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Neural predictive control of broiler chicken and pig growth

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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 predictive 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.

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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 broiler 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

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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 well understood (Gous, Moran, Stilborn, Bradford, & Emmans, 1999; Kyriazakis & Whittemore, 2006), which has enabled the development of mechanistic models to predict broiler and pig growth from feed inputs (Black, 2014; Emmans, 1995). 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, Kristensen, Aerts, and Berckmans (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, Whittemore, Knap, & Schofield, 2004; Schofield, Marchant, White, Brandl, & Wilson, 1999), supported the development of a mechanistic model and a real time controller for pig growth (Parsons, Green, Schofield, & Whittemore, 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 environmental 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, Aerts, Vranken, and Berckmans (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 growth 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.

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