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# Real-time Control of Pig Growth through an Integrated Management System*

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This paper describes the development and testing of the first prototype closed-loop, model-based, real-time system for the integrated control of pig growth and pollutant emissions. In each of two trials, growing pigs were reared from 30–50 kg to 65–125 kg in groups of 12 in 12 separate pens under controlled environment conditions at ADAS Terrington (Norfolk, England). They were fed *ad libitum* diets in which the protein content was controlled for each pen. Weight, estimated by visual image analysis, and feed intake were recorded daily for each pig. The control system was based on a mechanistic growth model. Each week, two model parameters were optimised using the data to improve the prediction, then the diet for each pen was optimised by adjusting the crude protein content between 140 and 190 g/kg [dry matter] to minimise the model error from a target for weight or fat depth. Part of the trial set weight gain targets of 50 kg and 60 kg over 70 days using two pens for each target. In three of the four pens the final mean weight of the pigs was within 2 kg of the target; in the fourth, growth was on target until it was interrupted close to the end of the trial. This trial has demonstrated the

potential of the system to control the growth rate of pigs and has given encouraging but not conclusive results for the control of back fat depth.

## 1. Introduction

Today, livestock production systems have multiple objectives imposed on them. As well as profit, they must maintain standards of animal welfare and reduce environmental impact (Frost *et al*., 1997). They have become complex interconnected processes: growth, health, welfare, and environmental emissions all depend on the animal's supply of nutrients. Managing growth by controlling nutrition will therefore affect these other factors.

Livestock management decisions are based almost entirely on the judgement and experience of the stockman, who must estimate or guess the likely effects of any control action, with each of the individual processed involved controlled separately. The farm manager will usually apply a prescriptive nutritional regime designed in the expectation that it will produce the required result. In a well-managed enterprise, the nutritional regime will be based on a growth model.

An integrated management system (IMS) is the combination of livestock models, monitoring equipment and feed control systems into an automatic system where control of these subsystems is delegated to an automatic controller (Frost *et al*., 1997, Whittemore *et al.,* 2001d). This allows closed-loop control decisions to be made in real time as and when data are collected. The improved economic efficiency and environmental gains offered by the IMS approach are becoming increasingly apparent to industry leaders. Integrated management systems can be used to improve welfare, by enhancing the ability to provide an ideal diet at all times, will allow better control of growth to obtain uniformity in the desired composition and quality, and by not providing nutrients to excess, reduce environmental pollution (*e.g.* nitrogen). This will reduce the time that farm staff must spend on decision making about feed provision, enabling them to concentrate on important issues such as health and welfare.

Integrated management systems have already been developed for poultry (Frost *et al.*, 2003; Stacey *et al.*, 2004; Aerts *et al.*, 2003a; Aerts *et al.*, 2003b). This paper describes the development of the first prototype closed-loop, model-based, real-time system for the integrated control of pig growth and pollutant emissions. It demonstrates the performance of a novel growth controller to achieve set growth rate and fat deposition targets.

## 2. Materials and methods

### 2.1. *Experimental facilities and data collection*

Experiments were carried out at ADAS Terrington, Norfolk, England. Two sets of trials, each with 144 pigs of a commercial breed (JSR white 12 boar-line) were performed in controlled environment facilities in six rooms each containing two pens capable of holding 12 pigs up to 100 kg. The temperature was maintained at approximately 19 C (which was adjusted if the pigs showed adverse behavioural responses) and lighting was on a 12/12 hour light/dark cycle.

Trial 1 contained equal numbers of male and female pigs; trial 2 contained males only. In each trial, half of the pigs were delivered at a nominal weight of 30 kg, the remainder at 50 kg; pigs of different weights were allocated to different rooms. There was considerable variation about the nominal weights, especially in trial 2: the range for the 30 kg pigs was 28–40 kg, and for the 50 kg pigs, 39–57 kg. Tables 1 and 2 show the allocation of pens and trial targets or treatments. The targets and treatments are described in more detail in section 2.5.

Each pen contained a feeder, which measured the weight of feed delivered to each pig at each visit, identified by radio frequency transponders embedded in the pigs' ear tags. The pigs were fed *ad libitum* diets that varied in crude protein (CP) content between pens, produced by manually blending two source diets with CP contents of 140 and 190 g/kg [dry matter]. At any time, all the pigs in a pen received the same diet.

Water was available *ad libitum* via nipple drinkers, and the total water use per pen was recorded weekly.

The pens had slatted floors and the slurry from each pen was collected in a separate pit. The total volume collected in each trial was recorded, and the slurry was sampled and analysed for total (Kjeldahl) nitrogen concentration. The ventilation rate for each room was logged at 1 minute intervals. The ammonia losses were measured continually using the acid trap technique (0.02 M orthophosphoric acid solution); the acid traps were changed twice weekly. It was thus possible to calculate the total mass of nitrogen emitted by the pigs in each pen and the combined weekly emissions of ammonia for each room.

A camera was mounted above each feeder, supplying images to a visual image analysis (VIA) system. This system measures areas and linear dimensions and estimates volumes quickly, frequently, and accurately, giving objective assessment of the size, shape, and hence growth of individual pigs. It has been shown to estimate the weights of individual growing pigs with average errors under 3.5% (Marchant *et al*., 1999; Schofield *et al.*, 1999, 2002; White *et al.*, 2004). The measured dimensions also enable assessment of lean meat and fatness (Doeschl *et al*., 2004; Doeschl-Wilson *et al*., 2005). The software was a version of Vista (Osborne (Europe) Ltd., North Shields, England) adapted to use the same identification transponders as the feeder and provide the data needed for the model and control program. It recorded the daily median values for weight and 12 physical dimensions for each pig in the herd.

Pigs were also weighed manually weekly, and backfat depth measurements were taken at the P2 position (65 mm from the midline at the last rib) using an ultrasound scanner fitted with a 3.5 MHz veterinary external probe (Concept MLV, Dynamic Imaging Ltd., Livingston, Scotland). Initial collation and processing of the collected data was carried out automatically by the computer on-farm. The processed data was then transferred to Silsoe Research Institute at least once a week for further processing.

In the initial stages of trial 1, faults in the feed delivery and monitoring equipment meant that there were periods for which the data were unreliable until repairs could be made. The worst affected pens were 1 and 5, but several others had shorter interruptions. These were resolved, so there were few problems in trial 2.

2.2. *Growth model*

The system was based on a mechanistic model of pig growth, as described by Green and Whittemore (2003, 2005), using algorithms described by Whittemore *et al*. (2001a, 2001b, 2001c). This model predicts the growth of an individual pig through change in composition given a description of the current status, growth potential, feed intake, and environment of the pig.

The pigs were allowed to become acclimatised to the feeding system for five days, during which both the intake and VIA data were discarded. Following this period, the median of the VIA-derived weights for the next three days was taken as the initial value for the model. Using the median guarded against occasional false readings. The initial fatness (lipid weight/body weight) of the pigs $F_0$ was unknown, so it was set according to the initial weight $W_0$ (kg) based on typical values observed in trials conducted during the development of the system:

$$F_0 = \begin{cases} 0.1 & W_0 \leq 35 \\ 0.269 - 5.924/W_0 & W_0 > 35 \end{cases} \quad (1)$$

Once initialised, the model was run using the recorded feed intakes for individuals and the blends supplied to pens as inputs, after filtering the data to remove occasional errors in the recording system. The mean squared error of prediction (MSEP) compared with the VIA estimated weight was calculated for each pig and the sum of these was used as a measure of how well the model fitted the data for a given pen.

In general, the unfitted model performed well (see the results below), but tended to underpredict the growth rate slightly. The agreement varied between pigs and between

pens, due to slight variations in genotype, environment, health status and behaviour. This was expected and the system included a mechanism to adjust the model parameters in response to observations.

### 2.3. *Model adaptation mechanism*

The system was designed to allow selected model parameters to be optimised within defined ranges to minimise the MSEP. The optimisation used the nonlinear revised simplex method of Nelder and Mead (1965) in a modified form that allowed constraints to be imposed (see Appendix 1). Experiments were conducted with other data sets using single parameters or up to three optimised jointly; good adaptation, without biologically unrealistic values, was obtained by optimising two parameters simultaneously. One of these, referred to as the 'illness factor' $F_{disease}$ (dimensionless), controlled the efficiency of use of dietary supplied nutrients (Green & Whittemore, 2005). This was allowed to vary over a range of 0.1–1.9 times its nominal value (3.0), where a low value represents high efficiency (good health). The other parameter $B$ ($d^{-1}$) controlled the maximum protein retention rate (Green & Whittemore, 2005), and was better determined, so was given a range of 0.7–1.3 times its nominal value.

### 2.4. *Controller*

When the system was required to make a control decision the model was first adapted for each individual in the pen using the data up to that time, as described in section 2.3 above, in order to improve its prediction of future growth. The individual models were then used predictively to model growth up to the end of the trial. In order to do so, a forecast of feed intake was required for each pig. Modelling voluntary intake is difficult and unreliable, and may best be obtained by observation (Schinkel & de Lange, 1996), so intake profiles were derived from results recorded in earlier trials (Green *et al.*, 2003). In trial 1, it was assumed that the pigs would follow these profiles. In trial 2, they were adjusted by the control system to account for variations between pigs, as follows. The mean ratio between the actual intake and the intake profile for the previous 14 days was calculated for each pig. It was then assumed that it would

continue to consume the same proportion of the intake profile for the next 14 days, then return to the profile over the next 14. This damped out daily fluctuations, while allowing substantial changes in intake to be accommodated, but remained conservative about long-term intake patterns.

The controller then optimised the dietary blend, and hence the crude protein content, to minimise the MSEP from the target for the remaining period. As the blend could only be controlled at the pen level, the objective function used was the sum of the MSEPs of all the pigs in the pen. There were separate sub-trials attempting to control weight and fat depth; joint control of both may be required in practice, so the objective function used a weighted sum of the errors in both variables. Furthermore, the objectives could be set either as a trajectory, that is a value for each day, or as up to four discrete points. Trial 1 used trajectories and trial 2 set target values for the end of the trial (day 70) only.

There was a single control variable, the dietary blend, but this could in principle be varied each day, giving up to 70 dimensions. This was reduced by having a control variable trajectory, in the form of a piecewise linear function, whose slope changed at discrete, equally-spaced nodes. Tests showed that the MSEP between target and prediction reduced as the number of nodes was increased from one to four, but showed insignificant improvement beyond four nodes. The optimisation problem was thus reduced to four dimensions. The slope was constrained to restrict the rate of change of the protein content. If the slope took the blend for any day outside the range [0,1], it was simply assumed to take the limiting value. A small penalty was added to the objective function when this happened, because it improved the efficiency of the optimisation by reducing the time spent exploring irrelevant regions of the control space.

Several optimisation algorithms were tested, including genetic algorithms, quasi-Newton methods and the nonlinear revised simplex method. The genetic algorithms were robust, that is, not prone to instability and consistent in finding the optimum, but they were slow. The quasi-Newton methods were capable of high precision, which was not required in practice, and became slow, or even unstable, in the presence of the full set of constraints. The constraints that represented simple bounds on the variables were

eliminated by transforming the state space using a *sine* function to transform an unbounded variable to a bounded one, but this did not improve the performance significantly. The mean speed of the revised simplex method was greater than the other methods, it remained stable, and the precision was acceptable, considering the precision that could practically be achieved in blending the feeds. This combination of features made it most the suitable method, and it was therefore used in all the trials.

### 2.5. *Targets and treatments*

The targets and treatments used in the two trials are shown in Tables 1 and 2. In each trial, the pigs in pens 1–4 were used for a sub-trial in which the targets were set as final P2 back fat depths. The pigs in pens 5–8 were used for a sub-trial with final weight targets. However, due to the large variation in initial weight within each pen in trial 2, the targets for this trial were set in terms of weight gain rather than target weight. The targets weight gains were 5 kg higher than those for trial 1, because the health of the pigs in the early stages of the trial was better, which enabled them to grow more quickly.

No targets were set for the pigs in pens 9–12. These were given fixed diets throughout using the high (190 g/kg) and low (140 g/kg) protein feeds without blending in order to promote the development of contrasting body conformation as part of the analysis of the visual imaging system results. These pigs, therefore, were not used in the controller trial, but were included in the model and adaptation testing.

## 3. Results and discussion

### 3.1. *Growth model and model adaptation*

In assessing the system performance, it is the ability to predict and control the liveweight of the pigs that is most important, rather than the prediction by the model of the VIA estimate of weight. All of the trial results were therefore compared with the results of manual weighings and P2 back fat assessments made shortly before slaughter.

Tables 3 and 4 summarise the ability of the model to predict the final weight and fat depth for trials 1 and 2, respectively. The results are shown for the initial values of the two parameters used for adaptation and after optimising them at the end of the trial.

It can be seen that the overall agreement between the model and the observed final weights was slightly better in trial 2 than trial 1. In both trials, optimising the model parameters at the end of the run using the VIA weight estimates reduced the root mean squared error of prediction (RMSEP) of the model compared with manual weights for the herd by about half. In each trial there were a few cases where the optimisation increased the RMSEP slightly for a pen; generally when the agreement was already good. The largest increase was in trial 1 pen 5, which was due intermittent substantial VIA overestimates of the weights of some of the pigs, which caused the optimisation to increase the prediction above the true weights, which were used in the calculation of the RMSEP. Better filtering of these outlying values would remove the problem. In general, the error in the prediction of fat depth was slightly increased by optimisation. This was not unexpected, because there was no feedback mechanism for fat depth, and therefore no reason why the prediction should improve. It should also be noted that the measurement of fat depth using ultrasound is itself prone to errors.

In addition to the incorrect VIA estimates noted above, it should be noted that some of the adaptation may have been to systematic errors in the feed intake data. In trial 2, the total mass of feed supplied to each pen was compared with the mass recorded by the feeding system. In 8 of the 12 pens, the feeding system record was within +/- 11% of the manual record. The worst cases were pen 1, in which the automatic system recorded 122% of the total supplied, and pen 5, which recorded 83%. Pen 1 was the only one where the adaptation mechanism did not consistently reduce the illness factor for the pigs (*i.e.* increase the efficiency), which would be consistent with achieving similar pig performance to the other pens, but recording a higher level of feeding than was actually the case.

To illustrate the results, it is useful to focus on a single pen and an individual pig. An example of the results for one pig up to the end of the trial is shown in *Fig. 1* (trial 2

pen 1 pig 249). It shows a close agreement between the model, VIA estimated weight and manual weight, with a small deviation at the end. The MSEP for this pig compared with the VIA weights over the whole run was 9 $kg^2$; for the pen (12 pigs) the total was 266 $kg^2$, and the highest in the pen was 66 $kg^2$. The predicted final weight for pig 249 was 96.7 kg compared with a measured weight of 94 kg; an error of 2.7 kg, which is consistent with the MSEP of 9 $kg^2$. The RMSEP of the model compared with the measured final weights, where the mean was taken over all the pigs in the pen, was 8.5 kg. After optimising the model parameters to minimise the errors from the VIA estimated weights, the RMSEP for the pen compared with the measured final weights was reduced to 2.5 kg.

As was the case for the whole herd, the prediction of back fat depth was generally less reliable. For pig 249, the measured depth was 10 mm and the predicted depth was 12.4 mm. The RMSEP for the pen was 1.9 mm. The optimisation procedure, based only on weight, increased the prediction for pig 249 to 12.9 mm and increased the RMSEP for the pen to 2.5 mm.

These results confirmed that the model gave generally good performance, and that optimising the chosen parameters using the VIA weight estimates could improve the prediction of weight. However, they used optimisation at the end of the run. In the trials, the optimisations were performed at each decision point using the data available at that time. A similar analysis to the above was performed by truncating the VIA record at day 39 and predicting the final weight based on actual intakes until the end of the trial. The results are shown in Tables 5 and 6. The results again show that optimisation reduced the RMSEP of weight, although by a smaller amount, as would be expected. The effects on the prediction of fat depth are also slightly less than when optimisation is performed using the full data set. These results confirm that the desired effect was obtained by this method of model adaptation.

3.2. *Operation as an offline growth and nutrition control system*

Table 7 shows the final result of the pens used for the controlled growth sub-trial in trial 1. Both weight and fat depth show only limited control. For both variables the lower target is exceeded and the higher one is not achieved. The maximum growth rate of the pigs may have been restricted by the health problems noted above, and the difficulties with the feed recording system, particularly in the earlier stages reduced the precision of the control system.

Table 8 shows the corresponding result for trial 2. Other than pen 7, which will be discussed below, the mean weight gain was within 2.5 kg of the target in each pen, and the back fat depth was within 1 mm of the lower target. The higher target for the pigs in pens 3 and 4 proved to be beyond the capability of the system given the range of possible diets and *ad libitum* feeding, but the pigs in these pens achieved greater back fat depth than those fed on the lower protein diet throughout.

The pigs in pen 7 grew at a rate very close to the target for about 8 weeks, then suffered an interruption in their growth, for reasons that cannot be determined, as shown in *Fig. 2*. Although they then started to recover, there was insufficient time for the controller to return them to the target. Their mean deviation from the target on day 54 was -2.3 kg.

3.3. *Other potential benefits*

In the course of the trials, it became clear that the combination of continuous monitoring of intake and the visual image of the pigs provided the potential for sophisticated problem detection. When a pig became lame, the change in posture often produced a sudden change in the area (shape) recorded by the VIA system, well before any effect on weight was detectable. If the feed intake of a pig dropped this was often not immediately obvious from the intake records, because intake was quite variable from day to day. The weight estimate from the VIA system usually required several days before the decline in growth rate, or weight loss, was obvious. The weight gain

predicted by the model often responded more quickly because some of the time constants in the model were shorter than in the metabolism of the animals. However, the magnitude of the change was usually comparable. On the other hand, a reduction in weight gain, or actual weight loss estimated by the VIA system when the model predicted continued growth, showed that intake was unaffected, but conversion efficiency was dropping, probably as a result of disease or other problems, such as scouring. By adding software to monitor the intake, VIA records, model predictions and possibly the corrections made by the adaptation algorithm over several days, the herdsman could be automatically alerted to health and welfare problems.

It was suggested in the introduction that IMS could offer environmental benefits, particularly by making more efficient use of protein in feeds to reduce nitrogen emissions. In the trials, the total nitrogen emitted in slurry (aggregated by pen) and ammonia (aggregated by pair of pens) were recorded. The ammonia emissions were allocated to pens in the same ratio as the recorded slurry nitrogen; since the ammonia typically accounted for about 3% of the nitrogen emitted, the errors this could introduce were small. Using these data for trial 2, the mean emission of nitrogen from the pigs in the controlled weight gain sub-trial (pens 5–8) was 35 g/kg weight gained. Those in pens 5, 6, and 8 emitted only 30–31 g/kg, but those in pen 7, where growth problems were observed in week 8, emitted 49 g/kg. The mean emission from the pigs on fixed feeding (pens 9–12) was 45 g/kg and from those in the fat gain sub-trial (pens 1–4) 51 g/kg. There were insufficient data to estimate the variances of the emission estimates, but the tentative conclusion from these data is that successful controlled weight gain could reduce nitrogen emissions substantially. Although the data were inadequate for proper validation, the trend in the prediction of nitrogen emissions by the model was correct within each trial. In theory, it would be possible to add a total nitrogen emission objective or constraint to the control system, to reduce the environmental burdens produced; the results obtained so far show that this merits further study. Controlling ammonia emission would be more complex, because it depends on environmental and behavioural factors.

## 5. Conclusions

The present study has shown that pig growth model optimisation can be performed in real time using visual image analysis (VIA) data, and that weight gain in pigs can be controlled through an integrated management system using *ad libitum* feeding and a range of diet crude protein (CP) content.

The results also indicate that some control of fat depth may also be possible, although the range of diets available to the trial meant that it was not possible to test this fully. Ideally, some form of feedback of fat content would be required, possibly by deriving a conformation measure from the VIA variables.

Successful feeding for controlled weight gain appears to reduce the total emissions of nitrogen. In principle, the system could be extended to include this as an objective or a constraint.

If VIA monitoring and intake recording were in operation, advanced detection of some health and welfare problems would become possible with little additional cost.

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## Appendix 1. Constraining the revised simplex method

Since its publication, the revised simplex method (RSM) (Nelder & Mead, 1965) has proved popular in many nonlinear optimisation applications where function derivatives are not available, despite its poor performance in higher dimensions, for the same reasons that it was used in this research: simplicity and robustness. The RSM was based on the earlier simplex method of Spendley *et al*. (1962); the key difference being that the RSM allowed the simplex to change shape to adapt to the topography of the search space. A limitation of both methods was the absence of an inbuilt method of handling constraints. Box (1965) found that introducing constraints into the original simplex method in the form of barrier functions often led to the simplex collapsing to a false optimum at a barrier. The method proposed by Box, the complex method, allowed the number of points used to increase. However, this was in part a response to the limitations already addressed by Nelder and Mead. More recently Subrahmanyam (1989) proposed another constrained version by introducing a new delayed reflection operation to prevent the simplex collapsing (the delayed reflection method, DRM). However, this was comparatively complex to implement, negating one of the attractions of the method.

The method used in this study was based on unpublished work by Parsons (1992) that tested several simple methods of applying constraints to the RSM for a range of test problems. The method chosen was referred to as the new maximum method (NMM). When a new point is generated for possible inclusion in the simplex, it is first tested for violation of any of the constraints. If a constraint is violated (referred to as an infeasible point), the new point is assigned a value mid way between the current maximum (*i.e.* the worst point) and the next highest point in the simplex. This allows it to be included in the simplex, reducing the likelihood of it collapsing, but ensures that no more than one point is infeasible at any time, subject to the constraint that all of the points in the initial simplex were feasible. The only overhead is thus the need to keep track of one point in addition to the maximum and minimum.

A modification of the RSM proposed by Parkinson and Hutchinson (1972) was also included. They noted that the RSM was inefficient where progress could be made by descent in a single direction on a scale substantially larger than the simplex (visualise a long downhill run), because this required several complete iterations, and could lead to elongation of the simplex. By introducing an operation that they called unlimited expansion and translation they reduced multiple iterations in the same direction to one.

The NMM was tested against fixed penalty (barrier) methods and others that allowed more infeasible points to enter the simplex, using a set of test problems with a sets of constraints that placed the minimum in a 'corner' of the feasible region in 5 dimensions, or set very tight bounds on one of the variables. The NMM gave the best performance on these problems and was the only one that consistently gave the correct result for the second type. It succeeded by adapting better to the geometry of the search space. The inclusion of unlimited expansion and translation was beneficial where the constraints forced a reduction in the scale of the simplex.

The NMM with unlimited expansion and translation was then compared with the results published by Subrahmanyam for the DRM using four test problems with non-linear constraints that were designed to be challenging. In two of these the NMM gave better results than the DRM, finding the optimum with equivalent or higher precision in many fewer iterations. In the third, which included an equality constraint, the DRM required 10 times as many iterations as the NMM, but achieved higher precision. Restarting the NMM allowed it to achieve similar precision to the DRM, but with more iterations. Whenever possible, equality constraints should be eliminated by reformulating the problem to reduce the dimension. In this case, it resulted in a problem with linear constraints, for which the NMM performed well. The fourth problem used a seven dimensional objective function with four constraints in five variables each. The NMM achieved significantly lower precision than the DRM.

It was concluded that the NMM was the best of the methods tested, except for high dimensional problems with complex nonlinear constraints. It was therefore well suited to the application described in this paper.

**Table 1**

**Allocation of pigs and targets to pens in trial 1**

| *Pen* | *Sex* | *Initial weight (nominal), kg* | *Target weight, kg* | *Target fat depth, mm* | *Treatment (protein level)* |
|---|---|---|---|---|---|
| 1 | F | 50 | | 16 | |
| 2 | M | 50 | | 16 | |
| 3 | F | 50 | | 12 | |
| 4 | M | 50 | | 12 | |
| 5 | F | 30 | 85 | | |
| 6 | M | 30 | 85 | | |
| 7 | F | 30 | 75 | | |
| 8 | M | 30 | 75 | | |
| 9 | F | 30 | | | High (190 g/kg) |
| 10 | M | 30 | | | High (190 g/kg) |
| 11 | F | 50 | | | Low (140 g/kg) |
| 12 | M | 50 | | | Low (140 g/kg) |

**Table 2**

**Allocation of pigs and targets to pens in trial 2**

| *Pen* | *Sex* | *Initial weight (nominal), kg* | *Target weight gain, kg* | *Target fat depth, mm* | *Treatment (protein level)* |
|---|---|---|---|---|---|
| 1 | M | 50 | | 12 | |
| 2 | M | 50 | | 12 | |
| 3 | M | 50 | | 16 | |
| 4 | M | 50 | | 16 | |
| 5 | M | 30 | 50 | | |
| 6 | M | 30 | 50 | | |
| 7 | M | 30 | 60 | | |
| 8 | M | 30 | 60 | | |
| 9 | M | 30 | | | Low (140 g/kg) |
| 10 | M | 30 | | | High (190 g/kg) |
| 11 | M | 50 | | | Low (140 g/kg) |
| 12 | M | 50 | | | High (190 g/kg) |

**Table 3**

**Results of optimising the model at the end of run in trial 1**

| *Pen* | *Final number of pigs* | *RMSEP of weight before optimisation, kg* | *RMSEP of weight after optimisation, kg* | *RMSEP of fat depth before optimisation, mm* | *RMSEP of fat depth after optimisation, mm* |
|---|---|---|---|---|---|
| 1 | 9 | 3.81 | 5.82 | 3.20 | 3.28 |
| 2 | 10 | 21.43 | 9.01 | 3.37 | 4.02 |
| 3 | 6 | 9.91 | 7.11 | 2.81 | 3.61 |
| 4 | 7 | 16.98 | 8.79 | 3.65 | 4.35 |
| 5 | 12 | 5.40 | 6.55 | 2.35 | 3.09 |
| 6 | 11 | 5.29 | 3.80 | 1.33 | 1.84 |
| 7 | 11 | 7.54 | 3.46 | 2.62 | 3.07 |
| 8 | 11 | 8.43 | 3.72 | 1.94 | 2.17 |
| 9 | 8 | 2.91 | 3.33 | 1.93 | 2.13 |
| 10 | 7 | 5.45 | 6.16 | 1.94 | 2.15 |
| 11 | 8 | 13.74 | 5.73 | 2.92 | 2.79 |
| 12 | 10 | 10.97 | 3.94 | 3.47 | 3.75 |
| Herd | 110 | 10.61 | 5.79 | 2.69 | 3.05 |

RMSEP, residual mean squared error or prediction

**Table 4**

**Results of optimising the model at the end of run in trial 2**

| *Pen* | *Final number of pigs* | *RMSEP of weight before optimisation, kg* | *RMSEP of weight after optimisation, kg* | *RMSEP of fat depth before optimisation, mm* | *RMSEP of fat depth after optimisation, mm* |
|---|---|---|---|---|---|
| 1 | 12 | 5.80 | 6.35 | 3.47 | 3.66 |
| 2 | 12 | 8.48 | 2.52 | 1.89 | 2.47 |
| 3 | 12 | 10.24 | 4.81 | 3.32 | 3.48 |
| 4 | 12 | 5.71 | 3.66 | 3.52 | 3.40 |
| 5 | 11 | 13.69 | 8.45 | 3.59 | 3.76 |
| 6 | 11 | 9.59 | 3.52 | 1.77 | 1.82 |
| 7 | 12 | 7.08 | 6.15 | 2.55 | 2.34 |
| 8 | 6 | 8.54 | 2.48 | 2.43 | 2.67 |
| 9 | 12 | 7.23 | 3.97 | 2.02 | 2.02 |
| 10 | 12 | 7.28 | 3.67 | 1.64 | 1.77 |
| 11 | 8 | 9.10 | 2.92 | 2.88 | 2.85 |
| 12 | 12 | 5.60 | 5.80 | 2.52 | 2.26 |
| Herd | 132 | 8.41 | 4.95 | 2.73 | 2.80 |

RMSEP, residual mean squared error or prediction

**Table 5**

**Results of the model at the end of run after optimising at day 39 in trial 1**

| *Pen* | *Final number of pigs* | *RMSEP of weight before optimisation, kg* | *RMSEP of weight after optimisation, kg* | *RMSEP of fat depth before optimisation, mm* | *RMSEP of fat depth after optimisation, mm* |
|---|---|---|---|---|---|
| 1 | 9 | 3.81 | 7.54 | 3.20 | 3.45 |
| 2 | 10 | 21.43 | 11.67 | 3.37 | 3.97 |
| 3 | 6 | 9.91 | 9.39 | 2.81 | 3.13 |
| 4 | 7 | 16.98 | 9.75 | 3.65 | 4.39 |
| 5 | 12 | 5.40 | 7.45 | 2.35 | 3.05 |
| 6 | 11 | 5.29 | 5.73 | 1.33 | 1.99 |
| 7 | 11 | 7.54 | 4.41 | 2.62 | 3.08 |
| 8 | 11 | 8.43 | 5.22 | 1.94 | 2.25 |
| 9 | 8 | 2.91 | 5.01 | 1.93 | 2.09 |
| 10 | 7 | 5.45 | 8.59 | 1.94 | 1.77 |
| 11 | 8 | 13.74 | 7.59 | 2.92 | 2.81 |
| 12 | 10 | 10.97 | 3.95 | 3.47 | 3.75 |
| Herd | 110 | 10.61 | 7.43 | 2.69 | 3.05 |

RMSEP, residual mean squared error or prediction

**Table 6**

**Results of the model at the end of run after optimising at day 39 in trial 2**

| *Pen* | *Final number of pigs* | *RMSEP of weight before optimisation, kg* | *RMSEP of weight after optimisation, kg* | *RMSEP of fat depth before optimisation, mm* | *RMSEP of fat depth after optimisation, mm* |
|---|---|---|---|---|---|
| 1 | 12 | 5.80 | 10.75 | 3.47 | 3.06 |
| 2 | 12 | 8.48 | 2.95 | 1.89 | 2.35 |
| 3 | 12 | 10.24 | 4.77 | 3.32 | 3.48 |
| 4 | 12 | 5.71 | 3.69 | 3.52 | 3.44 |
| 5 | 11 | 13.69 | 8.45 | 3.59 | 3.76 |
| 6 | 11 | 9.59 | 3.55 | 1.77 | 1.82 |
| 7 | 12 | 7.08 | 9.06 | 2.55 | 2.17 |
| 8 | 6 | 8.54 | 2.18 | 2.43 | 2.66 |
| 9 | 12 | 7.23 | 4.15 | 2.02 | 2.02 |
| 10 | 12 | 7.28 | 3.90 | 1.64 | 1.84 |
| 11 | 8 | 9.10 | 8.15 | 2.88 | 2.94 |
| 12 | 12 | 5.60 | 6.47 | 2.52 | 2.29 |
| Herd | 132 | 8.41 | 6.33 | 2.73 | 2.72 |

RMSEP, residual mean squared error or prediction

**Table 7**

**Results of trial 1: mean deviation from target (standard error)**

| *Pen* | *Target weight, kg* | *Target fat depth, mm* | *Mean deviation of weight from target, kg* | *Mean deviation of fat depth from target, mm* |
|---|---|---|---|---|
| 1 | | 16 | | -2.5 (2.9) |
| 2 | | 16 | | -0.4 (0.7) |
| 3 | | 12 | | 2.3 (2.4) |
| 4 | | 12 | | 1.9 (2.8) |
| 5 | 85 | | -4.0 (2.2) | |
| 6 | 85 | | -2.3 (2.3) | |
| 7 | 75 | | 0.9 (2.0) | |
| 8 | 75 | | 1.5 (3.2) | |

**Table 8**

**Results of trial 2: mean deviation from target (standard error)**

| *Pen* | *Target weight gain, kg* | *Target fat depth, mm* | *Mean deviation of weight gain from target, kg* | *Mean deviation of fat depth from target, mm* |
|---|---|---|---|---|
| 1 | | 12 | | -0.9 (0.53) |
| 2 | | 12 | | 0.2 (0.60) |
| 3 | | 16 | | -2.1 (0.72) |
| 4 | | 16 | | -2.4 (0.68) |
| 5 | 50 | | 2.1 (2.4) | |
| 6 | 50 | | 2.3 (0.9) | |
| 7 | 60 | | -5.8 (1.5)* | |
| 8 | 60 | | 2.0 (2.4) | |

* -2.3 kg on day 54

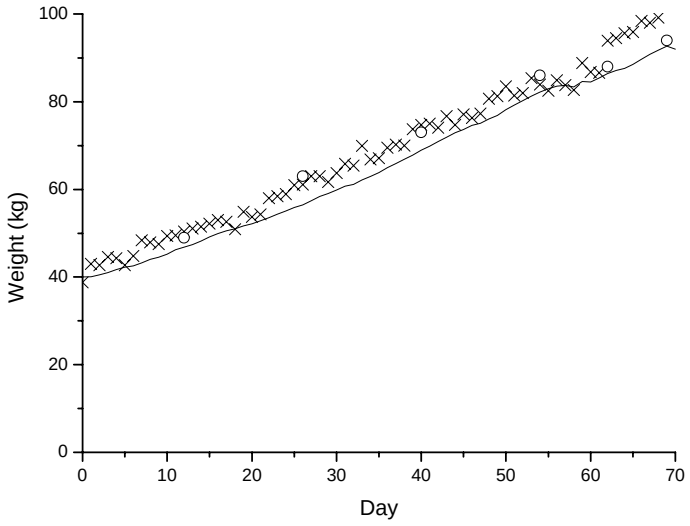


*Fig. 1. Example of growth model performance for trial 2 pen 1 pig 249:* x*, visual image analysis estimate;* o*, manual weight; —, model prediction*

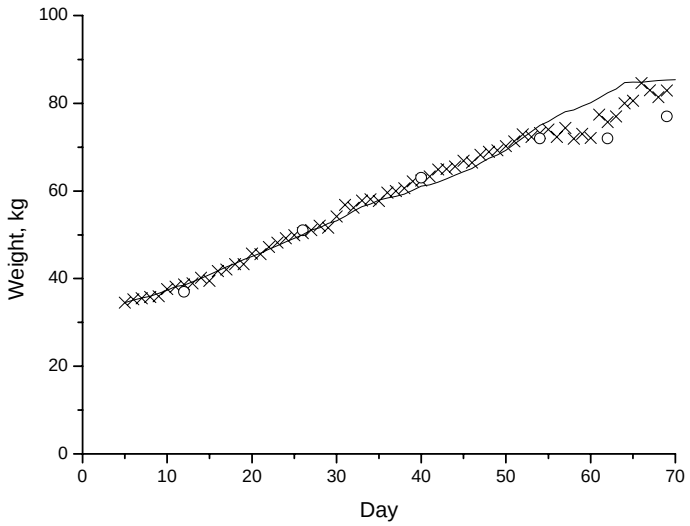


*Fig. 2. Growth of one pig in trial 2, pen 7, showing the interruption in growth around days 54–64:* x*, visual image analysis estimate;* o*, manual weight; —, model prediction*