% and the specificity was more than 99.5%. Thus all cases of clinical mastitis were detected (if there were no measurement errors) and the number of FP milkings was low: 64 (less than one per week) for a group of 25 non-mastitis cows. These levels appear to be appropriate for practical implementation of automated mastitis detection.

### *6.4.3 Classification of oestrus alerts*

The fuzzy logic model gave good results for Duiven and Lelystad. The results for Duiven were better than for Lelystad. Further analysis and adaptation of the fuzzy logic model, may improve the results for Lelystad. An example of differences between Duiven and Lelystad is given in Figure 6.7 where the relation between the cow status and FP alerts (99.9% confidence interval) is depicted.

The improvement of the fuzzy logic model over the statistical model, was mostly based on the inclusion of the status information. Most alerts of cows in calf were classified false by the fuzzy logic model. Adjusting of the deviations gave a second improvement. Inclusion of the cycle information was the least important factor in the fuzzy logic model to explain the improvements.

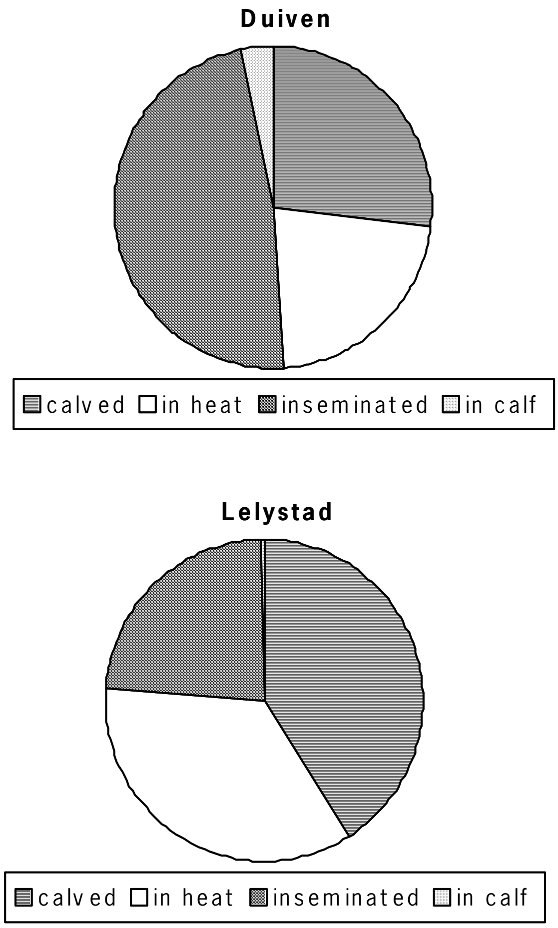


***Figure 6.7*** *Partition of false positive oestrus alerts of the fuzzy logic model (99.9% confidence interval) over cow status, for the Duiven and Lelystad data sets.*

Other ways to improve the fuzzy logic model are the use of 'expert knowledge' from the herdsman, or the use of advanced methods for the optimisation of fuzzy systems. Manual optimisation resulted in minimal improvement in results, and a neurofuzzy approach did not result in a better classification. There are several explanations for the poor performance of neurofuzzy technology in our case:

– The number of cases in the training set (or in the whole data set) was relatively small, compared to the total number of rules in the rule blocks in the fuzzy system. This limitation made optimisation without using inside knowledge difficult.

– There were two types of classification errors: $FP^{+}$ alerts and $TP^{-}$ alerts. In our case the $TP^{-}$ alerts should be given more emphasis, but that was not possible in the neurofuzzy approach.

– Defuzzification was performed by taking the maximum value of the terms of the output variable. This technique did conflict with the neurofuzzy approach where defuzzification by taking the mean of the terms of the output variable was assumed.

– Neurofuzzy without using any prior knowledge of the system was not possible given the high number of input variables. One rule block with all possible combinations of the terms of the input variables exceeded the system limits. The neurofuzzy approach could only be applied for rule blocks within a predefined structure, as in Figure 6.5.

The system was tested off-line. Using the fuzzy model on-line may give a (minor) improvement in the results because some input variables are based on previous alerts. In an on-line application only previous alerts that are classified 'true' should be used. Also the percentage of cows with an alert might be adapted when taking the classification results into account.

## 6.5 Conclusions

The fuzzy logic model gave a major improvement in the detection results, both in mastitis and oestrus detection. The number of false positive alerts was much lower. The number of true positive alerts remained at the same level. The combination of the statistical model for the calculation of alerts with the fuzzy logic model for the classification of alerts gave a detection method ready for practical usage.

## Acknowledgements

We are very grateful to the Research Station for Cattle, Sheep and Horse Husbandry for providing the data set that was used for the development and test of the classification model for mastitis alerts.

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# *Chapter 7*

# Discussion and conclusions

## 7.1 Introduction

The dairy farmer is facing several developments that influence his management: lower milk prices, increasing quality demands and increasing herd sizes. Detection of oestrus and diseases, like mastitis, by visual observation will become more difficult and may not be effective enough. Automated cow status monitoring can reduce the labour requirement and extend the intensity and frequency of monitoring. Automated monitoring can relief the management problems of the dairy farmer.

Two possibilities for the future of dairy husbandry are described in "Understanding the dairy cow" (Webster, 1987): a high technology and a low technology option. The low-tech option, small farms with one or two cows, only appears to be valid for certain third-world countries. In the high-tech option, an AMS and automated cow status monitoring are applied to make a more natural cow behaviour possible. In the latter option, the cow is not forced to fixed milking frequencies, but milked when she wishes. Also her feeding regime is more natural. Mastitis and metabolic diseases are detected in an early stage by application of robotics and computer techniques. The high-tech option has also advantages for the farmer: less repetitive work and more time for other tasks. Webster's outlook emphasises that automated cow status monitoring is not only profitable for the dairy farmer, but also of major importance for the cow. Cow status monitoring is the farmer's tool to fulfil the natural needs of the cow.

In the first chapter of this thesis, a framework for cow status monitoring has been presented. Depending on the application area, relevant variables have to be measured at an appropriate level (Tables 1.1 and 1.2). Measurement values are to be compared with chosen standards, so deviations can be detected. Monitoring makes it possible to perform the control function on a dairy farm. The elements of the framework will be evaluated in the next sections.

## 7.2 Application areas

The average herd size in The Netherlands has increased from 24 in 1975 till 48 cows in 1998. The number of farms with 100 or more cows increased in the same period from 636 to 1715 (LEI-DLO and CBS, 1999). Visual observation of oestrus and of disease symptoms is more difficult in larger herds. Thus a broader application range for automated cow status monitoring is emerging.

An automatic milking system (AMS) makes it possible to milk cows in the absence of a milker (Rossing et al., 1997). The number of farms in the Netherlands with an AMS at the turn of the century is estimated at 200. It is expected that this number will increase substantially in the near future. On an AMS farm, it is easier to increase the milking frequency, which results in a higher yield per cow. The introduction of an AMS also relieves the physical and mental load of the farmer. However, the absence of the farmer during milking makes automated cow status monitoring essential for dairy management. According to EU legislation (Directive 89/362), milk with abnormalities has to be removed. Abnormal milk can be detected by an automated monitoring system and subsequently be removed. As a consequence, false positive alerts lead to needless removal of good milk. The number of false positive alerts on an AMS farm should be as low as possible.

The described developments corroborate the role of automated cow status monitoring as a replacement for visual observation. Monitoring also comprises variables that are not yet available automatically for dairy management, but certainly have an added value. Examples of such variables are progesterone level and cell count in milk (see Table 1.2 for more). The inclusion of other variables should make it possible to monitor not only oestrus and mastitis, but also other infectious diseases and foot health. Each new variable needs its own detection model, which can be based on time series analysis or probability distribution combined with a Kalman filter, as described in Chapter 2. Other data processing techniques, however, may be better suited for new variables. In this thesis only techniques to detect fast changes of level (between successive milkings) in variables have been applied. Other techniques are certainly needed to detect slow changes in variables, e.g. in case of ketosis where the decrease in milk yield can be more gradually.

Reproduction control not only includes oestrus detection, but also pregnancy checking and timing of insemination. Monitoring can be an aid in reproduction control to establish calving intervals at preset targets.

An accounting system for minerals is compulsory for Dutch livestock farms. The inputs (feed, fertiliser) and outputs (milk, meat, manure) of nitrogen and phosphorus on a farm level are the quantities that have to be recorded. Monitoring the level of minerals in milk can be a help in mineral management. Several variables can be used for this purpose, e.g. urea and protein content of milk. Marshall and Fenwick (1999) describe several trends in dairy technology. One of them is a greater need for information on quality and safety. These demands from consumers will be implemented in the dairy production chain and be translated to the dairy farmers, e.g. as lower acceptable maximum levels for cell counts and residues of antibiotics in milk.

The monitoring methods described in this thesis may be applied in other areas of livestock farming. However, some characteristics of dairy farming can be an obstacle for application in other branches:

- Identification: individual treatment of cows is common practice and electronic cow identification is a means to make this possible. Electronic identification is mostly used for concentrate rationing, but is also a necessity for automated cow status monitoring. 'Precision farming' in dairy husbandry (Van 't Klooster and Amaha, 1998) is feasible if cows are identified automatically, and individual treatment, e.g. supply of concentrate rations, is adopted. Electronic animal identification is not common practise in other areas of livestock farming.
- Milking: cows are milked two or more times a day, which renders measurement of a lot of variables easy. Most variables used in the models in this thesis are related to milk (yield, temperature and electrical conductivity) or measured in the milking barn (cow's activity). Such an easy-to-use measuring point is not always available in other areas of animal husbandry.

Similar monitoring methods as for dairy cattle, are being applied in other fields (Chapter 2). Examples are condition monitoring in an industrial plant, river-flow forecasting and groundwater monitoring. Other applications can be found in econometry and in the biomedical area (e.g. Gordon and Smith, 1990).

## 7.3 Measurement methods

A lot of variables can be used for automated cow status monitoring (Table 1.2). The selection of variables depends on the actual area of application and desired measurement level. The objective, within an area of application, should be the starting point, and a combination of variables should be selected that can be measured in an adequate way, and that can be used for that objective. Variables that can be measured on-line during milking are logical candidates for application in monitoring. For example, the milk yield per quarter is easy to measure and can give valuable and detailed information for health control. Progesterone measurement in milk is an effective way to determine the reproductive status of a cow, and it is expected that in-line measurement is possible in the near future (Tang et al., 1998). The best methods available to measure other milk components are not yet fully developed, but further research may give opportunities to measure cell counts, and the contents of fat, urea and protein on-line.

Besides the milk variables, some other variables may be included in the monitoring process. Information on the cow's behaviour, like visiting patterns to feeding stations, may already be available in the process computer. The data on behaviour can be a help in health and reproduction control, but an appropriate data processing technique for this variable is still lacking.

The results of the previous chapters make clear that the quality of data collection has a major influence on the monitoring results. The worst mastitis detection results on three farms with the same conductivity sensor type (ALCQ, ANCQ1 and ANCQ2, Chapter 4) were found on the farm with the highest number of milkings with indeterminable conductivity. The sensitivity found on farms with conventional milkings systems (Chapter 4) and on an AMS farm (Chapter 5), was up to 80% and 100%, respectively. This difference can only be explained by the different location of the conductivity sensor in the milking parlour. Therefore, it is worthwhile to regard the implementation of the sensors and to monitor the performance of the equipment. The well-known rule "garbage in, garbage out" is also valid in the field of automated cow status monitoring.

The quality of the data also influences the complexity of the calculations. The model for electrical conductivity (Chapter 2) is complex, because deviations in conductivity may otherwise not be signalled. If there would always be a clear increase in conductivity in case of mastitis, and a cow without mastitis would never show such an increase, then a simple calculation might be appropriate. Complex calculations are only needed if the measurement signal is not enough discriminative.

## 7.4 Monitoring methods

Detection models are based on data processing techniques, that transform sensor measurements to alerts for aberrations (like oestrus or mastitis). Several data processing techniques have been used in the field of cow status monitoring, to determine standards and to compare measured levels with standard levels. A main distinction can be made in statistical techniques and intelligent techniques, although these terms may be confusing. Intelligent techniques are often based on a statistical technique (but often in a hidden form). Furthermore, one should not conclude from this distinction that statistical techniques are not intelligent. The distinction is mostly based on the difference in fields of application and disciplines from which the techniques emerged.

### *7.4.1 Statistical techniques*

Most detection models, applied in practice, are based on statistical techniques. A moving average or exponential smoothing model is a simple (and often effective) way to compare the actual measurement with the most recent preceding measurements (as in Hogewerf et al., 1992). The manufacturer's model, used as a reference in Chapters 4 and 5, is based on exponential smoothing. Statistical models in a broader sense, are the time series models, like the ARIMA models used in Deluyker et al. (1990), and the time series models used as a basis in Chapters 2 and 5. Alerts are generated when the probability of measured values, based on the calculated variance, is low. Parameters of an ARIMA model can be updated online using iterative regression analysis (Chapter 5) or a Kalman filter (Chapter 2). A main advantage of statistical techniques is the well-developed theoretical basis, which for example renders the determination of the significance of differences, between measured variables and standards, possible.

### *7.4.2 Intelligent techniques*

Intelligent techniques include fuzzy logic, neural networks, evolutionary computation and machine learning. Some of these techniques have been used for cow status monitoring. Neural networks were used for mastitis detection by Nielen et al. (1995). Some experiences with fuzzy logic and neural networks for oestrus detection are described in Eradus and Jansen (1999). Typical for neural networks is the need for training sets to train the network. This requirement can be a drawback because data can be specific for individual cows, and only limited data per cow may be available. So an appropriate training may not always be achievable in practice. Fuzzy logic is applied in Chapter 7 for the classification of alerts, generated by statistical techniques. The combination of statistical techniques and intelligent techniques turned out to be valuable to reduce the number of false positive alerts substantially, while keeping the sensitivity at the same level. Fuzzy logic resulted in an easy to grasp model that may be modified by dairy experts to add more inside knowledge and experience.

It is difficult to make a comparison of results based on the application of different techniques. Hamann and Zecconi (1998), in their meta-analysis of published data on electrical conductivity as a mastitis indicator, found that sensitivity results are divergent. High sensitivity was found in data sets with a high prevalence of mastitis. Results can be worse in practical circumstances, where prevalence of mastitis is low. The same hypothesis may be valid for oestrus detection. Good results are to be expected in small-scale experiments where everything is under control. Oestrus results may be worse in practice, where measurement errors and other disturbances will occur. In the research described in this thesis, the practical situation is approached as much as possible. Large data sets have been used without any preselection of data. This procedure gives detection results influenced by a lot of indeterminable variables in some cases. The results obtained with data sets without preselection, however, will give a good indication of the practical value of the detection models used.

## 7.5 Economic evaluation

Cow status monitoring will be introduced in practice only if there are economic benefits. The increase in economic results, reached by improved detection, should surpass the investments in equipment, time and support. This weighing is not straightforward because not all benefits and costs can be determined unequivocally.

Van Asseldonk et al. (1999a) found that an increase in oestrus sensitivity from 50 to 90%, resulted in an increased gross margin by Dfl. 1.28 (€ 0.58) per 100 kg fat and protein corrected milk per year under Dutch conditions. This assumed increase in sensitivity was based on a default sensitivity of about 50% by visual observation solely (Rougoor et al., 1997) and a sensitivity up to 90%, if appropriate sensors were installed (Chapter 2). The economic effects of mastitis are composed of reduced milk yield, treatment costs and premature culling (Houben, 1995). Early mastitis detection can reduce these costs.

The costs for different applications of cow status monitoring are interdependent, e.g. electronic cow identification can be used in automated concentrate feeders, but also for sensors in the detection of oestrus and mastitis. Dynamic programming was applied in Van Asseldonk et al. (1999b) to determine optimal investment patterns. The results depended on assumptions, as farm scale and other farm characteristics. The optimal investment pattern included automated concentrate feeders and activity sensors (if default oestrus sensitivity was average). The default sensitivity and specificity, used in Van Asseldonk et al. (1999b), were based on the opinions of experts (Van Asseldonk et al., 1998). The expected oestrus sensitivity on a farm with activity, yield and temperature sensors is 81%, with a specificity of 90%. These figures are lower than detection results found in this thesis (Chapter 3), which implies that investments in oestrus detection equipment might be beneficial in more cases than can be inferred from Van Asseldonk et al. (1999b). The expected clinical mastitis sensitivity on a farm with conductivity, yield and temperature sensors is 71%, with a specificity of 86%. These figures are also lower than the results found in this thesis (Chapter 3), and may increase the attractiveness of investment in mastitis detection equipment.

The results in Van Asseldonk et al. (1999b) were based on a conventional situation where cows are milked twice a day. For farms with an automatic milking system, the prospects for automated cow status monitoring are even better. The expected sensitivity and specificity, in a situation without sensors, are lower than on conventional farms, because visual observations during milkings are not available. Furthermore, the investments in sensor equipment will be lower for an AMS farm because a smaller number of milking stands (and thus of sensors) is required. The sensitivity and specificity for oestrus and mastitis in Chapters 5 and 6 are very high, compared with the figures expected by experts on conventional farms (Van Asseldonk et al., 1998). These good results are also in favour of the application of automated cow status monitoring on AMS farms.

## 7.6 Practical implementation

A successful introduction of cow status monitoring equipment is only possible if there are sufficient economic benefits (see previous section), but also if the equipment is enough user-friendly. As described in Chapter 1, monitoring (generation of alerts) should be followed by decisions to take appropriate actions in case of alerts. The main subject of this thesis is automated monitoring. Test results were evaluated afterwards by comparing alerts with reference data. These reference data are of course not available in practical situations, when the dairy farmer has to decide for himself whether he should believe the alert and maybe take some action. Monitoring is the first link in the chain. Taking appropriate decisions for actions will only be possible if monitoring is adequate.

The results of any detection model depend on the model settings. From the results in the previous chapters, it is easy to conclude that the sensitivity and specificity are negatively correlated: increasing the sensitivity will decrease the specificity and vice versa. A higher sensitivity indicates that more true cases will be detected, and a decreasing specificity indicates that there will be more false positive alerts, which will cause more inconvenience for the farmer. A higher specificity implies a lower sensitivity. More true cases will not be detected, which can give problems for the management, e.g. with insemination planning or with an increasing number of cases of clinical mastitis.

Sensitivity and specificity are not always good indicators for the applicability of detection models. The 'predicting value positive' can be more useful. The predicting value positive is defined as the proportion of the number of true positive alerts of the total number of alerts. For example in Section 6.3.2.1 (Table 6.6), the number of true positive alerts by the statistical model is 144, on a total number of 528 (in case of the 99.9% confidence interval), the predicting value positive is thus 27%. After the fuzzy classification, the predicting value positive is 138/(138+123) = 53%. The predicting value positive can be low (< 10%), even if the specificity may appear high (> 95%). The latter can happen if the prevalence is low (e.g. for mastitis). A low predicting value positive imposes a difficult task on the dairy farmer. He is supposed to consider every alert thoroughly and to reject the majority of the alerts, which can be an unsatisfactory job. Although false positive alerts appear to be inevitable, one should strive in practice for a predicting value positive of over 50%, implying that the majority of the alerts will be true positive. In that case, the farmer will consider each alert seriously and use his own expert knowledge and additional information to classify each alert.

For oestrus alerts, the dairy farmer should consider the stage of the oestrus cycle, other physiological symptoms, or take additional measurements (e.g. progesterone measurements), to decide whether or not an alert is true positive. Such a classification should be possible for an experienced farmer in most cases. In case of a true positive alert for a cow with status in oestrus, the farmer has to decide whether he wants to inseminate the cow or wait one or more cycles. This decision depends on the lactation stage of the cow, the planned calving interval and the expected success rate for insemination. If the cow is inseminated, the oestrus detection model will be an aid to determine the success; no alert is expected one cycle later in case of a successful insemination. If the cow is not inseminated, the classification of the alert will make it easier to detect successive cases of oestrus. This working method is implemented in the fuzzy logic model in Chapter 6. This process is elaborated further in handbooks like that of Brand et al. (1996).

The decision-making can be more difficult in case of mastitis alerts. The dairy farmer should inspect cows with a mastitis alert for visual abnormalities, and he can collect additional information (samples for cell count or bacteriological examination). The deviations, like increased conductivity, might be caused by another disorder. However, such actions are only useful if the predicting value positive is high. Furthermore, visual signs are only to be expected in case of clinical mastitis. Mastitis alerts may also be expected in case of subclinical mastitis. It may be difficult for the farmer to differentiate between false positive alerts and cases of subclinical mastitis. Also here, advisory services and handbooks (e.g. Brand et al., 1996) can be helpful.

Automated monitoring is also applicable for diseases, other than mastitis. Detection results for other diseases were characterised by a high sensitivity combined with a low specificity (Chapter 3). It is possible to detect most cases of disease by automated monitoring, but introduction in practice requires a lower number of false positive alerts.

## 7.7 Evaluation of research objectives

The objectives of the research, described in this thesis, were twofold (Section 1.3.1):

1. the development of a detection model for oestrus and mastitis, applicable on farms with a conventional milking system and on farms with an AMS;
2. a test of the model under practical conditions.

### *7.7.1 Model development*

The development of the detection model was step-wise, first a model for farms with a conventional milking system was developed (Chapter 2), based on advanced statistical techniques that have not been used in this field before. The relationship between successive values of a variable was made explicit in a time series model. Time series models have been derived for milk yield, milk temperature, cow's activity and milk conductivity. However, the parameters of these models appeared to vary with individual cows. A Kalman filter was applied to estimate the parameter values on-line. This approach provides each cow with her own model, which describes the characteristics and their variability of that individual cow. Furthermore, the Kalman filter makes it possible to process the variables in a combined way. An alert is given when the combination of measurement values falls outside the normal pattern of values for a particular cow.

A model for AMS farms (Chapter 5) was partly based on the model for farms with a conventional milking system. Again, time series models appeared to be an appropriate means to model the variables. These time series models are based on interpolated values of the variables, because the frequency is variable. The parameters appeared to be cow-dependent, also in an AMS. The parameter values, however, were not estimated by a Kalman filter, but iterative regression was applied. The resulting model had the same features: an individual approach, and alerts when the behaviour of the cow falls outside the normal pattern.

Additional to these models, a fuzzy logic model was developed to reduce the number of false positive alerts (Chapter 6). The alerts of the statistical models were input of the fuzzy logic model. Each alert is classified, using additional information describing other influences. The fuzzy logic model is a formalisation of the reasoning of the herdsman when he is judging alerts. The application of fuzzy logic for this purpose is new.

Although the models were developed for oestrus and mastitis detection, the same methodology can be used for other objectives, and in other fields. Measurements of variables can be modelled by time series models with on-line updating of parameter values by a Kalman filter or iterative regression. Fuzzy logic is an additional tool for interpreting signalled deviations.

*7.7.2 Test of the models*

Different data sets have been used to test to developed models. Major features of the results were the sensitivity (percentage of all cases detected) and the specificity (percentage of non-deviating milkings without an alert). The oestrus sensitivity differs for the different data sets, and detection models (Table 7.1). The results of Table 7.1 were obtained in different circumstances, and with different versions of the models, as described in the referred chapters. The sensitivity is always higher than the level reached in practice (ca. 50%, see Rougoor et al., 1997). The specificity (Table 7.2) should be high for practical implementation (> 99%) to get an acceptable balance between true and false positive alerts. This goal can be achieved by application of the fuzzy logic model.

The results of the present research imply that the performance goals for oestrus detection, as defined in Section 1.3.1, can be reached.

***Table 7.1***
*Oestrus sensitivity for different data sets and detection models.*

| data set | | | detection model | | | |
|---|---|---|---|---|---|---|
| reference | number of oestrus cases | farming system | IMAG [a] 95 | IMAG [a] 99 | IMAG [a] 99.9 | manu-facturer [b] |
| Table 3.2 | 537 | conventional | 94 | 87 | 83 | – [c] |
| Table 4.1 | 537 | conventional | 87 | 79 | 74 | – |
| Table 4.6 | 1452 | conventional | 80 | 71 | 63 | 63 |
| Section 5.3.1.1 | 8 | AMS | 100 | 100 | 100 | – |
| Table 6.7 | 179 | conventional | 71 | 70 | 67 | – |
| Table 6.9 | 358 | conventional | 79 | 78 | 73 | – |

[a] model developed in the present research, with confidence interval (%)
[b] model supplied with the sensors, used by default
[c] not determined

***Table 7.2***
*Oestrus specificity for different data sets and detection models.*

| data set | | | detection model | | | |
|---|---|---|---|---|---|---|
| reference | number of non-oestrus milkings | farming system | IMAG [a] 95 | 99 | 99.9 | manu-facturer [b] |
| Table 3.3 | 41,803 | conventional | 95.6 | 97.1 | 98.0 | – [c] |
| Table 4.1 | 60,665 | conventional | 93.7 | 96.4 | 97.8 | – |
| Table 4.7 | 354,674 | conventional | 93.6 | 96.7 | 98.1 | 97.7 [d] |
| Table 5.3 | 2,557 | AMS | 92.0 | 96.8 | 98.3 | – |
| Table 6.7 | 23,381 | conventional | 98.8 | 99.1 | 99.3 | – |
| Table 6.9 | 38,389 | conventional | 98.1 | 98.4 | 98.8 | – |

[a] model developed in the present research, with confidence interval (%)
[b] model supplied with the sensors, used by default
[c] not determined
[d] based on 206,907 non-oestrus milkings

Automated detection of all cases of clinical mastitis was not possible for most data sets (Table 7.3). The AMS farm was an exception to this rule. The detection difference may be caused by the different implementation of the conductivity sensor in an AMS. The specificity can reach the desired level by the additional use of fuzzy logic (Table 7.4). If the specificity equals 99.75%, the number of false positive alerts is acceptable for practical application.

***Table 7.3***
*Clinical mastitis sensitivity for different data sets and detection models.*

| data set | | | detection model | | | |
|---|---|---|---|---|---|---|
| reference | number of mastitis cases | farming system | IMAG [a] 95 | 99 | 99.9 | manu-facturer [b] |
| Table 3.4 | 52 | conventional | 96 | 90 | 65 | – [c] |
| Table 4.1 | 53 | conventional | 76 | 59 | 36 | – |
| Table 4.9 | 212 | conventional | 79 | 67 | 54 | 33 |
| Table 5.6 | 48 | AMS | 100 | 100 | 100 | 66 |
| Table 6.4 | 48 | AMS | – | 100 | – | – |

[a] model developed in the present research, with confidence interval (%)
[b] model supplied with the sensors, used by default
[c] not determined

***Table 7.4***
*Mastitis specificity for different data sets and detection models.*

| data set | | | detection model | | | |
|---|---|---|---|---|---|---|
| reference | number of non-mastitis milkings | farming system | IMAG [a] 95 | 99 | 99.9 | manu-facturer [b] |
| Table 3.5 | 6,495 | conventional | 95.3 | 98.2 | 99.4 | – [c] |
| Table 4.1 | 6,495 | conventional | 95.2 | 98.1 | 99.4 | – |
| Table 4.11 | 140,269 | conventional | 93.7 | 97.9 | 99.3 | 98.6 [d] |
| Table 5.8 | 29,033 | AMS | 87.4 | 95.1 | 97.6 | 99.3 |
| Table 6.9 | 29,033 | AMS | – | 99.75 | – | – |

[a] model developed in the present research, with confidence interval (%)

[b] model supplied with the sensors, used by default

[c] not determined

[d] based on 85,983 non-mastitis milkings

The commercially available sensors and detection models did not function well. The number of measurement errors under practical conditions (Chapter 4) was high. The detection results of the commercially available detection models were worse than the results of the models, developed in the present research. Both the sensitivity and specificity were higher, which means that the new models will detect more cases and, at the same time, give less false-positive alerts. The high number of false-positive alerts might be a reason for the low market penetration of existing systems. New models, based on a combination of statistical techniques and fuzzy logic, have a better market potential.

## 7.8 Main conclusions

– The results of automated oestrus detection are in between reasonable and good. They depend on the model settings and the circumstances (e.g. transponder around leg or neck). The sensitivity found in the different tests, always exceeds the sensitivity in practice (ca 50%). The specificity is at an acceptable level, especially if fuzzy classification is applied. Automated oestrus detection is ready for practical application.

– The results of automated mastitis detection are varying. Differences in the tests are mostly caused by different measurement methods (e.g. quarter or mixed milk) and implementation of sensors (difference between conventional farms and AMS farm). The poor results found in some cases, show that practical implementation is not always advisable. It is promising that the best results were found on an AMS farm, because in that case automated detection is mostly needed. A large-scale field test is recommended.

- Commercially available sensors and detection models require improvements. Sensors should become more reliable. The high number of measurement errors diminishes the practical applicability. The detection models should detect more cases and give less false-positive alerts.

- Detection models based on time series analysis, combined with a Kalman filter or iterative regression, require complex data processing techniques. These complex models outperform more simple models (based on exponential smoothing). The complex models make an individual cow approach possible. All relevant deviations in the sensor measurement values are detected, enabling detection of most cases of oestrus and mastitis.

- Application of fuzzy logic is well suited to interpret the detected deviations, and reduces the number of false positive alerts, thus making practical implementation easier. The combination of statistical models and fuzzy logic combines the best of both worlds. The statistical model detects deviating combinations of sensor measurements and the fuzzy logic model is an easy-to-interpret method to classify alerts, when additional information is available.

- The results in this thesis show good prospects for automated cow status monitoring. However, monitoring in itself is not enough, it should be followed by decision-making to take appropriate actions. Additional support for the farmer is required for field introduction of automated detection. A farmer should decide whether or not an alert is true positive, what the cause might be and how he should react to an alert. Monitoring might be improved by adding variables in the detection models. The decision-making is a field for further research.

- The significance of automated cow status monitoring is increasing while herd size increases, and the number of automatic milking systems (AMS) is expected to increase rapidly. An adequate detection of oestrus and mastitis is needed for adequate management, and the detection models described in this thesis meet the requirements.

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# *Summary*


**Introduction**

Monitoring is necessary to control dairy farming. Automated monitoring is a way to improve control. A modern dairy farmer may have various objectives for the application of automated monitoring systems: health control, reproduction control, quality control and others. The monitoring process is divided into three stages: 1) measurement of relevant variables, 2) determination of standards, and 3) comparison of measured values with the standards. For the latter stage of the monitoring process, reliable detection models are required.

The objectives of the research, described in this thesis, were twofold:

1. The development of a detection model for oestrus and mastitis in dairy cows, applicable on farms with a conventional milking system (twice a day with fixed intervals) and on farms with an Automatic Milking System (AMS). The detection model alerts for cows that need the farmer's attention, because of a possible oestrus or mastitis case. This model should be applicable, as part of a monitoring system, for the dairy farmer to support his operational management. The model is based on:
   - the application of commercially available sensors for measuring the milk yield, milk temperature, electrical conductivity of milk, cow's activity and concentrate intake;
   - a combined processing of the sensor data by applying advanced data processing techniques, selected after a structural analysis of the data characteristics.
2. A test of the detection model under practical conditions, with the following performance goals:
   - for oestrus detection: detection level at least as high as the current level reached in practice and meanwhile keeping the number of false alarms in practice at an acceptable level;
   - for mastitis detection: all cases of clinical mastitis should be detected timely (preferably before clinical signs are observable), cows suspicious of subclinical mastitis should be identified, and the number of false alarms should be acceptable;
   - the detection model should outperform the farmer (detection based on visual observation) as well as commercially available detection models (not based on combined processing).

### Detection model for farms with a conventional milking system

A detection model for cows milked twice a day was developed to process the measured variables in a combined way (Chapter 2). The model was based on time series models for milk yield, milk temperature, electrical conductivity of quarter milk and the cow's activity, and a probability distribution for the concentrate leftovers. The parameters of the time series models and the probabilities were fitted on-line for each cow after each milking by Kalman filters. Thus the variables could be combined to generate cow-specific alerts.

Sensor data, information from the management computer and reference data of two *experimental farms* (approx. 90 cows for two years) were available to test the detection model (Chapter 3). The test results were expressed as sensitivity (the percentage of all cases detected) and specificity (the percentage of normal milkings without an alert). For oestrus, sensitivity ranged between 94 and 83% (depending on the model setting), and was coupled with a specificity between 95 and 98%. For clinical mastitis, sensitivity ranged between 96 and 65%, for subclinical mastitis, this range was between 100 and 57%. The coupled specificity for mastitis (clinical and subclinical) ranged between 95.3 and 99.4%. For other diseases, the sensitivity ranged between 99.6 and 76.8% with a specificity between 86 and 97%.

Further testing was necessary, because information was lacking about the performance of the detection model *under field conditions*. The detection model was tested on four farms during several years (Chapter 4). The test gave insight into the field performance of the new model and the results were compared with the results of older models and with the results predicted by experts. Sensor data of milk yield, milk temperature, electrical conductivity of milk and cow's activity were the inputs for the new model. Results were compared with the manufacturer's model (supplied with the sensors), based only on exponential smoothing on data from one sensor. The sensor equipment differed between farms. The overall sensitivity for oestrus ranged between 80 and 63% (depending on the model setting). Specificity ranged between 94 and 98%. The sensitivity for clinical mastitis ranged between 79 and 54%. The specificity for mastitis ranged between 94 and 99%. There were great differences in sensitivity for oestrus and mastitis, between farms. The applied equipment could only partly explain the differences in oestrus and mastitis detection results between farms. The performance of the new detection model was better than that of the manufacturer's model and also better than expected by experts.

## Detection model for AMS farms

Especially in case of an *AMS*, automated detection of oestrus and diseases, such as mastitis, in dairy cows can be a good alternative for detection by observation during milking. A detection model (Chapter 5) was developed, based on a generalisation of a detection model for cows milked twice a day. Firstly, a model was described for cows milked three or more times a day, at fixed intervals. Secondly, a model was described for cows milked at variable times a day, at irregular intervals. The second model was appropriate for farms with an AMS and includes time series models for four variables (milk yield, milk temperature, cow's activity and electrical conductivity of milk), with interpolation on previous values. Parameter values and the residual variances were updated by linear regression after each milking. Alerts for oestrus or mastitis were given when the residuals fell outside given confidence intervals. Two data sets were used: the first set was complete and relatively small; the second set was large and only useful for mastitis detection. The first data set was used to develop the model for cows milked in an AMS and comprised 20 cows during 2.5 months. Measurements of all four variables were available. The test of the model on this data set showed good results: all cases of oestrus and mastitis were detected, the number of false positive alerts depended on the chosen confidence interval. The second data set, only used to test the model, comprised 111 cows during 16 months; only measurements of milk yield and electrical conductivity were available. The test of the model was only possible for mastitis detection: 42 to 44 (depending on the model setting) out of 48 cases of clinical mastitis were detected. The remaining cases were not detected because not all sensor data needed were available. These results were better than the results obtained with the model normally used on the farm where the second data set was collected. The number of false positive alerts depended on the chosen model setting and was higher than the number found with the model used normally.

## Reducing the number of false positive alerts with fuzzy logic

The occurrence of false positive alerts, generated by a detection model creates problems in practice. Fuzzy logic was used (Chapter 6) for the classification of mastitis and oestrus alerts, to reduce the number of false positive alerts, while keeping the level of detected cases of mastitis and oestrus at the same level. Input for the fuzzy logic model were alerts from the detection models and additional information, like the cow's status. The output was a classification, true or false, of each alert. Only alerts that were classified true should be presented to the farmer. The additional information was used to check whether deviating sensor measurements where caused by mastitis or oestrus, or caused by other influences. A fuzzy logic model for the classification of mastitis was tested on a data set from cows milked in an AMS. All clinical cases were classified correctly, if there were no measurement errors around the mastitis date. The number of false positive alerts from a subset of 25 cows, was reduced from 1266 to 64, by applying the fuzzy logic model. A fuzzy logic model for the classification of oestrus alerts was tested. The number of detected cases decreased slightly after classification and the number of false positive alerts decreased considerably. It was concluded that classification by a fuzzy logic model is very useful to increase the applicability of automated monitoring. The combination of a statistical and a rule-based approach works satisfactory. If the level of detected cases (true positives) is at an appropriate level, the developed fuzzy logic classification model reduces the number of false positive alerts.

**Main conclusions**

- The results of automated oestrus detection are in between reasonable and good. The sensitivity found in the different tests, always exceeds the sensitivity in practice (ca 50%). The specificity is at an acceptable level, especially if fuzzy classification is applied. Automated oestrus detection is ready for practical application.

- The results of automated mastitis detection are varying. Differences in the tests are mostly caused by differences in measurement methods and in implementation of sensors. The poor results found in some cases, show that practical implementation is not always advisable. It is promising that the best results were found on an AMS farm, because in that case automated detection is mostly needed.

- Commercially available sensors and detection models require improvements. Sensors should become more reliable. The high number of measurement errors diminishes the practical applicability. The detection models should detect more cases and give less false-positive alerts.

- Detection models based on time series analysis, combined with a Kalman filter or iterative regression, require complex data processing techniques. These complex models outperform more simple models (based on exponential smoothing). The complex models make an approach at the level of the individual cow possible. Most cases of oestrus and mastitis are detected.

- Application of fuzzy logic is well suited to interpret the detected deviations, and reduces the number of false positive alerts, thus making practical implementation easier. The combination of statistical models and fuzzy logic combines the best of both worlds.

- The results in this thesis show good prospects for automated cow status monitoring. However, monitoring in itself is not enough, it should be followed by decision-making to take appropriate actions. Additional support for the farmer is required for field introduction of automated detection.

- The significance of automated cow status monitoring is increasing while herd size increases, and the number of automatic milking systems (AMS) is expected to increase rapidly. An adequate detection of oestrus and mastitis is needed for adequate management, and the detection models described in this thesis meet the requirements.

# *Related publications by R.M. de Mol*


De Mol, R.M., R.T. van Zonneveld, B. Engel, A. Keen, W.J. Eradus, G.H. Kroeze, A.H. Ipema, K. Maatje and W. Rossing, 1992 - A model for monitoring health and reproduction based on a combined processing of variables. In: Ipema, A.H., A.C. Lippus, J.H.M. Metz and W. Rossing (eds.). - *Prospects for automatic milking. Proceedings of the international symposium on prospects for automatic milking Wageningen, Netherlands, 23-25 November 1992 (EAAP Publication No. 65, 1992)*. Pudoc Scientific Publishers, Wageningen, 527-530.

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# *Samenvatting*

**Inleiding**

Voor een melkveehouder is monitoring van koeien, ofwel afwijkingen bij koeien signaleren, belangrijk. Immers de melkveehouder moet weten wanneer een koe bronstig (tochtig) is, of mastitis (uierontsteking) of een andere ziekte heeft. De afwijkingen kunnen hiervoor een indicatie zijn. In geval van bronst zal de activiteit van een koe hoger zijn, daarnaast kan de melkgift lager en de melktemperatuur hoger zijn. Bij mastitis zal de elektrische geleidbaarheid van de melk hoger zijn, daarnaast kan ook in dit geval de melkgift lager en de melktemperatuur hoger zijn. Door toepassing van elektronische dieridentificatie (automatische herkenning) en sensoren in de melkput is het tegenwoordig vrij eenvoudig om, per koe en per melking, de melkgift, melktemperatuur, elektrische geleidbaarheid van de melk en de activiteit (met stappentellers) te meten. Een detectiemodel is vervolgens nodig om te bepalen of de gemeten waarden al dan niet afwijkend zijn.

Het doel van het onderzoek, dat in dit proefschrift wordt beschreven, was tweeledig:

1. De ontwikkeling van een detectiemodel voor bronst en mastitis bij melkkoeien, dat gebruikt kan worden op bedrijven die tweemaal daags melken en op bedrijven met een melkrobot (*automatic milking system, AMS*). Het detectiemodel moet, bij het melken, attenderen ('attenties' geven) op koeien die mogelijk bronstig zijn of mastitis hebben. Het model is, als onderdeel van een managementsysteem, een hulpmiddel voor de melkveehouder bij de dagelijkse bedrijfsvoering. Het model is gebaseerd op:
   - het gebruik van sensoren, voor melkgift, melktemperatuur, elektrische geleidbaarheid, activiteit en krachtvoeropname, die op de markt beschikbaar zijn;
   - een gecombineerde verwerking van de sensormetingen door toepassing van geavanceerde wiskundige technieken.
2. Een test van het detectiemodel onder praktijkomstandigheden, met de volgende doelstellingen:
   - voor bronstdetectie: minstens evenveel gevallen detecteren als nu in de praktijk gebeurt en tegelijkertijd het aantal gevallen van loos alarm op een acceptabel niveau houden.

– voor mastitisdetectie: alle gevallen van klinische mastitis (de acute gevallen) moeten tijdig gedetecteerd worden, het liefst voordat afwijkingen in de melk of aan de uier zichtbaar worden. Het aantal gevallen van loos alarm moet acceptabel blijven.
– het detectiemodel moet het beter doen dan de melkveehouder het doet door geregeld te kijken naar de koeien, en ook beter dan de modellen die al op de markt verkrijgbaar zijn (niet gebaseerd op een gecombineerde verwerking).

**Detectiemodel voor bedrijven die tweemaal daags melken**

Een detectiemodel voor koeien die twee keer per dag gemolken worden (zoals op de meeste Nederlandse bedrijven) is beschreven in hoofdstuk 2. Dit model is gebaseerd op zogenaamde tijdreeksmodellen voor vier variabelen (de melkgift, de melktemperatuur, de elektrische geleidbaarheid van de melk en de activiteit van een koe), en op een kansverdeling voor de niet-opgenomen krachtvoerporties. Deze kansverdeling geeft aan hoe waarschijnlijk het is dat een koe een bepaald deel van haar portie krachtvoer niet opneemt. De parameters in de tijdreeksmodellen en van de kansverdeling werden on line, voor elke koe en na elke melking, geactualiseerd met behulp van een Kalman-filter (een wiskundige techniek). Op deze manier kreeg elke koe haar eigen model en was het mogelijk om attenties te baseren op een gecombineerde verwerking van de variabelen.

Sensormetingen, informatie uit het managementsysteem en referentiemetingen van twee proefbedrijven van IMAG [1)] en ID-Lelystad [2)] (ca. 90 koeien gedurende twee jaar) waren beschikbaar om het detectiemodel te testen (hoofdstuk 3). De testresultaten waren uitgedrukt in de sensitiviteit (het percentage van alle gevallen dat gedetecteerd wordt) en de specificiteit (het percentage van normale melkingen waarbij terecht geen attentie wordt gegeven). De sensitiviteit voor bronst varieerde van 94 tot 83% (afhankelijk van de modelinstelling) gekoppeld aan een specificiteit van 95 tot 98%. Dat wil zeggen: bij een sensitiviteit van 94% was de specificiteit 95%; een hogere specificiteit ging ten koste van de sensitiviteit. De sensitiviteit voor klinische mastitis varieerde van 96 tot 65%, voor subklinische mastitis (de sluimerende gevallen) was dat 100 tot 57%. De gekoppelde specificiteit was 95,3 tot 99,4%. Voor andere ziekten dan mastitis, varieerde de sensitiviteit van 99,6 tot 76,8%, met een specificiteit tussen 86 en 97%.

[1)] Instituut voor Milieu- en Agritechiek; Wageningen
[2)] Instituut voor Dierhouderij en Diergezondheid; Lelystad

Deze testen werden uitgevoerd op proefbedrijven van onderzoeksinstituten, en geven een beperkte indruk van de prestaties van het detectiemodel onder praktijkomstandigheden. Daarom werd het model ook getest op vier bedrijven van het PR[3)] gedurende enkele jaren (hoofdstuk 4). De resultaten werden vergeleken met de resultaten van oudere modellen en met de verwachtingen van experts. Sensormetingen van melkgift, melktemperatuur, elektrische geleidbaarheid en activiteit waren de modelinput. De resultaten werden vergeleken met die van het model van de sensorfabrikant, gebaseerd op *exponential smoothing* (een wiskundige techniek) van enkelvoudige variabelen. De sensoruitrusting verschilde per bedrijf. De sensitiviteit voor bronst varieerde van 80 tot 63%, bij een specificiteit van 95 tot 98% (afhankelijk van de modelinstelling). De sensitiviteit voor klinische mastitis varieerde van 79 tot 54%, met een specificiteit voor mastitis van 94 tot 99%. Er waren grote verschillen in sensitiviteit tussen bedrijven. Deze verschillen konden slechts gedeeltelijk worden verklaard door de verschillen in sensoruitrusting. De resultaten waren beter dan verwacht op basis van het oude model en ook beter dan de verwachtingen van experts.

**Detectiemodel voor bedrijven met een melkrobot**

Automatische detectie van bronst en ziekten is speciaal voor bedrijven met een melkrobot belangrijk. Op deze bedrijven is er geen melker aanwezig tijdens het melken en waarneming van zichtbare afwijkingen tijdens het melken wordt niet gedaan. Een detectiemodel voor deze bedrijven, gebaseerd op een veralgemening van het model bij tweemaal daags melken, is beschreven in hoofdstuk 5. Eerst werd een model gemaakt voor koeien met een andere melkfrequentie (bijv. drie keer per dag). Daarna werd een model gemaakt voor koeien met een wisselende melkfrequentie, d.w.z. het aantal melkingen per dag en de intervallen tussen opeenvolgende melkingen is wisselend. Dit laatste model, bruikbaar voor bedrijven met een melkrobot, is gebaseerd op tijdreeksmodellen voor vier variabelen (melkgift, melktemperatuur, elektrische geleidbaarheid en activiteit) met interpolatie van voorgaande meetwaarden. De parameters in de tijdreeksmodellen werden per koe telkens geactualiseerd met iteratieve regressie (een statistische techniek). Voor het testen werden gegevens gebruikt van het proefbedrijf van IMAG (metingen van alle variabelen voor 20 koeien gedurende twee en een halve maand) en gegevens van het high-techbedrijf van het PR (metingen van melkgift en elektrische geleidbaarheid voor 111 koeien gedurende 16 maanden). De resultaten waren gunstig. Op het IMAG-bedrijf werden alle gevallen van bronst en mastitis gedetecteerd. Het aantal gevallen van loos alarm was afhankelijk van de modelinstelling. Op het PR-bedrijf was

[3)] Praktijkonderzoek Rundvee, Schapen en Paarden; Lelystad alleen een test voor mastitis mogelijk, 42 tot 44 (afhankelijk van de modelinstelling) van de 48 gevallen werden gedetecteerd. Bij de gemiste gevallen ontbraken sensormetingen, als gevolg van meetstoringen. Het model dat normaal werd gebruikt miste meer gevallen van klinische gevallen. Het aantal gevallen van loos alarm was afhankelijk van de modelinstelling en was hoger dan het aantal met het model dat normaal werd gebruikt.

**Vermindering van het aantal gevallen van loos alarm met fuzzy logic**

Gevallen van loos alarm, een ten onrechte gegeven attentie van het detectiemodel voor bronst of mastitis, kunnen in de praktijk problemen geven omdat de melkveehouder dan te vaak een koe nader moet bekijken terwijl er niets aan de hand is. Daarom werd *fuzzy logic* ('vage logica') gebruikt om het aantal gevallen van loos alarm te reduceren en tegelijkertijd de detectie van 'echte' gevallen van bronst en mastitis op een vergelijkbaar niveau te houden (hoofdstuk 6). De input voor het fuzzy-logicmodel bestond uit de attenties van het detectie-model en aanvullende informatie, zoals de status van de koe (bijv. drachtig of pas afgekalfd). De output was een classificatie van elke attentie: terecht of onterecht. Alleen de terechte attenties moeten worden doorgegeven aan de melkveehouder. De aanvullende informatie werd gebruikt om modelmatig te beoordelen of een attentie werd veroorzaakt door bronst (of mastitis), of door andere invloeden. Een fuzzy-logicmodel voor de classificatie van mastitisattenties werd getest met de gegevens van het high-techbedrijf van het PR. Alle gevallen van klinische mastitis werden juist geclassificeerd, indien er geen meetstoringen waren rond de mastitisdatum. Loos alarm daalde, voor een groep van 25 koeien, van 1266 naar 64 gevallen. Een fuzzy-logicmodel voor de classificatie van bronstattenties werd getest met gegevens van proefbedrijven van IMAG en ID-Lelystad. Het aantal gedetecteerde bronst-gevallen daalde licht, maar het aantal gevallen van loos alarm daalde aanzienlijk. Fuzzy logic bleek dus geschikt om de toepasbaarheid van automatische detectie te verbeteren. Als het aantal gedetecteerde gevallen op een geschikt niveau is, kan de classificatie met fuzzy logic het aantal gevallen van loos alarm sterk terugdringen.

**Belangrijkste conclusies**

– De resultaten van automatische bronstdetectie variëren van redelijk tot goed. De sensitiviteit, zoals gevonden in de verschillende testen, was altijd hoger dan in de praktijk (ca. 50%). De specificiteit is op een aanvaardbaar niveau, vooral als de classificatie met fuzzy logic wordt gebruikt. Automatische bronstdetectie is gereed voor praktijktoepassing.

- De resultaten van automatische mastitisdetectie variëren. De verschillen bij de testen werden grotendeels veroorzaakt door verschillen in meetmethoden en implementatie van de sensoren. De slechte resultaten in sommige gevallen, tonen aan de praktijktoepassing niet altijd is aan te bevelen. Het is hoopgevend dat de beste resultaten zijn bereikt op het melkrobotbedrijf, want in die situatie is de noodzaak tot automatische detectie het grootst.

- De sensoren en detectiemodellen die al op de markt zijn, behoeven verbetering. De sensoren moeten betrouwbaarder werken. De grote hoeveelheid storingen vermindert de praktische bruikbaarheid. De detectiemodellen zouden meer gevallen moeten detecteren en minder vaak loos alarm geven.

- Detectiemodellen gebaseerd op tijdreeksanalyse in combinatie met een Kalman-filter of iteratieve regressie zijn gebaseerd op complexe gegevensverwerkingtechnieken Deze complexe modellen geven betere resultaten dan de simpele modellen. De complexe modellen maken het mogelijk om de koeien individueel te beschouwen. De meeste gevallen van bronst en mastitis worden gedetecteerd.

- Fuzzy logic is heel geschikt om de gedetecteerde afwijkingen te interpreteren. Op deze manier kan het aantal gevallen van loos alarm sterk worden verminderd en de praktijktoepassing wordt gemakkelijker. De combinatie van statistische modellen en fuzzy logic combineert het beste van twee verschillende benaderingen.

- De resultaten in dit proefschrift geven aan dat de perspectieven voor automatische detectie goed zijn. Echter, detectie is op zich niet voldoende, de volgende stap is beslissen over ingrepen, zoals wel of niet insemineren, en wel of niet behandelen voor mastitis. Aanvullende hulp is noodzakelijk voor praktijkintroductie van automatische detectie.

- Het belang van automatische detectie neemt toe omdat de gemiddelde kuddegrootte blijft toenemen, en omdat het de verwachting is dat het aantal melkrobots snel zal toenemen. Goed management is alleen mogelijk bij een goede detectie van bronst en mastitis. De detectiemodellen, die in dit proefschrift zijn beschreven, kunnen daarbij helpen.

# *Curriculum vitae*

Rudolfus Maria de Mol werd op 29 juni 1961 geboren in Schaijk (N.Br.). Hij groeide op in Zeeland (N.Br.). In 1979 behaalde hij het diploma Voorbereidend Wetenschappelijk Onderwijs aan het College v.h. H. Kruis in Uden. Aansluitend begon hij aan de Technische Hogeschool Eindhoven aan de studie Wiskunde, die in juli 1986 werd afgerond met het doctoraal examen. Zijn afstudeeropdracht bij prof. J. Wessels had betrekking op het ontwerp van een uitbreiding van het personeelsplanningsysteem Formasy met pull-elementen en een andere dialoogopzet.

Sinds augustus 1986 werkt hij bij het instituut voor Milieu- en Agritechniek (IMAG) in Wageningen, momenteel bij de cluster Systeemkunde binnen de afdeling Technologie Open Teelten. In de eerste jaren werkte hij vooral aan de modellering van de mestlogistiek op regionaal niveau en op bedrijfsniveau. Later kwamen daar ook andere modelleertoepassingen in de landbouw bij, zoals de simulatie en de optimalisatie van de logistiek bij de inzameling van biomassa, de berekening van de ammoniakemissie bij het uitrijden en onderwerken van mest op bouwland in twee werkgangen, en de toepassing van datamining op gegevens van melkveebedrijven. Sinds 1992 is hij betrokken bij de ontwikkeling van detectiemodellen voor de melkveehouderij, waarvan dit proefschrift de weerslag is. Momenteel is hij ook betrokken bij het EGGQuality project, gericht op de ontwikkeling van ICT-toepassingen in de eiproductieketen.

# *Errata and adjustments*

de Mol, R.M., 2000. Automated detection of oestrus and mastitis in dairy cows. PhD thesis, Wageningen University, Wageningen, The Netherlands (177 pp., with summaries in English and Dutch).

| Page | Location | Text | Corrected |
|---|---|---|---|
| 59 | bottom of page | "submitted to Applied Engineering in Agriculture" | "published (with minor revisions) in Applied Engineering in Agriculture 17(3) 399-407" |
| 69 | equation | "(1)" | "(4.1)" |
| 75 | 3d paragraph | "Eq. (1)" | 'Eq. (4.1)" |
| 82 | 2d paragraph | "(Tables 9 and 11)" | "(Tables 4.9 and 4.11)" |
| 87 | bottom of page | "submitted to Preventive Veterinary Medicine" | "published (with major revisions) in Preventive Veterinary Medicine 49 (2001) 71-82" |
| 108 | Table 5.8 | totals from Table 5.7 are wrong | see below |
| 111 | 1st paragraph | "while the same conductivity sensors were used" | "because the same conductivity sensors were used" |
| 117 | bottom of page | "submitted to Journal of Dairy Science" | "published (with minor revisions) in Journal of Dairy Science 84 (2001) 400-410" |
| 121 | definition *true positive* (TP) | "the defined period each alert in this period was TP," | "the defined period; each alert in this period was TP," |
| 140 | last paragraph | "20 $FP^-$ alerts and 20 $FP^-$ alerts" | "20 $FP^-$ alerts and 20 $FP^+$ alerts" |
| 154 | Table 7.1 | "(Table 6.6)" | "(Table 6.9)" |
| 157 | Table 7.1 | "Table 6.7" | "Table 6.10" |
| 157 | Table 7.1 | "Table 6.9" | "Table 6.12" |
| 158 | Table 7.2 | "Table 6.7" | "Table 6.10" |
| 158 | Table 7.2 | "Table 6.9" | "Table 6.12" |
| 158 | Table 7.3 | "Table 6.4" | "Table 6.7" |
| 159 | Table 7.4 | "Table 6.9" | "Table 6.8" |
| 174 | 1st paragraph | "… miste meer gevallen van klinische gevallen" | "… miste meer gevallen van klinische mastitis" |

***Table 5.8***

*Mastitis detection for Data set 2, found with alerts of the model TSMx with three confidence intervals (% in brackets), and the model ESx, based on 29,033 milkings of 25 cows without mastitis signs, based on results in Table 5.7. Number of True Negative milkings (TN), number of False Positive milkings (FP), number of milkings with indeterminable conductivity (?), and specificity, defined as [TN/(TN+FP)]×100%.*

| model | TN | FP | ? | specificity (%) |
|---|---|---|---|---|
| *TSMx* (95) | 22,729 | 3,278 | 3,026 | 87.4 |
| *TSMx* (99) | 24,741 | 1,266 | 3,026 | 95.1 |
| *TSMx* (99.9) | 25,487 | 520 | 3,026 | 98.0 |
| *ESx* | 27,861 | 203 | 969 | 99.3 |

(30 November 2001)