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Neural Predictive Control of Broiler Chicken and Pig Growth

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Abstract

Active control of the growth of broiler chickens and pigs has potential benefits for farmers in terms of improved production efficiency, as well as for animal welfare in terms of improved leg health in broiler chickens. In this work, a differential recurrent neural network (DRNN) was identified from experimental data to represent animal growth using a nonlinear system identification algorithm. The DRNN model was then used as the internal model for nonlinear model predicative control (NMPC) to achieve a group of desired growth curves. The experimental results demonstrated that the DRNN model captured the underlying dynamics of the broiler and pig growth process reasonably well. The DRNN based NMPC was able to specify feed intakes in real time so that the broiler and pig weights accurately followed the desired growth curves ranging from −12% to +12% and −20% to +20% of the standard curve for broiler chickens and pigs, respectively. The overall mean relative error between the desired and achieved broiler or pig weight was 1.8% for the period from day 12 to day 51 and 10.5% for the period from week 5 to week 21, respectively.

Keywords: Predictive Control, Broiler, Pig, Growth, Optimal Control, System Identification, Neural Network Models

1. Introduction

This work forms part of a programme to determine, model and control the biological and physical responses and interactions of poultry and pigs to dynamic changes in their physical environment. In particular, it studies the growth and behaviour of broiler chickens and pigs reared for meat production and their ammonia emissions in response to dynamic changes in feed quantity, light intensity, temperature and relative humidity. This paper builds on early data for broilers growth published by Demmers et al. (2010) and focusses primarily on the growth of both broilers and pigs.

Growth of an animal integrates various physiological and environmental processes, so weight gain is not only a valuable measure of economic performance, but also a convenient measure of environmental response. Maximal growth rate as a function of feed intake is the most important parameter from the perspective of growers, because feed is the biggest cost in the production of housed livestock. Recently other physiological processes such as skeletal development of and activity of broiler chickens have also been considered. Slower growth in the early stages of broiler development reduces the incidence of lameness, the most important animal welfare issue in broiler production (Butterworth & Arnould, 2009), whilst liquid phase-feeding has the potential to improve pig health and growth (Scott et al., 2007).

Frost et al. (1997) argued that livestock production systems contain multiple interconnected processes that need to be managed to meet several performance criteria, including economic, animal welfare and environmental targets. Traditional management was, and still is, largely based on experience and is not good at integrating processes and performance criteria. An example is the use of climate (temperature) controllers. Development of the climate controller was through observing animal performance and behaviour (Charles & Walker, 2002). However, control was through temperature measurement alone, discarding any information from the animal. The stockman still had to intervene if the response of the animals indicated that the temperature control was imperfect. The proposed solution was to move towards integrated closed-loop, model-based control systems, by first developing controllers for the key processes, using sensor technology capable of measuring animal responses, that was becoming available.

The nutritional and environmental requirements of broilers and pigs are

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well understood (Gous et al., 1999; Kyriazakis & Whittemore, 2006), which has enabled the development of mechanistic models to predict broiler and pig growth from feed inputs (Emmans, 1995; Black, 2014). These models and the science underlying them have been used to create plans for nutrition and weight gain (Aviagen, 2002; PIC, 2005). However, the dynamic responses of animals to (sudden) changes in the environment are less well understood and fewer models exist. Furthermore, Wathes et al. (2008) states that in general mechanistic models are not suitable for control purposes, because they are often overly complex, with too many parameters, although these have biological meanings, and inaccurate, since parameter values may change over time and space.

Recently, data-based models describing the response of the growing broiler to changes in feed quantity have been explored as an alternative to mechanistic models. Data-based modelling techniques estimate the unknown model parameters of any abstract mathematical model structure from measurements of process inputs and outputs. In principle, the parameters can be estimated on-line resulting in an adaptive model that can cope with the characteristics of most biological processes, *i.e.* complex, individual, time variant and dynamic (Aerts et al., 2003b). This type of model has the advantage that no *a priori* knowledge of the process is required, although the latter is beneficial whilst developing the model. However, in contrast to mechanistic models, the parameters have no biological meaning. The resulting model will in general be more compact and therefore suitable for control purposes. As a result data-based models are widely used for process control in other industries. Various approaches to modelling broiler growth have been used, including hyperbolastic models (Ahmadi & Mottaghitalab, 2007), artificial neural networks (Ahmadi & Mottaghitalab, 2008) and recursive linear models (Aerts et al., 2003b).

Frost et al. (2003) and Stacey et al. (2004) described the development of a system based on a mechanistic model to control the feeding of broiler chickens to achieve a given time-weight performance. The system was developed on farm scale (over 30,000 birds/house) using a feeding system where the diet composition was controlled by blending two different feeds and growth was monitored by perch weighers. It aimed to optimise the feed blend to minimise the errors from a planned growth curve from the current day to slaughter, and was able to deliver birds of the correct weight, except when growth was inhibited by disease. A pig growth monitoring system based on image analysis (Doeschl-Wilson et al., 2004; Schofield et al., 1999), supported the development of a mechnistic model and a real time controller for pig growth (Parsons et al., 2007). The model was able to control mean pig weight in trials to within 2 kg of the target weight, by varying crude protein content of the diet. The use of a mechanistic simulation models for broilers and pigs based on the nutritional and envronmental requirements, required the specification of several genotype-dependent parameters and feed analysis in terms of several nutrients, rendering them less suitable for control purposes.

For the reasons discussed above, a data-based approach was followed on laboratory scale by Aerts et al. (2003a) and at a larger scale by Cangar et al. (2008), in which the quantity of feed presented was controlled using model predictive control. They used a recursive linear models with time varying parameters to predict weight 3–7 days ahead (Aerts et al., 2003b; Cangar et al., 2008). Using online prediction of the feed quantity, control of broiler growth along a target trajectory proved possible within certain boundary conditions. Most notably, the period during which growth could be restricted without affecting the ability of the broiler to reach the target weight was limited to the early stages of growth (age 7–30 days). Growing broilers to the required target weight using online control resulted in a mean relative error of 6–10% in live weight.

The method described here shares some of the characteristics of the above approaches and aims to overcome some of their limitations. The model is empirical, so does not require genetic parameters or detailed feed analyses, but simulates growth from hatching to slaughter. Based on this model, the controller is designed to optimise feeding over the complete period of growth instead of a fixed horizon. The control strategy aims to optimise the system by reducing the feed intake to save cost, minimising the deviation of bird weight from a predefined grow curve to ensure the final target is smoothly achieved and at the same time restricting the daily change in the intake to avoid potential stress on the birds. These objectives are combined into a single cost function as a weighted sum of these criteria.

This paper is organised as follows. In section 2, after a brief description of broiler and pig growth and the experimental data, the DRNN model is introduced and developed to represent the growth dynamics. The growth control problem is then defined in section 3 and solved using the DRNN model and the NMPC framework. The performance of the DRNN model and the NMPC algorithm are demonstrated through experiments in section 4. A discussion of the results and the conclusions are given in section 5.

2. Weight-Feed Model Identification

Growth of any organism is a complicated nonlinear dynamic process, which is difficult to model from first principles. Most conventional system identification approaches use linear model structures, such as the autoregressive moving average with exogenous input model (ARMAX). The latter can be adapted to account for variabiltiy in time and therefor non-lineair systems (RARMAX), but the time-varying nature is dependent on the actual state trajectory, which the linearisation takes as a reference trajectory. This potentially limits their use to specific applications where the trajectory of the model developed is similar to that of future applicaitons. Due to their ability to approximate any nonlinear function, recurrent neural networks (RNN) are widely used for nonlinear system identification. However, most available RNN models are in discrete time, which can only work for the specific sampling rate with which the model is trained. In order to develop a dynamic model to control the entire growth process with potentially variable sampling rate, the differential RNN (DRNN) and the associated automatic differentiation based training algorithm developed by Al-Seyab & Cao (2008b,a) were adopted for this work. DRNN models are black box models and the internal parameters are not transparent, unlike the external input and output variables, in this case feed intake and liveweight under various conditions, which can be interpreted from a biological point of view.

A first order DRNN model with two hidden nodes represented as follows, adopted to represent the broiler growth process.

$$\dot{x} = w_5\sigma(w_1x + w_3u) + w_6\sigma(w_2x + w_4u) \tag{1}$$

where x and u are the weight and feed intake, respectively, for a single bird, $\sigma(x) = \frac{e^x - e^{-1}}{e^x + e^{-1}}$ and $w_1, \ldots, w_6$ are model parameters to be determined. The model structure is determined based on the intuitive assumption that from any initial weight, x_0, if the feed intake is zero, then the animal's weight will gradually decay to a constant.

To represent the pig growth equally a first order model with one state and 2 hidden nodes was adopted:

$$\dot{x} = W_2\sigma(W_xx + W_uu + b_1) \tag{2}$$

where x and u are the weight of a pig and the feed intake, respectively, W_2, W_x, W_v and b_1 are model parameters to be determined and the current temperature is a disturbance in the growth models as this is gradually reduced over the experimental period for broilers and an experimental factor in the pig trials.

To generate data for training and validating the broiler models, broilers were grown from 1 day old to 51 days. The broilers were exposed to dynamic (sudden) changes in the inputs, feed amount, light intensity and relative humidity (RH) from day 12 onwards. To ensure a measurable response in output, the change in the input was set unrealistically large compared to normal broiler production practise. Feed amount was set at either 90% or 110% of recommended feed requirements for broilers (Aviagen, 2002). Light intensity was set at either 10 or 100 lux and RH at 56% or 70%. The frequency of change was set according to the time required to reach a new steady state in the output, *i.e.* hours for the light intensity and 3–7 days for feed amount and RH. A two-level (change or no change) of three-factor (feed amount, light intensity and RH) factorial design requiring $2^3 = 8$ identical rooms was used and repeated in three trials. Each possible combination of inputs was randomly allocated to a room in each of the three trials. This experimental design potentially allowed identification of interactions between the processes: growth, activity and ammonia emission, affected by feed amount, light intensity and RH, respectively.

Each room housed 262 broilers (Ross 308) on a bed of woodshavings up to a maximum stocking density of 33 $\mathrm{kg\,m^{-2}}$ at 50 days. The average bird weight was estimated continuously using a weighing platform suspended from a load cell (Fancom 747 series bird weight platform and computer). Specially produced animal feeds were weighed and dosed automatically to each room (Fancom 771 feed computer) four times a day. Feed quantity dosed and broiler weight in each room were recorded automatically four times per day from day 3-51. Other environmental variables, such as temperature, RH and light intensity, were monitored and recorded at 1 minute intervals.

To generate data for training and validating the pig models, pigs (Large white, Landrace and Pietran cross) were housed from 5 weeks of age to 22 weeks. Pigs were exposed to dynamic changes in feed amount and temperature from week 6 onwards. The change in feed amount was set at either 80% or 120% of recommended feed requirements for pigs and to +7 C above the recommended room temperature at 3 week intervals. A two-level of two-factor (feed amount and temperature) factorial design with four identical pens in two rooms was used and repeated in two trials, which potentially allowed identification of interactions between the processes growth and ammonia emission, affected by feed amount and temperature, respectively.

Each room was divided in 4 identical pens which housed 10 pigs on a part slatted floor with straw on the solid floor. The average pig weight was measured daily using the visual image analysis system (Osborn Ltd), validated by weighing the pigs every 14 days using a weighing crate. Specially produced animal feeds were weighed and dosed automatically to each pen twice daily. Feed quantity dosed was recorded automatically and animal weights averaged daily.

To determine the model parameters, experimental data from the trials described above were used. Each batch contained the input and output data for one room or pen from one trial. The training data set consisted of six batches, two from each trial, and five batches, drawn from both trials, for broilers and pigs respectively. Another six and three batches, for broilers and pigs respectively, were selected for validation.

The training process started from a set of randomly generated parameters. The growth of a batch was then calculated from the initial weight and the feed intakes recorded in the data by solving the model equation (1) using the automatic differentiation approach described by Cao (2005). Let the bird weight recorded in experiments and estimated from (1) at each sampling time be x_k and $\hat{x}_k$, $k = 1, \ldots, N$, respectively. Then the training process aimed to minimise the following cost function by adjusting the model parameters $w_1, \ldots, w_6$

$$\min_{w_1,\ldots,w_6} \sum_{k=1}^{N} (x_k - \hat{x}_k)^2 + \sum_{k}^{6} \alpha w_k^2 \tag{3}$$

where α is a weighting factor for the model parameters. The second term of the cost function is for rigid regulation, which improves the model generality.

The optimization in (3) was converted into a standard nonlinear least squares problem and solved using the Levenberg-Marquardt (LM) algorithm (Marquardt, 1963), where the model parameters were iteratively updated to reduce the cost function until the algorithm converged or the validation cost started to increase. To avoid the training process being trapped in a local minimum, the optimization procedure was repeated with different sets of randomly generated initial parameters until a satisfactory model was obtained. The final model parameters obtained for the broiler growth model were:

$$\begin{aligned} w_1 &= -2.8456 \times 10^{-4} & w_2 &= 1.0162 \times 10^{-4} \\ w_3 &= -2.5539 \times 10^{-3} & w_4 &= 4.2284 \times 10^{-3} \\ w_5 &= 756.5 & w_6 &= 1488.5 \end{aligned}$$

and for the pig growth model:

$$W_x = [-0.3649 \qquad 0.2254]^T$$

$$W_u = \begin{bmatrix} 0.6443 & -0.0912 \\ 0.3980 & 0.0621 \end{bmatrix}$$

$$\begin{aligned} b1 &= [0.0903 \qquad -0.0347]^T \\ W_2 &= [0.3870 \qquad 0.5538] \end{aligned}$$

The broiler growth system is stable at the equilibrium point $x = 0$ and $u = 0$. This can be verified by the pole of the system at this point, $p = w_1 w_5 + w_2 w_6 = -0.064 < 0$. Equally, the pig system is stable as $x = 0$ as $W_2 W_x = -0.0164 < 0$. Therefore, the model indicates that for zero intake, the weight of a bird or pig will in theory eventually decay to 0, but in practice will decay to a constant e.g. the carcass.

The performance of the trained DRNN model is given in table Table **??** Typical performance of the trained DRNN model is represented for one of the remaining 12 test batches in Figure 1, which shows that the trained DRNN was able to predict the bird weight satisfactorily even when the actual feed intake was modulated by regular step changes. As with the broiler growth model the pig growth DRNN model predicted the actual growth well, with an average validation index $\gamma^2 = 0.9889$, with $\gamma^2 = 1 - \sum(x - xmodel)^2 / \sum x - xmean)^2$.

3. Livestock Growth Control

In theory, using the identified DRNN model, many optimal control problems can be investigated, such as minimum time control, where feed intakes are calculated such that animals can grow as fast as possible to reach the

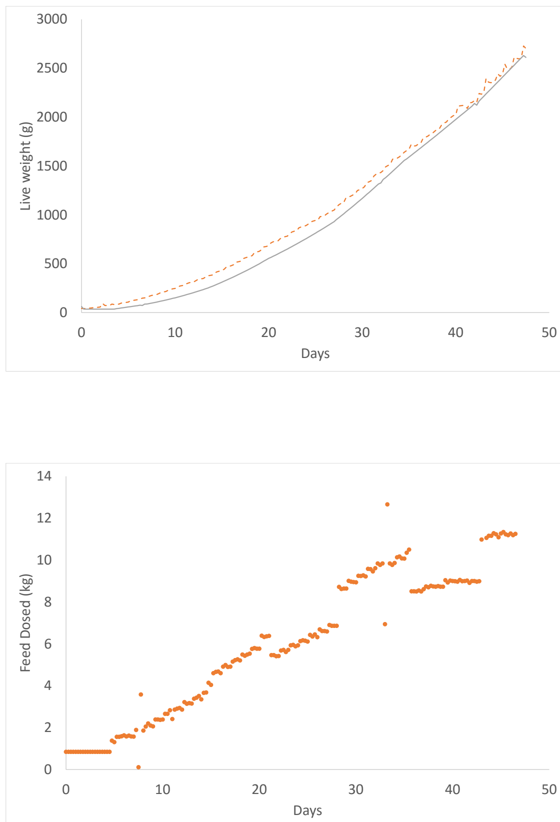

Figure 1: DRNN model testing. Top: the actual (solid-line) and predicted (dashed-line) broiler weight; Bottom: the actual feed dosed to the room holding 262 broilers (corrected for mortality).

Table 1: The performance of the Differential Recurrent Neural Network models for broiler or pig growth for each of the data sets. Factors used are changes in feed, light, humidity and temperature indicated by F,L, H or T for the active state and f, l, h and t for the corresponding control or normal state.

species	factor used	batch 1	batch 2	batch 3
broiler	f l h	0.9985	0.9976	0.9984
broiler	f L h	0.9989	0.9968	0.9943
broiler	f l H	0.9637	0.9976	0.9983
broiler	f L H	0.9862	0.9970	0.9965
broiler	F l h	0.9993	0.9981	0.9989
broiler	F L h	0.9886	0.9957	0.9965
broiler	F l H	0.9898	0.9984	0.9982
broiler	F L H	0.9954	0.9970	0.99887

species	factor used	batch 1	batch 1a	batch 2	batch 2a
pig	f t	0.9901	0.9882	0.9901	0.9910
pig	f T	0.9947	0.9889	0.9952	0.9924
pig	F t	0.9560	0.9856	0.9884	0.9904
pig	F T	0.9931	0.9944	0.9933	0.9920

target weight, and the minimum food problem, where optimal feed intake is designed such that the total food consumption is minimized to achieve the same target weight on the target day. However, due to the limited experimental data, upon which the model was based, it would not be applicable to some extreme situations, such as very low and high feed intakes. To ensure the model was working within a reliable range that would not compromise animal welfare, a regulation control problem was constructed to design optimal feed intake such that the actual animal growth followed a predesigned curve smoothly with the minimum feed intake.

The above regulation problem was solved through a nonlinear model predictive control (NMPC) scheme. In the NMPC, at each sampling point, t_0, the average weight of an animal predicted by the model, x_0 is compared with the measured weight, x_m. The difference, $n = x_m - x_0$ is treated as the disturbance. This disturbance is assumed to be constant within the prediction horizon, $t_0 \leq t \leq t_f$. Therefore, to correct the error caused by this disturbance, the actual set-point at a time point, t, within the prediction horizon is biased as $\hat{x}(t) = x_r(t) + n$, where $x_r(t)$ is the target weight. Then, the optimal control problem to be solved at each sampling point, t_0 is stated as follows.

$$\begin{aligned}
\min_{u} \quad & \sum_{t=t_0}^{t_f} \left[\alpha_1^2(x(t)-\hat{x}(t))^2 + \alpha_2^2 v^2(t) + \alpha_3^2(\Delta v(t))^2\right] && (4)\\
\textbf{s.t.} \quad & \dot{x} = w_5\sigma(w_1x + w_3u) + w_6\sigma(w_2x + w_4u) && (5)\\
& x(t_0) = x_0 && (6)\\
& x(t_f) = x_f && (7)
\end{aligned}$$

where, $v^2(t) = u(t)$ is the feed intake at day t, $\Delta v(t) = v(t) - v(t-1)$, t_0 and t_f are current and final days, respectively, x_0 and x_f are current and final weights, respectively, α_1, α_2 and α_3 are weights of the optimization problem for weight accuracy, food consumption and smoothness respectively. Note that although the optimal control problem in (4) is open loop, the correction of modelling error, $\hat{x}(t) = x_r(t) + x_m(t_0) - x_0$ uses the real measured weight, $x_m(t_0)$, hence the actual control is feedback control.

The problem can be cast as a standard nonlinear least square problem, $\min_{\mathbf{u}} \mathbf{e}^T\mathbf{e}$, with residuals, $\mathbf{e}$ defined as follows.

$$\mathbf{e} = \begin{bmatrix} \alpha_1(x(t_0+1) - \hat{x}(t_0+1)) \\ \vdots \\ \alpha_1(x(t_f) - \hat{x}(t_f)) \\ \alpha_2 v(t_0) \\ \vdots \\ \alpha_2 v(t_f - 1) \\ \alpha_3 \Delta v(t_0) \\ \vdots \\ \alpha_3 \Delta v(t_f - 1) \end{bmatrix} \tag{8}$$

The corresponding Jacobian, $\mathbf{J} = \partial\mathbf{e}/\partial\mathbf{u}$ can be derived through automatic differentiation as explained by Al-Seyab & Cao (2008b). The optimal values of $\mathbf{v} = \begin{bmatrix} v(t_0), & \cdots, & v(t_f-1) \end{bmatrix}^T$ are then obtained iteratively using the LM algorithm (Marquardt, 1963):

$$\mathbf{v}_{k+1} = \left(\mathbf{J}_k^T\mathbf{J}_k + \mu\mathbf{I}\right)^{-1}\mathbf{J}_k^T\mathbf{e}_k \tag{9}$$

where $\mathbf{e}_k$ and $\mathbf{J}_k$ are the residuals and the Jacobian corresponding to $\mathbf{v}_k$, μ is a parameter adjusted by the algorithm to maintain a fast convergence.

Once the iteration had converged, the first instance of the obtained optimal solution, $\mathbf{v}$ was converted into the feed intake, $u(t_0) = v^2(t_0)$ and applied to the real system. The whole procedure will be repeated at next sampling time when a new measured average animal weight, x_m is available.

4. Validation of the Growth Control Algorithm

To validate the control algorithm developed in the previous section, fresh experiments were designed and carried out. In these experiments, new growth curves were devised for the controller to attempt to follow as closely as possible by predicting the required feed intake. These new growth curves were derived from the recommended (standard) growth curve for broilers provided by Aviagen (2002), e.g. reaching a weight of 2.85 kg at 50 days of age and the recoommneded growth curve for pigs PIC (2005), e.g. reaching a weight of 92 kg at 21 weeks of age and were used for the development of the controller. The broilers were grown according to the standard curve up to day 12 and from day 12 to 50 followed the new growth curves. The pigs were grown according to the standard curve till week 6 and then followed the new growth curves. The new growth curves for broilers were specified as,

- standard curve
- +12% of standard curve
- −12% of standard curve
- −12% to day 30 followed by +12% of standard curve (slow growth followed by recovery growth)

and for pigs as

- standard curve
- alternating each 3 weeks between −20% and +20% of the standard curve

The broiler growth controller was tested using four of the eight available rooms. Each growth curve was tested with one room. Each room was initially stocked with 265 day-old chicks (Ross 308). The pig growth controller was tested using 8 pens in two rooms with the growth curves tested in paired pens, each holding 10 pigs. Environmental conditions were kept identical to the conditions used in the training and model validation trials, apart from the frequency of light intensity change and number of meals fed daily for broilers and room temperature for pigs. The total daily intake of each room or pen was set by the controller. The controller was used for on-line calculation of the feed intake, however with a 24-hour delay in implementation of the calculated feed intake through a manual adjustment of the feed dosed.

The production results for broilers from the 4 batches and pigs from the 2 batches are summarised in Table 2 and Table 3, where the four controlled (actual) weights at the end of the growth curve are compared with their corresponding target values taken from the prescribed growth curves. The predicted total feed intake was calculated from the sum of the controller–predicted feed dosage rate. The actual total feed intake was calculated from the sum of the feed dosed, corrected for the actual number of birds present. The mean relative error and maximum deviation of the actual weights from day 12–50 for broilers or week 6 to 21 for pigs were calculated as percentages, where the mean relative error, $\bar{\varepsilon}$ and the maximum deviation, $\sigma_{\max}$ are defined based on the actual weight, w_{act} and the corresponding target weight, w_{th} as follows.

$$\bar{\varepsilon} = \frac{1}{39}\sum_{d=12}^{50}\left|\frac{w_{\text{act}}(d)-w_{\text{th}}(d)}{w_{\text{th}}(d)}\right| \tag{10}$$

$$\sigma_{\max} = \max_{12\leq d\leq 50}\left|\frac{w_{\text{act}}(d)-w_{\text{th}}(d)}{w_{\text{th}}(d)}\right| \tag{11}$$

Daily comparisons of controlled against modelled and standard growth curves for broilers are shown in Figures 2 to 5 for the standard growth curve and +12%, −12% and −12% followed by +12% of standard growth curves, respectively.

The results for broilers clearly indicate that the controller is capable of predicting the feed intake required to reach the end weight and follow the reference growth curves well with an mean relative error less than 2%, except for the −12% curve. The larger mean relative error in the −12% growth curve was caused by a malfunction in the feeding equipment from day 16–19 (see Figure 6). Allthough the room recieved the correct feed amount for each feeding period, due to blockages the feed was delivered to the birds at very irregular intervals, potentially inhibiting growth (maximum deviation from curve was −16%). However, the controller was able to return the

Table 2: Target live weight and achieved live weight of the broilers at age 50 days and goodness of fit of the achieved live weight compared to the set growth curve from day 12–50. Predicted and actual total feed intake per bird and feed conversion ratio (FCR) for the period of day 12–49. The standard growth curve had been derived from the optimal growth curve provided by Aviagen (2002).

Growth curve	unit	Standard	+12% of standard	−12% of standard	−12% & +12% of standard
		Bird weight at 50 days			
Target	kg	2.85	3.20	2.51	2.85
Actual	kg	2.73	3.10	2.44	2.72
Mean relative error	%	1.8	1.8	2.8	1.6
Maximum deviation	%	5.2	6.0	16.3	5.0
		Total feed intake from day 12–49			
Predicted	$kg.bird^{-1}$	4.66	4.99	4.30	4.62
Actual	$kg.bird^{-1}$	4.59	5.04	4.31	4.62
Feed conversion Ratio	-	1.91	1.84	2.02	1.93

Table 3: Theoretical live weight and achieved live weight of the pigs at age 21 weeks and goodness of fit of the achieved live weight compared to the set growth curve from age 6 to 21 weeks. Predicted and actual total feed intake per bird and feed conversion ratio (FCR) for the period of week 6–21. The standard growth curve had been derived form the optimal growth curve provided by PIC (2005).

Growth curve	unit	Standard	$-20\%/+20\%/-20\%$ of standard
		Pig weight at 21 weeks	
Target	kg	91.9	88.4
Actual	kg	98.4	90.5
Mean relative error	%	10.5	10.9
Maximum deviation	%	34.1	35.3
		Total feed intake from age 6 – 21	
Predicted	$kg.pig^{-1}$	170.9	158.7
Actual	$kg.pig^{-1}$	187.9	179.0
Feed conversion Ratio		2.40	2.50
Feed conversion Ratio	(to 35kg)	1.54	1.73
Feed conversion Ratio	(35-100kg)	2.71	2.79

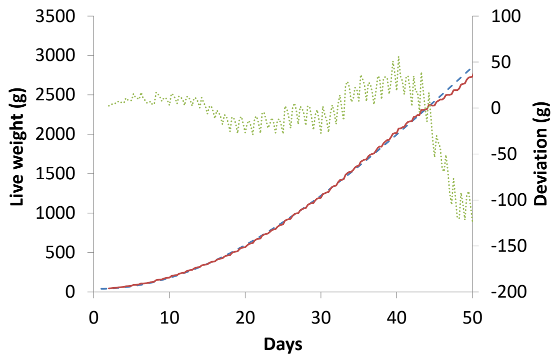

Figure 2: The target standard (dashed line) and actual achieved (solid line) growth curves of broilers and the deviation of the target curve (dotted line, secondary axis).

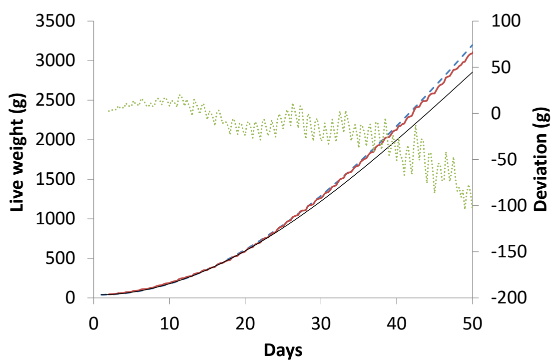

Figure 3: The target +12% above standard (dashed line) and actual achieved (solid line) growth curves of broilers and the deviation of the target curve (dotted line, secondary axis). The standard growth curve (Aviagen) is plotted for comparison.

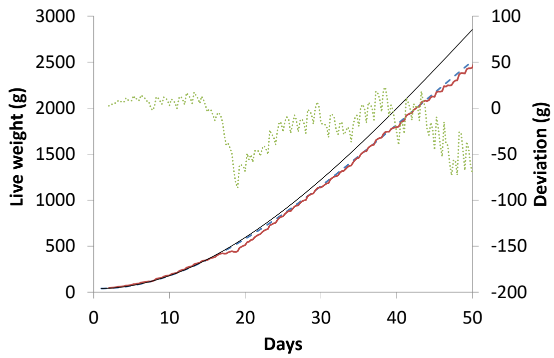

Figure 4: The target -12% below standard (dasehed line) and actual achieved (solid line) growth curves of broilers and the deviation of the target curve (dotted line, secondary axis). The standard growth curve (Aviagen) is plotted for comparison.

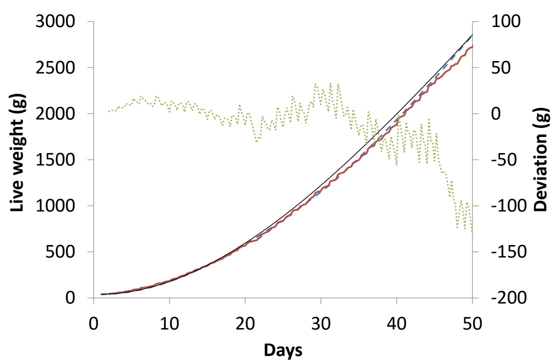

Figure 5: The target -12% followed by $+12\%$ of standard (dashed line) and actual achieved (solid line) growth curves of broilers and the deviation of the target curve (dotted line, secondary axis). The standard growth curve (Aviagen) is plotted for comparison.

growth to the set curve within 4 days, by feeding more than originally anticipated. Excluding this period reduced the mean relative error to 1.9%. Overall the mean relative error in this work is much lower than the 7–9% reported by Cangar et al. (2008). The authors suggested that this high error might be largely due to different conditions and systems for the weighing and feed delivery used for generating data for creating and validating their model (small scale, "ideal" conditions) and for the validation of the control algorithm (commercial conditions). In our work all steps were done on the same scale, same conditions and with the same equipment. further more the number of birds used in their trials was substantially higher, especially in the commercial validation trials.

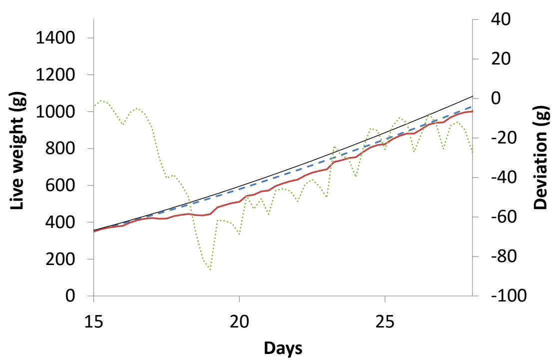

Figure 6: The target −12% below standard (dashed line) and actual achieved (solid line) growth curves of broilers and the deviation of the target curve (dotted line, secondary axis) for the period the feed system malfunctioned.

For all four broiler growth curves, the projected end weight was met within small tolerances. From day 42 onwards the actual bird weight started to deviate from the theoretical bird weight (slower growth). This could be a undesirable feature of the DRNN model used. However, it also coincided with the introduction of the withdrawal grower diet which in theory differs in composition from the normal grower diet in the absence of coccidiostats only. The absence of the coccidiostats should not affect the growth or feed conversion, but it is not evident from the feed analysis if other minor changes were made to the feed composition between the two deliveries that could have affected the growth. In contrast to findings by Cangar et al. (2008) in these trials the Ross 308 bird appeared to be capable of recovery growth (see Figure 5), *i.e.* the broilers were capable of regaining weight in excess of equivalent growth by the standard growth curve beyond 31 days. One reason for this difference is the lower energy and protein content of the diets used in this work compared with current industry standards (approximately 15% lower). The standard growth curve used was also set below the maximum potential growth curve given by Aviagen (2002). Hence, the broilers were capable of utilising the additional protein and energy provided as the maximum growth potential had not yet been reached.

The growth controller for pigs equally indicates that the controller is capable of predicting the feed intake to meet the desired growth curve and end weight (see Figure 7). However, the mean relative error was significantly higher at 10.5% and 10.9%, for the standard and recovery growth curves, respectively. The larger mean relative error is potentially due to the lower number of data sets available for determining the DRNN model parameters, compared to the broiler DRNN model, 5 v 6, respectively, and the lower number of changes in feed amount. Equally, the slower rate of growth meant the dynamic changes in weight due to the changed feed intake reqime were smaller compared to the broiler, potentially resulting in a less accurate model. Creating even larger changes in the feed intake regime were however deemed to be too detrimental for the pigs welfare. Another contributing factor is the variation in temperature in the experimental conditions (standard versus standard +7C). The effect of temperature on growth is well documented. Pigs decrease their voluntary feed intake with increasing temperatures and hence their average daily gain is lower (Hyun et al., 1998; Sutherland et al., 2006). However, the FCR for the two temperature regimes was not significantly different as was expected (Sutherland et al., 2006).

The DRNN model used in the controller controlled not only the daily feed intake on line, but predicted accurately the required feed intake for the whole of the growing period. This novel addition will be very useful to farmers when deciding on a growth curve suitable for various scenarios. From the four broiler growth curves used in this trial the +12% of standard growth curve is better from an economic point of view, as it has by far the lowest feed conversion ratio (FCR). The authors suggest this is largely due to making better use of the genetic potential of the broilers. Using the slow growth with recovery growth option, has potential advantages for animal welfare in terms of leg health and proved to be no worse in achieving the final weight with a similar FCR and total feed intake requirement, compared to the standard growth curve. The FCR's achieved here are however significantly higher than those commonly achieved on commercial farms, where the best producers achieve 1.6 -1.7 FCR, approximately. The purposely lower protein content of the feed used in these trials, approximately 15% less, appears to be the root cause of the poorer FCR. The otherwise optimal environmental conditions had no negative effect on the FCR. Using optimal diets for the genetic growth potential might reduce the effectiveness of the model to recover lost growth over a number of days as shown in this work, as the maximum daily weight gain had already been reached (Cangar et al., 2008). The feed conversion ratio for pigs in these trials and expecially the for the standard growth curve which had the best performance in economic terms, compares favourably to the industry average of 2.35 reported by BPEX (2011, 2015) for rearer/finisher pigs combined (8-100 kg), as well as the individual FCR's for rearer and finisher at 1.71 and 2.67, respectively, despite the suboptimal lower protein content of the feed used in these trials. The optimal environmental conditions in the new animal welfare facility and therefor the significant reduction in disease burden on the pigs will have contributed to the good growth performance.

5. Conclusions

An accurate differential recurrent neural network model of broiler and pig growth has been identified, validated and tested successfully. The DRNN model accurately described the dynamic time variable growth of housed livestock. Typically the mean square error and standard deviation between the broiler growth model and data were of the order of 0.02 and 0.03, respectively and the equivalent figures for the pig growth model were of the order of 0.02 and 0.05, respectively.

The nonlinear model predictive controller, incorporating the DRNN model, was constructed to predict the feed quantity required for the broilers to grow following predetermined growth curves. The NMPC accurately predicted the feed quantity to achieve a range of predetermined growth curves. The mean relative error for the period from day 12–50 was 1.8% for broilers and for pigs 10.5% for the period from 6 to 21 weeks. The NMPC was capable of accurately predicting compensatory growth rates following two days of retarded growth rates due to feeding equipment failure. In addition, the controller was able to predict the total feed intake for the whole growth period accurately.

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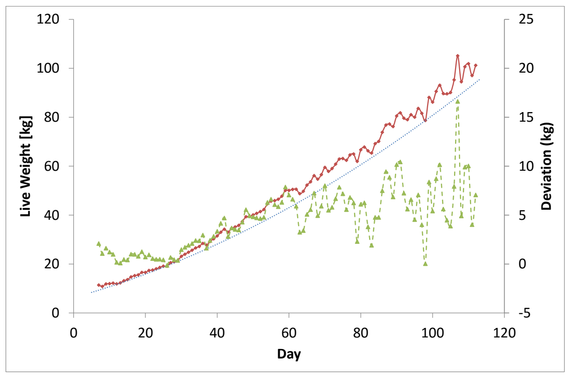

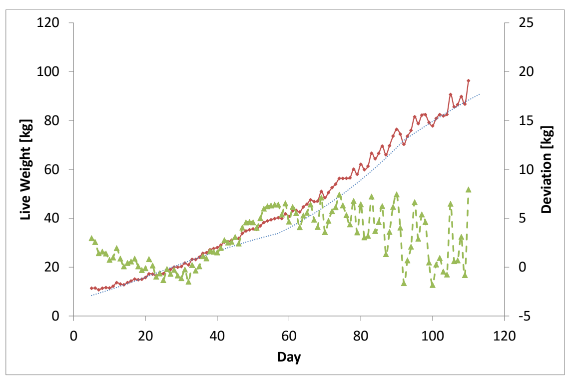

Figure 7: The target standard (top graph, dashed line) and variable (bottom graph, dashed line) and actual achieved (solid) growth curves for pigs and the deviation of the target curve (dotted line, secondary axis).

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