ONLINE MODEL PREDICTIVE MONITORING FOR CONTROLLING AND OPTIMIZING THE PERFORMANCE OF AGRICULTURAL PRODUCTION PROCESSES

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ABSTRACT The biological uniqueness of the members of an agricultural production unit results in a large variability between production units of the same production process and of the same production unit in time. As a result, monitoring and controlling such processes using general standards is not very effective. It would be of interest to have Production Unit Specific Standards (PUSS). In this paper, a procedure is presented to develop such a PUSS for production data of a flock of laying hens. As these standards should only be based on in-control data, the technique of statistical control charts is used to detect out-of-control observations in order to exclude them from the PUSS estimations. This procedure debuts with a parametric trend model that is estimated to describe the time dependent trend present in the production data. The autocorrelation structure of the data series of prediction errors from the trend model, is in its turn modeled by an autoregressive moving average (ARMA) model. The stationary and independent data series of prediction errors of the ARMA model are then analyzed by a control chart and out-of-control points are excluded from further model estimations. This sequence is repeated for each new observation. The final PUSS is formed by the time series of predictions of the parametric model. The PUSS development procedure forms the basis of a monitoring scheme for controlling performance of agricultural processes and can be part of a tool for management support.

Keywords: model predictive monitoring, production unit specific standards, optimizing agricultural production systems, management support system

INTRODUCTION Uniqueness is the key issue when dealing with biological production systems – no two subjects are the same. This uniqueness is the result of the variability which is inherent to all biological systems. Biological variability plays on different levels and can be categorized as inter subject variability and intra subject variability. Inter subject variability plays between subjects – subjects of different species – but also between subjects of the same species, even when their environment is the same. Intra
subject variability denotes the variability that is present when a given subject is followed in time – they grow and are subject to timely variations, possibly induced by a changing environment.

For issues such as performance and health status assessment, this variability is an inevitable burden. Indeed, when trying to set arbitrary general limits for defining performance or health status – for instance a minimal amount of eggs produced by a flock of laying hens – it is evident that such limits will be broad in order to allow for the inter (e.g. to cover the whole population of the considered subjects) and the intra (day-to-day variations) subject variability.

Therefore it would be of interest to have specific standards for the production unit of the considered production process. A production unit is defined as the minimum level at which data can be collected, e.g. in the production process of consumption eggs, data are collected at flock level (large group birds), in dairy production data can be collected at individual cow level.

In this work, a procedure is presented to develop Production Unit Specific Standards (PUSS) for agricultural production systems. This procedure starts from the concept of uniqueness and uses a combination of model predictive monitoring and statistical process control to generate the PUSS. In this paper, the procedure is explained based on data of flocks of laying hens, more specific based on the hen-day egg production (EP) data.

CONCEPTS OF PROCESS MONITORING

The developments in precision livestock farming (PLF), a relatively new discipline to improve livestock production by means of applying process engineering technologies to the complex, heterogeneous systems of animal production (Frost, 1997; Wathes, 2008), enabled precision monitoring of livestock production units. This means that repeated sampling of the same production unit (e.g. flock of hens, cow) is performed. Hence, ample data are available to apply specific process monitoring concepts.

Two concepts which are especially interesting for performing process optimization through monitoring are Engineering Process Control (EPC) and Statistical Process Control (SPC). EPC is the whole of activities that focus on the mathematical modelling of (production) systems (del Castillo, 2002), and SPC is a collection of tools which aim at discerning between normal and abnormal process variation (Montgomery, 2005). An SPC tool which is widely used for the detection of abnormal variability is the quality control chart. A control chart graphically visualizes the occurrence of abnormal variability by defining control limits based on normal variability. Here the cumulative sum (cusum) chart is used. A cusum chart accumulates deviations from a certain target value and signals when this cumulative sum crosses the predefined control limit. The cusum is useful for detecting small process shifts (< 1.5σ).

In this work, both concepts are combined to build the PUSS for the production unit of laying hens. EPC is used as a starting point for modeling the time series of EP data. The cusum control chart is used to control the data series and to provide feedback for the PUSS development. As such, the production unit of laying hens is used as its own, unique, reference. Figure 1 shows the general outline of the procedure for the PUSS development.
MODELING OF EGG PRODUCTION DATA

The EP data series consist of daily registrations of the total egg production of the flock of laying hens, where the EP is calculated from:

\[
EP = \frac{\text{Total eggs}}{\text{Total hens present}} \times 100 \% \quad (1)
\]

Figure 2 provides an example of an EP data series of a flock of layers in an aviary housing system. As can be seen from this figure, the EP data display a certain trend as function of time, or in fact as function of the age of the laying hens. The age of the hens is expressed in days of lay (DOL), with DOL=1 at an EP of > 40 % (Mertens, 2009). The trend of EP is characterized by a steep increase towards the peak production at about the 30th to 50th DOL followed by a more or less plateau phase with a stable production (persistent production). Thereafter, a gradual decrease is seen (Lokhorst, 1996). The PUSS development starts with a first modeling step in which this trend is described. This first model also forms the basis of the final PUSS.

A non-linear trend model for trend description

Amongst others, Lokhorst (1996) has presented a non-linear parametric model which is capable of describing the relation between the age of the hens and the EP. Mertens (2009) modified this model for use in an online monitoring scheme. The non-linear model proposed by Mertens (2009) is used in this work and is given by:

\[
EP_t = 100 \left( \frac{1}{1+2.25 r \sqrt{t}} \right) - (b + c \cdot \sqrt{t} + d \cdot \sqrt{t}) \quad (2)
\]

with \(a, r, b, c\) and \(d\) the model coefficients and \(t\) the age of the hens in DOL. In this formula, the first part with coefficients \(a\) and \(r\) describes the quick increasing phase. The second part consists of a second order polynomial with coefficients \(b, c\) and \(d\) for describing the plateau phase and the gradual decrease. The estimation of these coefficients for development of the model is performed by means of the Gauss-Newton method (Nocedal and Wright, 1999), with the EP as dependent variable and the DOL as independent variable.

Figure 2.a presents an example of a trend model development based on the available data series of a flock of laying hens in an aviary. This model was estimated offline and post-hoc, meaning after all data are available. The estimated model is given in equation 3:

\[
EP_t = \frac{100}{1+9.52 \cdot 0.17 \sqrt{t}} - (23.86 - 4.36 \cdot \sqrt{t} + 0.24 \cdot t) \quad (3)
\]
Recursive model estimation In order to develop an accurate PUSS, it is necessary to perform the model development in an ad-hoc or online way. This means that the model has to be updated by using the information from newly acquired observations. As such, the principle of recursive model estimation is applied: each time a new measurement is performed, the model coefficients are re-estimated.

For the first model estimation, a reference period of \( n=21 \) (3 weeks) observations is chosen. When observation \( n+1 \) becomes available, the model coefficients are re-estimated and the new model is fit on the \( n+1 \) data points. This method was chosen over the recursive least squares (RLS) method (del Castillo, 2002) because the proposed model is non-linear in its coefficients. Furthermore, since only five model coefficients have to be estimated and the datasets are relatively small - maximum about 450 data points corresponding with a laying period of maximum 450 days - the computation time for repeated parameter estimation is acceptable. Figure 2(b) shows an example of the result of the online trend description.

The estimated online trend is subtracted from the original data series. For the implementation of the feedback procedure, which has to exclude out-of-control observations from the PUSS development, the resulting residuals are to be introduced into a cusum control scheme.

Investigation of the model residuals The proper use of the basic cusum control scheme for detecting a shift in a normal mean, is bounded to several assumptions of the statistical model underlying the cusum calculations: (1) the monitored process has to be stationary meaning observations have to fluctuate or drift around a certain fixed target or mean value; (2) the process data have to be independent meaning no autocorrelation should be present; and (3) the distribution function underlying the data of the considered variable has to be normal with known mean and variance \( N(\mu, \sigma^2) \) (Hawkins and Olwell, 1998).

Graphical investigation of the residuals resulting from the recursive estimation of the trend model, shown in figure 3, shows that the residual data series displays stationarity (figure 3.a) and that it is nearly normally distributed (figure 3.b). Only a minor deviation from normal distribution seems to be present, probably as a result of actual out-of-control observations. From the autocorrelation function (figure 3.c) it can be seen that the
residuals of EP display significant autocorrelation. Such autocorrelation or serial correlation between observations can greatly compromise the performance of the cusum control chart (Hawkins and Olwell, 1998). Because of the autocorrelation, a second model is necessary to remove this autocorrelation before a cusum control scheme can be applied to the residuals. This autocorrelation issue is dealt with in the next paragraph.

![Graphical investigation of the residual data after subtraction of the recursively estimated trend model from the original data.](image)

Figure 3. Graphical investigation of the residual data after subtraction of the recursively estimated trend model from the original data. (a) Residual time plot to check for stationarity. (b) Residual histogram to check normality. (c) Residual autocorrelation function (acf) to check for dependence between the residuals. For more information, see Montgomery (2005).

**ARMA models for eliminating the autocorrelation in the residuals** To deal with the issue of autocorrelation in the framework of SPC, amongst others, del Castillo (2002) and Montgomery (2005) suggested to use an AutoRegressive Moving Average (ARMA) model to describe and correct for the autocorrelation structure present in the data. More information concerning the development and estimation of ARMA models can be found in Montgomery et al. (2008).

An extra complication in the framework of this work is that, since only in-control observations are to be included in the model estimations, the data series will practically always contain missing values as a result of out-of-control situations. Only theoretically it might be possible to have a perfect production without out-of-control situations. Estimating ARMA models on time series with missing values is not straightforward, because the estimation procedure has to be robust for the unequal spacing between observations resulting from the presence of missing values.

The work of Broersen et al. (2004a,b) and Broersen and Bos (2006) presented a solution for this problem. They advised estimating the ARMA model coefficients directly to the available observations by using Maximum Likelihood (ML) estimation method. The basics for the application of this method in the field of ARMA estimation were first published by Jones (1980). Based on this ML estimation algorithm, Broersen (2006) presented a procedure which automatically selects the best time series model for a time series with missing data. The algorithm consists of three steps. First, possible AR models are estimated and based on these AR models, MA and ARMA models are estimated. Next, the best model orders are defined to select the most accurate AR, MA and ARMA model. Finally, the type of model (AR, MA or ARMA) most suitable for the considered data is selected using a generalized information criterion (GIC). Using this algorithm, the autocorrelation structure of the trend model residuals is modeled. Analogue to the estimation of the trend model, also the ARMA model is estimated recursively as each
new observation becomes available. The prediction of the ARMA model is subtracted from the residuals to obtain corrected residuals. These corrected residuals are stationary, independent and normally distributed and can hence be introduced into a cusum control scheme.

**INTELLIGENT FEEDBACK OF THE CUSUM CONTROL CHART** The introduction of “intelligence” into the algorithm, is the construction of a cusum control chart based on the corrected residuals after the two EPC steps (trend model and ARMA model). Again using the online approach, the algorithm "learns" from the previous observations, and with the cusum scheme discriminating between normal variation and abnormal variation, only in-control observations are included in the development of the models and hence of the PUSS (see figure 1).

**Design of the cusum control chart** In the cusum control scheme for detection of a shift in mean of normally distributed data, the upper cusum \( C^+ \) accumulates deviations above target:

\[
C^+_t = \max(0, x_t - (T + K) + C^+_t-1)
\]

and the lower cusum \( C^- \) accumulates deviations below target:

\[
C^-_t = \max(0, -x_t + (T - K) + C^-_{t-1})
\]

with \( T = \) target value, the mean of the process; starting values \( C^+_0 = 0 \) and \( C^-_0 = 0 \); \( x_t \) the observation at time point \( t \); and the reference value \( K = k \cdot \sigma \) with \( \sigma \) a measure of the normal variation of the in-control observations which defines process variability. An observation will be out-of-control when \( C^+_t > H \) or \( C^-_t > H \) with \( H = h \cdot \sigma \) the control limit and \( h \) the decision interval. In general, a cusum control scheme accumulates deviations above or below the target value \( (T) \) which are larger than the reference value \( (K) \). When this cumulative sum is larger than the control limit \( (H) \), an alarm is generated.

The cusum chart is governed by the standard deviation \( \sigma \), the reference value \( K \) and the control limit \( H \). The values for these factors will define the shift that can be detected in a certain time span. The choice of \( k \) and \( h \) for calculating \( K \) and \( H \) respectively depends on the variability of the observed process parameter and of the desired Average Run Lengths (ARL). The in-control ARL (ARL₀) measures the in-control behaviour and hence indicates the average time between false alarms. This in-control ARL should be sufficiently long because false alarms are undesirable as they cause waste of time and energy and disrupt operations looking for non-existent special causes. The out-of-control ARL (ARL₁) is the average number of observations until an alarm is given after a shift of the process. Hence this number indicates the speed of detection. The out-of-control ARL should be as short as possible. Cusum parameters have to be chosen in function of an acceptable ARL (Hawkins and Olwell, 1998; Montgomery, 2005). For the EP data \( k \) was set to 0.5 and \( h \) was set to 3 which results in an ARL of 120, which is a false alarm once every four months (see ARL table on page 48 in Hawkins and Olwell (1998)).

**The “intelligent” algorithm** Using this cusum scheme, a feedback mechanism was designed providing information concerning newly recorded observations: are they within or outside expectations? In the first case the observation is included, in the latter
excluded. The algorithm basically works as follows. In a first phase the algorithm needs a series of \( n \) real observations to perform a first model estimation (both trend and ARMA model). Therefore a reference period of 21 days \([y_1; y_{21}]\) or 3 weeks was chosen. Based on these observations the non-linear trend model is estimated and the residuals \([e_1; e_{21}]\) are calculated. Next, an ARMA model is fit on these residuals to correct for the autocorrelation and the corrected residuals \([e_{corr,1}; e_{corr,21}]\) are calculated. It was chosen to develop these ARMA models up to a lag of 7, corresponding to the observations of the preceding week. The corrected residuals are then introduced into a cusum scheme to detect possible out-of-control observations. If any out-of-control observations are detected, these observations are discarded from the reference period and the models are re-estimated. This loop is repeated until all out-of-control points are removed. As such, the initial estimates of model coefficients and in-control variance \( \sigma_0 \) are available.

In the second phase, the online recursive calculations start. When the 22\(^{nd} \) observation \( y_{22} \) is recorded, the reference trend model is used to make a prediction \( \hat{y}_{22} \) for this observation. The predicted value is compared to the actual observation from which the residual \( e_{22} \) can be calculated. Then the reference ARMA model is used to make a prediction \( \hat{e}_{22} \) for this residual and the corrected residual \( e_{corr,22} \) is calculated. This corrected residual is inserted into the cusum scheme (based on \( \sigma_0 \)) and if no alarm is given, observation \( y_{22} \) is included in further model estimations. As a matter of fact, before a new observation is recorded, the model coefficients (both trend model and ARMA) are re-estimated (updated) including observation 22. If, on the other hand, the residual of observation 22 causes a cusum alarm because being out-of-control, observation \( y_{22} \) is excluded from all further calculations. This loop is repeated for all newly recorded observations.

**THE PRODUCTION UNIT SPECIFIC STANDARD** The PUSS is calculated by means of the above described procedure. The final PUSS which is shown to the poultry manager, is actually the time series of EP predictions obtained via the recursively estimated trend model. So in fact, the PUSS is not only accurately developed by means of the cusum control chart, but it also serves as the basis for quickly detecting emerging problems in the production process of consumption eggs by means of the cusum control chart. Figure 4 provides an example of the developed PUSS for the considered dataset of EP data including the cusum control chart which was calculated to provide feedback for the model estimation and for problem detection. As can be seen, four main problems cause alarms in the cusum chart on DOL 186, 247, 349 and 349. The first alarm (DOL 186 to 188) was generated by the transition to the second phase feed. The second alarm (DOL 247 to 250) was caused by a wrong feed formulation. It was elucidated that the vitamin content of the feed was insufficient. For the next important alarm (DOL 349 to 351) no reference was found in the farmer’s log. The last range of alarms (DOL 375-377) occurred in the final days of the laying period and were probably caused by the less good collecting management in this busy period at the end of production. The single alarm at DOL 236 was not confirmed by consecutive alarms. In the chart two consecutive (235 and 236) lower observations could be seen at this time, yet the production numbers were normal again after these two recordings.
DISCUSSION In this work, a synergistic procedure is presented for development of a Production Unit Specific Standard on the one hand and early problem detection, using this PUSS, on the other hand. The term synergism, introduced by Box and Paniagua-Quiñones (2007), refers to the fact that in this procedure the concepts of Engineering Process Control (EPC) and Statistical Process Control (SPC) are combined. The EPC adjusted data, by means of a recursively estimated trend and ARMA model, are the input of the cusum control chart (SPC) which is able to detect registrations which result from an out-of-control situation as a result of an emerging problem or disease. A signal of the control chart is fed back to the model estimation in order to exclude such out-of-control observations. Besides, the signal of the control chart can be used by management for early detection of problems.

Nowadays, agricultural production performance is usually assessed and monitored by comparing mean values of a recent measurement period (e.g. week or month) with past performances or predetermined performance standards (Reneau and Kinsel, 2001). Determination of such standards is typically arbitrary or the limits of such standards are set wide to give in to the high variability within and between groups of animals at different locations in the world. This is usually done without the interference of statistical analysis. But excessive variation interferes with the evaluation of performance. High variability makes performance outcome unpredictable and difficult to interpret. However,
understanding variability is the diagnostic key for improving process performance (Reneau and Lukas, 2006). The concepts of SPC, and more specifically the control charts, are highly advised for this purpose. The use of control charts in agricultural production, and especially in livestock production, is gaining interest considerably (de Vries, 2001; Reneau and Lukas, 2006).

The synergistic concept presented in this work has been proposed by several authors (Hawkins and Olwell, 1998; del Castil lo, 2002; Montgomery, 2005; Box and Paniagua-Quiñones, 2007), yet it has been rarely applied to agricultural production. Since the data of most agricultural production processes are non-stationary and dependent, this procedure can form the basis for the development of an intelligent management support tool for other agricultural production systems like diary production, pig production, crop production, etc.

There is also a broader application scope for the PUSS. Besides the fact that it can be used to compare a production unit with other units, at the same farm or at other farms, it might also prove to be useful for genetic selection. This is specifically of interest if the level of the production unit is located at the individual animal level, like for instance dairy cows. The accurately estimated PUSS could be used for comparing production results (milk yield) and hence for selection purposes.

**CONCLUSION** A procedure based on recursive model estimation and which combines the concepts of EPC (modeling) and SPC (monitoring), is capable of developing very accurate Production Unit Specific Standards which can be used for process monitoring and optimization.

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