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Prediction of Egg Production Using Artificial Neural Network

Research Article

S. Ghazanfari[1], K. Nobari[2*] and M. Tahmoorespur[2]

[1] Department of Animal and Poultry Science, College of Aboureihan, University of Tehran, Tehran, Iran
[2] Department of Animal Science, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran

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*Correspondence E-mail: k_nobari_ir@yahoo.com

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ABSTRACT

Artificial neural networks (ANN) have shown to be a powerful tool for system modeling in a wide range of applications. The focus of this study is on neural network applications to data analysis in egg production. An ANN model with two hidden layers, trained with a back propagation algorithm, successfully learned the relationship between the input (age of hen) and output (egg production) variables. High R^2 and T for ANN model revealed that ANN is an efficient method of predicting egg production for pullet and hen flocks. We also estimated ANN parameters of a number of eggs on four data sets of individual hens. By increasing the summary intervals to 2 wk, 4 wk and then to 6 wk, ANN power was increased for prediction of egg production. The results suggested that the ANN model could provide an effective means of recognizing the patterns in data and accurately predicting the egg production of laying hens based on investigating their age.

KEY WORDS artificial neural networks, back propagation algorithm, egg production.

INTRODUCTION

A typical egg production curve for a flock increases rapidly during the first 8 or 9 weeks of production and then decreases at a constant rate to the end of the production period (North and Bell, 1990). However, a typical egg production curve for an individual, increases rapidly during the first 2 weeks, maintains a constant production for a while, and then decreases slowly (North and Bell, 1990). Mathematical models have been used to describe egg production curves for a flock (Fairfull and Gowe, 1990) or for an individual (Koops and Grossman, 1992). Models for egg production have been used to predict total production from partial production or to predict decline in post-peak production, however, there is no mathematical model for egg production of a flock or an individual that includes an explicit measure for prediction of egg production.

ANN (Artificial Neural Network) technique is used to solve a wide range of problems in science and engineering, particularly for some areas where the mathematical modeling methods fail. Nowadays, the ANNs are one of the most powerful modeling techniques to model complex nonlinear, multidimensional function relationships without any prior assumptions about the nature of the relationships. Artificial neural network models are different from mathematical modeling approaches in their ability to learn relationships between dependent and independent variables through the data itself rather than assuming the functional form of the relationships (Mittal and Zhang, 2000). A well trained ANN can be used as a predictive model for a specific application. The prediction by a well trained ANN is normally faster than the mathematical models. Several authors have shown greater performances of ANN as compared to regression models (Lek *et al*. 1996; Park *et al*. 2005). An ANN model can predict multiple 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 basic element of an artificial neural network is shown in Figure 1. The applications of ANN in agriculture include the prediction of amino acid levels in feed ingredients in broiler chicken, milk performance, and Probabilistic Neural Network Prediction of ascites in Broilers (Roush *et al*. 1997; Edriss *et al*. 2008; Cravener and Roush, 1999). Therefore, the objectives of this research were to test the fitness of an ANN model to egg production data sets collected from pullet and hen flocks and also individuals.

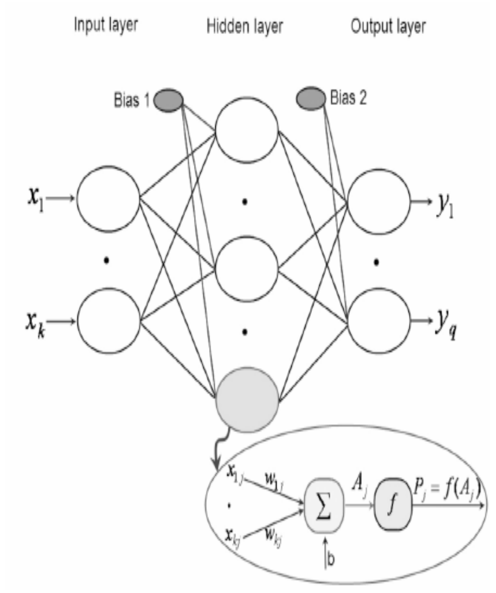

Figure 1 A simplified three-layers fully connected artificial neural network

MATERIALS AND METHODS

To illustrate the ANN model, six data sets were used: two sets from flocks (one pullet flock and one hen flock) and four individual ones. For the pullet flock (Cason, 1990), data were weekly percentage hen-day egg production for one first-cycle flock selected from among 45 flocks with an average of about 43,000 pullets per flock (in total 1935000) (Table 1). Age flock was 22 week. This data set was previously used to compare linear and curvilinear decreasing terms for pullet flocks (Cason, 1990). For the hen flock (Cason, 1991), data were weekly percentage hen-day egg production for one flock selected from among 47 molted flocks (second-cycle flock) with an average of about 44,000 hens per flock (in total 2068000) (Table 1).

This data set was previously used to compare egg production models for hen flocks (Cason, 1991). For individual hens, data were provided by W. M. Muir (Muir, 1999: Purdue University, West Lafayette, IN 47907, personal communication). Hens selected for this study started production between 15 to 19 wk of age. Individual hens were 24 week old. Eggs were collected daily, and number of eggs was summarized weekly for each hen for 52 wk from beginning

Table 1 Actual weekly percentage hen day egg production for a pullet flock[1] and a hen flock[2]

Week	Pullet flock	Hen flock	Week	Pullet flock	Hen flock
1	0.3	1.2	25	84.7	70.5
2	4.2	21.5	26	84.8	71.0
3	15.0	56.1	27	84.2	69.9
4	32.5	70.2	28	82.9	69.0
5	53.0	77.8	29	83.1	67.1
6	69.6	79.1	30	82.1	69.1
7	78.7	80.6	31	82.0	68.2
8	86.7	80.1	32	80.3	66.5
9	87.1	80.5	33	79.5	67.2
10	89.6	80.4	34	80.5	65.2
11	89.7	79.2	35	79.9	66.1
12	89.3	78.2	36	79.6	64.9
13	89.4	78.2	37	78.8	65.1
14	89.5	77.1	38	78.5	65.0
15	89.9	76.0	39	76.2	66.7
16	88.8	74.7	40	76.5	
17	89.4	75.5	41	79.1	
18	87.0	74.2	42	76.6	
19	88.1	75.8	43	75.1	
20	86.9	74.6	44	75.0	
21	87.1	73.3	45	74.5	
22	86.1	73.1	46	73.9	
23	85.7	72.0	47	73.6	
24	85.5	72.1			

[1] Source: Cason, 1990.
[2] Source: Cason, 1991.

of production (Table 2). In practice, it might be difficult to obtain weekly production summaries; data might be summarized, for example, only on a 2 wk or 4 wk interval. The effect of interval of summarized data on estimations of ANN model parameters was examined by ANN. Furthermore, it might be interesting, to use early part of egg production records to predict full record production, especially as a selection criterion to improve annual egg production (Bohren *et al*. 1970; Muir, 1990). Data sets obtained from the experiments were used for training and testing the neural networks. Seventy five percent of patterns were used for training and 25% were used as a testing dataset. A multilayer Perceptron (MLP) ANN model trained by back propagation algorithms was developed to predict egg production.

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

Table 2 Actual number of eggs four individual hen for 1 week, 2 week, and 4 week intervals

Week	Interval			Interval			Interval			Interval			Week	Interval			Interval			Interval			Interval		
	Hen 1			Hen 2			Hen 3			Hen 4				Hen 1			Hen 2			Hen 3			Hen 4		
	1	2	4	1	2	4	1	2	4	1	2	4		1	2	4	1	2	4	1	2	4	1	2	4
1	2				1			1			3		27		6			5			6			6	
2	6	8		2	3		5	6		3	6		28	6	12	23	5	10	22	6	12	24	6	12	24
3	4				6			6			5		29		5			6		4				7	
4	6	10	18	7	13	16	7	13	19	6	11	17	30	6	11		5	11		6	10		5	12	
5	6				6			7			5		31		4			4			5			6	
6	6	12		4	10		7	14		7	12		32	4	8	19	5	9	20	5	10	20	6	12	24
7		6			7			7			7		33		6			5			6			3	
8	7	13	25	7	14	24	7	14	28	6	13	25	34	6	12		6	11		5	11		6	9	
9		6			6			7			7		35		6			5			5			6	
10	7	13		7	13		6	13		7	14		36	6	12	24	6	11	22	6	11	22	6	12	21
11		6			7			7			7		37		5			6			6			5	
12	6	12	25	6	13	26	6	13	26	6	13	27	38	5	10		5	11		6	12		5	10	
13		6			6			7			7		39		6			6			5			6	
14	6	12		7	13		6	13		7	14		40	5	11	21	6	12	23	6	11	23	6	12	22
15		6			7			6			7		41		6			4			6			4	
16	6	12	24	7	14	27	5	11	24	7	14	28	42	5	11		6	10		5	11		6	10	
17		6			4			6			5		43		6			6			6			3	
18	6	12		6	10		6	12		7	12		44	5	11	22	5	11	21	6	12	23	5	8	18
19		6			6			7			5		45		5			5			4			6	
20	6	12	24	6	12	22	6	13	25	7	12	24	46	5	10		5	10		5	9		5	11	
21		7			6			6			7		47	5				5			6			6	
22	7	14		7	13		6	12		6	13		48	5	10	20	6	11	21	5	11	20	4	10	21
23		5			6			6			7		49		5			5			6			6	
24	6	11	25	6	12	25	6	12	24	7	14	27	50	5	10		6	11		5	11		5	11	
25		6			6			6			6		51		6			5			5			5	
26	5	11		6	12		6	12		6	12		52	5	11	21	6	11	22	5	10	21	5	10	21

Source: Muir W.M., Purdue University, West Lafayette, IN 47907.

size. 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 including RMSE (Root Mean Square Error), T value and R^2 (Equation 1) were used to determine the adequacy of the neural networks output response for a given dataset. The T statistic measures the scattering around line (1:1). When the T is cl-

Table 3 The MLP structure and optimum values of the ANN parameters used to predict egg production pullet and hen flock

	Parameters									
	MLP Structure*	η	α	Transfer function	*RMSE train	RMSE test	T	R^2	Epochs×10^3	MRE
Pullet flock	1-9-3-1	0.3	0.4	TanH*	0.007	0.007	0.998	0.998	150	0.65
Hen flock	1-6-4-1	0.3	0.4	TanH	0.009	0.015	0.923	0.941	150	1.35

η=learning rate.
α=momentum.
*TanH=hyperbolic Tangent.
*RMSE=Root Mean Square Error.
*MLP Structure: Multilayer Perceptron Structure (input, first hidden layer, second hidden layer, output).

Table 4 The final structure and optimum values of the ANN parameters used to predict egg production for 1 week, 2 week, and 4 week intervals

	Parameters									
	MLPStructure*	η	α	Transfer function	*RMSE train	RMSE test	T	R^2	Epochs×10^3	MRE
1 week	1-15-5-1	0.3	0.4	TanH*	0.115	0.093	0.304	0.323	150	10.4
2 week	1-15-5-1	0.3	0.4	TanH	0.084	0.096	0.300	0.353	150	10.5
4 week	1-15-5-1	0.3	0.4	TanH	0.105	0.124	0.95	0.691	150	22.36

η=learning rate.
α=momentum.
*TanH=hyperbolic Tangent.
*RMSE=Root Mean Square Error.
*MLP Structure: Multilayer Perceptron Structure (input, first hidden layer, second hidden layer, output).

ose to 1.0, the fitting is desirable (Khazaei *et al.* 2005).

(1)

$$PMSE = \sqrt{1/n} \sum_{i=1}^{n} (Xm,i - Xp,i)^2$$

$$T = 1 - \frac{\sum_{i=1}^{n} (Xm,i - Xp,i)^2}{\sum_{i=1}^{n} (Xm,i - \frac{Xm}{n})^2}$$

Where, n is the number of data points, i is the line of data, Xm/n is the average of X over the n samples, and Xm and Xp are the measured and predicted values, respectively. The final network was selected on the basis of the lowest error on the train and test sets of data. The prediction accuracy of the ANN was also evaluated by calculating the mean relative error (MRE) as the percentage of difference between the measured and predicted values relative to the measured values (Equation 2). The ANN configuration that minimized the RMSE and MRE measures and optimized the T and R^2 values was selected as the optimum (Khazaei *et al.* 2008).

(2)

$$MRE = \frac{100}{n} \sum_{i=1}^{n} \left| \frac{Xm,i - Xp,i}{Xm,i} \right|$$

The range of neural networks parameters tried was: Number of hidden layers (one and two layers); number of neurons/hidden layer (from 3 to 30); activation function (sigmoid, linear, and tanh); learning rate (0.1-0.9); momentum (0.1-0.9); and number of epochs. Since the transfer functions are bound between either [0, 1] or [-1, 1] so the input and output data should be normalized to the same range as the transfer function uses. As a result of normalization, all variables acquire the same significance (importance) 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).

RESULTS AND DISCUSSION

The aim of this study is to obtain an ANN model with minimal dimensions and minimum errors in training and testing.

The best combination of the network parameters that were used for predicting egg production in pullet and hen flock are shown in Table 3. Based on the RMSE of the training examples, it was clear that the 1-9-3-1 and 1-6-4-1 structures had the lowest RMSE (0.007) and (0.009) among all the structures for egg production in pullet and hen flock, respectively. This result also implied that the designed ANN was able to properly learn the relationship between the input and output parameters predicting egg production in pullet and hen flock. We also estimated ANN parameters for a number of egg of four hens. When intervals of summary increased firstly to 2 wk, then to 4 wk, ANN power increased for egg production prediction. The best combination of the network parameters that were used for predicting egg production for 1 week, 2 week, and 4 week intervals are shown in Table 4.

The network will perform with little error on training data but will not be able to generalize well for testing data. The next stage of ANN modeling involved testing the predictive ability of the trained ANN model. Ideally, the RMSE values should be close to zero, indicating that, on average, there were no significant differences between predicted and meas- ured values. It was found that the ANN parameters, including the number of neurons per layer, number of epochs, learning rate and momentum values, affected the ANN performances significantly (Table 3 and 4).

It was evident that, as the momentum decreased and the learning rate increased, both training and testing RMSE tended to fall. This result is in agreement with Grossman *et al*. (2000), who tried to fit an empirical egg production model to the same data sets. Cravener and Roush (1999) showed that ANN computation is a successful alternative to statistical regression analysis for predicting AA levels in feed ingredients. Fernandez *et al*. (2006) predicted weekly milk production in goat flocks and clustering of goat flocks by using self organizing maps. Achieved results show the usefulness of neural networks in two animal science applications (Fernandez *et al*. 2006). Salle *et al*. (2003) concluded that it is possible to explain the performance variables of production birds, with the use of artificial neural networks.

CONCLUSION

The obtained results revealed that the ANN model may efficiently be fitted into the weekly percentage of hen day egg production of a pullet and hen flock. Increase of summarized data intervals to 2 and 4 weeks, increased the ANN power for predicting egg production in individual hens.

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