ARTICLE IN PRESS

BIOSYSTEMS ENGINEERING XXX (2018) 1–10

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Special Issue: Engineering Advances in PLF

Research Paper

Feed-forward and generalised regression neural networks in modelling feeding behaviour of pigs in the grow-finish phase☆,☆☆

Amanda J. Cross [a], Gary A. Rohrer [b], Tami M. Brown-Brandl [b], Joseph P. Cassady [a], Brittney N. Keel [b,*]

[a] Department of Animal Science, South Dakota State University, Brookings, SD 57007, USA
[b] USDA, ARS, U.S. Meat Animal Research Center, Clay Center, NE 68933, USA

ARTICLE INFO

Article history:
Published online xxx

Keywords:
Pigs
Feeding behaviour
Artificial neural network
Fruit fly optimization algorithm

Feeding patterns of pigs have been investigated for use in management decisions and identifying sick animals. Development of models to predict feeding behaviour has been limited due to the large number of potential environmental factors involved and complex relationships between them. Artificial neural networks have been proven to be an effective tool for mapping complicated, nonlinear relationships between inputs and outputs. However, they have not been applied to feeding behaviour prediction. In this study, we compared the use of feed-forward (FFNN) and generalised regression neural networks (GRNN) in forecasting feeding behaviour of pigs in the grow-finish phase, using time of day and temperature humidity index as inputs. Models were calibrated on data from 1923 grow-finish pigs collected from 2008 to 2014, and their predictive ability was tested using data from four additional grow-finish groups collected from 2014 to 2016. Results indicated that FFNN trained with the Levenberg–Marquardt (LM) and scaled conjugate gradient (SCG) algorithms were the most accurate forecasting models. In three of the four validation groups, models trained with LM and SCG algorithms exhibited strong performance, with correlations between predicted and observed feeding behaviours ranging from 0.623 to 0.754. Large deviations between predicted and observed behaviours in the fourth validation group were probably the result of an outbreak of pneumonia, which demonstrates the potential for the model to be used in automated detection of disease outbreak and other stress events. This work is the first step in developing a fully automated system for detecting changes in feeding behaviour.

Published by Elsevier Ltd on behalf of IAgrE.

☆ Mention of a trade name, proprietary product, or specified equipment does not constitute a guarantee or warranty by the USDA and does not imply approval to the exclusion of other products that may be suitable.
☆☆ The USDA is an equal opportunity provider and employer.

* *Corresponding author.*
E-mail address: brittney.keel@ars.usda.gov (B.N. Keel).

https://doi.org/10.1016/j.biosystemseng.2018.02.005
1537-5110/Published by Elsevier Ltd on behalf of IAgrE.

Table of nomenclature and abbreviations

α_k	Step size in neural network training process
ANN	Artificial neural network
β_k	Conjugate gradient update parameter
BR	Bayesian regularisation algorithm
$\boldsymbol{d}_k$	Search direction in neural network training process
Dist_i	Distance between the ith fruit fly position and the origin
$\boldsymbol{e}$	Residual error vector
$\nabla E(w_k)$	Gradient of the error function
FFNN	Feed-forward neural network
FFNN-BR	Feed-forward neural network trained with Bayesian regularisation algorithm
FFNN-LM	Feed-forward neural network trained with Levenberg–Marquardt algorithm
FFNN-SCG	Feed-forward neural network trained with scaled conjugate gradient algorithm
FOA	Fruit fly optimisation algorithm
γ_k, ρ_k	Regularization parameters in Bayesian regularisation training algorithm
GRNN	Generalised regression neural network
I	Identity matrix
J	Jacobian matrix of output errors
k	Iteration count in the neural network training process
LM	Levenberg–Marquardt algorithm
LMS	Least-mean-square algorithm
maxgen	Number of iterations in fruit fly optimisation algorithm
μ	Scalar that controls the learning process in the Levenberg–Marquardt training algorithm
N	Number of input–output pairs in the training data set
$\boldsymbol{o}$	Vector of observed feeder visits
$\boldsymbol{p}$	Vector of predicted feeder visits
$P(\boldsymbol{w}_k)$	Penalty term in the Bayesian regularisation training algorithm
p_i	Measure of the distance between the input and the stored pattern in the ith pattern layer of a generalised regression neural network
popsize	Population size in the fruit fly optimisation algorithm
r	Pearson correlation coefficient
R^2	Coefficient of determination
RH(%)	Percent relative humidity
$\boldsymbol{r}_k$	Negative gradient of the error function
RMSE	Root mean square error
SCG	Scaled conjugate gradient algorithm
S_i	Parameter being tested in fruit fly optimisation algorithm
σ	Smoothing parameter (spread)
S_s	Simple summation of pattern layer outputs in a generalised regression neural network
S_w	Weighted summation of pattern layer outputs in a regression neural network
$\boldsymbol{t}$	Vector of observed outputs
T(°C)	Outside temperature in degrees Celsius
THI	Temperature humidity index
$\boldsymbol{w}$	Vector of connection weights in a neural network
$\boldsymbol{a}$	Input to a generalised regression neural network
$\boldsymbol{a}^i$	Pattern vector for neuron i in a generalised regression neural network
X_axis, Y_axis	Initial fruit fly swarm location in fruit fly optimisation algorithm
$\boldsymbol{y}$	Vector of predicted outputs

1. Introduction

Feeding behaviour of grow-finish pigs can be used to inform producers of both health status and stress level. Many parameters have been studied to better understand feeding behaviour of pigs, including feed intake, meal length, meal interval, number of meals, and total time spent eating (Morgan, Emmans, Tolkamp, & Kyriazakis, 2000; Nienaber, McDonald, Hahn, & Chen, 1990; Nienaber, McDonald, Hahn, & Chen, 1991; Quiniou, Dubois, & Noblet, 2000). Most of these measurements have been obtained from feeding systems that allow only one pig to feed at any given time, which is not representative of commercial production where pigs typically feed in a group setting (Brown-Brandl, Rohrer, & Eigenberg, 2013).

Feeding behaviour is dependent on several environmental and genetic factors, including but not limited to temperature, humidity, gender, breed, and time of day. Deviations from normal feeding behaviour may indicate that grow-finish pigs are experiencing a stressful event, such as illness, issues with feed quality, or heat-related stress. Models of feeding behaviour could be used as a management tool to assess stress levels within a population and to identify sick animals.

Several different approaches have been used to analyse and model feeding behaviour of pigs. Linear regression and analysis of variance models have been used extensively (Brown-Brandl et al., 2013; Nienaber et al., 1990, 1991; Quiniou, Noblet, van Milgen, & Dubois, 2001). However, application of these methods is limited due to complex, non-linear relationships between multiple input variables (Comrie, 1997). Gaussian models (Morgan et al., 2000), three-process random models (Berdoy, 1993), and logistic models (Tolkamp & Kyriazakis, 1999) have also been applied to predict feeding behaviour. There are two major drawbacks to these types of models. They tend to be very complex, and they require prior knowledge of relationships between input variables, i.e. a predefined functional form for the model.

Artificial neural networks (ANN) have emerged as a powerful tool in applications where complexity of relationships between inputs and outputs makes formulating a comprehensive mathematical model nearly impossible (Hecht-Nielsen, 1989). An ANN is a set of computing systems that imitates learning abilities of neurons in the brain.

Please cite this article in press as: Cross, A. J., et al., Feed-forward and generalised regression neural networks in modelling feeding behaviour of pigs in the grow-finish phase, *Biosystems Engineering* (2018), https://doi.org/10.1016/j.biosystemseng.2018.02.005