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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 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 10 processes, so weight gain is not only a valuable measure of economic perfor-11 mance, but also a convenient measure of environmental response. Maximal 12 growth rate as a function of feed intake is the most important parameter 13 from the perspective of growers, because feed is the biggest cost in the pro-14 duction of housed livestock. Recently other physiological processes such as 15 skeletal development of and activity of broiler chickens have also been con-16 sidered. Slower growth in the early stages of broiler development reduces 17 the incidence of lameness, the most important animal welfare issue in broiler 18 production (Butterworth & Arnould, 2009), whilst liquid phase-feeding has 19 the potential to improve pig health and growth (Scott et al., 2007). 20

Frost et al. (1997) argued that livestock production systems contain mul-21 tiple interconnected processes that need to be managed to meet several per-22 formance criteria, including economic, animal welfare and environmental 23 targets. Traditional management was, and still is, largely based on expe-24 rience and is not good at integrating processes and performance criteria. 25 An example is the use of climate (temperature) controllers. Development 26 of the climate controller was through observing animal performance and be-27 haviour (Charles & Walker, 2002). However, control was through tempera-28 ture measurement alone, discarding any information from the animal. The 29 stockman still had to intervene if the response of the animals indicated that 30 the temperature control was imperfect. The proposed solution was to move 31 towards integrated closed-loop, model-based control systems, by first devel-32 oping controllers for the key processes, using sensor technology capable of 33 measuring animal responses, that was becoming available. 34

<sup>35</sup> The nutritional and environmental requirements of broilers and pigs are

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well understood (Gous et al., 1999; Kyriazakis & Whittemore, 2006), which 36 has enabled the development of mechanistic models to predict broiler and pig 37 growth from feed inputs (Emmans, 1995; Black, 2014). These models and 38 the science underlying them have been used to create plans for nutrition and 39 weight gain (Aviagen, 2002; PIC, 2005). However, the dynamic responses 40 of animals to (sudden) changes in the environment are less well understood 41 and fewer models exist. Furthermore, Wathes et al. (2008) states that in 42 general mechanistic models are not suitable for control purposes, because 43 they are often overly complex, with too many parameters, although these 44 have biological meanings, and inaccurate, since parameter values may change 45 over time and space. 46

Recently, data-based models describing the response of the growing broiler 47 to changes in feed quantity have been explored as an alternative to mechanis-48 tic models. Data-based modelling techniques estimate the unknown model 49 parameters of any abstract mathematical model structure from measure-50 ments of process inputs and outputs. In principle, the parameters can be 51 estimated on-line resulting in an adaptive model that can cope with the char-52 acteristics of most biological processes, *i.e.* complex, individual, time variant 53 and dynamic (Aerts et al., 2003b). This type of model has the advantage 54 that no *a priori* knowledge of the process is required, although the latter is 55 beneficial whilst developing the model. However, in contrast to mechanistic 56 models, the parameters have no biological meaning. The resulting model 57 will in general be more compact and therefore suitable for control purposes. 58 As a result data-based models are widely used for process control in other 59 industries. Various approaches to modelling broiler growth have been used, 60 including hyperbolastic models (Ahmadi & Mottaghitalab, 2007), artificial 61 neural networks (Ahmadi & Mottaghitalab, 2008) and recursive linear mod-62 els (Aerts et al., 2003b). 63

Frost et al. (2003) and Stacey et al. (2004) described the development of a 64 system based on a mechanistic model to control the feeding of broiler chickens 65 to achieve a given time-weight performance. The system was developed on 66 farm scale (over 30,000 birds/house) using a feeding system where the diet 67 composition was controlled by blending two different feeds and growth was 68 monitored by perch weighers. It aimed to optimise the feed blend to minimise 69 the errors from a planned growth curve from the current day to slaughter, 70 and was able to deliver birds of the correct weight, except when growth 71 was inhibited by disease. A pig growth monitoring system based on image 72 analysis (Doeschl-Wilson et al., 2004; Schofield et al., 1999), supported the 73

<sup>74</sup> development of a mechnistic model and a real time controller for pig growth <sup>75</sup> (Parsons et al., 2007). The model was able to control mean pig weight in <sup>76</sup> trials to within 2 kg of the target weight, by varying crude protein content <sup>77</sup> of the diet. The use of a mechanistic simulation models for broilers and <sup>78</sup> pigs based on the nutritional and envronmental requirements, required the <sup>79</sup> specification of several genotype-dependent parameters and feed analysis in <sup>80</sup> terms of several nutrients, rendering them less suitable for control purposes.

For the reasons discussed above, a data-based approach was followed on 81 laboratory scale by Aerts et al. (2003a) and at a larger scale by Cangar 82 et al. (2008), in which the quantity of feed presented was controlled using 83 model predictive control. They used a recursive linear models with time 84 varying parameters to predict weight 3–7 days ahead (Aerts et al., 2003b; 85 Cangar et al., 2008). Using online prediction of the feed quantity, control 86 of broiler growth along a target trajectory proved possible within certain 87 boundary conditions. Most notably, the period during which growth could 88 be restricted without affecting the ability of the broiler to reach the target 89 weight was limited to the early stages of growth (age 7–30 days). Growing 90 broilers to the required target weight using online control resulted in a mean 91 relative error of 6-10% in live weight. 92

The method described here shares some of the characteristics of the above 93 approaches and aims to overcome some of their limitations. The model is 94 empirical, so does not require genetic parameters or detailed feed analyses, 95 but simulates growth from hatching to slaughter. Based on this model, the 96 controller is designed to optimise feeding over the complete period of growth 97 instead of a fixed horizon. The control strategy aims to optimise the system 98 by reducing the feed intake to save cost, minimising the deviation of bird 99 weight from a predefined grow curve to ensure the final target is smoothly 100 achieved and at the same time restricting the daily change in the intake to 101 avoid potential stress on the birds. These objectives are combined into a 102 single cost function as a weighted sum of these criteria. 103

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.

#### 111 2. Weight-Feed Model Identification

Growth of any organism is a complicated nonlinear dynamic process, 112 which is difficult to model from first principles. Most conventional system 113 identification approaches use linear model structures, such as the autoregres-114 sive moving average with exogenous input model (ARMAX). The latter can 115 be adapted to account for variability in time and therefor non-lineair systems 116 (RARMAX), but the time-varying nature is dependent on the actual state 117 trajectory, which the linearisation takes as a reference trajectory. This po-118 tentially limits their use to specific applications where the trajectory of the 119 model developed is similar to that of future applications. Due to their abil-120 ity to approximate any nonlinear function, recurrent neural networks (RNN) 121 are widely used for nonlinear system identification. However, most available 122 RNN models are in discrete time, which can only work for the specific sam-123 pling rate with which the model is trained. In order to develop a dynamic 124 model to control the entire growth process with potentially variable sampling 125 rate, the differential RNN (DRNN) and the associated automatic differenti-126 ation based training algorithm developed by Al-Seyab & Cao (2008b,a) were 127 adopted for this work. DRNN models are black box models and the internal 128 parameters are not transparent, unlike the external input and output vari-129 ables, in this case feed intake and liveweight under various conditions, which 130 can be interpreted from a biological point of view. 131

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

$$\dot{x} = w_5 \sigma(w_1 x + w_3 u) + w_6 \sigma(w_2 x + w_4 u) \tag{1}$$

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:

$$\dot{x} = W_2 \sigma (W_x x + W_u u + b_1) \tag{2}$$

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 146 were grown from 1 day old to 51 days. The broilers were exposed to dynamic 147 (sudden) changes in the inputs, feed amount, light intensity and relative 148 humidity (RH) from day 12 onwards. To ensure a measurable response in 149 output, the change in the input was set unrealistically large compared to nor-150 mal broiler production practise. Feed amount was set at either 90% or 110%151 of recommended feed requirements for broilers (Aviagen, 2002). Light inten-152 sity was set at either 10 or 100 lux and RH at 56% or 70%. The frequency 153 of change was set according to the time required to reach a new steady state 154 in the output, *i.e.* hours for the light intensity and 3–7 days for feed amount 155 and RH. A two-level (change or no change) of three-factor (feed amount, 156 light intensity and RH) factorial design requiring  $2^3 = 8$  identical rooms 157 was used and repeated in three trials. Each possible combination of inputs 158 was randomly allocated to a room in each of the three trials. This experi-159 mental design potentially allowed identification of interactions between the 160 processes: growth, activity and ammonia emission, affected by feed amount, 161 light intensity and RH, respectively. 162

Each room housed 262 broilers (Ross 308) on a bed of woodshavings up 163 to a maximum stocking density of 33 kg m<sup>-2</sup> at 50 days. The average bird 164 weight was estimated continuously using a weighing platform suspended from 165 a load cell (Fancom 747 series bird weight platform and computer). Specially 166 produced animal feeds were weighed and dosed automatically to each room 167 (Fancom 771 feed computer) four times a day. Feed quantity dosed and 168 broiler weight in each room were recorded automatically four times per day 169 from day 3-51. Other environmental variables, such as temperature, RH and 170 light intensity, were monitored and recorded at 1 minute intervals. 171

To generate data for training and validating the pig models, pigs (Large 172 white, Landrace and Pietran cross) were housed from 5 weeks of age to 22 173 weeks. Pigs were exposed to dynamic changes in feed amount and temper-174 ature from week 6 onwards. The change in feed amount was set at either 175 80% or 120% of recommended feed requirements for pigs and to +7 C above 176 the recommended room temperature at 3 week intervals. A two-level of two-177 factor (feed amount and temperature) factorial design with four identical 178 pens in two rooms was used and repeated in two trials, which potentially 179 allowed identification of interactions between the processes growth and am-180

<sup>181</sup> monia 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. 195 The growth of a batch was then calculated from the initial weight and the 196 feed intakes recorded in the data by solving the model equation (1) using the 197 automatic differentiation approach described by Cao (2005). Let the bird 198 weight recorded in experiments and estimated from (1) at each sampling time 199 be  $x_k$  and  $\hat{x}_k$ ,  $k = 1, \ldots, N$ , respectively. Then the training process aimed 200 to minimise the following cost function by adjusting the model parameters 201  $w_1,\ldots,w_6$ 202

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

where  $\alpha$  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:

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

and for the pig growth model:

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

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

b1 = [0.0903]	$-0.0347]^{T}$
$W_2 = [0.3870]$	0.5538]

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,  $p = w_1w_5 + w_2w_6 = -0.064 < 0$ . Equally, the pig system is stable as x = 0 as  $W_2W_x = -0.0164 < 0$ . 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 ?? 211 Typical performance of the trained DRNN model is represented for one of the 212 remaining 12 test batches in Figure 1, which shows that the trained DRNN 213 was able to predict the bird weight satisfactorily even when the actual feed 214 intake was modulated by regular step changes. As with the broiler growth 215 model the pig growth DRNN model predicted the actual growth well, with an 216 average validation index  $\gamma^2 = 0.9889$ , with  $\gamma^2 = 1 - \sum (x - xmodel)^2 / \sum x - xmodel$ 217  $xmean)^2$ . 218

#### 219 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	bat	ch 1	batc	h 2	bate	h 3	
-	broiler	f l h		0.9	985	0.99	)76	0.99	984	-
	broiler	f L h		0.9	989	0.99	68	0.99	943	
	broiler	flH		0.9	637	0.99	976	0.99	983	
	broiler	fLH		0.9	862	0.99	070	0.99	965	
	broiler	Flh		0.9	993	0.99	81	0.99	989	
	broiler	F L h		0.9	886	0.99	57	0.99	965	
	broiler	F l H		0.9	898	0.99	984	0.99	982	
	broiler	F L H		0.9	954	0.99	070	0.99	887	
specie	es factor	r used	batch	1	batch	1a	bate	h 2	bat	ch 2a
pig	f t		0.990	1	0.988	32	0.99	901	0.9	9910
pig	fΤ		0.994	7	0.988	89	0.99	952	0.9	9924
pig	F t		0.956	0	0.985	66	0.98	884	0.9	9904
pig	F T		0.993	1	0.994	4	0.99	933	0.9	9920

target weight, and the minimum food problem, where optimal feed intake is 223 designed such that the total food consumption is minimized to achieve the 224 same target weight on the target day. However, due to the limited experi-225 mental data, upon which the model was based, it would not be applicable to 226 some extreme situations, such as very low and high feed intakes. To ensure 227 the model was working within a reliable range that would not compromise 228 animal welfare, a regulation control problem was constructed to design op-220 timal feed intake such that the actual animal growth followed a predesigned 230 curve smoothly with the minimum feed intake. 231

The above regulation problem was solved through a nonlinear model pre-232 dictive control (NMPC) scheme. In the NMPC, at each sampling point,  $t_0$ , 233 the average weight of an animal predicted by the model,  $x_0$  is compared with 234 the measured weight,  $x_m$ . The difference,  $n = x_m - x_0$  is treated as the dis-235 turbance. This disturbance is assumed to be constant within the prediction 236 horizon,  $t_0 \leq t \leq t_f$ . Therefore, to correct the error caused by this distur-237 bance, the actual set-point at a time point, t, within the prediction horizon 238 is biased as  $\hat{x}(t) = x_r(t) + n$ , where  $x_r(t)$  is the target weight. Then, the 239 optimal control problem to be solved at each sampling point,  $t_0$  is stated as 240

241 follows.

$$\min_{u} \sum_{t=t_{0}}^{t_{f}} \left[ \alpha_{1}^{2} (x(t) - \hat{x}(t))^{2} + \alpha_{2}^{2} v^{2}(t) + \alpha_{3}^{2} (\Delta v(t))^{2} \right]$$
(4)

s.t. 
$$\dot{x} = w_5 \sigma(w_1 x + w_3 u) + w_6 \sigma(w_2 x + w_4 u)$$
 (5)

$$x(t_0) = x_0 \tag{6}$$

$$x(t_f) = x_f \tag{7}$$

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,  $\alpha_1$ ,  $\alpha_2$  and  $\alpha_3$  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.

$$\mathbf{e} = \begin{bmatrix} \alpha_1(x(t_0+1) - \hat{x}(t_0+1)) \\ \vdots \\ \alpha_1(x(t_f) - \hat{x}(t_f)) \\ \alpha_2 v(t_0) \\ \vdots \\ \alpha_2 v(t_f - 1) \\ \alpha_3 \Delta v(t_0) \\ \vdots \\ \alpha_3 \Delta v(t_f - 1) \end{bmatrix}$$
(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  $\mathbf{v}_k$ ,  $\mu$ 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, **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.

#### <sup>261</sup> 4. Validation of the Growth Control Algorithm

To validate the control algorithm developed in the previous section, fresh 262 experiments were designed and carried out. In these experiments, new growth 263 curves were devised for the controller to attempt to follow as closely as pos-264 sible by predicting the required feed intake. These new growth curves were 265 derived from the recommended (standard) growth curve for broilers provided 266 by Aviagen (2002), e.g. reaching a weight of 2.85 kg at 50 days of age and 267 the recommended growth curve for pigs PIC (2005), e.g. reaching a weight 268 of 92 kg at 21 weeks of age and were used for the development of the con-269 troller. The broilers were grown according to the standard curve up to day 270 12 and from day 12 to 50 followed the new growth curves. The pigs were 271 grown according to the standard curve till week 6 and then followed the new 272 growth curves. The new growth curves for broilers were specified as, 273

- 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 294 2 batches are summarised in Table 2 and Table 3, where the four controlled 295 (actual) weights at the end of the growth curve are compared with their 296 corresponding target values taken from the prescribed growth curves. The 297 predicted total feed intake was calculated from the sum of the controller-298 predicted feed dosage rate. The actual total feed intake was calculated from 299 the sum of the feed dosed, corrected for the actual number of birds present. 300 The mean relative error and maximum deviation of the actual weights from 301 day 12–50 for broilers or week 6 to 21 for pigs were calculated as percentages, 302 where the mean relative error,  $\bar{\varepsilon}$  and the maximum deviation,  $\sigma_{\text{max}}$  are defined 303 based on the actual weight,  $w_{\rm act}$  and the corresponding target weight,  $w_{\rm th}$  as 304 follows. 305

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

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

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 310 predicting the feed intake required to reach the end weight and follow the 311 reference growth curves well with an mean relative error less than 2%, ex-312 cept for the -12% curve. The larger mean relative error in the -12% growth 313 curve was caused by a malfunction in the feeding equipment from day 16–19 314 (see Figure 6). Allthough the room recieved the correct feed amount for 315 each feeding period, due to blockages the feed was delivered to the birds 316 at very irregular intervals, potentially inhibiting growth (maximum devia-317 tion from curve was -16%). However, the controller was able to return the 318

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	-12% of	-12% & +12%				
			$\operatorname{standard}$	standard	of standard				
Bird weight at 50 days									
Target	kg	2.85	3.20	2.51	2.85				
Actual	$\mathrm{kg}$	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 <sup><math>-1</math></sup>	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	$\mathrm{kg}$	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	$\rm kg.pig^{-1}$	187.9	179.0				
Feed conversion Ratio		2.40	2.50				
Feed conversion Ratio	(to 35kg)	1.54	1.73				
Feed conversion Ratio	(35-100 kg)	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 an-319 ticipated. Excluding this period reduced the mean relative error to 1.9%. 320 Overall the mean relative error in this work is much lower than the 7-9%321 reported by Cangar et al. (2008). The authors suggested that this high error 322 might be largely due to different conditions and systems for the weighing 323 and feed delivery used for generating data for creating and validating their 324 model (small scale, "ideal" conditions) and for the validation of the control 325 algorithm (commercial conditions). In our work all steps were done on the 326 same scale, same conditions and with the same equipment. further more the 327 number of birds used in their trials was substantially higher, especially in the 328 commercial validation trials. 329



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 330 within small tolerances. From day 42 onwards the actual bird weight started 331 to deviate from the theoretical bird weight (slower growth). This could be 332 a undesirable feature of the DRNN model used. However, it also coincided 333 with the introduction of the withdrawal grower diet which in theory differs 334 in composition from the normal grower diet in the absence of coccidiostats 335 only. The absence of the coccidiostats should not affect the growth or feed 336 conversion, but it is not evident from the feed analysis if other minor changes 337 were made to the feed composition between the two deliveries that could have 338 affected the growth. In contrast to findings by Cangar et al. (2008) in these 339

trials the Ross 308 bird appeared to be capable of recovery growth (see Figure 340 5), *i.e.* the broilers were capable of regaining weight in excess of equivalent 341 growth by the standard growth curve beyond 31 days. One reason for this 342 difference is the lower energy and protein content of the diets used in this 343 work compared with current industry standards (approximately 15% lower). 344 The standard growth curve used was also set below the maximum potential 345 growth curve given by Aviagen (2002). Hence, the broilers were capable of 346 utilising the additional protein and energy provided as the maximum growth 347 potential had not yet been reached. 348

The growth controller for pigs equally indicates that the controller is 340 capable of predicting the feed intake to meet the desired growth curve and 350 end weight (see Figure 7). However, the mean relative error was significantly 351 higher at 10.5% and 10.9%, for the standard and recovery growth curves, 352 respectively. The larger mean relative error is potentially due to the lower 353 number of data sets available for determining the DRNN model parameters. 354 compared to the broiler DRNN model, 5 v 6, respectively, and the lower 355 number of changes in feed amount. Equally, the slower rate of growth meant 356 the dynamic changes in weight due to the changed feed intake reqime were 357 smaller compared to the broiler, potentially resulting in a less accurate model. 358 Creating even larger changes in the feed intake regime were however deemed 359 to be too detrimental for the pigs welfare. Another contributing factor is 360 the variation in temperature in the experimental conditions (standard versus 361 standard +7C). The effect of temperature on growth is well documented. Pigs 362 decrease their voluntary feed intake with increasing temperatures and hence 363 their average daily gain is lower (Hyun et al., 1998; Sutherland et al., 2006). 364 However, the FCR for the two temperature regimes was not significantly 365 different as was expected (Sutherland et al., 2006). 366

The DRNN model used in the controller controlled not only the daily 367 feed intake on line, but predicted accurately the required feed intake for the 368 whole of the growing period. This novel addition will be very useful to farm-369 ers when deciding on a growth curve suitable for various scenarios. From the 370 four broiler growth curves used in this trial the +12% of standard growth 371 curve is better from an economic point of view, as it has by far the lowest feed 372 conversion ratio (FCR). The authors suggest this is largely due to making 373 better use of the genetic potential of the broilers. Using the slow growth with 374 recovery growth option, has potential advantages for animal welfare in terms 375 of leg health and proved to be no worse in achieving the final weight with 376 a similar FCR and total feed intake requirement, compared to the standard 377

growth curve. The FCR's achieved here are however significantly higher 378 than those commonly achieved on commercial farms, where the best pro-379 ducers achieve 1.6 -1.7 FCR, approximately. The purposely lower protein 380 content of the feed used in these trials, approximately 15% less, appears to 381 be the root cause of the poorer FCR. The otherwise optimal environmen-382 tal conditions had no negative effect on the FCR. Using optimal diets for 383 the genetic growth potential might reduce the effectiveness of the model to 384 recover lost growth over a number of days as shown in this work, as the 385 maximum daily weight gain had already been reached (Cangar et al., 2008). 386 The feed conversion ratio for pigs in these trials and expecially the for the 387 standard growth curve which had the best performance in economic terms, 388 compares favourably to the industry average of 2.35 reported by BPEX 389 (2011, 2015) for rearer/finisher pigs combined (8-100 kg), as well as the indi-390 vidual FCR's for rearer and finisher at 1.71 and 2.67, respectively, despite the 391 suboptimal lower protein content of the feed used in these trials. The optimal 392 environmental conditions in the new animal welfare facility and therefor the 393 significant reduction in disease burden on the pigs will have contributed to 394 the good growth performance. 395

#### 396 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, 404 was constructed to predict the feed quantity required for the broilers to grow 405 following predetermined growth curves. The NMPC accurately predicted the 406 feed quantity to achieve a range of predetermined growth curves. The mean 407 relative error for the period from day 12-50 was 1.8% for broilers and for pigs 408 10.5% for the period from 6 to 21 weeks. The NMPC was capable of accu-409 rately predicting compensatory growth rates following two days of retarded 410 growth rates due to feeding equipment failure. In addition, the controller was 411 able to predict the total feed intake for the whole growth period accurately. 412

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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).