

A Comparison of Neural Network and Nonlinear Regression Predictions of Sheep Growth

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Abstract: This study evaluated the potential of Artificial Neural Networks (ANN) as an alternative to the traditional statistical regression techniques for the purpose of predicting Baluchi sheep growth. Weekly body weight data of 70 Baluchi lambs were recorded from birth to approximately 150th days of age. About 6 nonlinear regression forms of von Bertalanffy, Gompertz, Logistic (with 3 and 4 parameters) Brody and Richards were employed as counterparts to ANN. Goodness of fit and accuracy of the models were determined by coefficient of determination (R^2), Mean Absolute Deviation (MAD), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and the bias. These forecasting error measurements are based on the difference between the estimated and observed values. ANN generated a slightly better descriptive sheep growth curve than the best one which generated from nonlinear models and made the most accurate prediction. It is concluded that ANN represents a valuable tool for predicting of lamb body weight.

Key words: Artificial neural network, nonlinear regression, growth, sheep, biological process, Iran

INTRODUCTION

Growth is a trait of interest in the domestic animals. The phenomenon of growth is a very complex subject which has been studied through many different approaches. A widely used approach is to fit growth data with mathematical functions or growth curve equations. Those functions are based on deterministic differential equations that seek a biological interpretation. Even though growth is variable among individuals, it follows a well-defined course in populations of animals with age. Generally, growth follows a sigmoid or S-shaped curve through which the growth rate varies with age. The rate slowly declines to zero reaching a plateau when the animal achieves mature weight (Arango and van Vleck, 2002).

Artificial Neural Networks (ANN) are mathematical models that learn non-linear relationships between two data sets. They have the ability to find complex relationships in data (Haykin, 1999; Ripley, 1996). ANN consist of a set of processing elements also known as neurons or nodes whose functionality is loosely based on biological neurons.

These units are organized in layers that process the input information and pass it to the following layer. The processing ability of the network is stored in the inter unit

connection strengths (or weights) that are obtained through a process of adaptation to a set of training pattern (Haykin, 1999). With the ANN models a priori model is not required and they are potentially advantageous in the modeling of biological processes which often characterized as highly non-linear. However, the ANN takes a black box approach which does not give insight into the internal working of an ANN and does not provide estimates of parameters that may be useful for comparative and developmental purposes (Dayhoff and DeLeo, 2001; Roush *et al.*, 2006).

ANN have been widely used for both prediction and classification tasks in many fields of knowledge. However, few studies are available on animal science. Very little research has been conducted to model animal growth using artificial neural networks. Yee *et al.* (1993) compared the modeling of a data set of Sprague-Dawley rats with traditional regression and a back-propagation neural network. They found that both methods produced models that adequately predicted the body weight.

Roush *et al.* (2006) compared the modeling by the Gompertz nonlinear regression equation and neural network modeling using a set of broiler growth data. They concluded that the fitness of ANN model to the broiler growth curve is relatively better than that of Gompertz

Model. Some valuable properties of ANN for its application in animal science problems are as follows (Fernandez *et al.*, 2007; Haykin, 1999; Ripley, 1996):

- No priori knowledge of the problem is needed. The adjustment between the output and input variables is done without any assumption, avoiding errors produced by false suppositions
- Since the output of the neuron is non-linear, the ANN will act like a nonlinear model. Thus, it can find non-linear relationships between the inputs and the outputs. In fact, it is possible to mathematically demonstrate that a multilayer perceptron is a universal regression model, i.e., it can find the relationship between any pair of data sets (if they are related and they represent sufficiently the problem)
- The aim of the present study was a comparison between neural network modeling and modeling by nonlinear regression equations

MATERIALS AND METHODS

Animal data: The body weights by age of 70 Baluchi lambs from the Research Farm of Faculty of Agriculture, Ferdowsi University of Mashhad, Iran were used in this study. Body weight data of the lambs were recorded weekly from birth to approximately 150th days of age. Lambs were suckled by their dams up to 6 weeks of age. Body weights of lambs were used as the data points for the growth curve to be modeled.

Neural network model: The ANN model was developed with Neural Net of JMP program (JMP, 2007). The ANN model in this work was a Multi-Layer Perceptron (MLP). A MLP model consists of an input layer, a hidden layer and an output layer. Data were introduced at the input layer. The hidden layer generates numerous mathematical relationships. The output layer reports ANN's responses (Haykin, 1999; Ripley, 1996). The hidden nodes, overfit penalty, number of tour, maximum iteration and converge criteria were set at 2, 0.001, 20, 100 and 0.00001, respectively. To avoid the local optima, the platform estimate the model in many different times from different random starting estimates. Each starting estimate and consequent iteration is called a tour.

Nonlinear models: Parameter estimates of the growth curves models were performed using NCSS statistical package program (Hintze, 2007). Functions describing growth-age relationship in Baluchi lambs were given as follows:

von Bertalanffy:

$$W_t = A*(1-B*\exp(-K*t))^3$$

Gompertz:

$$W_t = A* \exp (-B* \exp (-K*t))$$

Logistic with 3 parameters:

$$W_t = A/(1+B* \exp (-K*t))$$

Brody:

$$W_t = A*(1-B* \exp (-K*t))$$

Logistic with 4 parameters:

$$W_t = A+(A-M)*(1+B* \exp (-K*t))$$

Richards:

$$W_t = A*(1-B* \exp (-K*t))^M$$

Where:

W_t = Body weight at age t

A = The asymptotic or mature weight when age (t) approaches infinity

B = The rate of body weight gained after birth to mature body weight or point of inflection

k = The maturing rate

M = The shape parameter relating inflection point which become where the predictable growth rate changes from an increasing to a decreasing function

t = The age in days (Bilgin *et al.*, 2004)

These growth curves models were evaluated as counterparts to the ANN model in this study.

Model comparison: The accuracy of the model through goodness of fit was determined by coefficient of determination (R^2), Mean Absolute Deviation (MAD), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and the bias (Oberstone, 1990):

$$MAD = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|}{n}$$

$$MSE = \frac{\sum_{t=1}^n |y_t - \hat{y}_t|^2}{n}$$

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{y_t - \hat{y}_t}{y_t} \right|}{n} \times 100, (y_t \neq 0)$$

$$\text{Bias} = \frac{\sum_{t=1}^n (y_t - \hat{y}_t)}{n}$$

Where:

- y_t = Equals the observed value at time t
- \hat{y}_t = Equals the estimated value
- n = Equals the number of observations

Goodness of fit may be demonstrated by high R² and/or low other forecasting error measurement.

RESULTS AND DISCUSSION

Goodness of fit and predictive accuracy based on the differences between the predicted model and the observed values for the various models are shown in Table 1. The models with higher R² and lower other forecasting error measurements are preferred.

The ANN model and two nonlinear functions (von Bertalanffy and Gompertz) all had fairly good fits. Among these three models, the ANN model showed the best R² and other forecasting error measurements indicators. Meanwhile, von Bertalanffy and Gompertz functions remained the best among the set of nonlinear regression models.

The overall calculated statistical values MSE, MAD, MAPE and bias have shown that ANN may be used efficiently for prediction of lamb body weight. In general, the application of neural network does not require the data meeting the assumption that must otherwise be met in a regression model.

However, the results from ANN model are not interpretable, since there is an intermediate layer rather than a direct path from the dependent variable(s) to the independent variable(s) as it is in the case of regular regression. Furthermore, ANN presents a clear advantage for handling complex, multi-variable situations compared to the frequently troublesome convergence of

nonlinear regression models. Although, some studies attempted to interpret the biological significance of the estimates of the parameters in an equation, it may be more practical to ignore the relevance of the parameter estimates and focus on the ability of ANN to predict responses (Roush *et al.*, 2006; Yee *et al.*, 1993).

CONCLUSION

In this study, the potential of ANN as an alternative to traditional regression models was evaluated for the purpose of predicting sheep growth. After comparing results from using various regression functions and ANN model, the ANN model was concluded to be the most appropriate and accurate. The ANN model performed slightly better than the best nonlinear models and made the most accurate predictions when new data was presented.

The dataset in this study only covers growth for one year which may not include sufficient variability in environmental effects.

Moreover, since the dataset used in this study is from one farm, it may not be appropriate to generalize the findings that ANN is superior to traditional regression models in predicting sheep growth. However, in this study ANN gave the most reliable prediction of Baluchi sheep growth.

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Table 1: Comparisons of the goodness of fit and accuracy

Models	Goodness of fit and accuracy criteria ¹				
	R ² (%)	MSE	MAD	MAPE	Bias
ANN	99.95	0.06506	0.21082	1.59682	-0.00003
von Bertalanffy	99.73	0.34274	0.42790	4.45851	-0.00932
Gompertz	99.69	0.38836	0.42263	4.78583	-0.01409
Logistic with 3 parameters	99.58	0.51864	0.40753	5.37395	-0.02685
Brody	96.03	4.95612	1.88967	11.96341	0.39157
Logistic with 4 parameters	97.28	3.41659	1.55536	9.73443	0.63969
Richards	99.62	0.47043	0.45358	5.21788	0.02185

¹R² = coefficient of determination; MSE = Mean Square Error; MAD = Mean Absolute Deviation and MAPE = Mean Absolute Percentage Error

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