J. Dairy Sci. 84:400–410

Application of Fuzzy Logic in Automated Cow Status Monitoring

R. M. de Mol* and W. E. Woldt†
*Institute of Agricultural and
Environmental Engineering (IMAG),
P.O. Box 43, 6700 AA Wageningen,
The Netherlands,
†University of Nebraska,
Dept. of Biological Systems Engineering,
Institute of Agricultural and Natural Resources,
253 L.W. Chase Hall,
Lincoln, NE 68583-0726

ABSTRACT

Sensors that measure yield, temperature, electrical conductivity of milk, and 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. We used fuzzy logic to classify mastitis and estrus alerts; our objective was to reduce the number of false-positive alerts and not to change the level of detected cases of mastitis and estrus. Inputs for the fuzzy logic model were alerts from the detection model and additional information, such as the reproductive 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. Additional information was used to check whether deviating sensor measurements were caused by mastitis or estrus, 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 over time 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 estrus 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 in increasing the applicability of automated cow status monitoring.
(**Key words:** fuzzy logic, monitoring, estrus, 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.

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., 1997). The sensor measurements are input data for a detection model, with alerts for estrus, mastitis, and other diseases as output data. A detection model for estrus 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, 1998). After a cow is milked, the model gives an alert for estrus or mastitis if the combination of sensor measurements deviates from the normal cow pattern. The model in De Mol et al. (1997) 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 the 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 estrus 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 are not necessarily associated with the presence of estrus or mastitis. A way of classifying alerts of the detection model as true or false is necessary.

Fuzzy sets are used to describe uncertainty, imprecision, and vagueness in a nonprobabilistic framework (Klir and Yuan, 1995; Zimmerman, 1996). This goal is largely accomplished through by extending 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

Received March 27, 2000.
Accepted July 31, 2000.
Corresponding author: R. M. de Mol; e-mail: R.M.deMol@imag.wag-ur.nl.

fuzzy inference systems, may be considered as a subset of fuzzy set theory. Typical applications include control, analysis of images and patterns, and data mining. Additional applications include decision support systems and modeling and simulation of natural and engineered systems. Fuzzy logic attempts to capture imprecise relations, and then use these relations to make inferences about system behavior with 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 estrus 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 formalization of the reasoning of the herd manager when (s)he is judging alerts. Alerts are classified as true or false by taking into account both the sensor measurements and other information about the cow. It is not possible to increase the number of true-positive alerts with this model.

The aim of this research was to develop and test a fuzzy logic model for the classification of mastitis and estrus 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 estrus 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 were 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.

MATERIALS AND METHODS

The detection models developed in earlier research (De Mol et al., 1997; De Mol and Ouweltjes, 2000) were developed by the application of sensor data and reference data, combined with a thorough statistical 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 assess cases of estrus 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 estrus and mastitis in case of deviating measurements. The reference data were used to test the alerts.

Table 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

Classification of Milkings and Cases

After each milking of a cow, the detection model could give an alert for mastitis or estrus. Thus, a milking of a cow not suffering from mastitis (or not in estrus) was classified (see Table 1):

- True negative (**TN**) if there was no alert;
- False positive (**FP**) if there was an alert.

The specificity was defined as the percentage of TN milkings over all milkings outside mastitis (or estrus) periods:

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

For each case of mastitis or estrus, there was a period when alerts were expected from a detection model. For mastitis, this was defined as a 7-d period before the day mastitis was observed. The preceding days were included because mastitis signs might have been noticeable by then. For estrus, this period was a combination of the day estrus was recorded, the previous day, and the morning of the next day. Because estrus signs might already have been observed after the last milking of the day and would be detected at the first milking of the next day, the next morning was included. The previous day was included in this period because estrus signs might have been present and detected by the model.

The definitions of mastitis and estrus periods imply that each case of mastitis or estrus was (see estrus example in Figure 1):

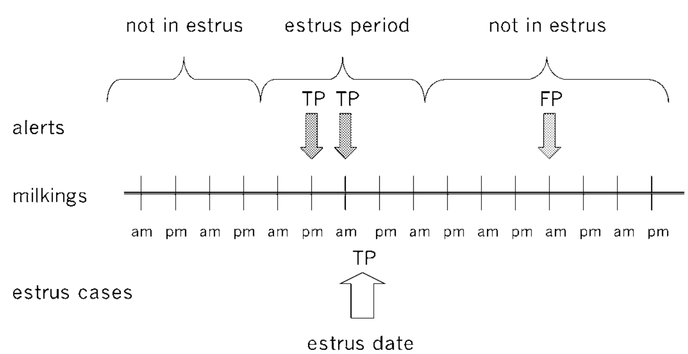

Figure 1. Example of classification of estrus alerts and an estrus case: 16 milkings with one true positive (TP) estrus case with two TP alerts in the estrus period and one false positive (FP) alert outside the estrus period.

- 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:

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

Sometimes, the detection model classification was complicated by measurement errors and startup 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 estrus, 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 have been 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 (clots in the milk or swollen quarters), 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 signs of mastitis (no clinical cases, cell counts always below 500,000 cells/cc) throughout the experimental period (18 mo).

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 considered for the analysis.

Alerts from the Statistical Model

Alerts from the statistical models (De Mol et al., 1997, 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 considering the variance of the deviations. 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 estrus might have increased activity along with decreased milk yield and increased temperature;
- A cow with mastitis might show increased milk conductivity in addition to decreased milk yield and 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, 1998; De Mol and Ouweltjes, 2000).

Fuzzy Logic

In the current application, fuzzy logic is applied to classify alerts for mastitis and estrus. Mastitis alerts are based on relative deviations in a number of measured variables, and they were evaluated by the value of the measured conductivity. 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 L 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 that have to be transformed back to real variables, e.g., a cow is yes or no healthy.

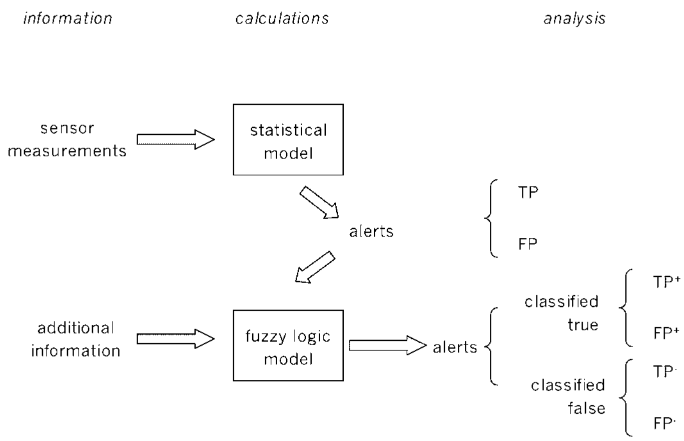

Figure 2. Scheme for automated cow status monitoring based on a combination of calculations of the statistical model and the fuzzy logic model. See Table 2 for a description of variables.

There is a mixture of qualitative and quantitative factors in estrus detection, so an approach with analytical models may not be sufficient to produce results that are applicable in practice. 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 reproductive status is "in heat," then the estrus alert is 'likely' to be true. Otherwise, if the activity is high, many cows show increased activity and the reproductive status is "in calf," the credibility of the estrus 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 situations. 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.

Alerts from the Fuzzy Logic Model

A general scheme for the current application is given in Figure 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 the case of estrus detection, the percentage of other cows with deviations and information on the reproductive status were used as additional information. Automated cow status monitoring was thus realized 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.

Table 2. Division of alerts by the fuzzy logic model.

	Classified true	Classified false
Confirmed TP	TP^+	TP^-
Confirmed FP	FP^+	FP^-

The resulting alerts from the statistical model were analyzed 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 analyzed and compared with the confirmed true cases, which yielded four categories (see Table 2). The TP alerts are divided into classified true alerts (**TP^+**) and classified false alerts (**TP^-**); the FP alerts are divided into classified true alerts (**FP^+**) and classified false alerts (**FP^-**). The main goal of this research was to develop a fuzzy logic model to maximize the number of FP^- alerts, while at the same time minimizing the number of TP^- alerts. The FP^- alerts are favorable because these FP alerts won't be presented to the farmer; TP^- alerts are unfavorable because these TP cases are lost for the farmer.

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., 1998). 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, the latter data set was selected to develop and test a fuzzy logic model for the classification of mastitis alerts.

A fuzzy logic model was developed using the fuzzyTECH software (fuzzyTECH, 1999). The scheme for the mastitis alerts classification model is given in Figure 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;

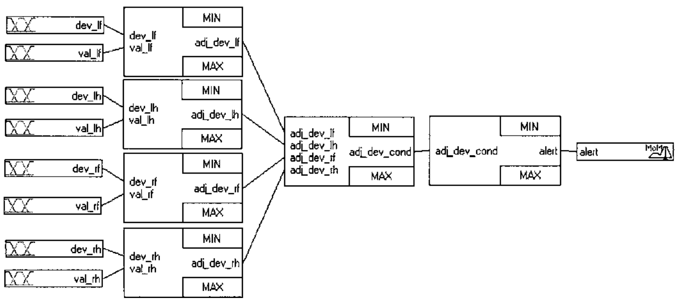

Figure 3. Scheme for the fuzzy logic model for classification of mastitis alerts. For explanation, see Tables 4 and 5, and text.

Table 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.

			Threshold for confidence intervals (%)	
Quarter	Average	Variance	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

4: rule block for the composition of the output variable; and

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:

- Standardized deviation in conductivity of each quarter: left fore (dev_lf, Figure 3), left hind (dev_lh), right fore (dev_rf), and right hind (dev_rh). These variables were also applied to determine the alerts of the statistical model. The standardized deviation is the difference between the expected and the measured value that is standardized by the variance of these differences.
- Measured conductivity value of each quarter: (val_lf, val_lh, val_rf, and val_rh; Figure 3). These values were additional information for the fuzzy logic model and were only indirectly used in the statistical model.

Some 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 standardized deviation, then the standardized deviations of all quarters were decreased by the standardized deviation of the quarter with the minimal standardized 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 3.

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 standardized 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 3. The membership functions for the right hind quarter are given in Figure 4. The membership functions for other quarters were similar. If, for example, the standardized deviation is 2.5, the membership values for increased and for high are both 0.7, and the membership value for the other two membership functions is zero. This indicates that the standardized deviation of 2.5 is both rather increased and rather high, to the same extent, but not very high.

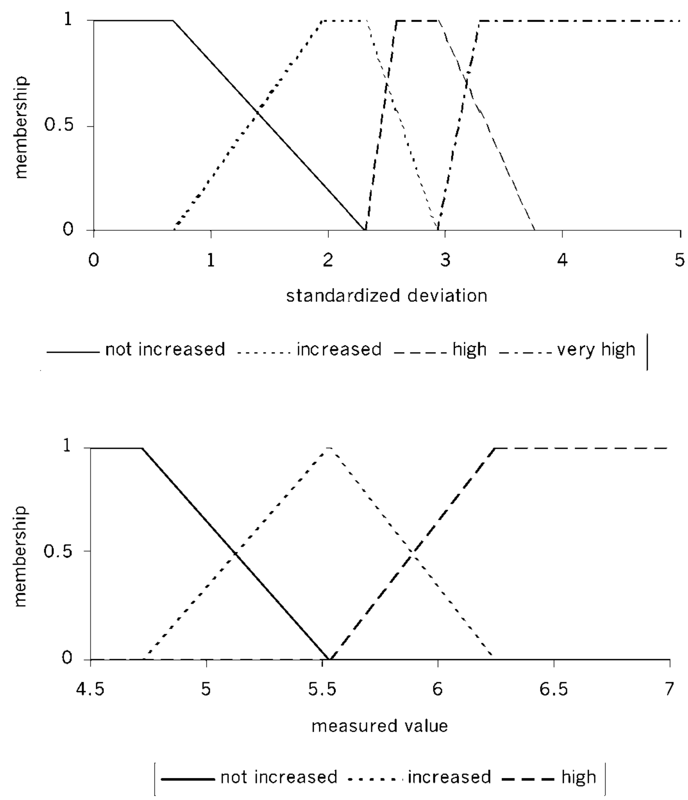

Figure 4. Fuzzification of input variables of the right hind quarter as applied in Figure 3 for mastitis alerts: standardized deviation of electrical conductivity (top) and measured value (mS/cm, bottom).

Table 4. Rule block for the determination of the intermediate variable 'adjusted deviation right hind' (adj_dev_rh in Figure 3), based on the deviation and value of the conductivity of the right hind quarter (dev_rh and val_rh in Figure 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

The fuzzy logic model contained six rule blocks: Four rule blocks in the second column in the scheme of Figure 3 were used to combine the standardized 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 standardized deviation of the right hind quarter is contained in Table 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 standardized deviation, but adapted if the conductivity value was not increased or increased.

In the subsequent rule block (column 3 in Figure 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 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 5. Rule block for transforming the 'adjusted deviation conductivity' (adj_dev_cond, see Figure 3) to an alert classification.

IF	THEN
Adjusted deviation conductivity	Alert
Not increased	False
Increased	False
High	True
Very high	True

Fuzzy Logic Model for the Classification of Estrus Alerts

The fuzzy logic model for the estrus 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 estrus and never been inseminated were excluded from testing.

The relation between the statistical model and the fuzzy logic model is depicted in Figure 2. The statistical model calculates estrus 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 estrus alerts after a milking were:

- Reproductive status: calved, in heat, inseminated, or in calf. Estrus was not expected for cows in calf or in the first days after calving. Estrus might be expected for cows in heat or inseminated, especially around 3 wk after the last recorded case of estrus (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 estrus, but by some other influence: noise 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 something really was happening with the cow.

The fuzzy logic model for the classification of estrus alerts is depicted in Figure 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

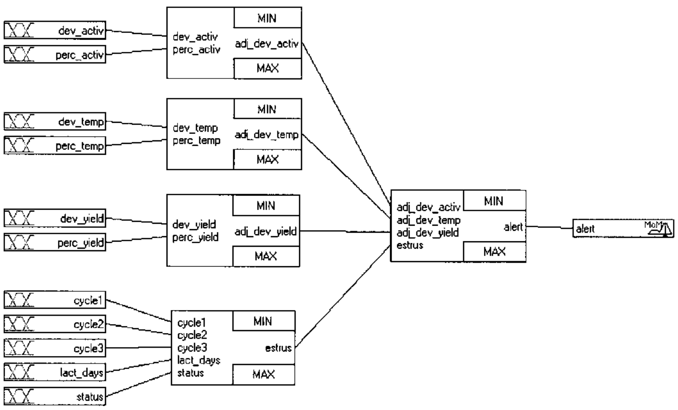

Figure 5. Scheme of the fuzzy logic model for the classification of estrus alerts. For explanation, see Table 6 and text.

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 estrus alerts was comparable to the model for the classification of mastitis alerts, described in the previous section.

The input variables were:

- The standardized deviation in activity (dev_activ, Figure 5), standardized deviation in temperature (dev_temp), and standardized 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 partially. The weighed percentage is 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 behavior of other cows.

The reproductive status was used for the classification of estrus alerts with the following input variables:

- A reproductive status code (status in Figure 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).

Estrus normally shows a cycle of about 3 wk, so information about previous estrus cases was useful in the classification. The following input variables represented this estrous information:

- The number of 21-d cycles since the last recorded case of estrus (cycle1, Figure 5); used for cows with reproductive status in heat, estrus might be expected if this number approached an integer value.
- The number of days since last insemination date, divided by 21 (cycle2, Figure 5); used for cows with reproductive status inseminated, estrus might be expected if this number was close to 1 (and the insemination appeared to be not successful).
- The number of days since the estrus alert that was closest to d 21 before the actual day (cycle3, Figure 5); used for cows with reproductive status in heat or inseminated to take estrus cases into account that have 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 5 were used to determine the adjusted deviation of activity, temperature and yield, taking into account the behavior of the other cows. The rule block for the adjusted deviation in activity is given in Table 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 5) was used to determine whether or not estrus was to be expected, given the cycle and reproductive status information of the cow. The intermediate variable estrus had two terms: "expected" and "not expected."

All intermediate variables were used in the rule block in the third column of Figure 5 where the fuzzy classification was determined, given all information on the activity, temperature, and yield and on the cow's cycle and reproductive status. The combination of intermediate variables was given a classification: true or false.

Table 6. Example of a rule base from the scheme in Figure 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

Table 7. Cases of clinical mastitis detected by the statistical model, as in De Mol and Ouweltjes (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 last column in the scheme of Figure 5 is the defuzzification of the fuzzy variable 'alert.' This was done by taking the maximum membership value over the terms "true" and "false."

The classification model for estrus alerts was based on the experiences with the statistical model in previous research (De Mol et al., 1997, 1998). Attempts to further improve this model were made in two ways:

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

RESULTS

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 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.

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 8). The total number of FP alerts was reduced from 1265 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 520 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 8. Number of milkings, indeterminable milkings, false-positive (FP) alerts with the statistical model with the 99% confidence interval, as in De Mol and Ouweltjes (2000), and false-positive alerts classified true (FP^+) by the fuzzy logic model, for 25 cows without any mastitis signs.

			Number of FP alerts	
Cow number	Number of milkings	Number of indeterminable milkings	Statistical model (FP)	Fuzzy logic model (FP^+)
51	1689	274	73	1
164	1018	202	47	9
174	1276	117	74	2
301	1122	80	68	1
534	1345	75	69	0
544	1431	76	89	6
566	1290	133	53	0
663	1390	68	74	0
665	1335	110	50	4
666	1460	143	53	0
701	1064	211	27	2
723	1576	67	54	0
773	1353	87	31	0
803	1614	432	45	0
827	830	20	15	1
829	1115	53	42	0
877	912	31	31	0
929	907	245	23	1
997	612	47	11	1
1000	580	63	19	0
4143	1326	193	54	5
5225	999	74	46	5
5698	1086	69	79	0
5804	1202	77	121	26
9318	501	79	17	0
Total	29033	3026	1265	64

Classification of Estrus Alerts

Duiven. The classification of the estrus alerts in Duiven, using the fuzzy logic model is given in Tables 9 and 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, six TP^- alerts were classified false, and there were three TP estrus cases fewer, resulting in a small decrease in sensitivity. The latter three cases related to:

1. Cow 732 (with reproductive 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).

Table 9. Number of estrus 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	1377
99	152	16	176	482	826
99.9	138	6	123	261	528

Table 10. Number of true positive (TP) estrus cases, sensitivity (percentage of all estrus cases detected) and specificity (percentage of nonestrus 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

2. Cow 815 (with reproductive 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 estrus cases and alerts.
3. Cow 825 (with reproductive status in heat) for the afternoon milking of February 16, 1994. This cow was seen in heat only 7 d after calving on February 12, 1994. On February 16, it was thus 11 d in lactation with reproductive status in heat, but an estrus was not yet expected because the last one was 3 d earlier.

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). The higher the value of the fuzzy output variable, the more likely the alert was TP.

Lelystad. The results of the classification of the estrus alerts in Lelystad by the fuzzy logic model are given in Tables 11 and 12. Also in this case, the sensitivity decreased slightly and the specificity increased considerably (decreased number of FP alerts).

The estrus classification results after optimization. The classification model for estrus alerts has been optimized manually first, by analyzing the fuzzy inference for alerts in a subset. This subset contained 66 alerts. Selection was based on the results of Table 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 estrus detection results after manual optimization are given in Tables 13 and 14.

Secondly, optimization 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 optimized if an appropriate training set is given. The same subset as for the manual optimization was used as training set for the neurofuzzy approach. It appeared that this approach was not worthwhile in our situation, because the classification results did not improve after the neurofuzzy training.

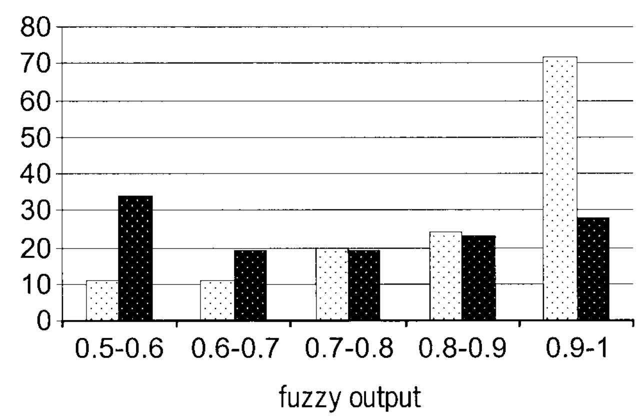

Figure 6. Histogram of the fuzzy output variables classified as true estrus alerts (number of alerts on the ordinate, 99.9% confidence interval), divided into 138 true positive alerts (light bars) and 123 false positive alerts (dark bars).

DISCUSSION

Fuzzy Logic

Fuzzy logic has been used to classify alerts originating from a statistical detection model. This two-step approach (Figure 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 3 and 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 modeling expert.

Classification is a well-known application field of fuzzy logic (Zimmerman, 1996). Fuzzy logic applications

Table 11. Number of estrus 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	1461	2594
99	397	31	545	663	1636
99.9	368	18	395	355	1136

Table 12. Number of true-positive (TP) estrus cases, sensitivity (percentage of all estrus cases detected) and specificity (percentage of nonestrus 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

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.

Classification of Mastitis Alerts

The fuzzy logic model for the classification of mastitis alerts is simple. 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 optimization 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 good performance of the fuzzy logic model is high sensitivity. 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, because results from other field-scale experiments showed (much) lower detection levels (De Mol et al., 1998).

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 mastitic cows or for cows that are suspected of 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 nonmastitis cows. These levels appear to be appropriate for practical implementation of automated mastitis detection.

Classification of Estrus 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 7, where the relation between the reproductive 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 reproductive status information. Most alerts of cows in calf were classified false by the fuzzy logic model. Adjusting the deviations gave a second improvement. Including the cycle information was the least important factor in explaining the improvements in the fuzzy logic model.

Other ways to improve the fuzzy logic model are the use of 'expert knowledge' from the herdsman, or the

Table 13. Number of estrus alerts in the Duiven data set, classified by the fuzzy logic model after manual optimization 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	1377
99	152	16	156	502	826
99.9	137	7	106	278	528

Table 14. Number of true-positive (TP) estrus cases, sensitivity (percentage of all estrus cases detected) and specificity (percentage of non-estrus milkings without an alert), in the Duiven data set detected by the fuzzy logic model after manual optimization, 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

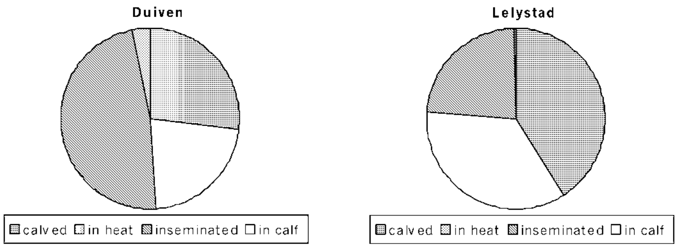

Figure 7. Partition of false positive estrus alerts of the fuzzy logic model (99.9% confidence interval) over reproductive status, for the Duiven and Lelystad data sets.

use of advanced methods for the optimization of fuzzy systems. Manual optimization 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 with the total number of rules in the rule blocks in the fuzzy system. This limitation made optimization 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 5.

The system was tested off-line. Using the fuzzy model on-line may provide 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.

CONCLUSIONS

The fuzzy logic model gave a major improvement in the detection results, both in mastitis and estrus 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.

ACKNOWLEDGMENTS

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.

REFERENCES

De Mol, R. M., G. H. Kroeze, J.M.F.H. Achten, K. Maatje, and W. Rossing. 1997. Results of a multivariate approach to automated estrus and mastitis detection. Livest. Prod. Sci. 48:219–227.

De Mol, R. M., W. Ouweltjes, and G. H. Kroeze. 1998. Detection of estrus and mastitis: Field performance of a model. Pages 865–883 *in* 7th International Conference on Computers in Agriculture, Orlando, FL, Am. Soc. Agric. Eng.; St. Joseph, MI.

De Mol, R. M., A. Keen, G. H. Kroeze, and J.M.F.H. Achten. 1999. Description of a detection model for estrus and diseases of dairy cattle based on time series analysis combined with a Kalman filter. Comput. Electron. Agric. 22:171–185.

De Mol, R. M., and W. Ouweltjes. 2000. Detection model for estrus and mastitis in cows milked in an automatic milking system. Pages 97–107 in Proc. International Symposium on Robotic Milking, August 17–19, Lelystad, the Netherlands.

Frost, A. R., C. P. Schofield, S. A. Beaulah, T. T. Mottram, J. A. Lines, and C. M. Wathes. 1997. A review of livestock monitoring and the need for integrated systems. Comput. Electron. Agric. 17:139–159.

fuzzyTECH. 1999. fuzzyTECH 5.3 User's Manual. INFORM GmbH.

Geers, R., B. Puers, V. Goedseels, and P. Wouters. 1997. Electronic identification, monitoring and tracking of animals. CAB International, Wallingford UK.

Hamann, J., and A. Zecconi. 1998. Evaluation of the electrical conductivity of milk as a mastitis indicator. Bulletin of the IDF, no. 334.

Klir, G. J., and B. Yuan. 1995. Fuzzy sets and fuzzy logic: Theory and applications. Prentice Hall, Upper Saddle River, NJ.

Zimmerman, H.-J. 1996. Fuzzy set theory and its applications, third ed. Kluwer Academic Publishers, Boston, MA.