2950 Niles Road, St. Joseph, MI 49085-9659, USA
269.429.0300 fax 269.429.3852 hq@asabe.org www.asabe.org

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Real-time grower-finisher pigs' growth monitored and forecasted using a dynamic linear regression model

A. Peña Fernández¹, T. Norton¹, E. Vranken^{1,2}, D. Berckmans¹

¹*Department of Biosystems, Division M3-BIORES: Measure, Model & Manage of Bioresponses, KU Leuven, Kasteelpark Arenberg 30, 3001 Heverlee, Belgium.*

²*FANCOM B.V., Research Department, P.O. Box 7131, 5980 AC Panningen, The Netherlands*

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ABSTRACT. *Feed is the largest item cost in pig production, constituting around 70% of the total cost of growing a pig. Over the last years there has been an increase of the costs of feed ingredients while the market price for pig meat has remained the same, making the situation critical for farmers. Today's feeding strategies at commercial farms are set at group level according with the needs of the most demanding pig. The aim of this work is to show the potential of monitoring and forecasting feed consumption and weight development of grower-finisher pigs at individual level to develop individual feeding strategies.*

In this preliminary work, 14 pigs housed in a pen of 16 m² equipped with two feeding stations supplying two types of feed were studied. Both, Transfer Function and Dynamic Linear Regression modelling approaches were applied to the feed consumption and weight time-series of each individual pig to monitor and forecast the level of response in the pigs to the different changes in feed amount and/or composition, respectively. On average, the TF model fitting agreement is 99% and the Mean Relative Prediction Error of applying the DLR approach with a window size of four days and a forecasting horizon of one day is 1.35%. These properties allow to establish the point in time when a change in the performance of a pig takes place along the growing-finishing phase, allowing to determine set points for design of feeding strategies at individual level.

Keywords. *Fatteners, feed, forecasting, weight*

Introduction

Feeding represents up to 70% of production costs in pig farming (Woyengo et al., 2014). Thus, for a pig farmer, an adequate feeding strategy is of vital importance to maintain a profitable business, specially taking into account recent

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volatility in the market prices for feed components (Gaines et al., 2012; Douglas et al., 2015). Today's commercial feeding strategies are set at group level and the growth-stage related nutrient demand is managed using feeding curves that adjust feed ration during either 2- or 3- phase feeding programs (Cloutier et al., 2015). However, as pigs are living organisms, they should be considered as Complex, Individually different, Time-varying and Dynamic (CITD) systems (Berckmans, 2004). Thus, the efficiency to convert nutrients into lean meat can vary between individuals and during the stage of the fattening period (Brossard et al., 2009; Brown-Brandl et al., 2013). Conventional feeding strategies do not account for this variation, thus the efficient use of feed is restricted with them (Andretta et al., 2014; Mayer et al., 2013).

Precision Livestock Farming (PLF) techniques can provide a tool to monitor individual animals 24/7 in an automated and continuous way (Wathes et al., 2008). It has been already shown that pig's growth efficiency is an important part of efficient pork production (Patience, 2012; Kashiha et al., 2014). Also, there are examples in literature showing that automatic and continuous monitoring techniques can be used to develop precision feeding systems (Aerts et al., 2003; Pomar et al., 2011; van Milgen et al., 2012). The aim of these systems is to provide the right amount of nutrients to each individual in the herd to improve both, the profit for the farmer and the health of the animals (Hauschild et al., 2012; Andretta et al., 2014). Very few precision feeding systems are currently available, mainly based in mechanistic or grey-box model approaches (Parsons et al., 2007; van Milgen et al., 2008; Hauschild et al., 2012). However, it is expected of them to be widely used in the near future, as a small improvement in the feed use on the farm can have a positive impact on the production (Pomar et al., 2009).

Thus, the objective of this study is to evaluate the performance of data-based mechanistic models to relate pig weight development to the feed supply. An experiment was designed in order to test the performance of transfer function models in monitoring and forecasting the pigs' growth response due to feed supply changes by combining two types of feed in different diets. A multi-input single-output transfer function model was used for offline estimation of the model structure and a dynamic linear regression model, as simplest form of time-variant parameter transfer function model, was tested to evaluate the forecasting properties. It is expected that the data-based or black-box approach will allow to determine the model structure needed for this. Afterwards, it will be checked which biological information can be extracted from this model, leading to the data-based mechanistic approach.

Materials and methods

Animals and housing

In this project, three different experiments with 80 growing-finishing pigs in each one of them have been performed. In these experiments, the pigs' responses were evaluated in relation to sudden changes in the amount and/or composition of the feed. For this study, a subset of 14 growing-finishing pigs (Pietrain x Topigs 20), was used during an experiment in which the diet was determined by combining two type of feeds, namely feed A and feed B. Feed A was a typical commercially available starter feed, meanwhile feed B was a typical finisher feed, both used widely in current commercial production systems. At the beginning of the experimental period, only feed A was supplied to the pigs. From day 36 till day 51 of the fattening period, feed B was added in small increasing ratios to the global mixture conforming the diet supply to the pigs. From day 51 till day 66, the last day of the experimental period, the dietary mixture was set with equal proportions of feed A and feed B. The feed B addition to the mixture was performed in 5 days intervals, from day 36 to 51, as 20, 30 and 40 % of the mixture, respectively. From day 51 on, the mixture was 50% of each feed. This procedure was follow in order to induce sudden changes in the dietary supply of the pigs and evaluate model's performance to capture these changes.

The housing conditions were typical for Dutch pig husbandry. The research facility operates according to the Dutch 'Integrale Keten Beheersing' (Integrated Chain Management) farm standards. The pigs were housed in a pen (measuring 2.67 m x 6.26 m; 16.71 m², effective 16.14 m², 0.81 m² per animal) equipped with two Schauer® Electronic Sow Feeding stations. All pigs had ad libitum access to feed and water during the whole experimental period. All pens had a partially slatted floor and were situated in a room which was climate-controlled based on the pigs thermoneutral zone.

The weight of each pig was measured on arrival to the growing-fattening unit of the farm, being on average ± 25 kg. During the experiments, pig growth response was monitored by the Schauer® Electronic Sow Feeding stations for half of the growing-finishing phase ending at ± 60 kg live weight. They were equipped with a weighing platform consisting of front and back scales in order to monitor the weight of the pigs while feeding. The feed supply was measured individually daily through the Schauer® feeding stations by means of a RFID system.

Data Analysis

The relation between the feed supply for each individual pig and its weight development was determined by means of a Multi-Input, Single-Output (MISO) Transfer Function (TF) model. Moreover, a Dynamic Linear Regression (DLR) approach was tested in order to evaluate its potential to monitor and forecast the growth of the pigs in real-time and evaluate which biological information can be retrieved from it. A general scheme of the modelling process is shown in figure 1.

Figure 1. Block diagram showing the modelling process in which the amounts of feed A and feed B supplied to the pig are used as inputs and the weight of the pig is used as output for a transfer function model, i.e. MISO or DLR modelling approaches in this work.

Transfer Function (TF) Modelling

Using MATLAB® (The Mathworks, Inc.) Software and the CAPTAIN Toolbox (Taylor et al., 2007) the relation between daily supply of feeds A and B and weight for each individual pig was studied by using a MISO TF model. The model has the following general structure for two inputs (Young, 1984),

$$y(k) = \frac{B_1(z^{-1})}{A(z^{-1})} u_1(k) + \frac{B_2(z^{-1})}{A(z^{-1})} u_2(k) + \xi(k) \quad (1)$$

where $y(k)$, $u_1(k)$ and $u_2(k)$ are the output (weight), and the inputs (feed A supply and feed B supply) of the model, respectively; $\xi(k)$ is additive noise assumed to be zero mean, serially uncorrelated sequence of random variables with variance σ^2 , accounting for measurement noise, modelling errors and effects of unmeasured inputs to the process; k is the sample of the measurement; $A(z^{-1})$ and $B_i(z^{-1})$ with $i = 1, 2$ are two series given by:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_{n_a} z^{-n_a} \quad (2)$$

$$B_i(z^{-1}) = b_{i0} + b_{i1} z^{-1} + b_{i2} z^{-2} + \dots + b_{i n_{Bi}} z^{-n_{Bi}} \quad (3)$$

where a_j and b_{ij} are the model parameters to be estimated; z^{-1} is the backward shift operator, i.e. $z^{-1}y(k) = y(k-1)$, with y and k defined as in equation (1) and n_a and n_{Bi} are the orders of the respective polynomials. The model parameters were estimated using a Refined Instrumental Variable (RIV) approach (Young, 1984). The performance of the different models was evaluated using the value of the goodness of the fitting agreement, R^2 .

Dynamic Linear Regression (DLR)

Following Aerts et al. (2003), a Dynamic Linear Regression modelling approach was also tested. In this study, on each discrete time instant k , for feed amount or composition the linear relation can be written as:

$$W_k = c_{1,k} + c_{2,k} FD_{A,k} + c_{3,k} FD_{B,k} \quad (4)$$

with W the measured average weight (kg) and $FD_{A,k}$ and $FD_{B,k}$ the feed A and B supply (kg) at time k , respectively. $c_{1,k}$ (kg), $c_{2,k}$ (kg/kg) and $c_{3,k}$ (kg/kg) are the time-variant model parameters estimated at time k . More specifically, the parameters $c_{2,k}$ and $c_{3,k}$ are expected to resemble the feed efficiency at time k (defined as change of pig weight per change of feed intake). The parameter $c_{1,k}$ is expected to resemble the general weight offset exhibit by each individual pig.

At every discrete time instant k , the time-variant parameters, $c_{i,k}$, are estimated based solely on feed and weight measurements during a time window of a previous S samples, minimizing the effect of obsolete data as described in Aerts et al. (2003). Then, forecasts using these estimated parameters are performed for different prediction horizons, F (F -days ahead prediction). To investigate the accuracy of the model predictions, window sizes S ranging from 3 to 20 days and prediction horizons F ranging from 1 to 7 days were tested. The DLR goodness of the prediction estimations were quantified by means of the Mean Relative Prediction Error (MRPE), which is defined as:

$$MRPE = \frac{1}{N} \sum_{k=1}^N \sqrt{\left(\frac{W_k - \hat{W}_k}{W_k} \right)^2} \cdot 100 \quad (5)$$

where MRPE is a percentage; N is the number of samples; W_k is the weight measured with the automatic weighing systems at time k (kg) and $\hat{W}_k$ is the predicted weight at time k (kg) (Aerts et al., 2003).

Results and discussion

In figures 2 and 3, the weight development of each individual pig during the experimental period and the feed A and B supplied daily to each individual pig are shown. It is clear from these figures that each individual pig shows a completely different growth and eating pattern. Also, it can be seen that from day 36 on, once feed B is added to the feed supply mixture, the response of each pig is different as well. It is possible to see some drops and variability in the feed consumption data (Figure 3). The drops close to zero are due to non-recorded visits of that individual pig for that day, either due to malfunction of the system or due to the pig visiting less the feeding station that given day. The daily variability in feed A and B consumption is due to each individual pig feeding differently every day, as they had ad libitum access to the feed during the whole experimental period.

Figure 2. Daily weight measurements (kg) for each of the 14 individual pigs used in this study from the starting day of the experimental trial till the last day (day 66).

Figure 3. Daily feed supply A (kg) and daily feed supply B (kg) for each of the 14 individual pigs used in this study from the starting day of the experimental trial till the last day (day 66) in graphs (a) and (b), respectively.

Using the feed A and B supply as inputs and the weight as output, the performance of a MISO TF model to evaluate this relation was tested. Firstly, a system identification process to determine the order of the model needed to relate the feed supply with the weight for an individual pig was tested. The outcome of this procedure showed that a first order model with a first order Bi for both, supply of feed A and feed B, can model this relation showing, on average, a coefficient of determination of $R_T^2 = 0.99$, as displayed in table 1. In figure 4, an example of this first order MISO TF model is shown.

Table 1. Mean, median and standard deviation (SD) of the coefficient of determination (R_T^2) representing the goodness of fit of the MISO TF model application, the MRPE as percentage representing the performance of the 1-day-ahead forecasts of the DLR model using a 4-day time window and the coefficient of correlation (r) between the feed efficiency exhibited by the pigs in the trial and the DLR time-variant estimated parameters.

	R_T^2	MRPE [%]	r
<i>Mean</i>	0.992	1.35	0.75
<i>Median</i>	0.992	1.34	0.86
<i>Standard Deviation (SD)</i>	0.003	0.44	0.25

Figure 4. Example of the comparison between the first order MISO TF output and the weight data used as output for an individual pig in the trial (a). The daily supply of feed A and feed B to the pigs used as inputs are displayed in graph (b).

In figure 4, it can be seen that little discrepancies between the MISO TF model outcome and the weight data arise when there is a change in the growth rate of the pig. This is expected, as the growth rate of the pig will be affected by several factors along the growing-finishing period, such as environmental conditions in the pen or the health status of the pig. In order to account for these changes and taking into account the previous result showing that a first order model performed well to relate the feed supply and the growth, a DLR approach with time-variant parameters was tested. On the one hand, it is expected that this time-variant behavior of the model parameters will account for the changes in growth rate induced by external factors to the model. On the other hand, the capabilities of the model to be used in real-time monitoring of the growth of the pigs will be tested by evaluating its forecasting properties according to the feed mixture supply to the pigs.

In figure 5, an example of the forecasting performance of the DLR for an individual pig in the experiment is shown for different combinations of time windows (3 to 20 days) and different prediction horizons (1 to 7 days). It can be seen that for 1-day ahead prediction, the window size leading to the minimum MRPE is 4 days, being 3 and 5 days also a feasible alternative. In table 1 the average result obtained when applying a DLR model approach to forecast the weight development of the pigs in the experimental trial in real-time is displayed. For a time window of four days and a prediction horizon of one day, the MRPE is exhibiting a value of $MRPE = 1.35 \pm 0.44 \%$ (mean $\pm$ SE), on average. It is possible to increase the prediction horizon to for instance 7 days, in case it would be of interest to assess the weight development of the pig in longer time intervals. Then, the optimal time window is again obtained as 4 days but the MRPE goes up to 9 %, on average. Although it would be possible to forecast the weight development of a pig for seven days, it could be more interesting to perform daily predictions and updates of the model to have a closer understanding of the pig responses to the feed supply. Even though the changes in the feed supply will be applied every 4 to 7 days due to practical reasons, monitoring daily the development of the pig can provide insight in how fast the pig is reacting to the feed supply changes. Thus, the DLR allows

to make reliable prediction of the weight of the pigs according to the feed A and feed B supplied to the pigs for the prediction horizon set.

Figure 5. Example of the Mean Relative Prediction Error (MRPE), as percentage, for different combinations of time windows and prediction horizons when applying the DLR model to the datasets of an individual pig in the trial.

Finally, the time-evolution of the DLR parameters was compared with the feed efficiency exhibited by the pigs in the experiment. On average, the coefficient of correlation obtained was $r = 0.75 \pm 0.25$ as displayed in table 1. In figure 6, a comparison between the feed efficiency calculated from the data against the time evolution of the DLR parameters is shown. It can be seen that the dynamic evolution of both is similar, but still further work is needed in order to define the best way of relating the time evolution of the parameters with the feed efficiency.

Figure 6. Example of the comparison between the feed efficiency (F_{Eff}) calculated for an individual pig in the trial and the time evolution of time-variant parameters from the application of the DLR model to the same pig.

Conclusions

This study aimed to identify real-time dynamic models that predict the impact of sudden dietary changes on the growth response of pigs. The performance of transfer function models to monitor and forecast the weight development of pigs in terms of the diet supplied was investigated.

The MISO TF modelling approach shows that a first order, with an average 99% fitting agreement, is sufficient to model the relation between the daily feed supply to the pig and its weight development. Moreover, using a DLR modelling approach, it is possible to forecast the weight development of a pig according to a pre-defined A and B mixture diet with a 4-day time window and 1-day prediction horizon with an average MRPE of 1.35%. Time windows of either 3 or 5 days show similar results and could be applied as well. Moreover, longer prediction horizon windows, such as 7 days, can be forecasted but at the cost of an increasing MRPE. It may be better to follow closer the weight development of the pig even though the feed supply changes would be applied in longer intervals due to both, gain a better insight in the weight

development of the pig and obtained more accurate forecasts. The time evolution of the DLR time-variant parameters shows a correlation with the feed efficiency exhibited by the pigs ($r = 0.75$). Thus, the data-based mechanistic approach seems to be an adequate procedure to monitor and forecast the weight development of pigs according to their feed supply, providing insight in the feed efficiency.

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