Dynamic feeding intake monitoring in growing-finishing pigs reared under precision feeding strategies

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Abstract. *Pigs exposed to challenges with no prior experience change their daily feeding intake pattern. A method identifying deviations from normal feeding patterns could be used to develop a model framework to estimate individual nutrient requirements of challenged pigs fed with precision feeding systems. The objective of this study was to develop a tool for early identification of feed intake deviations in precision fed growing-finishing pigs. Feed intake measurements collected during 84 d in 126 growing–finishing pigs were used in this study. Electronic feeder systems automatically recorded the amount of feed consumed per meal. The recorded database was used to calculate the feed intake (DFI) per day of each pig. Individual feed intake dynamics were described by a univariate dynamic linear model (DLM) with Kalman filtering. The DLM is composed of a linear growth component, which allows the underlying level of the series to growth with a local growth factor. An unknown, but constant observation variance was dynamically estimated in the DLM. An optimized discount factor was used to specify the system variance. Finally, a standardized tabular two-side Cumsum (TC) was applied to the forecast errors generated by DLM to give warnings when pigs showed deviations of its normal feeding pattern. As the objective was identifying reduction on feed intake only alarm generated from the lower side of TC charts were considered. The DLM model was effective in following a feed intake trajectory for each individual pig over the growing period. In total, 22 pigs (17%) showed at least one deviation from normal feeding pattern. During the deviation period, when comparing forecast with the smoothed estimates, an average reduction of 30% on the DFI was observed. The system for monitoring the feeding behaviour of individual pigs based on a combination of a DLM and TC chart has proven to be a useful tool in modelling feed intake in pigs including forecasts of altered patterns. Thus, the proposed empirical approach has high potential to be integrated in a model used to estimate real-time nutrient requirements for pigs with deviation from normal feeding pattern.*

Keywords. *automatic feeders, Kalman filtering, feeding patterns, pigs*

Introduction

Meeting the individual pig nutrient requirements daily using precision feeding techniques has been considered a valuable approach of improving nutrient efficiency while ensuring the sustainability of growing pigs' production systems (Pomar et al., 2017). This approach represents a paradigm shift in pig feeding, since the optimal dietary nutrient level is no longer considered a static population attribute, but rather a dynamic process that evolves independently for each animal (Pomar et al., 2009). Previous studies showed that precision feeding techniques reduced lysine intake and nitrogen excretion without compromising pig performance (Andretta et al., 2014; Andretta et al., 2016).

In this modern approach, pigs are fed individually using diets adjusted in real time according to a mathematical model (Hauschild et al., 2012) and applying modern feeding techniques (Pomar et al., 2009). This proposed mathematical model estimates in timely manner nutrient requirements based on actual feed intake and growth pattern. Despite the good accuracy to follow an average feed intake trajectory in real time, this model was not developed to deal with individuals exposed to challenges. Pigs with no prior experience with different aversive stimuli or stressors can change their daily feeding intake pattern (Sandberg et al., 2006). Moreover, as each pig shows different ability to cope when exposed to these stressors (Wellock et al., 2004), different pattern responses can be observed in challenged animals. Pigs raised under farm conditions are frequently exposed to different challenges. These can be sanitary (including challenges without clinical signals), environmental (stocking density, space allowance, temperature), nutritional (changing diet composition or raw material, mycotoxin contamination, some antinutritional factors) or social (animal mixing). Despite the current benefits achieved by the precision feeding system, a framework development to identify pigs with modified feed intake pattern allow to move toward a more efficiency approach to be implemented in commercial swine farms. Accordingly, the purpose of this study was to develop a method for early identification pig with deviations of its normal feeding pattern.

Material and Methods

Data Base and Editing

Data on a reference population of growing-finishing pigs [130 animals of a high-performance genotype previously described by Andretta et al. (2014) and Andretta et al. (2016)] were used to build and evaluate the model's performance. Pigs consumed feed and gained weight according to the expected performance of the genotype throughout both trials. No health problems were observed during the experiment, except for rectal prolapse that was identified on one pig of the first trial and severe inflammatory foot problems that were identified in three barrows during the second trial. All animals with diagnosed clinical problems were isolated from the group and their data were not considered in the analysis. In these studies, were evaluated different feeding programs were evaluated; however, these treatments did not influenced daily feed intake. Pigs were group housed in a single pen and had free access to feeders and drinkers that provided ad libitum feed and fresh water throughout the experiments. Feed was provided individually with 5 feeding stations (Automatic and Intelligent Precision Feeder; University of Lleida, Lleida, Spain) installed side by side in front of the pen. The functioning of these feeders was described previously (Pomar et al., 2011). Briefly, the feeding station identified each pig when its head entered the feeder, and the station then delivered a blend of feeds in response to each animal's estimated allowance. Pigs tended to empty the feeder hopper or leave only very small amounts of feed behind at each visit, providing assurance that each pig received the assigned amount of blended feeds (Pomar et al., 2011). The feeders were equipped with a monitoring tool that continuously registered each visit of each pig with start and stop finish time (day, hour, minute, and second) and the amount of feed consumed. The feeder calibration (match between recorded and provided amounts of feed) was checked weekly. Finally, the feeder software calculated the total feed intake per day of each individual pig.

All data editing, modeling, and calculations were done using the statistical language and environment R (The R Core Team, 2013). Three data set were edited: Exp.1 (I Andretta et al. 2014), Exp.2 (Andretta et al. 2016) and all data (I Andretta et al. 2014; Andretta et al. 2016).

Modelling the Normal Feed Intake and Growth Pattern of Pigs – Univariate Dynamic Linear Model and Kalman filter

First, a dynamic linear model (DLM) is proposed to model the normal feed intake and growth pattern of pigs. The DLM can model fluctuations over time in the underlying mean, which makes it well suited for modeling the evolution in pigs' daily feed intake (DFI) over time. In addition, DLM allow also making forecasts, based on prior knowledge including former observations. The following DLM description is mainly based on West and Harrison (1997) and it has a structure similar for those developed by Madsen et al. (2005). However, the model doesn't have diurnal cyclic component.

The DLM consists of an observation equation and a system equation (Equations [1] and [2], respectively) as follows:

$$Y_t=F^{'}\theta_t+v_t,\ v_t\sim N(0,\ V_t) \qquad [1]$$

$$\theta_t=G\theta_{t-1}+w_t,\ w_t\sim N(0,W_t) \qquad [2]$$

where $\mathbf{Y_t}$ is the observation vector (DFI), $\mathbf{F'_t}$ is the transposed design matrix, $\mathbf{v_t}$ is a random observation error, $\boldsymbol{\theta_t}$ is the unobservable parameter vector, $\mathbf{V_t}$ is the observational covariance matrix, $\mathbf{G_t}$ is the system matrix, $\mathbf{w_t}$ is the a random system evolution error, and $\mathbf{W_t}$ is the systematic covariance matrix. Equation [1] describes how the values of an observation vector (Y_t) depend on an unobservable parameter vector (θ_t) to time t. The system equation [2] describes how the parameter vector may change over time. To describe both level and trend, the parameter vector ($\boldsymbol{\theta_t}$) contains the underlying values for each of the continuous variables, as well as the trend of the variable. The system matrix ($\mathbf{G_t}$) describes the evolution of the parameter vector $\boldsymbol{\theta}$ from time t-1 to time t. The transposed design matrix ($\mathbf{F'_t}$) allows extracting the expected values of the observable variables from the parameter vector. The transposed design matrix has the following structure:

$$F'=[1 \quad 0] \qquad [3]$$

The system matrix for a local linear trend model is given as:

$$G'=\begin{bmatrix}1 & 1\\ 0 & 1\end{bmatrix} \qquad [4]$$

All the information available (Y) at time t and also the initial information (t=0) is defined as $\mathbf{D_t}$ and is expressed by follow equation:

$$D_t=D_{t-1}\cup\{Y_t\} \qquad [5]$$

The Kalman filter estimates the prior distribution for $\boldsymbol{\theta_t}$, 1-step forecast distribution for $\mathbf{Y_t}$, and posterior distribution for $\boldsymbol{\theta}_t$ given $\mathbf{D}_t$ based on all information available at time t-1. The mean and variance-covariance matrix of the posterior distribution are represented as $\mathbf{m}_t$ and $\mathbf{C}_t$, respectively, so that $(\boldsymbol{\theta}_t|\mathbf{D}_t) \sim N(\mathbf{m}_t, \mathbf{C}_t)$. In order to initialize the model, prior information is required $\mathbf{D}_0$ (before any observation are made, t=0) on the initial distribution of the parameter vector $(\boldsymbol{\theta}_0|\mathbf{D}_0) \sim N(\mathbf{m}_0, \mathbf{C}_0)$. The observation and evolution error sequences $\mathbf{v}_t$ and $\mathbf{w}_t$ are assumed to be internally and mutually independent, and are independent of $(\boldsymbol{\theta}_0|\mathbf{D}_0)$. Using the description of Stygar and Kristensen (2016) for the Kalman filter, the recursively obtained prior distribution for $\boldsymbol{\theta}_t$ at time t-1 is described as:

$$(\theta_t|D_0)\sim N(a_t, R_t), \qquad [6]$$

where $\mathbf{a}_t = \mathbf{G}_t\mathbf{m}_{t-1}$ and $\mathbf{R}_t = \mathbf{G}_t\mathbf{C}_{t-1}\mathbf{G}'_t + \mathbf{W}_t$. The 1-step forecast for $\mathbf{Y}_t$ at time t is

$$(Y_t|D_{t-1})\sim N(f_t, Q_t), \qquad [7]$$

where $\mathbf{f}_t = \mathbf{F}'_t\ \mathbf{a}_t$ and $\mathbf{Q}_t = \mathbf{F}'_t\ \mathbf{R}_t\mathbf{F}_t + \mathbf{V}_t$. Finally, the posterior distribution for $\boldsymbol{\theta}_t$ at time t is

$$(\theta_t|D_t)\sim N(m_t, C_t), \qquad [8]$$

Where $\mathbf{m}_t = \mathbf{a}_t + \mathbf{A}_t\mathbf{e}_t$ and $\mathbf{C}_t = \mathbf{R}_t - \mathbf{A}_t\mathbf{Q}_t\mathbf{A}'$ with the adoptive matrix ($\mathbf{A}_t$) specified as $\mathbf{A}_t = \mathbf{R}_t\mathbf{F}_t\mathbf{Q}_{t-1}$. The vector of 1-step forecast errors ($\mathbf{e}_t$) is calculated as $\mathbf{e}_t = \mathbf{Y}_t - \mathbf{f}_t$. The vector $\mathbf{m}_t$ and the matrix $\mathbf{C}_t$ are referred to as the filtered mean and variance-covariance matrix of the parameter vector at time t, respectively.

Sequential forecast for k steps ahead is calculated as follows for j = 1, …, k:

$$(\theta_{t+j}|D_t)\sim N[a_t(j), R_t(j)], \qquad [9]$$

Where $\mathbf{a}_{t(j)} = \mathbf{G}_{t+j}\mathbf{a}_{t(j-1)}$ and $\mathbf{R}_{t(j)} = \mathbf{G}_t\mathbf{+1R}_{t(j-1)}\mathbf{G}'_{t+1} + \mathbf{W}_{t+j}$ with the initial values $\mathbf{a}_{t\,(0)} = \mathbf{m}_t$ and $\mathbf{R}_{t(0)} = \mathbf{C}_t$. Based on this parameter vector distribution, the following forecast distribution is obtained:

$$(Y_{t+j}|D_t)\sim N[f_t(j), Q_t(j)], \qquad [10]$$

where $\mathbf{f}_{t(j)} = \mathbf{F}'_{t+j}\mathbf{a}_{t(j)}$ and $\mathbf{Q}_{t(j)} = \mathbf{F}'_{t+j}\mathbf{R}_{t(j)}\mathbf{F}_{t+j} + \mathbf{V}_{t+j}$. The proposed model works with one-step ahead forecast (j=1).

Variance components

The observational variance **V** due feeding pattern differences between individual pigs should be rather constant within the same time series. This problem was solved in the model by considering a variance constant and unknows for each individual pig times series. Due to this aspect, the updated parameter vector $\boldsymbol{\theta}_t$ is distributed according to a Student T distribution which converges to the standard normal distribution as t increases and that the estimated precision ($\boldsymbol{\phi} = \mathbf{V}^{-1}$) becomes Gamma distributed. Further details were presented by West and Harrison (1997).

The system variance (**W**) changes as the pigs grow up for DFI. To handle with this evolution error, the system, variance was modeled using a discount factor ($\boldsymbol{\delta}$), as previously described by Madsen et al. (2005).

Reference analysis

The specification of prior distributions is necessary to initialize the model. For that, the reference analysis is used to estimate the initial parameters **D0 ~ (m0, C0)** as described by West and Harrison (1997). In this model, the reference analyses use the first three observations of the series in question to estimate the parameters.

The discount factor (**δ**) was determined according the method proposed by Kristensen et al. (2010). The objective was selected a discount factor value in order to optimize the performance of the DLM forecast (i.e. minimizing the normalized forecast errors $\mathbf{e_t^{norm}}$). The DLM was run for each individual pig (all data: 130 pigs) using different δ-values ranging from 0.1 up to 1 in increments of 0.01. The δ-value that minimized the sum of the square normalized forecast errors was chosen for the analysis. The forecast errors were normalized with respect to the forecast variance **Q**, such that $\mathbf{e_t^{norm} = e_t/\sqrt{Q_t}}$. The optimize δ-value for DFI was 0.88.

Monitoring Method to Identify Deviation from Normal Feeding Pattern

In this framework, the DLM is used to make a prediction of the DFI one step ahead in time. The difference between the one step forecast at time t − 1 and the observation $\mathbf{Y_t}$ is then used as a measure of the deviation from the "normal" feeding pattern. The deviation or forecast error can be considered as an independent random error term with zero mean as long as the process model is valid. However, if the pig changes its feeding pattern, data will no longer conform to the model predictions, and the numerical value of the forecast errors will increase. For practical purposes, one has to distinguish between deviations from the normal feeding pattern caused by a change in the growth rate of the pigs, and deviations caused by some challenge (diet modification, environmental, diseases, etc.) that implies decrease in DFI. To identify the "modified" feeding pattern for each pig the proposed monitoring method is based on a DLM used in conjunction with a tabular cumulative-sum (CUMSUM) control chart. The tabular upper CUMSUM works by accumulating deviations from zero that are above the target, and the lower CUMSUM accumulates the deviations that are below the target. When the sum of accumulated deviations exceeds a given threshold the process is said to be out of control (modified feeding pattern). This method is useful when only small changes are expected in the data (Montgomery, 2009). The Tabular CUMSUM for day t were calculated as described by Montgomery (2009). This method accumulates deviations from **T0** (target value) that are above the target with one statistic **C+**, and below the target with another statistic **C-**. The **C+** and **C-** for a given day (t) were as:

$$\mathrm{C}_t^+ = max\{0,\ e_t^{norm} - (T_0 + K) + C_{t-1}^+\} \qquad [12]$$

$$\mathrm{C}_t^- = min\{0,\ (T_0 - K)\ e_t^{norm} + C_{t-1}^-\} \qquad [13]$$

Where **T0** = 0 and **K** is the reference value expressed as **k** = (1 * σ_t)/2. Alarms are raised if $\mathbf{C_t+}$ or $\mathbf{C_t-}$ exceed a threshold **H** (expressed in terms of the standard deviation, H=5) in a given day t. The starting values of $\mathbf{C_t+}$ or $\mathbf{C_t-}$ are defined as zero. As the interested is only identify reduction in feed intake, only the alarms generated when $\mathbf{C_t-}$ exceed the threshold **H** are considered.

Model evaluation

The model evaluation consisted in a procedure to check how the model fits DFI with reference data set. First, the model performance of all individuals DFI was analyzed for each data base separately (Exp. 1 and Exp.2). Posteriorly, one individual pig who presented normal and other modified feeding patterns were taken from the reference data set (all data) to be analyzed separately.

Since the interest is in predictive fit of the model, the one-step forecast errors $\mathbf{e_t}$ were used for the model assessment. Under the assumptions of the model, similar to the forecast distribution, the random error term has also predictive distribution. Thus, observed deviations in the error sequence away from predicted behavior are indicative of model inadequacies. To check it, the standardized error $\mathbf{e_t^{norm}}$ was used. Finally, the tabular CUMSUM was applied to the series of forecast errors from the DLM. Each time an out-of-control alarm was issued, the sum was reset to zero. Graphical analyses were performed for individual forecast DFI, sum of normalized errors and number of alarms generated in function of the simulated period simulated.

Results and Discussion

The DLM in association with tabular CUMSUM is basically used to identify pigs with deviation from normal feeding pattern. Moreover, the DLM based on the filtering and smoothing procedures make possible to estimate DFI one-step ahead (1 d) of each individual pig in real time. To provide an overview of the filtered and sum of normalized errors estimates of each data base (Exp.1 and 2), all the DFI individual times-series (each pig) were plotted in function of the simulated period (Figure 1A, 1 B, 1D and 1E). In addition, the total number of alarms observed in each data base over the simulated period was plotted (Figure 1C and 1F). The results of this study according to the mean estimates show a linear increased in the filtered DFI for both data bases. Concerning the sum of normalized errors, in the Exp.1 was observed three negative shifts over the simulated period (from 7 to 20 d, from 40 to 60 d and from 75 to the end of studied period). In the Exp.2, three negative shifts over the simulated period were observed as well (from 15 to 20 d, from 40 to 45 d and from 70 to the end of studied period). The first negative shift for both experiments was probably caused by the non-stable feeding pattern right after the pigs were allocated in the growing-finishing facilities. The others shifts may be related to the period of in vivo body composition measures done in both experiments. The strong correlations in residuals within these periods with consequent negative shift of the sum of normalized errors resulted in alarms raised (Figure 1C and 1F). In total, 22 pigs (17%) showed at least one deviation from normal feeding pattern. It should be noted that these deviations and alarms were due by the experimental interferences (body composition measures) during the growing-finishing period and not diseases. Thus, it is still necessary evaluate this model on commercial condition where pigs are challenged by different diseases and stressors. However, it should be noted that two pigs (one from Exp1 and other from Exp2) had one alarm generated outside of the period related to the body composition measured. These results clearly show that even in a good management conditions (feed, environmental, sanitary, etc.) as those provide in Exp. 1 and 2, some pigs can show deviations from its normal feeding pattern.

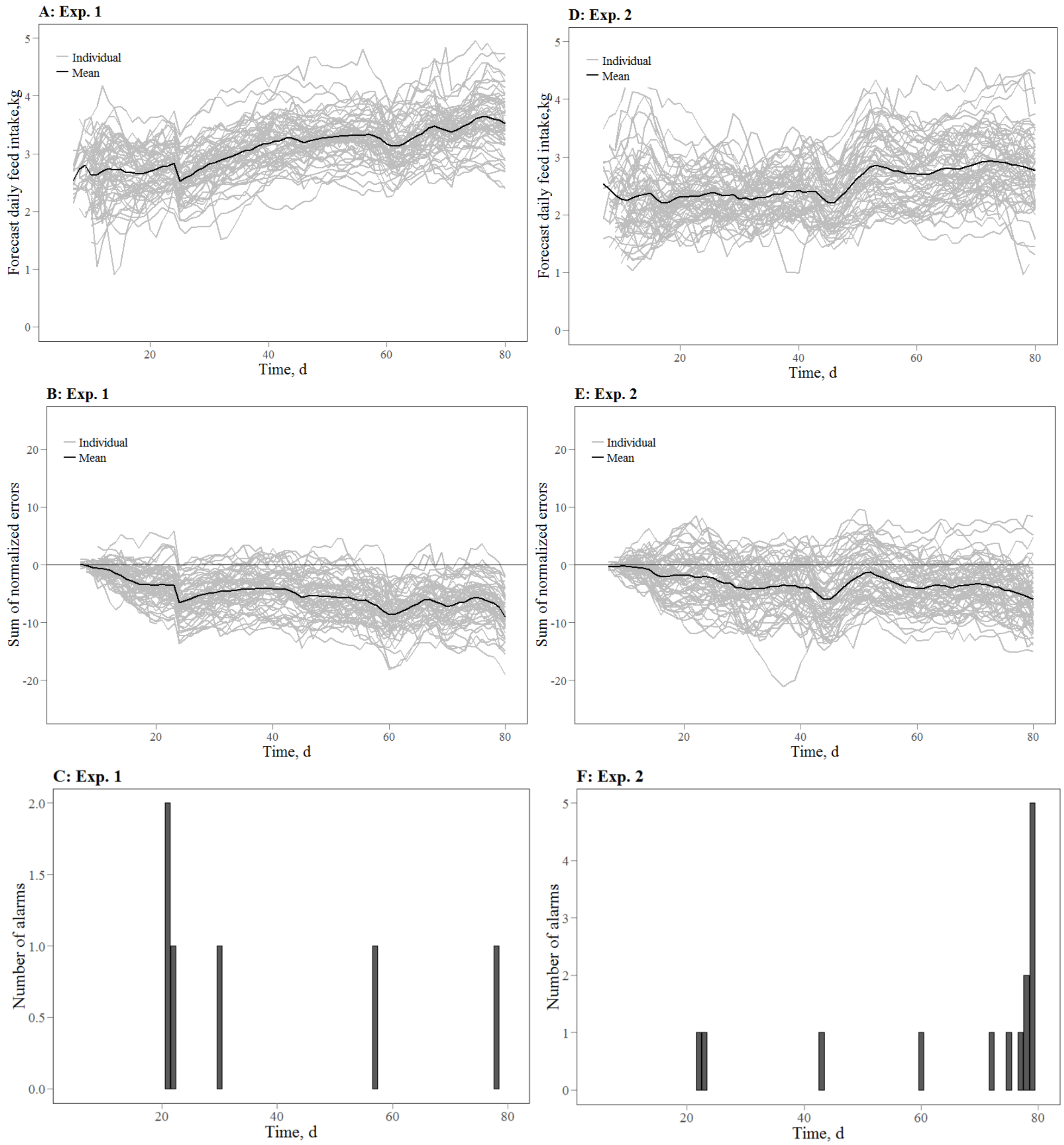

Figure 1. Forecast (filtered), sum of the normalized forecast errors (mean and individual) and number of alarms generated from Exp.1 (A, B and C, respectively) and Exp.2 (D, E and F, respectively) of daily feed intake.

To illustrate that the DLM in association with tabular CUMSUN is able to identify pigs with deviation from normal feeding pattern, an evaluation based on specific individuals was performed (Figure 2). To this end, results of DFI (Observed, filtered and smooth), sum of normalized errors and CUMSUM from one individual with normal (Figures 2A, 2B and 2C) and other with modified feeding pattern (Figure 2D, 2E and 2F) were plotted in function of the simulated period. The optimized discount factor (0.88) used in the DLM model allowed fits the observed values well considering the fact that the objective was to track the average trajectory of DFI of each individual (filtered vs observed values, Figure 2A and 2D). In the DLM model the filter is calculated sequentially until time t over the growing-finishing period as new information is collected. However, the smoothened is estimated retrospectively at the end. Thus, the smoothened will always follow a linear trend whereas the filtered are affected by the impact of any negative events over the growing-finishing period. Therefore, for the individual with modified feeding pattern, there was a negative impact on daily feed intake around the day 30. However, the smoothened show that for the individual with normal feeding pattern there was not an expressive negative impact on DFI. The DFI alteration (reduction) for the individual with modified feeding pattern did not allow the DLM fit well the observed data in a determined period (from 30 to 36d). This implies correlated forecast errors in the number of times steps the model needed to adapted to the new patterns. In the proposed approach, this correlated errors can be identify by the increase of the sum of the normalized errors (Figure 2E) and CUMSUM with consequent alarm generated (Figure 2F). Thus, it should be noted that the procedure developed was able to identify the feeding pattern changed for this individual. The individual with modified feeding pattern also presented small deviations in determined periods, but with regard to the long term (trend) it was not enough to affect the linear increase on DFI smoothened.

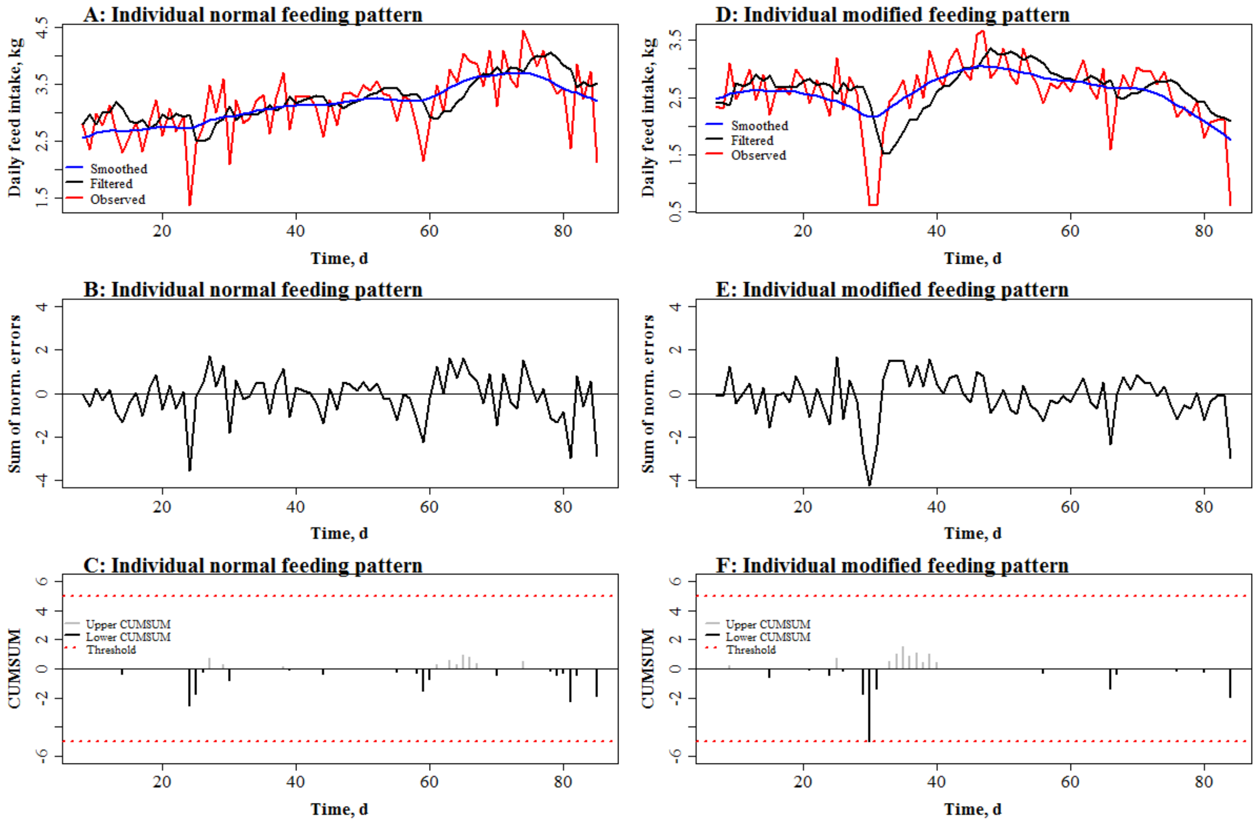

Figure 2. Observed, filtered, smoothed, sum of the normalized forecast errors and tabular CUMSUM of DFI of individuals with normal (A, B and C, respectively) and modified feeding pattern (D, E and F, respectively).

Conclusions

The pigs showed a very stable feeding pattern as long as they were healthy whereas the pattern often changed when the pigs were affected by some challenge. A method using a state-space model in conjunction with a Cusum control chart is presented as a tool for on-line monitoring of growing-finishing pigs, based on the daily feed intake. However, this method should be further evaluated under commercial conditions where pigs are challenged by different diseases and stressors. For the instance, the proposed empirical approach has high potential to be integrated in a model used to estimate real-time nutrient requirements for pigs with deviation from normal feeding pattern.

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