Assessment of the dynamic growth of the fattening pigs from body weight measured daily and automatically to elaborate precision feeding strategies

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Abstract

Growing pigs are often fed below *ad libitum* to increase their feed efficiency and carcass leanness. When energy supply is under control, precision feeding is implemented through the amino acids (AA). As the AA requirement depends on the body weight (BW) for the maintenance part and on its daily variation (ΔBW) for the growth part, the adequacy between requirements and supplies on day D+1 depends on the adequacy of predicted BW_{D+1} and ΔBW_{D+1}. Data sets from four trials were used to forecast BW from time series analyses based either on multivariate adaptive regression splines (MARS) or double exponential smoothing (HWα) methods using the *k* latest data (8, 14 or 20). Pigs (n = 117) were group-housed and restrictively fed, and their BW was recorded daily and individually with an automatic scale (n = 11 736). With $HW_{0.6}$, the RMSEP of BW_{D+1} was the smallest one (1.21 kg) and not influenced by *k*. Linear regression on the *l* latest forecasted BW was used to assess ΔBW_{D+1}. At the beginning of the trial, ΔBW_{D+1} was more difficult to predict from BW forecasted with MARS than with $HW_{0.6}$. Descriptive statistics of individual variation of ΔBW_{D+1} based on MARS and $HW_{0.6}$ were comparable with *k* = *l* = 20 only after removal of the first 19 days. Compared to other methods studied, the method $HW_{0.6}$ seems to be the best compromise to forecast BW_{D+1} and ΔBW_{D+1} of restrictively fed pigs.

Keywords

Pig, precision feeding, body weight, time series, dynamic growth, modelling, nutrition

Introduction

In growing pigs, precision feeding has been implemented for around 15 years toward an improved adequacy of amino acids (AA) supply to requirements (Pomar *et al.*, 2009). The first aim is to avoid a deficiency that would decrease carcass leanness and feed efficiency and subsequently the farmer's income. The second aim is to limit the excess that increases the price of feeds and the environmental impact of pig production through N output. More recently the need to improve the efficient use of protein-rich resources has emerged.

New devices have been developed recently that can mix different diets in specific proportions adapted to meet the daily requirement of each pig in the group. Such devices can be used either by pigs fed *ad libitum* (Pomar *et al.*, 2009) or restrictively fed (Marcon *et al.*, 2015). Requirements have to be assessed from the individual characteristics of pigs, especially its body weight (BW) or body weight gain (ΔBW) at a given age. According to the factorial approach, BW is one of the major determinant of the AA requirement for maintenance, and the AA requirement for growth depends on ΔBW. On day D+1, the supply of AA depends on BW_{D+1} and ΔBW_{D+1} forecasted from available data, i.e. from BW recorded up to day D.

Like in many other species, BW increases with age according to a S shape in pigs fed *ad libitum*. Under feed restriction, this trajectory is modified but growth rate still varies in a dynamic way. With devices equipped with an automatic weighing scale, individual BW are recorded continuously. As pigs can be weighed many times per day at different fulfillment stages of their digestive tract and udder, average daily BW can temporary drop or rocket from one day to another even after removal of outliers and without any health problem. Then, the difficulty is to extract the dynamics of growth from the short-term variations of BW. Individual and daily BW measurements performed during four trials were used to investigate different methods to forecast future BW and BW gain using different numbers of past data.

Material and methods

Data sets

Four groups of pigs were successively studied in the IFIP experimental station at Romillé (Brittany, France) during a research program on the environmental impacts of the feeding management.. At the end of the post-weaning period (around 66 days of age), 96 pigs were identified by RFID ear tags and group-housed in a single pen that is equipped with a weighing-sorting station placed on four force sensors allowing for weighing pigs individually, with a 0.1 kg accuracy. Other details on the experimental room can be found in Marcon *et al.* (2015). In each trial different feeding strategies were compared, but one of them was the reference strategy that was repeatedly studied in all trials. It corresponded to a 2-phase strategy with diets formulated at 9.75 MJ net energy (NE)/kg and 0.9 g of digestible lysine/MJ NE as long as the pigs from this group weighed less than 67 kg on average, and 0.7 g/MJ afterwards. Daily feed allowance depended on initial BW, stage of fattening and gender: 4% of the initial BW on D1, then + 27 g/d up to 2.4 kg/d for gilts and 2.7 kg/d for barrows. Only pigs of the reference groups studied until slaughter around 110 kg were kept in the final data set, i.e. 39, 22, 25 and 31 pigs in trials 1, 2, 3 and 4, respectively (corresponding to 11 736 BW).

Forecasting methods of BW_{D+1}

Time series prediction were performed using either multivariate adaptive regression splines (MARS) or double exponential smoothing model (HWα) where α is the smoothing parameter.

MARS: This method is a nonparametric regression procedure that does not imply any assumption on the relationship between the dependent and the independent variables (StatSoft Inc., 2013). It is most often used in case of difficult data mining problems, i.e. without simple and monotone variation of the variable studied. The earth function from the earth R package was used (Milborrow, 2011).

HWα: When a lot of past BW are available, a derivative function of the Gompertz function can be used to describe the pig's growth curve. This is not possible when only few BW are available at the beginning of the fattening period. Yet it indicates that the BW time series evolves in time with a form of trend that can be taken into account in the HW model. It assigns different weights to historical data depending on how recent they are, using a smoothing parameter α. The greater α is, the greater is the influence of the last measurement; values ranging from 0.1 to 0.9 by 0.1 were studied. The HoltWinters function from stats R package was used to fit a non-seasonal HW model (R Core Team, 2016), with the trend factor determined by minimizing the squared prediction error.

The k latest data used: Based on the hypothesis that the future BW depends on the *k* latest data, different values for *k* were investigated from 8 to 20. At the beginning of the trial, the number of most recent values used was lower than *k* as long as the trial has started less than *k* days earlier:

- *k* = 8: it is the lowest number of past data required for implementing the MARS,
- *k* = 14: it takes into account data obtained on the 2 previous weeks,
- *k* = 20: the time interval between 20 and 14 is the same as between 8 and 14

Missing values: None of the forecasting methods deals with missing values. As some days some pigs were not weighed or the BW was considered as an outlier, corresponding missing data had to be fulfilled. Before D = 4, a BW gain of 0.75 kg was assumed and added to the previous BW. Later, the BW forecasted on this day, with the same model, same value of *k* and eventually same value of α, was retained.

Prediction of BW_{D+1} and ΔBW_{D+1}, and other statistics

Forecasting of BW_{D+1} was performed every day for each pig. Each forecasted value after D4 was compared to the measured BW. The residual mean square error of prediction (RMSEP) was calculated per pig and submitted to an analysis of variance (proc GLM, SAS v9.4, Inst. Inc. Cary, NC) with the forecasting method (n = 10, MARS or HWα with α ranging from 0.1 to 0.9), the value of *k* (n = 8, 14 or 20), and the batch as the main effects. Average RMSEP per method were compared.

Due to day to day variation of BW, ΔBW_{D+1} cannot be calculated as the simple difference between the forecasted BW_{D+1} and the measured BW_D. Then linear regressions (proc Reg, SAS v9.4) were performed from the forecasted BW available over the *l* latest days (ranging from 10 to 20 by 2 d increment). For each pig, variation of ΔBW with time was characterized by its descriptive statistics (proc Univariate, SAS): 5th percentile, median, range of values observed, minimum and mean.

Table 1: Average RMSEP of BW[1] and comparison of the 10 methods run with three pools of recent data (*k*)[2]

Method		MARS	$HW_{0.1}$	$HW_{0.2}$	$HW_{0.3}$	$HW_{0.4}$	$HW_{0.5}$	$HW_{0.6}$	$HW_{0.7}$	$HW_{0.8}$	$HW_{0.9}$
	8	2.39^a	3.29^d	1.82^c	1.84^c	1.48^h	1.27^j	1.21^j	1.23^j	1.34^i	1.56^g
k	14	1.97^b	3.35^d	1.72^f	1.56^g	1.37^i	1.26^j	1.21^j	1.23^j	1.34^i	1.56^g
	20	1.84^c	2.09^e	1.75^f	1.53^{gh}	1.37^i	1.26^j	1.21^j	1.23^j	1.34^i	1.56^g

1. Arithmetic mean of the average RMSEP per trial (n =4). 2. Across the 3 lines and 10 rows, different letters indicate a statistical difference among methods with P *< 0.05 from the analysis of variance with the method combined with the* k *value (M_{30}, n = 30,* P *< 0.001), the batch (B, n = 4,* P *< 0.001) and the interaction M_{30}×B (*P *< 0.001) as main effects.*

Results and discussion

Prediction of BW on day D+1

In contrast to methods $HW_{0.1 \text{ to } 0.4}$ or MARS, the average RMSEP obtained with methods $HW_{0.5 \text{ to } 0.9}$ are not significantly influenced by *k* (Table 1). With the HW model, the RMSEP significantly increases when α increases from 0.7 to 0.9 or when it decreases

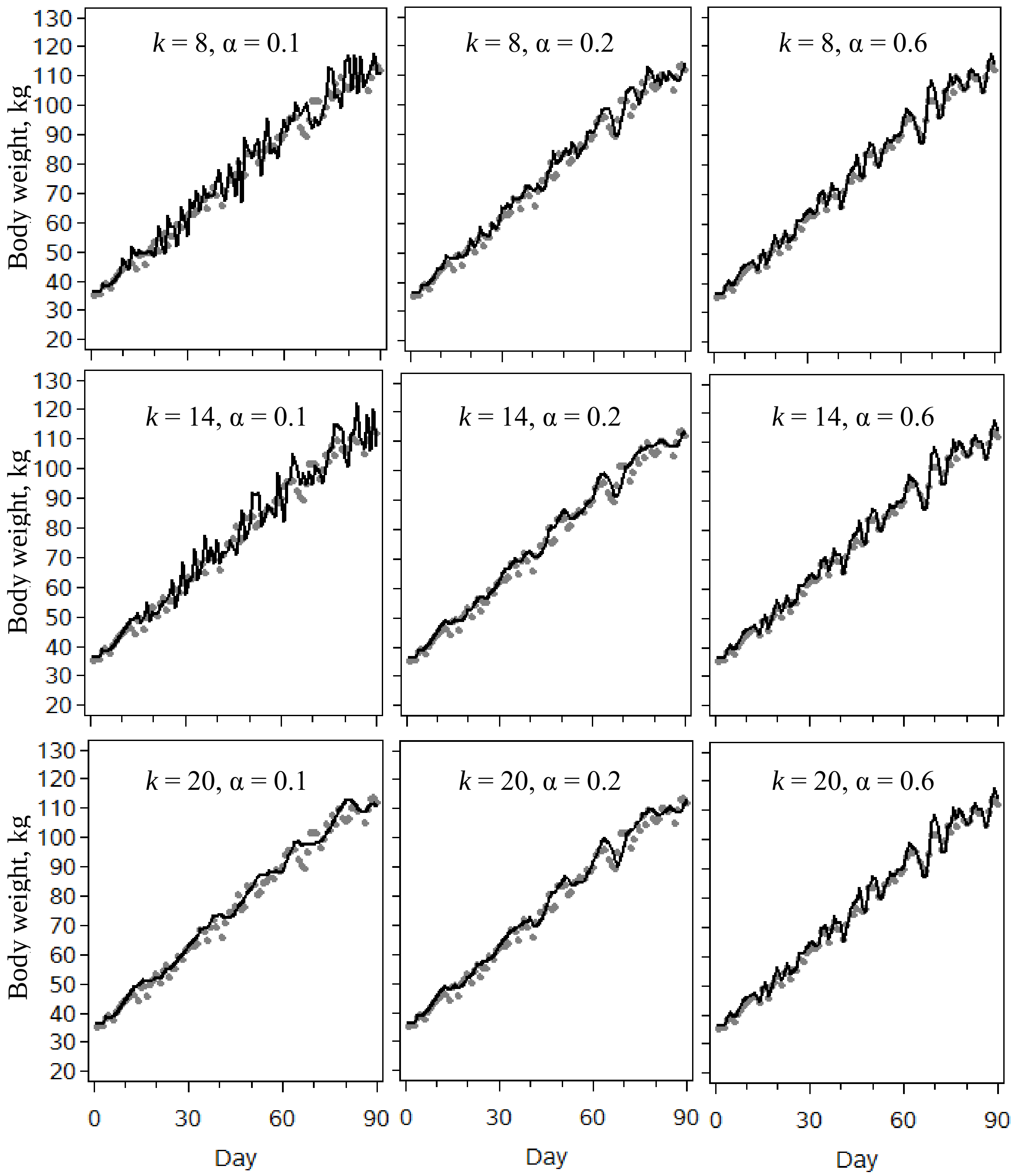


Figure 1 part 1: Example of comparison of measured (●) to forecasted (—) BW with the HW method implemented with different *k* latest values and three values for the smoothing parameter α (pig 310 in trial 1). To be continued…

from 0.5 to 0.1 (Table 1). The lowest RMSEP is obtained with the $HW_{0.6}$ method. It does not differ significantly from those obtained with $HW_{0.5}$ and $HW_{0.7}$, but allows for the lowest difference among batches (not presented). In agreement with Hauschild *et al.* (2012), a smoother trajectory of BW is obtained with $HW_{0.1}$ than with $HW_{0.6}$ (Figure 1), resulting in a higher RMSEP. With MARS, the RMSEP is intermediate between $HW_{0.1}$ and $HW_{0.2}$, even when the first 8 days are removed (instead of only the first 4 days). Figures 1 and 2 illustrate how the BW predicted with $HW_{0.1}$, $HW_{0.2}$, $HW_{0.6}$ and MARS fit the data for one given pig with different *k* tested.

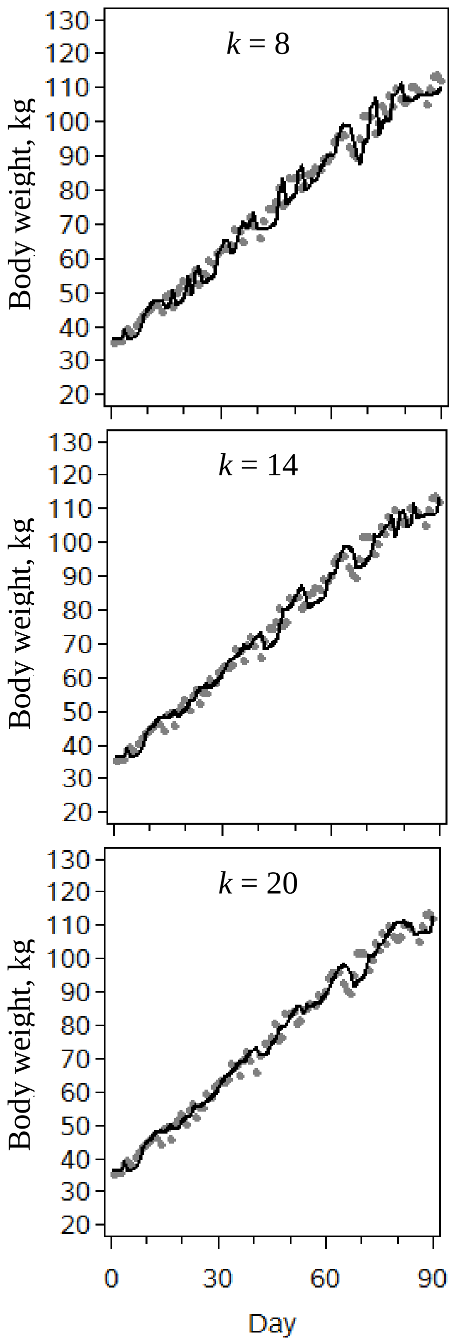
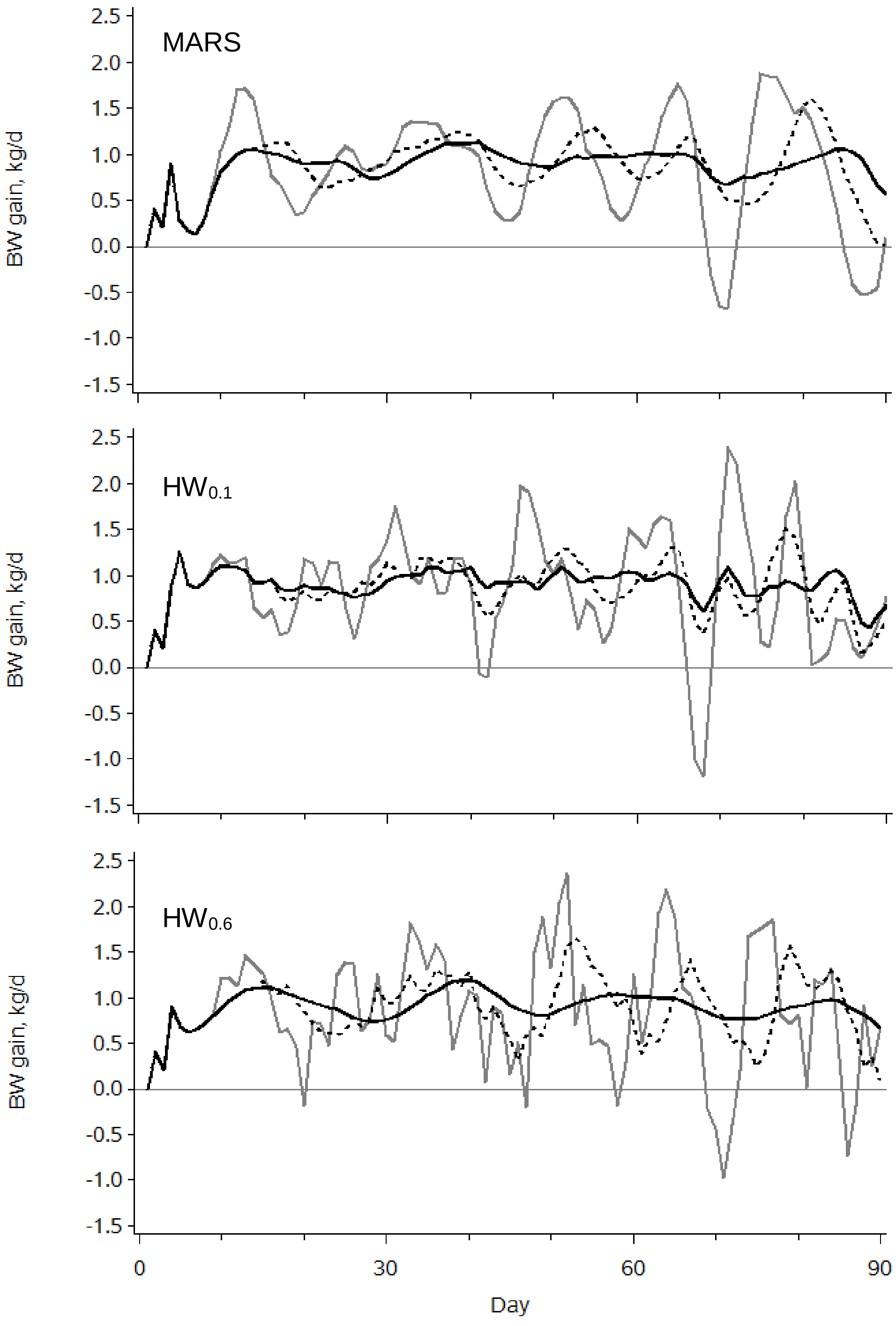


Figure 2: End of Figure 1 with the MARS method
(pig 310 in trial 1)

Prediction of ΔBW on day D+1

Based on results presented above, prediction of ΔBW was investigated from BW forecasted with $HW_{0.6}$, $HW_{0.1}$ and MARS. When daily ΔBW is assessed by regression over the *l* latest days, the smaller the *l* value, the more erratic is the variation of ΔBW whichever the method considered (MARS, $HW_{0.1}$ or $HW_{0.6}$ with k = 20). It can even be negative on certain days for some pigs (Figure 3).



W gain assessed from BW predicted with methods MARS, $HW_{0.1}$ and $HW_{0.6}$ by linear regression with k = 20 and l = 8 (▬), 14 (---) or 20 (▬)

(pig 310 in trial 1)

As illustrated for one pig in Figure 3, the prediction of ΔBW is very difficult at the beginning of the trial when only few data are available. Therefore, descriptive statistics of daily variation of ΔBW were calculated for each pig after removal of the ΔBW assessed on the 4 first days (see paragraph "*Missing values*") or on the 20 first days (allowing regression on 20 latest data when l = 20). Descriptive statistics were obtained for ΔBW assessed from the forecasted BW: with methods MARS, $HW_{0.1}$ or $HW_{0.6}$ with k = 20 and l = 20, or with $HW_{0.6}$ with k = 20 and l ranging between 10 and 20 by 2. From individual criteria per pig, an average per batch was calculated (proc Means, SAS) and results were pooled by an arithmetic mean in Table 2.

In agreement with what could be expected from Figure 3, differences among methods are more important when only the first 4 predicted values are removed from the analysis, compared to removal of the first 20 ones (Table 2). In this latest case, when regressions are performed from the 20 available BW (k = l = 20), descriptive statistics of ΔBW based on MARS and $HW_{0.6}$ are comparable and not so different from those obtained with $HW_{0.1}$. Additionally, means and medians are comparable for the three methods, but $HW_{0.6}$ results in higher values for the minimum ΔBW and the 5th percentile and a reduced range of variation. In other words, ΔBW obtained from BW forecasted with $HW_{0.6}$ seems secured.

Table 2: Descriptive statistics[1] on ΔBW (g) obtained by linear regressions based on forecasted BW with different methods and number of available data

Method (k = 20)	$HW_{0.6}$						$HW_{0.1}$	MARS
l value[2]	10	12	14	16	18	20	20	20
Day D ≥ 5								
5th percentile	238	339	410	452	484	510	291	361
25th percentile	621	653	676	690	700	706	674	683
Median	816	812	811	811	811	807	816	801
Range	1608	1311	1093	974	909	858	1363	1020
Minimum	-128	48	165	229	265	292	-3	42
Mean	792	792	791	791	791	789	787	764
Day D ≥ 21								
5th percentile	251	372	465	511	550	554	481	534
25th percentile	642	680	702	720	730	736	706	733
Median	841	837	832	830	827	822	826	825
Range	1516	1180	905	743	640	546	705	559
Minimum	-56	143	295	386	447	503	420	500
Mean	812	813	813	813	813	812	812	814

1. Proc Univariate (SAS, v9.4) on variation of ΔBW per pig; arithmetic mean of average results per trial.
2. Number of previous forecasted BW with methods $HW_{0.1}$, $HW_{0.6}$ or MARS used to assess ΔBW on day D by linear regression.

Using less than 20 past data to predict ΔBW from forecasted BW with $HW_{0.6}$ has limited consequences on the mean and the median but impacts more the other criteria when regression is obtained from less than 16 past BW. With l = 16 or 18, values of the 5^{th} and 25^{th} percentiles remain rather high. But with a value of l below 16, the range of values increases markedly and the average minimum decreases so that ΔBW can punctually reach negative values for some pigs. These results agree those published by Zumbach *et al.* (2010). These authors obtained similar average daily gain when it was calculated over different time intervals (1, 7 or 14 days) but reducing the time interval increased the variability.

Conclusion

Combined with a linear regression from the last 16 to 20 forecasted BW, the method $HW_{0.6}$ seems to be the most interesting one to predict BW_{D+1} and ΔBW_{D+1} in restrictively fed pigs. Compared to other forecasting methods investigated in this study, it presents a low sensitivity to the number of k latest values used. It allows for a secured prediction of BW soon after the beginning of the growing phase, which contributes to the low residual mean square error of prediction of BW and to smooth variations of predicted ΔBW.

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