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Application of Linear Regression and Artificial Neural Network for Broiler Chicken Growth Performance Prediction

Research Article

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ABSTRACT

This study was conducted to investigate the prediction of growth performance using linear regression and artificial neural network (ANN) in broiler chicken. Artificial neural networks (ANNs) are powerful tools for modeling systems in a wide range of applications. The ANN model with a back propagation algorithm successfully learned the relationship between the inputs of metabolizable energy (kcal/kg) and crude protein (g/kg) and outputs of feed intake, weight gain and feed conversion ratio variables. High R^2 and T values for the ANN model in comparison to linear regression revealed that the artificial neural network (ANN) is an efficient method for growth performance prediction in the starter period for broiler chickens. This study also focused on expanding the experiment with more levels of inputs to predict outputs the using best ANN model.

KEY WORDS artificial neural network, back propagation algorithm, broiler chicken, growth performance, linear regression.

INTRODUCTION

Dietary protein and energy content influence all aspects of growth in chickens (Swennen *et al.* 2007). Although various systems are used to describe the energy and protein requirements of broiler chickens, predicting the growth performance from the dietary energy and protein patterns in practice is still difficult. This difficulty is due to non linear responses in growth to changes in dietary nutrients (Hruby *et al.* 1996). Artificial neural networks (ANNs) have a great ability for relating complex non linear systems. The ANN is a mathematical model based on biological neurons, which recognizes non linear relationships and can be applied to a wide variety of fields (Lacroix *et al.* 1995). An ANN model can predict dependent variables based on multiple independent variables, where a mathematical model is only able to predict one dependent variable at a time (Zhang *et al.* 2002). The prediction by a well trained ANN is normally faster than by mathematical models. Several authors have shown greater performance by ANN than by regression models (Lek *et al.* 1996; Park *et al.* 2005). The basic element of an ANN is shown in Figure 1. Back propagation (Back prop) is an ANN algorithm. Back prop can be used for system modeling, prediction, classification, filtering and many other general problems. Back prop calculates an error between the desired and actual output and propagates the error information back to each node in the network. The back propagated error drives the learning at each node. The back-prop uses two important parameters to encourage learning. The first, learning rate (also known as learning coefficient), refers to the rate at which errors modify the outputs. The second, momentum, implies that if an outputs changes in a certain direction, then there is a tendency for an output to continue changing in that direction. In recent years, ANNs have been applied in the field of poultry nutrition (Ghazanfari *et al.* 2011; Ahmadi *et al.* 2007; Ahmadi *et* *al.* 2008; Ahmadi and Golian, 2010). Moharrery and Kargar (2007) were found that ANN most effective to identify performance, plasma hormones or liver enzymes for broiler chickens fed the diets on the known range of the energy and protein concentration. The objectives of this study were: 1) modeling of different energy and protein levels as inputs on weight gain, feed intake and feed conversion ratio of the starter period (1-21 d of age) using linear regression and ANN; 2) comparison of the result of linear regression with those from ANN and 3) expansion of experiment by creating more levels of inputs from the biological data to predict the outputs using the best ANN model. This last objective would address the question of what levels of dietary energy and protein may be used to achieve maximum weight gain and feed intake and minimum feed conversion ratio in the starter period for broiler chickens.

MATERIALS AND METHODS

Data source

This study took place at the Poultry Research Station in Ferdowsi University in Mashhad, Iran, in 2011. Data were collected from 864 day old Ross male broiler chickens. Initial body weights of broilers were 43.85 ± 1.1 g. Broilers were assigned randomly to diets with 3100, 2950 or 2800 kcal/kg ME and protein levels were set to 223, 193 and 163 g/kg during the starter period. The diets were prepared daily and animals were fed from 1 to 21 days of age.

Feed ingredients and the composition of experimental diets are shown in Table 1. Diets were based on Ross recommendations except of energy and protein levels and were written using of UFFDA software. According to the treatment groups, the chickens were arranged in a 3 × 3 factorial in a completely randomized design experiment. Each treatment group consisted of 8 replicates of 12 chickens and groups were randomly allocated in cages, where light was provided 23 hours daily during the experiment. The temperature started at 32°C and was reduced 2.8 °C each week.

Model optimization

The collected data consisted of metabolizable energy (ME; kcal/kg) and crude protein (CP; g/kg) as the input variables and weight gain, feed intake and feed conversion ratio as the output variables. Data lines (*i.e.*: 72=3×3×8) were randomly divided into 2 subsets: training (n=50) and testing (n=22), seventy % of the data lines were used for the training set and 30% for the testing dataset. A multilayer Perceptron ANN model trained by back propagation algorithms was developed to predict broiler chicken growth performances in the starter period. Three steps were taken to select an optimal ANN model. The first step was to determine the best number of hidden layers, number of neurons in each hidden layer, and activation function. The best models were selected on the basis of training and prediction accuracy. The second step was to work with the selected models to find the optimum epoch size.

Table 1 Feed ingredients and composition of experiment diets (1-21 days of age)

Ingredients	Treatment diets								
	1	2	3	4	5	6	7	8	9
Corn	54.5	61.9	69.4	53.2	59.1	65.6	52.0	56.4	61.7
Soybean meal 44%	28.6	24.9	21.0	31.7	25.0	20.4	34.8	25.1	19.8
Corn gluten	7.9	4.7	1.6	5.5	3.9	1.1	3.0	3.0	0.6
Vegetable oil	3.5	3.0	2.5	2.2	2.0	1.7	1.0	1.0	1.0
Wheat bran	1.5	1.5	1.5	3.6	7.2	7.4	5.7	10.9	13.3
Dicalcium phosphate	1.69	1.74	1.79	1.50	1.56	1.62	1.32	1.39	1.44
Limestone	1.17	1.20	1.24	1.17	0.19	1.22	1.16	1.17	1.20
Vitamin premix[1] and mineral premix[2]	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.50	0.5
Salt	0.44	0.44	0.44	0.43	0.43	0.42	0.41	0.41	0.40
DL-methionine	0.09	0.08	0.07	0.12	0.08	0.07	0.13	0.09	0.08
L-lysine	0.06	0.03	0.01	0.03	0.03	0.01	-	-	-
Total	100	100	100	100	100	100	100	100	100
Compositions (analysis results)									
Metabolizable energy (kcal/kg)	3100	3100	3100	2950	2950	2950	2800	2800	2800
Crude protein (g/kg)	223	193	163	223	193	163	223	193	163
Ca (g/kg)	9.7	9.7	9.7	9.2	9.2	9.2	8.8	8.8	8.8
Available P (g/kg)	4.4	4.4	4.4	4.1	4.1	4.1	3.9	3.9	3.9
Na (g/kg)	1.9	1.9	1.9	1.9	1.9	1.9	1.8	1.8	1.8
Arginine (g/kg)	12.7	11.2	9.7	14.8	11.5	9.9	14.1	11.8	10.1
Lysine (g/kg)	11.4	9.2	7.8	11.4	9.2	7.8	11.4	9.2	7.8
Met + Cys (g/kg)	8.7	7.5	6.4	8.7	7.5	6.4	8.7	7.5	6.4

[1] Provided per kg of diet: Retinol: 9000 IU; Cholecalciferol: 2000 IU; α-tocopherol: 11 IU; Menadione: 2 mg; Thiamine: 1.775 mg; Riboflavin: 6.6 mg; Pantothenic acid: 9.8 mg; niacin: 29.7 mg; Pyridoxine: 1.176 mg; Folic acid: 1 mg; Cyanocobalamin: 0.015 mg; Biotin: 0.1 mg; Choline chloride: 500 mg;
[2] Mineral premix per kg of diet: Mn: 76 mg; Zn: 66 mg; Fe: 40 mg; Cu: 4 mg; I: 0.64 mg and Se: 0.2 mg.

The third step was to find the optimum learning rate and momentum values. The evaluating method for selecting the optimal ANN was based on the minimization of deviations between predicted and measured values. In one and two hidden layer networks, the number of hidden neurons varied from 0 to 30 with a step of 2. Three activation functions were also tried for each structure: sigmoid, linear and hyperbolic tangent.

Three statistical parameters included Root Mean Square Error (RMSE), T value and R^2 were used to determine the adequacy of the neural networks output response for a given dataset. The T statistic measures the scattering around the line (1:1). When the T is close to 1.0, the fitting is desirable (Khazaei *et al*. 2005).

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_{m,i}-X_{p,i}\right)^2}$$

$$T=1-\frac{\sum_{i=1}^{n}(X_{m,i}-X_{p,i})^2}{\sum_{i=1}^{n}(X_{m,i}-\bar{X})^2}$$

Where:
n: the number of data points.
i: the line of data.
$\bar{X}$: the average of X over the n samples.
X_m and X_p: the measured and predicted values.

The final network was selected on the basis of the lowest error on the training and testing sets of data. The ANN configuration that minimized the RMSE measures and optimized the T and R^2 values was selected as the optimum (Khazaei *et al*. 2008). The range of neural network parameters tried was: one and two hidden layers; 3 to 30 neurons/hidden layer; sigmoid, linear, and tanH activation function; learning rate of 0.1-0.9; momentum of 0.1-0.9; and number of epochs. Since the transfer functions are bound between either [0, 1] or [-1, 1], the input and output data should be normalized to the same range as the transfer functions.

As a result of normalization, all variables acquire the same significance during the learning process. In this work, the input and output data were normalized between [0, 1] with respect to the corresponding maximal and minimal values. The ANN modeling was implemented using the Neural Work Professional 11/PLUS (ver. 5.23) software (Khazaei *et al*. 2008).

Statistical analysis

All analysis was conducted using GLM procedures of SAS (SAS, 2001). The linear regression was compared with the results of the ANN model using adequacy parameters (R^2 and RMSE) of the models. The statistical model was:

$$Y=(\mu+ME+CP+(ME\times CP)+e)$$

Where:
μ: the overall mean.
ME: metabolizable energy (kcal/kg).
CP: crude protein (g/kg).
ME × CP: an interaction of dietary energy and protein.
e: the model error.

Expansion of the experiment

After detecting the optimal ANN model, the experiment was expanded with more inputs combinations (ME and CP) to predict outputs (weight gain, feed intake and feed conversion ratio). A total of 441 scenarios containing different levels of inputs were considered (Table 2; 21 ME levels×21 CP levels).

Table 2 Different levels of input variables (energy and protein) used for the extension of the experiment

Row	Energy (kcal/kg)	Protein (g/kg)
1	2800	163
2	2815	166
3	2830	169
4	2845	172
5	2860	175
6	2875	178
7	2890	181
8	2905	184
9	2920	187
10	2935	190
11	2950	193
12	2965	196
13	2980	199
14	2995	202
15	3010	205
16	3025	208
17	3040	211
18	3055	214
19	3070	217
20	3085	220
21	3100	223
Mean	2950	193
SE	93.07	18.6

SE: standard error.

RESULTS AND DISCUSSION

The best combination of the network parameters that were used for predicting weight gain, feed intake and feed conversion ratio in broiler chickens during the starter period are shown in Table 3.

Based on the RMSE of the training and testing examples, it was clear that the 2-4-2-1 structures had the lowest RMSE among all the structures for weight gain, feed intake and feed conversion ratio in broiler chickens in the starter period. The multilayer perceptron structure consisted of input, first hidden layer; second hidden layer and output, respectively (Figure 1).

Table 3 The MLP structure and optimum values of the best ANN parameters used to predict performance and adequacy parameters of the ANN model at 21 days of age in broiler chickens

		Feed intake			Weight gain			Feed conversion ratio		
	Parameters	Entire data	Testing data	Training data	Entire data	Testing data	Training data	Entire data	Testing data	Training data
21 d of age	R^2	0.95	0.92	0.96	0.99	0.98	0.99	0.94	0.92	0.99
	T	0.95	0.92	0.96	0.99	0.98	0.99	0.90	0.90	0.99
	RMSE	25.25	27.48	24.48	5.04	5.69	4.76	0.05	0.08	0.03
	MLP structure	2-4-2-1								
	η	0.3								
	α	0.4								
	Transfer function	TanH								
	Epochs	5000								

RMSE: root mean square error; MLP structure: multilayer perceptron structure (input, first hidden layer, second hidden layer and output); η: learning rate; α: momentum and TanH: hyperbolic tangent.

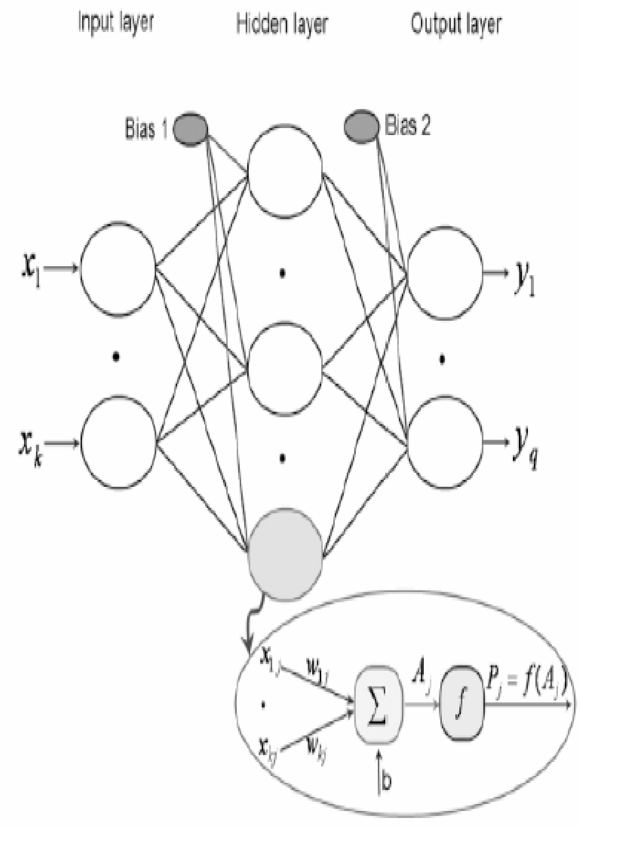

Figure 1 A simplified three layer fully connected artificial neural network (Ghazanfari *et al*. 2011)

This result also implied that the designed ANN was able to properly learn the relationships between the input and output parameters, predicting weight gain, feed intake and feed conversion ratio in broiler chickens. Also, the comparison of R^2 and RMSE of the models indicated that predicting performance using ANN is better than the linear regression in broiler chickens. The ANOVA results of the linear regression are shown in Table 4. The variation of performance of the expanded experiment with more levels of inputs for predicting the outputs using the best ANN model is shown in Figure 2. The 3-dimensional response graphs obtained by the expanded experiment using the ANN model are useful for understanding the relationship between the increase in energy and protein levels and performance.

In a nutrition optimization plan, it appears that the 3-dimensional graphs obtained by the ANN model may be used to optimize growth based on dietary nutrients. Also, the expansion of experiments using the best ANN model can be useful for the investigation of more levels of treatments. ANN technology has been shown to be a useful tool in agricultural experiments. Cravener and Roush (1999) showed that ANN computation is a successful alternative to statistical regression analysis for predicting amino acid levels in feed ingredients. Salle *et al*. (2003) concluded that it is possible to explain the performance variables of production birds, with the use of artificial neural networks.

Table 4 ANOVA results of the linear regression at 21 days of age in broiler chickens

	Feed intake			Weight gain			Feed conversion ratio		
Variable	Energy (kcal/kg ME) (n=24)	Protein (g/kg) (n=24)	Energy protein (n=8)	Energy (n=24)	Protein (n=24)	Energy protein (n=8)	Energy (n=24)	Protein (n=24)	Energy protein (n=8)
P-value	0.03	0.01	0.04	0.02	0.01	0.01	0.03	0.05	0.04
df	2	2	4	2	2	4	2	2	4
R^2	0.76			0.86			0.77		
RMSE	42.14			20.67			0.1		
P-value	0.04			0.01			0.05		

RMSE: root mean square error and df: degrees of freedom.

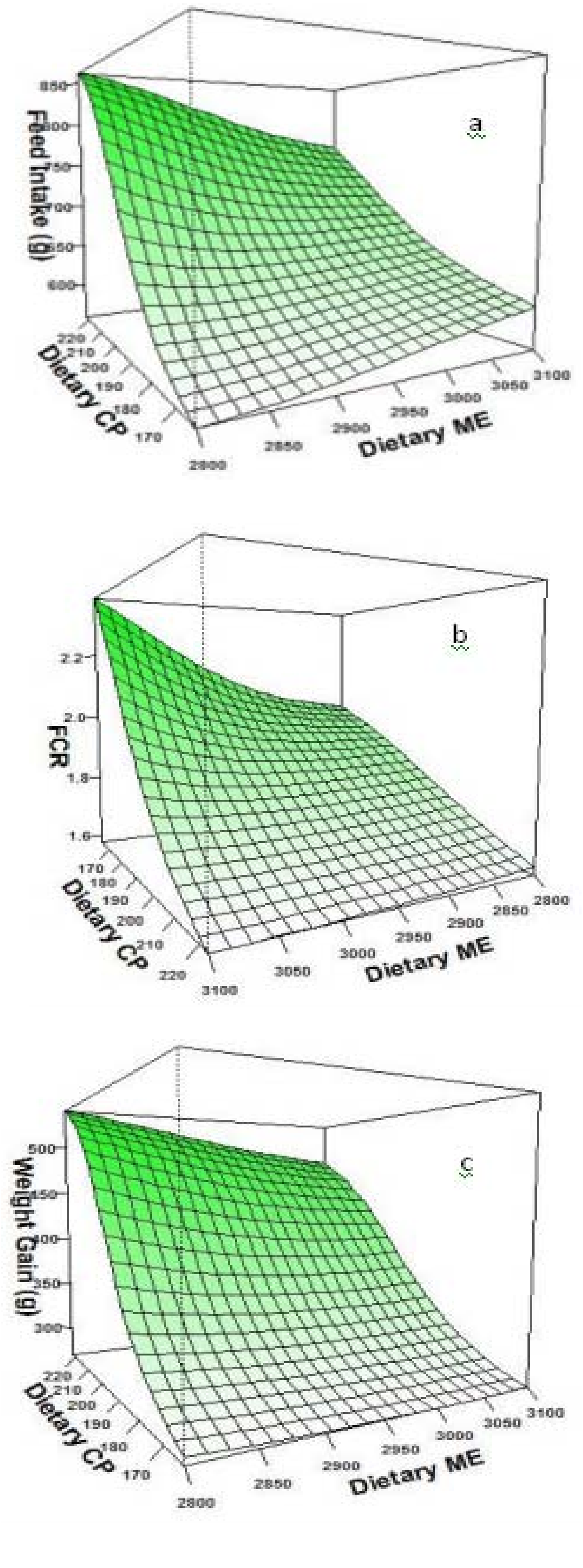

Figure 2 The three dimensional display of predicted values from different dietary ME (kcal/kg) and CP (g/kg) in the expanded experiment at 21 days of age using ANN

a: feed intake (g); b: feed conversion ratio (FCR) and c: weight gain (g)

Also, Ghazanfari *et al*. (2011) suggested that the ANN model could provide an effective means of recognizing the patterns in data and accurately predict the egg production of laying hens based on their age. Huang *et al*. (2012) to predict the poultry growth performance parameters to help future production and management. Observational study is proposed for seasonal broiler growth performance prediction. Systematic observational study with statistical analysis and data mining technology is adopted including macro analysis, exploratory data analysis, and modeling.

CONCLUSION

The obtained results revealed that the ANN model may efficiently learn the relationship between dietary energy and protein and growth performance in the starter period in broiler chickens. In comparison with the linear regression, ANN performed better when predicting growth performance (feed intake, weight gain and feed conversion ratio). Also, this study shows that expanding the experiment using the best ANN model could be useful for evaluation of more levels of treatments.

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