

# **A DETECTION MODEL FOR HEAT AND DISEASES OF DAIRY CATTLE BASED ON TIME SERIES ANALYSIS COMBINED WITH A KALMAN FILTER**

**R.M. de Mol<sup>1</sup>, A. Keen<sup>2,1</sup>, G.H. Kroeze<sup>1</sup> & J.M.F.H. Achten<sup>1</sup>**

<sup>1</sup>DLO Institute for Agricultural and Environmental Engineering  
(IMAG-DLO), P.O.Box 43, 6700 AA Wageningen, The Netherlands,  
telephone +31 317 476459, telefax +31 317 425670,  
e-mail r.m.demol@imag.dlo.nl

<sup>2</sup>DLO Agricultural Mathematics Group (GLW-DLO)

**Abstract:** Sensor measurements can be used in dairy farming for the detection of heat 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 yield, temperature, conductivity and activity, and a probability distribution for the concentrates 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 attentions. Some results are given.

**Keywords:** heat detection, disease detection, time series, Kalman filter, management information systems

## **1 INTRODUCTION**

Timely recognition of heat and diseases is very important in dairy farming. Heat 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 of the farmer. Cows in heat 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 (see De Mol *et al.*, 1993 for a survey).

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. Automated methods have also been developed for disease detection.

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

The qualitative relationships between the measured variables and the occurrence of heat and diseases is shown in Table 1. This shows that temperature and activity are increased in case of heat, yield and feed intake may be decreased and conductivity is unchanged. The conductivity increases strongly during mastitis.

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

Models based on one variable have been developed in previous research for the detection of heat and diseases: for example the activity for heat (Erasmus *et al.*, 1992) or the conductivity for mastitis. Different variables are taken into account separately in later research (e.g. Maatje *et al.*, 1992).

It is clear from Table 1 that it is a significant improvement to consider the combination of variables for the interpretation of the measurements. An increased temperature can have different causes, but if it is coupled with an increased activity, heat 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 heat and diseases that can be a part of a MIS (De Mol *et al.*, 1992). This study is a co-operation among Alfa Laval Agri in Sweden, IMAG-DLO, DLO Research Institute for Animal Husbandry and Animal Health (ID-DLO).

## 2 THE STRUCTURE OF THE MODEL

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

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

For each cow and each day:

- the concentrates intake and the ration.

Table 1. The relations between measured variables and the occurrence of heat and diseases, *pos* = a significant positive influence, *neg* = a significant negative influence and - = no influence (after Hogewerf *et al.*, 1992).

	Yield	Temperature	Conductivity	Activity	Feed intake
Heat	<i>neg/-</i>	<i>pos</i>	-	<i>pos</i>	<i>neg/-</i>
Mastitis	<i>neg</i>	<i>pos</i>	<i>pos</i>	-	<i>neg/-</i>
Other infective dis-	<i>neg</i>	<i>pos</i>	-	<i>neg</i>	<i>neg/-</i>
Metabolic diseases	<i>neg</i>	-	-	<i>neg</i>	<i>neg</i>
Lameness	<i>neg</i>	-	-	<i>neg</i>	<i>neg</i>

Measurements are available from the experimental farms of IMAG-DLO in Duiven and from ID-DLO in Lelystad obtained in 1993 and 1994. See Maatje *et al.*, 1992 for more information on 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 can be used for the development of the model. In the past mostly quite simple statistical techniques were used, like the moving average. A structure that is based on more advanced statistical techniques, namely time series analysis combined with a Kalman filter, is described here.

Time series analysis has already been used for the milk yield in Deluyker *et al.*, 1990 where a generally applicable model is 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 the underlying model to calculate predictions for the measurements with standard errors;
- 2 read the actual new measurements;
- 3 compare the actual and the predicted values and generate an attention if the combination of variables is aberrant;
- 4 use 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 attentions in case of abnormal behaviour, possibly due to heat or illness. The underlying models for yield,

temperature, conductivity and activity are time series models (described in Section 3), for the concentrates intake a probability distribution is used (Section 4). Kalman filters are used to update the parameters in these models (Section 5).

### 3 TIME SERIES MODELS FOR COW VARIABLES

Time series are observations of a phenomenon made sequentially in time (see Chatfield, 1989 for an introduction). Consequently, the measurements of the variables are time series. A characteristic of time series is the fact that in general the successive observations are not independent, but related in some way or another. 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. A great deviation may point to a heat or a disease. It is assumed that the model is valid for healthy cows that are not in heat, 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 and fit the chosen model. This procedure has been applied for the separate cow variables (de Mol, 1993). Appropriate time series models have been found for the cow variables yield, temperature, conductivity and activity. 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 quite different for different 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 (5.1).

#### 4 A STOCHASTIC MODEL FOR THE CONCENTRATES LEFTOVERS

The concentrates 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 the percentage of the leftover of the concentrates ration, defined by:

$$p_0 = P(\text{leftover} = 0\%),$$

$$p_1 = P(0\% < \text{leftover} \leq 10\%),$$

$$p_2 = P(10\% < \text{leftover} \leq 30\%),$$

$$p_3 = P(30\% < \text{leftover} \leq 50\%),$$

$$p_4 = P(50\% < \text{leftover} \leq 100\%).$$

This distribution can be used to calculate the probability  $p_{\text{conc}}$  of the measured leftovers at a certain milking. If this probability  $p_{\text{conc}}$  is low an attention for low concentrates intake will be given.

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 5.2).

#### 5 THE KALMAN FILTER

A Kalman filter is applied while the parameters in the models for the different variables are cow-dependent and while a model for the dependency between the variables is wanted. The Kalman filter 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 is improved after each new observation by using the new information. First, a general description is given and later two applications:

- 1) the state consists of the parameters in the time series models (5.1);
- 2) the state consists of the probability distribution of the percentage of the concentrates leftover (5.2).

It is needed to describe the system with state-space equations to apply the Kalman filter, consisting of observation equation:

$$y_t = C_t x_t + v_t \quad (1)$$

and a system equation:

$$x_t = A_t x_{t-1} + w_t \quad (2)$$

In these equations  $x_t$  is the state vector,  $y_t$  the observation vector,  $C_t$  and  $A_t$  are system matrices,  $v_t$  is the random observation error and  $w_t$  is the random system error. The observation equation describes the relationship between the measurements and the state, the state itself is not directly measurable in general. The system equation gives the relation between the state at successive times. The distribution of  $v_t$  is  $N(0, V_t)$  and of  $w_t$  is  $N(0, W_t)$ .

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

The Kalman filter is an estimation procedure with two stages:

- An estimate of the state and variance-covariance matrix is based on the previous state is calculated in the first stage.
- This estimation is updated in the second stage with the help of the observation  $y_t$  and the estimation error  $e_t$  (difference between actual and estimated observation).

The resulting estimates can be used in the next time step.

It can be proved (Harvey, 1989) that the Kalman filter gives the minimum mean square linear estimator of  $x_t$ . The variance-covariance matrix of the estimation error  $e_t$  can also be calculated.

### 5.1 Fitting the parameters of the time series models

In standard usage of the Kalman filter the state would consist of the measured variables. It 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 new measurement values are forecasted so that highly deviant measurements can be signalized. Also the variance-covariance matrix of the estimated state is given which is used to relate the variables mutual.

### 5.2 Fitting the probability distribution in the concentrates leftover model

Again, a Kalman filter is applied. A description with state space equations (1) and (2) is needed for this. In this case the following definitions apply:

$$x_t = \begin{bmatrix} p_0 \\ p_1 \\ p_2 \\ p_3 \\ p_4 \end{bmatrix}, y_t = \begin{bmatrix} r_0 \\ r_1 \\ r_2 \\ r_3 \\ r_4 \end{bmatrix}, A_t = I, C_t = I \quad (3)$$

The vector  $x_t$  is the state, here the probability distribution (see Section 3),  $y_t$  is the observation with  $r_i$  defined as:

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

The matrices  $A_t$  and  $C_t$  are equal to the identity matrix  $I$ ,  $V_t = I$  and  $W_t = 0.01 \cdot I$ .

With this definitions the estimation error is:

$$e_t = \begin{bmatrix} r_0 - p_0 \\ r_1 - p_1 \\ r_2 - p_2 \\ r_3 - p_3 \\ r_4 - p_4 \end{bmatrix} \quad (4)$$

A component of  $e_t$  is positive when  $r_i = 1$  and negative when  $r_i = 0$ .

## 6 DETECTION METHOD

The detection model is meant to attend the farmer to possible deviations in his cows, the model should generate attentions for that purpose. Attentions 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 (1). The estimate is compared with the real measurement and get the error vector  $e_t$ . The estimate of the state based on the measurements up to the preceding milking, is used for this. It is assumed that the distribution of  $e_t$  is approximately normal. The variance-covariance matrix of  $e_t$  can also be calculated. This matrix is used to standardize  $e_t$ .

There are two methods to generate attentions:

#### 1) Single attentions

Each component of the standardized error vector has a standard-normal distribution. Observations outside some confidence intervals get an attention. An attention mark \* corresponds with errors outside the 95% confidence interval, \*\* corresponds with 99% and \*\*\* with 99.9%.

A single attention for the concentrates leftover is given when the calculated probability is below 5% (\*), 1% (\*\*) or 0.1% (\*\*\*).

## 2) Combined attentions

The components of the standardized error vector are mutually comparable, due to the special form chosen for  $V_t$ . This makes it possible to consider combinations of the elements. Attentions marks are \*, \*\* and \*\*\*, corresponding with a combination falling outside a 95%, a 99% and a 99.9 confidence region. A heat attention is given when the activity is rather high and the combination of activity, yield and temperature falls outside a certain confidence interval. A mastitis attention is given when the conductivity error is rather high and the combination of conductivity, yield and temperature falls outside a certain confidence interval. An illness attention is based on the combination of yield, temperature, activity and concentrates intake.

## 7 RESULTS

The described model has been implemented (with some practical adjustments) and tested on the experimental farms of IMAG-DLO in Wageningen and ID-DLO in Lelystad.

Cases of heat or disease that were signalled by the model are true positive (TP), not signalled cases are false negative (FN). Milkings outside a heat or illness period are true negative (TN) if there is not an attention from the model, otherwise they are false positive (FP). Measurements for the model performance are the sensitivity and the specificity.

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

The specificity is the percentage of truly not signalled milkings outside heat or disease periods:  $(TN/(FP+TN)) \cdot 100\%$ .

Some results are given in Table 2, 3 and 4. The specificity for mastitis is calculated by regarding cows without any mastitis case during the test period.

Table 2 The sensitivity and specificity for heat based on 537 cases and 41803 milkings outside heat periods.

attention	sensitivity	specificity
*	94.2%	94.5%
**	86.5%	96.9%
***	82.5%	98.1%

Table 4 The sensitivity for diseases (mastitis excluded) and specificity of the detection model, based on 263 cases and 40286 milkings outside illness periods.

attention	sensitivity	specificity
*	99.6%	86.0%
**	90.5%	93.5%
***	76.8%	96.7%

## 8 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.

Table 3 The sensitivity for four different mastitis types and the specificity for mastitis.

attention	sensitivity clinical mastitis (52 cases)	sensitivity subclinical mastitis (21 cases)	sensitivity latent mastitis (35 cases)	sensitivity secretion disturbance (36 cases)	specificity
*	96%	100%	89%	97%	95.3%
**	90%	76%	57%	86%	98.2%
***	65%	57%	37%	67%	99.4%

A general model that can be used for each cow as in Deluyker, 1990 was not searched 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 which 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 heat or ill. An attention is given in that case.

The distribution of the concentrates leftovers is a appropriate model for this different behaving variable.

A Kalman filter is also applied in 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 of a change of level. A normal behaviour is assumed here and deviant measurements do not fit in our model.

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 attentions.

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