CHAPTER 4

An Application for Detection of Growth Rate Changes in the Slaughter Pig Production Unit

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**Abstract:** A new method for monitoring productivity in the slaughter pig production unit has been developed. The method is implemented as a stand-alone application, based on data from an existing farm management system. With the new method the information on productivity increases from quarterly to weekly estimates of daily gain. A time series is made by calculating average daily gain each time a group of slaughter pigs is delivered to the slaughterhouse. Among other features, the application allows the user to monitor the time series graphically. Because of random fluctuation in the estimates, the user may choose to smooth the graph by means of a Kalman filter technique.

**Keywords**: Slaughter pigs, growth rate, Kalman filter, herd management

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4.1 Introduction

The Integrated Farm Management System consists of an integrated set of PC programs for production control and financial management of farms. The system has been developed by The Danish Agricultural Advisory Centre for the use of local advisory centres and farmers. The first version of the program was deployed in 1990. The system is divided into modules of five sectors: cattle production, plant production, pig production, economies, and buildings/machinery. See e.g. Pedersen et al. (1997) for a further description of The Integrated Farm Management System. This paper is concerned with the pig-production module, more specifically, the part of the module that measures productivity in the slaughter pig production unit. Productivity is defined, more or less, as the pigs’ ability to grow, estimated as average daily gain of weight in the herd.

The traditional way of calculating average daily gain is to define a valuation period (usually 3 months) in which all animals that enter or leave the barn are registered by date, weight and action (enter or leave). Based on these registrations and a valuation weighing at the beginning and at the end of the period, the average daily gain is estimated. This method has some disadvantages. First of all, weighing every animal in the herd involves considerable manpower. Secondly, the usual valuation period of 3 months means that a decline in average daily gain is detected 1 - 3 months after its actual occurrence. This delay in information reduces the value of estimated daily gain as a tool for herd management. Finally, a 3-month average, in some cases, could cover up considerable fluctuations in productivity. More information can be obtained by reducing the valuation period length. However, this requires more frequent (labor-demanding) valuation weighing. Furthermore, a shorter valuation period increases the effect of measurement errors.

4.2 Method

A new method has been developed which provides estimates of daily gain each time a batch of pigs is delivered to the slaughterhouse. The method also eliminates the need for valuation weighing. Instead, the daily gain is estimated by assuming that the heaviest animals are also the oldest. The age of each piglet that enters the barn is estimated on the basis of its weight, using Gompertz growth curve, see e.g. Whittemore (1993). The mathematical expression is:

\[ V_t = \exp(\ln(A) - \ln(A) - \ln(V_0)) \exp(-kt)) \]  \hspace{1cm} (4.1)
4.2 Method

where \( V_t \) is the weight at time \( t \), \( A \) is the weight of a full grown pig, \( V_0 \) is the weight of a pig at birth, and \( k \) is the growth rate.

The weight of the piglets is, in most cases, recorded as an average of the animals in each batch entering the production unit. Based on a record of the animals having entered the barn (sorted by estimated age), it is simple to pick out the oldest animals each time a group is delivered to the slaughterhouse, and calculate average daily gain.

A simplified example of how the method works in a continuous slaughter pig production unit is given in Figure 4.1. There is a record of piglets having

\[
\begin{array}{cccccccc}
\ldots & 9 & 12 & 10 & 8 & 13 & \ldots & \text{out} \\
\ldots & 10 & 10 & 10 & 10 & 10 & 10 & \ldots & \text{in} \\
6 & 7 & \ldots & 13 & 14 & 15 & 16 & 17 & 18 & \text{week} \\
\end{array}
\]

Figure 4.1: An illustration of the principle in calculating weekly estimates of daily gain.

entered the production unit (label "in"), 10 each week, and a record of the number of slaughter pigs leaving each week (label "out"). The "in"-table is sorted by estimated age by use of Gompertz growth curve. It is necessary to count all animals in the production unit to get the estimation algorithm started. In week 13 a status count is made. The actual number of pigs in the production unit at that time is 80. The oldest pigs present at the status are assumed to be the ones that entered the unit at week 6. This is obtained by simply summing up backwards in the "in"-table from week 13, until the status number 80 is reached. The trick is to pick out the oldest pigs from the "in"-record each time some pigs leaves the unit. The pigs leaving the unit for slaughtering are represented in the "out"-record. In week 14, 9 pigs are
delivered to the slaughterhouse and they are all supposed to have entered in week 6. An estimate of average daily gain is made, based on the registrations of weight and date. In week 15 there is a delivery of 12 pigs and they are identified as the last one from week 6, all 10 from week 7 and one from week 8. The estimation procedure continues in that way.

As it appears from the above description does the calculations depend on Gompertz growth curve. When the growth curve is used to estimate the age of the pigs, based on their weight, it is assumed that slope of the curve (expressed by the term $k$ in equation 4.1) corresponds to the growth rate in the herd. To ensure that this is always the case, the estimation algorithm is made as an iterative procedure. Initially, the term $k$ is set to a value that conform to a common growth rate of, say 800 grams per day. Then the iterative procedure is performed in two steps:

Step 1 The weekly estimates of daily gain are calculated based on the given value of $k$.

Step 2 The term $k$ is set to a value corresponding to the average of the estimated daily gain over all the weeks in question (the result of step 1).

The two steps are repeated until the value of $k$ is the same (within some tolerance) in two successive loops.

So, based on one status count and all the date and weight registrations, it is straight forward to calculate estimates of daily gain each time a delivery has taken place.

### 4.2.1 Monitoring the time series

In the existing farm management system, the calculated average daily gain is presented as a single figure in a production report among a lot of other key figures. The new way of calculating daily gain results in a time series which is presented in the application. The application displays the results in a table and in an $X/Y$-diagram which has time (weeks) on the $X$-axis and average daily gain on the $Y$-axis. Because of random fluctuation in the estimates, the user may choose to smooth the graph by means of a Kalman filter technique.

Recent examples of the use of Kalman filtering techniques include the detection of changes in feed consumption in broilers (Rosh et al., 1992), detection of changes in daily milk production (Thysen, 1992), monitoring bulk tank somatic cell counts by a multi-process Kalman filter (Thysen, 1993), visual monitoring of reproduction in dairy herds (Thysen and Enevoldsen, 1993).
1994) and estimation of the lactation curve of a dairy cow (Goodall and Sprevak, 1985). The filter used in the present application is based on the following Dynamic Linear Model or DLM. For each time step, \( t \), the model is defined by:

\[
\begin{align*}
\text{Observation equation:} & \quad Y_t = \mu_t + v_t, \quad v_t \sim N(0, V), \\
\text{System equation:} & \quad \mu_t = \mu_{t-1} + w_t, \quad w_t \sim N(0, W),
\end{align*}
\]

with initial information \( (\mu_0 \mid D_0) \sim N(m_0, C_0) \). The error terms \( v_t \) and \( w_t \) are independent and mutually independent, in addition they are independent of \( (\mu_0 \mid D_0) \) (West and Harrison, 1997). The observation equation describes the observation \( Y_t \) (the weekly estimates of daily gain) as a function of the current level \( \mu_t \) and \( v_t \), where \( v_t \) represents the observational error. Examples of sources that contribute to the observational error term are: inaccuracy in the weighing of the piglets that enters the barn, biological variation in growth rate and cases where the assumption that the heaviest animals are the oldest do not hold.

The system equation is a simple random walk with evolution error \( w_t \). The evolution error term allows level \( (\mu_t) \) to change as the true level of daily gain changes in the herd. The mean \( m_0 \) is a prior estimate of the level, and the variance \( C_0 \) a measure of uncertainty about the mean. Finally, the information set at time \( t \) is expressed as \( D_t = \{Y_1, \ldots, Y_t\} \), \( D_0 \) being a set of initial information.

For monitoring and learning, the model components are the distributions summarized below. These are based on the sequential updating equations that define the evolution of information about the model and the series over time. For each time step, \( t \), we have the following one-step forecast and posterior distributions (West and Harrison, 1997):

(a) Posterior for \( \mu_{t-1} \):

\[
(\mu_{t-1} \mid D_{t-1}) \sim N(m_{t-1}, C_{t-1}),
\]

for some mean \( m_{t-1} \) and variance \( C_{t-1} \);

(b) Prior for \( \mu_t \):

\[
(\mu_t \mid D_{t-1}) \sim N(m_{t-1}, R_t),
\]

where \( R_t = C_{t-1} + W \);

(c) 1-step forecast:

\[
(Y_t \mid D_{t-1}) \sim N(f_t, Q_t),
\]

where \( f_t = m_{t-1} \) and \( Q_t = R_t + V \);
(d) Posterior for $\mu_t$:

$$(\mu_t \mid D_t) \sim N(m_t, C_t),$$

with $m_t = m_{t-1} + A_t e_t$ and $C_t = A_t V$, where $A_t = R_t / Q_t$ and $e_t = Y_t - f_t$.

The random variable $e_t$ is the $1$-step forecast error, the difference between the observed value $Y_t$ and the expected value $f_t$. The variable $A_t$ is the prior regression coefficient of $\mu_t$ upon $Y_t$. An alternative representation for $m_t$ is

$$m_t = A_t Y_t + (1 - A_t) m_{t-1} \quad (4.4)$$

showing that $m_t$ is a weighted average of the prior estimate of level $m_{t-1}$ and the observation level $Y_t$.

### 4.2.2 Variance estimation

The quantities $V$ and $W$ have been estimated, using the EM-algorithm on data from 46 commercial slaughter pig farms. See e.g. Tanner (1993) for description of the EM-algorithm. The estimation is based on the assumption, that the terms $V$ and $W$ are constant in time. For constant variance components $A_t$ (equation 4.4) converges rapidly to a constant value as follows (West and Harrison, 1997):

$$\lim_{t \to \infty} A_t = A = \frac{r}{2} \left( \sqrt{1 + \frac{4}{r}} - 1 \right)$$

where $r = W / V$.

Based on these limiting results were the corresponding adaptive coefficient $A_t$ (equation 4.4) found to be in the range from 0.37 to 0.42 with mean 0.39 and standard deviation 0.0068.

### 4.3 Implementation

The method is implemented with a graphical user interface as a stand-alone application. All data needed for the calculations are drawn from the database of the existing farm management system. A time series is made by calculating average daily gain each time a group of slaughter pigs is delivered to the slaughterhouse.
4.3 Implementation

4.3.1 Filtering the time series

Among other features, the application allows the user to monitor the time series graphically in a chart. As it is shown in Section 4.2.1 the degree of filtering (expressed by $A$) depends on the relative relation between the observational error $V$ and the evolution error $W$. The more $V$ is increased relatively to $W$, the more is the time series filtered. The weekly estimates of daily gain are arithmetic means, or averages, over the number of pigs delivered to the slaughterhouse a given week. The number of pigs delivered are not the same every week, in general. Assuming that the daily gain among the individual pigs is uncorrelated, the variance of $Y_t$ is $V_t = V/n_t$, where $n_t$ is the known number of pigs delivered in week $t$. The user interface contains a slider which allows the end user to determine the degree of filtering. The variance of the evolution error term $W$ is held constant while the variance of the observational error term $V_t$ is affected by the number of pigs, $n_t$, delivered in week $t$ and by the position of the slider.

Each time the slider is moved it calls a procedure that calculates the filtered values of the time series and redraws the graph. The system value is held constant $W = c_1$, while the observational variance is calculated as:

$$V_t = \exp(x/c_2) \frac{1}{n_t}$$  \hspace{1cm} (4.5)

where

\begin{align*}
x & = \text{the position of the slider} \ (1, \ldots, 100) \\
n_t & = \text{the number of pigs delivered in week } t
\end{align*}

The constant values $W, c_1$ and $c_2$ are chosen so that the adaptive coefficient $A$ changes continuously from 1 to 0.3 as the slider is moved from 0 % to 100 %, ignoring the scaling factor $\frac{1}{n_t}$. The right hand side of equation 4.5 makes the visual impression of the filtering process look intuitively right, that is, the adaptive coefficient $A$ changes approximately linear as slider position (expressed as $x$) changes linear.

By way of illustration, a data set from a slaughter pig production unit containing approximately 900 pigs is used to calculate average daily gain over a period of 39 weeks. The traditional way of calculating daily gain is shown in Figure 4.2. The graph is based on 3- month periods, and is only made for illustration, as the existing farm management system does not contain any kind of graphical interface. The weekly calculated estimates of daily gain are plotted in Figure 4.3, and finally in Figure 4.4 the weekly estimates are filtered by means of the Kalman filter. From Figure 4.3 and Figure 4.4 it appears that there is an increasing tendency in the first part of the
Figure 4.2: Quarterly estimates of daily gain.

Figure 4.3: Weekly estimates of daily gain.
4.4 Discussion

Figure 4.4: Filtered weekly estimates of daily gain.

period followed by a decreasing tendency in the last part. The overall trend is reflected in Figure 4.2, to some extent, but the two local drops starting in week 14 and week 28 are not detected at all with the traditional way of calculating daily gain.

One advantage of the filtered time series is that it makes it easier to detect change points in the series. In the herd used in the example, lack of protein in the feedstuff in weeks 27-32 caused the drop in daily gain starting in week 28. Using the traditional method of calculating average daily gain one would never find out that lack of protein in a 6-week period actually results in a temporary decrease in daily gain of more than 100 grams.

Other production traits like leanness, weight at delivery, temperature, humidity and stocking density may be selected interactively for display in the same window as daily gain. By comparison it is possible, in some cases, to detect the reason for a decline in the estimated daily gain. The application is further described in Raadgivningscenter (1997).

4.4 Discussion

Weekly estimates on average daily gain improves the information on productivity, compared to the traditional quarterly estimates. As exemplified
in Section 4.3, a drop in the growth rate caused by e.g. poor quality of the feedstuff, is reflected within a few weeks. It is important to detect a decrease in productivity as soon as possible so that the management strategy can be changed.

Because of the fact that the new estimation method only measures growth rate on the pigs that are delivered to the slaughterhouse, some aspects has to be taken into consideration. First of all, a growth problem that only strikes the young pigs, will not affect the growth rate estimate until those pigs come to delivery. Furthermore, a drop in the growth rate that affects all pigs only shows gradually in the weekly estimates, depending on the time the delivered pigs have been affected by the problem.

The results from the growth rate estimation, is presented as a time series. Usually there is some fluctuation in the series that covers up information. The Kalman filter has proven to be well suited to smoothen the time series resulting in an improvement in the ability to detect change points visually. In the smoothing process, the observations are weighted according to the number of pigs delivered. The correct degree of filtering depends on the variance structure in data. The variance structure may differ among farms and therefore the application contains a slider that allows the user to determine the degree of filtering. It sometimes improves the visual detection of change points if the series is filtered more than conditioned by the variance in data. By doing so, only the serious level changes in daily gain are reflected in the filtered chart.

The Kalman filter is based on a so-called constant model and it has been considered whether the addition of a growth term would improve the model. But since the model is only used as a smoother to ease the visual detection of change points in data, the constant model has been found sufficient.

It has also been considered to implement the EM-algorithm in the application and thereby estimate the variance components, on farm level, before the Kalman filter is applied. Then a marker could be placed on the slider on that particular degree of filtering that corresponds to the variance estimates. This improvement will be implemented in a later version of the application.

The application is mainly intended to be used in continuous systems for fattening pigs with weekly deliveries to the slaughter house, although the weekly deliveries is no condition. The method presented in this paper applies as well for production in batches with all-in all-out operations as for the production with continuous delivery. Although it of course doesn’t provide weekly estimates of daily gain. But if the production is based on all-in all-out operations it would be straightforward to calculate the average daily gain for a particular batch by the traditional way, since all pigs enter the
housing section at the same time and they also leave at the same time.

It should be noted that the estimation algorithm is based on the assumption that the growth rate of all the pigs in a unit is roughly the same, even though it is a common assumption that the growth rate of slaughter pigs is normal distributed (see e.g. Kure (1997)). This simplification in the model might affect the time series of weekly estimates and give some extra fluctuation, but it will not cover up considerable changes in growth rate. A system with individual identification of all pigs would solve this problem and give more exact estimates. It would also make it possible to correlate the growth rate of the individual pigs to their parents, and thereby improve the foundation on which animals are selected for breeding.

4.5 Conclusion

Calculating estimates of daily gain weekly instead of quarterly is an example of making productivity control more dynamic. It helps the manager to react on changes in productivity. But there is still a lot of improvement to do. The key issue is to use the information as soon it is available. Even though the method presented in this paper increases the information on productivity, it still only provides historical data, in the sense that the growth rate of a particular batch of pigs, are known at a time when the pigs are already slaughtered. It would be useful to know exactly when a change in the growth rate occurs. At the moment research is going on to investigate whether real time information on the pigs water intake can be used as a marker of the growth rate.

References


