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Original papers

Data-based design of an intelligent control chart for the daily monitoring of the average egg weight

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ABSTRACT

Both animal dependent and non-dependent factors and their interactions have an effect on the quality of consumption eggs. With the recent development of fast, objective and non-destructive measurement methods for egg quality, extensive information on all input and output aspects of the production process of consumption eggs are available. This enables the application of the concepts of statistical process control (SPC), such as control charts, in order to detect anomalies. In this paper a quality control chart is presented for the daily monitoring of the average egg weight.

In a first step for the design of the control chart, a non-linear model was developed to detect the natural increasing trend of the egg weight with the increasing hen age. This trend was then subtracted from the measured egg weight and the residual values were inserted into a cusum control chart.

The data originating for two flocks of laying hens, a small flock (72 hens, deliberately subjected to challenges), and a large-scale experimental flock (500 hens) in an aviary housing, were used to evaluate the developed control charts.

The results show that the quality control chart enables to quickly detect a decrease of the average egg weight. Similar algorithms for all variables on both input and output will make it possible to monitor the whole egg laying process to detect or to prevent a decreasing egg quality and hence increase profits for the poultry farmer.

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1. Introduction

The quality of consumption eggs is the result of the interaction between many factors, both animal dependent and external, that influence the functioning of the laying hen as an egg producing domestic animal. The final quality the eggs produced on a layer farm has to meet the customer's demands and enables the producer to make a profit (Frost et al., 1997). Therefore, the production process is focused on a product that responds to these changing demands, and it is of great importance to detect a quality decrease as soon as possible, to track the cause and to take appropriate measures. However, in practice there is often a large time span between the onset of a process shift and the detection of the resulting quality decrease. The performance of a flock of laying hens depends largely on the skill, experience and assessment capability of the stockman to monitor his hens. Process monitoring on this basis makes it difficult to quickly detect quality decreases which results in a time gap between the process shift and the quality decrease observation and hence results in economical damage.

In manufacturing, where uniformity of the quality of products is of the utmost importance, the concepts of statistical process control (SPC) already exist as a part of quality assurance since the mid 1920s when Shewhart introduced the first control chart. The basic principle of SPC is to formulate quality limits based on the natural process variability or the *common cause variation*. Occasionally other kinds of variability, not normal within the considered process, may occur. In this case of *special cause variation* the quality of the products will fall outside the formulated limits. For detection and visualization of such process shifts, SPC provides the technique of quality control charts. The most known control charts are the Shewhart chart, used for detection of large shifts ($>3\sigma$). These charts can be supplemented with “run rules” in order to detect smaller changes, but in practice the exponentially weighted moving average (EWMA) chart and the cumulative sum (cusum) chart have a better performance on the detection of small shifts ($<1.5\sigma$) (Devor et al., 1992; Montgomery, 2005).

In agricultural production processes, many techniques and devices have been developed to measure and record production parameters (e.g. ambient temperature, relative humidity, feed consumption and water consumption, etc.) on a regular basis (Belyavin, 1988; Frost et al., 1997). Techniques for assessing output quality parameters of agricultural products in a fast and non-destructive way and on a regular basis became available only recently. For example in egg quality assessment, Coucke (1998) introduced a technique to measure shell strength and Kemps et al. (2006) presented a method to assess the internal egg quality using vis/NIR spectroscopy. The direct availability of both input and output parameters creates the opportunity to use control charts for monitoring the evolution of these parameters and the relationship between them. However, the use of this methodology in agricultural production processes is rather complicated because they are seldom stationary, complicating the classical use of control charts.

In recent research on the use of control charts in agricultural production processes, De Vries and Conlin (2003, 2004) used Shewhart and cusum charts for detecting heat of dairy

cows, while Engler et al. (2005) used cusum and EWMA charts for sow farm analysis. For the egg production process, some methods of process monitoring have been proposed. Breeding and feeding companies develop standards (e.g. laying curve for hen-day egg production, curve for evolution of average egg weight, curve for evolution of average hen weight), based on their own experience in field tests. Unfortunately, these standards usually only consist of weekly data on a limited number of variables (Lokhorst, 1996). Roush et al. (1992) used a Kalman filter to detect significant changes in feed consumption of laying hens. Schmisser and Pankratz (1989) developed a more elaborate expert system for complete layer management based on the weekly monitoring of the process parameters. However, the laying process implies a wide range of continuous variables and parameters, which are subject to daily variation. Hence this requires continuous monitoring for control of animal health, welfare and production (Frost et al., 1997). Lokhorst and Lamaker (1996) presented an expert system on a daily basis to detect shifts in the daily production process of hens in an aviary system. The general idea was to detect process shifts by comparing the actual observations of a production parameter with a standard.

In this paper, the technique of cusum control charts is adjusted for improving the production process of consumption eggs. Using the average egg weight as an example, a strategy for an integrated monitoring system of the complete egg production process is proposed. More specific, a data-based strategy for designing a quality control chart for detecting a shift in the evolution of the average egg weight (one of the most important quality traits for economic turnover) within 2 days after occurrence of a specific incident is presented. This is done in three major steps: first a plausible mathematical model for the increase of the egg weight during lay is derived based on post hoc data, second an on-line approach for the parameter estimation is developed and third the quality control chart is designed.

2. Data description

In the first phase a mathematical model for the average egg weight was constructed. This was done using 25 historical observational datasets. These data originate from large-scale experimental flocks housed in furnished cages (21 flocks of 250 Isa Brown® hens) or in an aviary system (four flocks of 500 Isa Warren® hens).

In the second phase, the control chart for average egg weight was developed and validated on new experimental data of two flocks. The first flock consisted of 72 Isa Brown® laying hens housed per 2 in a three tier battery cage with 36 cages. The cage was located in a climate-controlled room. The birds were fed ad lib with a standard commercial layer mash and had free access to drinking water. The hens were monitored daily for a whole laying period until an age of 63 weeks or 301 days of lay. Each day all the eggs were collected and the average weight was registered. Furthermore, a log was kept to register all events like treatments, mortality, technical failures etc. To test the principles of the cusum control chart, these hens were subjected to three heat stress challenges of a constant (24/24 h) temperature of 32 °C. The

first and the second challenge lasted for 8 days while the third challenge lasted for 4 days. The choice for heat stress as the main stressor in order to generate changes in the production process was made based on practical considerations and on the chance for accomplishing the goal. It was chosen to apply a step heat stress since it became clear from previous experiments (unpublished results) that this has a large effect on the average egg weight. Nevertheless, it has to be mentioned that it was not the goal of this research to study the effect of heat stress per se, the experiments were only designed to generate changes in the average egg weight in order to develop the proposed control chart. Besides the heat stress challenge on the chickens, there was a serious natural challenge of red mite (*Dermanyssus gallinae*) infestation, especially in the beginning of the laying period. From blood sampling (data not presented) it was seen that the hens suffered from anemia due to the red mites. After treatment this red mite infestation remained present yet under control. This aspect has to be taken into account when evaluating the results.

The second, larger, flock consisted of 2000 Isa Warren® laying hens housed in an experimental aviary system. The housing system was divided into 4 pens of 500 hens each. The experimental unit was a pen: for our experiment, 1 pen with 500 hens was followed. The considered pen was located at the far end of the henhouse. The birds were fed ad lib with a standard commercial layer mash and had free access to drinking water. This group of laying hens was followed during 295 days of lay. Each day all the eggs were collected and the average weight was registered. Furthermore, a log was kept of all events. Since no log was kept for the historical data, the 25 historical datasets could not be used for the second phase validation.

3. Development of a mathematical curve for egg weight

Lokhorst (1996) described the evolutionary character of the average egg weight as a function of the age of the hen. This age is usually expressed in days of lay (DOL) where the first DOL coincides with the 141st day of life (20 weeks of age) (Siplu, 1990). The average egg weight shows a fast increase in approximately the first 40 days of the laying period (this might vary between different flocks of hens). It is followed by a period of about 10 days in which the rate of increase reduces, and from around DOL 50 a seemingly gradual linear increase can be observed. Fig. 3 shows a typical course of the average egg weight of a flock of laying hens during a whole laying period.

Description of the natural trend was performed fitting a non-linear model on the available data. Lokhorst (1996) proposed the following model:

$$Y_{\text{egg weight}}(g) = a + b_1 \times r^T \quad (1)$$

with a the maximum egg weight, b_1 the difference between a and the initial egg weight at the start of the laying period ($b_1 < 0$), r the growth rate factor of the model ($0 < r < 1$) and T the age of the hens in DOL, with starting point $T = 1$ at an effective

age of 141 days. The goodness-of-fit of this model for the 25 available datasets was investigated and this implied also the suitability of the model for use in an aberrations detection scheme. Fitting the models was done using the Gauss–Newton method (Nocedal and Wright, 1999), with the average egg weight as dependent variable and the number of days in the laying period as independent variable. From the analysis it was seen that it would be desirable to adjust the proposed model to the one given in Eq. (2).

$$Y_{\text{egg weight}}(g) = a + c\sqrt{T}^{-1} + b_2 r^{\sqrt{T}} \quad (2)$$

with a , b_2 , r and T the same as in the model in Eq. (1), and c a controlling factor on the rate of increase of the egg weight. The addition of the term $c\sqrt{T}^{-1}$ offers more flexibility in describing the transition from the fast increase towards the more or less linear behavior in the second phase of the laying period. The effect of the parameters is illustrated in Fig. 1.

The main problem in Eq. (1) is the smaller flexibility of the model due to the larger influence of the hen's age. This flexibility is important for application of the model in a control scheme (as will be explained further).

A comparative study between both models was performed. This was done by post hoc off-line application of both models on 25 data series of average egg weight. Investigating the goodness-of-fit of the models per flock was performed by comparing the mean relative percentage deviation modulus, P , the root mean square error RMSE and the adjusted coefficient of determination R_{adj}^2 given below:

$$P(\%) = \frac{100}{N} \sum \frac{|Y_i - \bar{Y}_i|}{Y_i} \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum (Y_i - \bar{Y}_i)^2} \quad (4)$$

$$R_{\text{adj}}^2 = 1 - \left(\frac{N-1}{N-p} \right) \frac{\sum (Y_i - \bar{Y}_i)^2}{\sum (Y_i - \bar{Y})^2} \quad (5)$$

where Y_i the average egg weight in gram on day i , $\bar{Y}_i$ the predicted egg weight in gram for day i , $\bar{Y}$ the average egg weight of the whole period, N the total number of data points in the data series and p the number of parameters in the model. The relative percentage deviation modulus is a robust (less sensitive to outliers) measure and a model is considered to accurately describe the data when the mean relative percentage deviation modulus (P) is less than 10% (Lomauro et al., 1985). And while the R_{adj}^2 indicates how much of the variation in the data is explained by the model, the RMSE provides an absolute error measure, in the unit of the considered variable, for the difference between observed and predicted data (Kutner et al., 2005). Fig. 2 gives an overview of the results of this analysis, with Model 1 being Lokhorst's (1996) model and Model 2 the adjusted one. Furthermore, a plot from the observed data to the predicted values was made to check for systematic errors in the predictive capacity of the model.

As an example, Fig. 3 illustrates the fitting of both models on the standard for average egg weight of Isa Brown® lay-

Fig. 1 – Illustration of the different influences of the parameters involved in Model 2 (Eq. (2)). Every graph (a–d) presents the effect of a change in one of the parameters on the model while keeping the other parameters constant. The basic values for the parameters are $a = 75$, $c = -4$, $b_2 = -20$ and $r = 0.900$. The changing values for the different parameters were for $a = 60, 70, 75, 80$ and 90 ; for $c = -1, -5, -10, -15$ and -20 ; for $b_2 = -10, -15, -20, -25$ and -30 ; for $r = 0.800, 0.850, 0.900, 0.950$ and 0.990 .

ing hens. This standard is developed by the poultry breeding company based on their own research and is used as a guideline for production results of a flock of the concerned line of laying hens. The standard assumes quasi-perfect production circumstances without occurrence of special causes and thus represents the ideal curve for a flock. In such a standard weekly data are provided for the egg weight. For example, at a hen age of 23 weeks, the egg weight should reach an average of 56.4 g, while at an age of 55 weeks it should be 64.7 g (Isa Brown Layer Management Guide, 2005). Looking at both Figs. 2 and 3 clearly shows the second model to better describe egg weight data (with an average RMSE amelioration of ± 0.2 equivalent to $\pm 22\%$, and an average R^2_{adj} of 0.95 vs. 0.92). From the observed versus predicted plot no systematic model errors came out. Therefore the second model was used in the remaining part of this study.

4. On-line parameter estimation of the mathematical model

Until now, fitting the mathematical model for trend detection was done using all the data in a post hoc off-line manner, meaning after all data of the complete laying period were available. Monitoring a process in real-time implies daily on-line model fitting incorporating the new daily observations.

On-line model fitting is done in the following way. For the first model estimation, a reference period was chosen consisting of the first 40 observations, coinciding with the first 40 days of the laying period. When the 41st observation becomes available, the model parameters are estimated again and the new model is fitted to the data. This means that when a new observation becomes available, the model parameters are estimated again based on all in-control data. This method was chosen over the recursive least squares (RLS) method, because the proposed model is non-linear in its parameters. Moreover, since only four parameters have to be estimated and the datasets are relatively small (maximum 400 data points) the computation time for repeated parameter estimation is acceptable.

Since the goal of this study was to develop a detection algorithm, only in-control observations should be used to develop the model. To decide whether an observation was in or out-of-control, a cusum control scheme was used as described below.

In general, at a certain time point T , a model is fit through the in-control data from time points 1 to $T - 1$, and based on this model a prediction is made for the expected value on time point T . This approach is formulated in the following equation:

$$\hat{Y}_{\text{egg weight}}(T) = a_{T-1} + c_{T-1}\sqrt{T}^{-1} + b_{T-1}r_{T-1}^{\sqrt{T}} \quad (6)$$

Fig. 2 – Graphical representation of the goodness-of-fit analysis of the two mathematical models for post hoc description of the average egg weight of 25 available datasets of different flocks of hens. Model 1 (proposed by Lokhorst (1996)) is formulated in Eq. (1) and Model 2 is formulated in Eq. (2). For both models the goodness-of-fit was evaluated based on the root mean square error (RMSE), the adjusted coefficient of determination (R^2_{adj}) and the mean relative percentage deviation modulus (P).

5. Construction of the cusum control chart for average egg weight

When developing a control chart for a process parameter, the choice of type of control chart depends on the

characteristics of the considered variable: what is the variable's distribution (normal, Poisson, binomial), is it stationary, is autocorrelation present, etc. The average egg weight is a continuous auto-correlated variable with a clear non-stationary character i.e. it shows a trend as a function of the increasing age of the hens. This evolution is well known

Fig. 3 – Representation of the fit of the two mathematical models on the standard data for average egg weight of Isa Brown® laying hens. Measures for the goodness-of-fit of each model, i.e. the mean relative percentage deviation modulus (P), the root mean square error (RMSE) and the adjusted coefficient of determination (R^2_{adj}), are respectively: $P = 0.6198\%$, $RMSE = 0.4710$ g and $R^2_{adj} = 0.9706$ for Model 1 (Eq. (1)), while $P = 0.2065\%$, $RMSE = 0.1486$ g and $R^2_{adj} = 0.9970$ for Model 2 (Eq. (2)).

and described in literature, amongst others by Lokhorst (1996).

In general, for this kind of biological variable usually cusum charts or exponentially weighted moving average (EWMA) charts¹ are used (Devor et al., 1992). Here the cusum chart was used. de Vargas et al. (2004) stated that the EWMA and the cusum control chart are comparable in their capacity of monitoring a process and detecting the presence of special causes. Although different cusum schemes are available for different distributions (Hawkins and Olwell, 1998), the model assumptions for these schemes state that measures of the observed variable are statistically independent and identically distributed and that the parameters of the distribution, the true mean and standard deviation for a normal distribution, are known. In order to satisfy the latter assumptions, it was necessary to subtract the evolutionary trend of the average egg weight. This trend detection and subtraction was accomplished using the non-linear mathematical model of the average egg weight. After detection and subtraction of the expected biological trend, the residual value, e , of the difference between the observed and the predicted value was used to make the control scheme. Before introducing the residuals into a cusum control scheme, it was tested whether the assumptions for the cusum hold (independent and normally distributed) by means of the Durbin–Watson test for autocorrelation and the Kolmogorov–Smirnov test for the normal distribution (Kutner et al., 2005). For all datasets used, there were no indications of violations against the cusum assumptions. In the cusum control scheme, the upper cusum C^+ (Eq. (7)) accumulates deviations above target

$$C_T^+ = \max[0, e(Y_T) - (0 + K) + C_{T-1}^+] \quad (7)$$

and the lower cusum C^- (Eq. (8)) accumulates deviations below target:

$$C_T^- = \max[0, (0 - K) - e(Y_T) + C_{T-1}^-] \quad (8)$$

with, target value = 0, starting values $C_0^+ = C_0^- = 0$; $e(Y_t)$ the residual value between the observed and the predicted egg weight at T days of lay, and the reference value $K = k\sigma_e$ with σ_e the error variance of the model fit (on the in-control observations) which defines process variability.

An observation will be out-of-control when $C_i^+ > H$ or $C_i^- > H$ with $H = h\sigma_e$ the control limit and h the decision interval. The cusum technique directly incorporates information in the sequence of sample values by calculating the cumulative sums of the deviations of the sample values from a desired target value that are greater than K . This makes the chart sensitive to small process shifts ($\leq 1.5 \sigma_e$) (Montgomery, 2005; Devor et al., 1992).

The cusum chart is governed by the standard deviation σ_e , the reference value K and the control limit H . The values for these factors will define the shift that can be detected in a cer-

tain time span. For egg weight data the aim was to develop a control chart to detect a shift of mean of $1 \sigma_e$ or 0.5 g within 2 days after occurrence. If a real drop in egg weight of 0.5 g remains unnoticed for more than 3 days, the economical damage will already be significant (e.g. in a flock of 50,000 hens). 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 length (ARL). The ARL represents the number of observations between false alarms. False alarms are inherent to a control scheme but are undesired. Parameters have to be chosen in function of an acceptable ARL (Hawkins and Olwell, 1998). For the production of consumption eggs, an ARL of 30 observations or 30 days is considered acceptable, and with k set on 0.5, the table on page 48 in the work of Hawkins and Olwell (1998) was used to define the value of h . With $h=2$ an ARL of between 30 and 40 days may be expected. Furthermore, only the negative cusum C_i^- was calculated since in practice only abnormal decreasing egg weight should be signaled.

Any cusum control scheme should be constructed in two phases. In phase 1 the process variability and mean are studied by taking the 40 first samples. For the presented cusum the mean and hence target value is fixed on 0. Using the expression for the lower cusum C^- (Eq. (8)), the negative cusum chart for these 40 samples is constructed. Next, the cusum chart is recalculated without the out-of-control observations. This is repeated until the cusum chart parameters are calculated based only on in-control observations. In phase 2, the process monitoring starts using the control scheme with target value and control limits developed in phase 1. In a classic cusum scheme, these values are fixed during the monitoring process. In the presented cusum scheme, only the target value of 0 is fixed. The control limits (H) and reference value (K) are variable since σ_e varies when new observations are added into the model calculations.

The flowchart, Fig. 4, summarizes the different steps in the development of the control chart for the average egg weight.

6. Validation of the control chart

Validation of the obtained control chart procedures was done by applying the chart to the datasets from the small-scale experimental flock and from the large-scale experimental flock in the aviary. Fig. 5 shows the result of the control chart for the average egg weight of the small-scale flock which was subjected three times to a step heat stress. The figure shows the measured data series and the fitted model in the upper graph and the cusum control chart of the residual values (observed value minus predicted value) together with the control limit (H) in the lower graph. For reasons of visual representation and clarity, cusum values for all out-of-control observations are replaced by a value of two times the value of the control limit H . Inspecting Fig. 5, alarms are generated at days of lay number 50, 111, 158, 188, 208, 230, 239 and 288. The alarms at days 111, 230, 239 and 288 were expected by the application of heat stress. The alarm at day 239 is still caused by preceeding effect of the heat stress. The alarm at day 50 was due to a severe red mite (*Dermanyssus gallinae*)

¹ EWMA charts plot a weighted moving average value. The weighting factor, chosen by the user, determines how older data points affect the mean value compared to more recent ones (Devor et al., 1992).

Fig. 4 – Flowchart of the different steps for the construction of the quality control chart of the average egg weight.

infestation which caused the egg weight to drop significantly. After the treatment for these ectoparasites at DOL 62, a meaningful increase of the average egg weight is observed. The alarms at days 158, 188 and 208 could be considered as “false alarms” since no challenge was planned in these periods and no special cause noticeably occurred. The alarm at day 111 was due to heat stress and is given 2 days after starting the stress period. The alarms at days 230 and 288 are also due to heat stress and are both given only 1 day after starting the stress. These results show that the control chart gener-

ated an alarm when a shift in egg weight of 1 g or $0.25\sigma_e$ occurred.

Fig. 6 displays the result of the control chart for the large-scale flock in the aviary housing system. Here alarms are given at days 62, 93, 106, 125, 175 and 265 of the laying period. Based on the recorded log, it was found that, for the first alarm the feed was restricted due to technical problems, resulting in a reduction of the average egg weight. The stockmen only noticed this problem at laying day 69, which means that a detection gain of 5 days could have been accomplished by

Fig. 5 – Control chart of the average egg weight during a whole laying period of the small-scale experimental group subjected to heat stress. (a) Course of the measured egg weight together with the fitted mathematical model. (b) Cusum chart for the residual value between measured value and predicted value based on the fitted model. Crosses represent out-of-control observations. The vertical lines indicate the periods of heat stress (32 °C).

the algorithm. The alarm at day 265 was probably caused by the rigid change of phase feeding. The other alarms at days 93, 106, 125 and 175 were not registered in the log. Looking at the observed egg weight, it can be clearly seen that the measured egg weight stayed under the expected values pointing out these were not false alarms and that perhaps not all important events are being logged. All the unnoticed problems caused the egg weight to be too low for in total more than 35 days. Further investigation of the log indicated that two other technical problems were not signaled by the chart since they did not have a large effect on the observed average egg weight.

7. Discussion

The work presented aimed at developing a production process control chart based on monitoring the average egg weight, an important and economical relevant parameter in the production of consumption eggs. The average egg weight was chosen as the example variable. In practice, average egg weight is one of the most commonly measured quality parameters. Also

many environmental problems (e.g. disturbance in food supply, decrease of water quality, heat stress etc.) that cause the animal to go out of its physiological balance, will be strongly reflected in the egg weight (Cavalchini et al., 1990).

An important challenge for developing the control chart for egg weight, was detecting the natural trend inherent to this biological parameter. This issue was addressed using a non-linear mathematical model. For matters of detection of aberrations, it is important that the model describes the actual trend as good as possible. Therefore, an adjustment of an existing model proposed by Lokhorst (1996) was suggested (see Eq. (2)). The improvement of the model lies in the fact that the smaller effect of age (root squared) and the addition of a small linear part made the model more flexible for use in a control scheme. When applying this modified model to the available recorded data, the results showed a significant decrease ($\pm 22\%$) in the residual variability (RMSE) of the model (Fig. 2). To cope with the issue of the natural trend, Roush et al. (1992) used a Kalman filter to detect significant changes in feed consumption data (increasing trend as a function of increasing hen age). When this technique is used for detection, the algorithm of the Kalman filter could be compared to

Fig. 6 – Control chart of the average egg weight during a laying period of 300 days of the large-scale flock in an aviary system. (a) Course of the measured egg weight together with the fitted mathematical model. (b) Cusum chart for the residual value between measured value and predicted value based on the fitted model. Asterisks represent out-of-control observations.

a moving average displaying a backlog to the actual course of the observed time series and making it less sensitive for quick detection purposes on a daily basis (Brockwell and Davis, 1991).

After modelling of the natural trend of the egg weight during the laying cycle, an online approach for a monitoring algorithm was developed. Application of this algorithm on a heat stress challenged small-scale flock of laying hens revealed a fast indication of the weight loss due to the high temperatures. For the first, second and third heat stress period, alarms were respectively given 2 days (DOL 111), 1 day (DOL 230) and again 1 day (DOL 288) after start of the heat stress. From Fig. 5 it also became clear that it takes a while before the average egg weight can recover from the high temperatures. While the alarm at DOL 188 could be due to a bad measurement (isolated lower egg weight), the alarms at DOL 158 and 208 could be considered as false alarms, with an interruption of 50 days which is acceptable referring to the postulated ARL of 30–40 days. False alarms in control charts do occur because they are proper to the statistical calculations made for construction of the control chart. Alarms are also considered false if no event was logged leading up to this

alarm. So maybe it might be useful to log additional parameters. The numbers of false alarms that occur are dependent on the values of the cusum parameters (k and h) (Montgomery, 2005). Defining these values is the most important step in the designing process of the cusum chart. Taking the process variability into account, a balance has to be found between a desired detection speed and an acceptable number of false alarms. For the egg production process, a false alarm could be a trigger for an extra control action of the animals by the poultry farmer. Yet, too many false alarms make a monitoring system unreliable and hence not worth the investment. Making this balance between detection speed and number of false alarms is often driven by economical considerations. Defining the control limits is different for every process and has to be a well-considered developmental stage based on theoretical work like Hawkins and Olwell (1998), Montgomery (2005) or Devor et al. (1992).

Finally, the alarm at DOL 50 is related to the severe red mite infestation of the flock. Red mites are haematophagous ectoparasites that feed on their host in dark periods. The reduction of average egg weight due to the red mites was in accordance with what was found in Chauve (1998) and

Cosoroaba (2001). It took until DOL 62 before any treatment was given. During data collection, the cusum control chart algorithm was not operational yet and hence a decreasing egg weight was only seen by the farmer after more than a week. After the chickens were treated a fast increase in egg weight could be observed. Yet, it took more than 8 days for the average egg weight to get back to the level before the alarm. In total, this is a period of 20 days in which the average egg weight was lower than predicted or expected, resulting in significant economical loss.

In general, the detection speed of the control chart is governed by the applied model for the natural trend and hence the variability of the residuals, the cusum parameters (k and h) and the number of observations. Looking at the detection speed for the small-scale experiment, the desired goal of detecting abnormalities within 2 days after the start of a challenge was reached. An inadequate descriptive model would cause a slower detection speed, as would be the case using Lokhorst's model. Inevitably it has to be taken into account that from a physiological point of view it takes a certain time before a challenge (e.g. red mite, reduced feed supply) displays an effect on the egg weight. Moreover, the detection speed is also a function of the number of eggs used each day to construct the charts: a higher number of eggs will result in a lower detection time.

When the cusum control chart algorithm was applied on a large-scale experimental group of laying hens in an aviary system, several problems were signaled by the control chart. Most of these remained unnoticed during the actual production period. A loss of more than 35 days of lower egg weight could have been avoided if the control chart had been used in real time and online. Although no such calculations were made in the work presented here, future validation of the control chart should involve economic calculations as well. As with every new tool, a farmer will only consider using it when he can actually increase his earnings.

From the presented data it can also be seen that different problems will have a different impact on the average egg weight and hence a different economic impact. Recovering from a heat stress challenge took approximately 6 days, from red mite infestation almost 8 days and from restriction from feed around 4 days.

The size of the experimental flocks producing the data for developing and validating the algorithm is rather small. For developmental matters it was necessary to start at small-scale since challenges had to be induced, to investigate the common cause and special cause variation, and good measurements were an absolute prerequisite. The next step in the development of the control chart is to perform a validation on farm level. This will further contribute to the fine-tuning of the algorithm.

The developed cusum control scheme for average egg weight only looks at a decreasing egg weight. It might also be interesting to detect increasing egg weight as a sign of bad measurements due to technological failure or human error, or when a farmer wants to keep his egg weight as low as possible in the last weeks of the lay. Yet, also looking for increasing egg weight can interfere with the model development and hence deteriorate detection performances on later age. This is certainly the case in the first 100–150 days when

the growth rate of the weight determines the values at later age.

Analogous to the algorithm for average egg weight, control charts for all important process and quality parameters could be constructed: hen-day egg production, percentage second grade eggs, feed consumption, water consumption, climate parameters (temperature and relative humidity), chicken weight and mortality.

The development of control charts for the process parameters will be specific for each of them. First, for every parameter that changes as a function of the age of the hens, the natural trend has to be modeled. Second, the nature of the variable (continuous variable, count data, proportions, etc.) will imply which cusum scheme should be used. For each kind of variable, a cusum scheme is available (Hawkins and Olwell, 1998).

While Schmisser and Pankratz (1989) and standards of feeding and breeding companies (Isa Brown Layer Management Guide, 2005) considered weekly information, Lokhorst and Lamaker (1996) were the first to introduce the idea of daily data collection and analysis. The presented paper shows that the latter idea is the only option to closely monitor a flock of laying hens. Working on a weekly basis can lead to late detected or undetected problems causing economical damage.

8. Conclusion

Considering the average egg weight as model variable for the production process of consumption eggs, the presented control chart for egg weight enables one to quickly detect possible weight loss. The control chart uses a new strategy based on on-line parameter estimation to cope with the normal dynamic behavior of the studied variable. Developing similar algorithms for all variables on both input and output, including quality parameters acquired from new non-destructive measuring methods, will make it possible to monitor the whole egg laying process in order to detect or to prevent a decreasing egg quality and hence increase profits for the poultry farmer.

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