

Neural Network Model for Egg Production Curve

H. Ahmadi and A. Golian

Center of Excellence, Department of Animal Science,
Ferdowsi University of Mashhad, P.O.Box 91775-1163, Mashhad, Iran

Abstract: The Neural Network (NN) is an alternative to regression analysis for system modeling. It is a set of nonlinear equations used to predict output variable(s) from input variable(s) in a flexible way using layers of linear regressions and S-shape functions. The purpose of this study was to evaluate the fitness of the NN model to 2 sets of empirical weekly data obtained from first and second cycle of egg production. The goodness of fits for the obtained NN model were calculated by R^2 value, adjusted R^2 , Mean Square Error (MSE), Residual Standard Error (RSE), Mean Absolute Percentage Error (MAPE) and the bias. The NN model adjusted R^2 for first and second cycle of egg production were 0.999 and 0.998, respectively. These very high adjusted R^2 revealed that the NN model is a better fit than those previously reported by the estimated regression models. It is concluded that the NN model may provide an effective mean to draw the pattern of egg production during the first and second cycle.

Key words: Egg production model, neural network, laying hen

INTRODUCTION

Some models have been developed and used to describe egg production curves for a flock (Fairfull and Gowe, 1990; Koops and Grossman, 1992; Grossman *et al.*, 2000). These models are based on non-linear regression analyses which have long been convenient methods of predicting a dependent (egg production) variable based on independent variable (time). The recently used Neural Network (NN) model seems to finely fit an egg production curve. The NN model is a set of nonlinear equations that predict output variable(s) from input variable(s) in a flexible way using layers of linear regressions and S-shape functions. With the NN models a priori model is not required and they are potentially advantageous in the modeling of biological processes often characterized as highly non-linear. However, the NN takes a black box approach which does not give insight into the internal working of a NN and does not provide estimates of parameters that may be useful for comparative and developmental purposes (Dayhoff and DeLeo, 2001; Roush *et al.*, 2006).

Roush *et al.* (2006) compared the NN model fitness with the Gompertz nonlinear regression (an empirical method) using a set of broiler growth data. They concluded that the fitness of NN model to the broiler growth curve is relatively better than that of Gompertz Model. It should be noted that the behavior of broiler

growth curve is S shape and has a point corresponds to the asymptote, but a typical egg production curve increases from first to 8 or 9th weeks and then decreases from thereafter to the end of an egg production cycle.

The purpose of this study was to test the fitness of a NN model to two empirical egg production data sets collected during the first and second cycle of egg production.

MATERIALS AND METHODS

Data source: Two empirical egg production data sets collected during the first and second cycle of laying were used to train the NN model (Table 1). The data were previously reported by Cason 1990 and 1991. The first cycle data set consisted of the average of 47 weekly hen-day egg production values collected from 45 flocks of about 43000 hen each (Cason, 1990). The second cycle or molted hen data set was the average of 39 weekly hen-day egg production values collected from 47 molted flocks of about 44000 hen each (Cason, 1991).

Model development: The NN model was developed with Neural Net of JMP program (JMP, 2007). Prior to fit the NN model to the first and second cycle of egg production curves, each data set was divided into two sets of training (80%) and validation (20%) values. The selected data sets of 47 and 39 weekly egg production values were not too

Table 1: Training and validation of empirical and neural network model predicted values for weekly percentage of hen-day egg production during the first and second cycle

	First cycle			Second cycle		
	Week	Empirical	Predicted	Week	Empirical	Predicted
Training sets	1	0.3	-0.1	1	1.2	0.6
	2	4.2	4.5	3	56.1	53.9
	4	32.5	32.5	4	70.2	71.6
	5	53.0	52.1	5	77.8	77.5
	6	69.6	68.6	7	80.6	79.9
	7	78.7	79.4	8	80.1	80.2
	8	86.7	85.8	9	80.5	80.2
	9	87.1	87.6	10	80.4	80.1
	11	89.7	89.5	11	79.2	79.6
	12	89.3	89.6	12	78.2	78.9
	13	89.4	89.6	13	78.2	78.0
	14	89.5	89.5	14	77.1	76.9
	15	89.9	89.3	15	76.0	75.9
	17	89.4	88.7	17	75.5	75.0
	18	87.0	87.6	18	74.2	75.0
	20	86.9	87.3	20	74.6	74.6
	24	85.5	85.3	21	73.3	74.0
	25	84.7	84.8	22	73.1	73.2
	26	84.8	84.4	23	72.0	72.4
	27	84.2	83.9	24	72.1	71.6
	28	82.9	83.4	26	71.0	70.2
	29	83.1	82.9	27	69.9	69.6
	30	82.1	82.4	28	69.0	69.1
	31	82.0	81.8	30	69.1	68.0
	32	80.3	80.6	31	68.2	67.5
	33	79.5	80.7	32	66.5	67.1
	35	79.9	79.6	34	65.2	66.2
	36	79.6	79.0	35	66.1	65.7
	37	78.8	78.5	36	64.9	65.4
	38	78.5	77.9	37	65.1	65.0
	39	76.2	76.9	38	65.0	64.7
	40	76.5	76.8			
	41	79.1	77.9			
	42	76.6	75.8			
	43	75.1	75.3			
	46	73.9	74.0			
	47	73.6	73.6			
Validation sets	3	15.0	15.5	2	21.5	23.2
	10	89.6	89.0	6	79.1	79.3
	16	88.8	89.1	16	74.7	75.2
	19	88.1	87.8	19	75.8	75.0
	21	87.1	86.8	25	70.5	70.9
	22	86.1	86.3	29	67.1	68.5
	23	85.7	86.1	33	67.2	66.6
	34	80.5	80.2	39	66.7	64.4
	44	75.0	74.9			
	45	74.5	74.2			

large and it was recommended to divide them by the ratio of 80:20 for training: validation sets, respectively (JMP, 2007). The training sets which consisted of 37 and 31 weeks of data were used to train NN model for the first and second cycle, respectively. The validation sets including 10 values related to week 3, 10, 16, 19, 21, 22, 23, 34, 44, 45 and 8 values related to week 2, 6, 16, 19, 25, 29, 33 and 39 were randomly extracted from empirical data of the first and second cycle, respectively. These values used merely to test the prediction ability of the NN during the training processes.

The data sets were imported into Neural net of JMP program for training. Fifteen hidden nodes were

considered for each model. The overfit penalty, number of tour, maximum iterations and converge criteria were set at 0.0001, 30, 300 and 0.0001, respectively.

The accuracy of the model through goodness of fit was determined by R^2 value, adjusted R^2 , Mean Square Error (MSE), Residual Standard Error (RSE), Mean Absolute Percentage Error (MAPE) and the bias (Oberstone, 1990).

RESULTS AND DISCUSSION

The empirical and the NN model predicted values of weekly percentage of hen-day egg production for the first

Table 2: The neural network model statistics and information for training and validation data sets of egg production in the first and second cycle

Statistic ¹	Training sets		Validation sets	
	First cycle	Second cycle	First cycle	Second cycle
R ²	0.999327	0.997774	0.999787	0.995706
Adjusted R ²	0.999325	0.997668	0.999717	0.994622
MSE	0.29	0.47	0.13	1.49
RSE	0.54	0.69	0.38	1.3
MAPE	8.97	4.17	0.66	2.05
Bias	0.08	0.09	0.06	-0.05
Hidden nodes	15		15	

¹MSE = Mean Square Error; RSE = Residual Standard Error; MAPE = Mean Absolute Percentage Error; Hidden nodes = number of nodes are added to fit the neural network model

and 2nd cycles including training and validation sets are shown in Table 1. It appeared that the NN model is fitted into the egg production curve efficiently and produced good validation values for the egg production. However, the NN model fitness for the first cycle of laying curve was relatively better than that of the second cycle for both training and validation values. This is in agreement with Grossman *et al.* (2000), who tried to fit an empirical egg production model to the same data sets. It should be noted that the obtained results are specific to the overfit penalty, number of tour, maximum iterations and the converge criteria chosen in our model development.

The NN model statistics and information for weekly percentage of egg production are shown in Table 2. The calculated adjusted R² for NN model showed a better fitness than those reported by other author through regression model (Grossman *et al.*, 2000) for the same empirical egg production curves (0.999 and 0.998 vs. 0.997 and 0.991 for the first and second cycle, respectively). In addition, the NN model showed lower residuals distribution in terms of RSE than those of regression model reported by Grossman *et al.* (2000) (0.54 and 0.69 vs. 1.16 and 1.42 for the first and second cycle, respectively).

In general, the advantages of using NN are that: It can efficiently and flexibly model different response surfaces with any accuracy given enough hidden nodes. And the application of NN does not require the data meeting the assumptions that must otherwise be met in a regression model. However, the results from NN model are not as interpretable, since there is an intermediate layer rather than a direct path from the dependent variable(s) to the independent variable(s) as in the case of regular regression. 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 to predict responses (Yee *et al.*, 1993; Roush *et al.*, 2006).

CONCLUSION

The obtained results revealed that the NN model may efficiently be fitted into the weekly percentage of hen-day egg production of a flock in the first or second cycle.

REFERENCES

- Cason, J.A., 1990. Comparison of linear and curvilinear decreasing terms in logistic flock egg production models. *Poult. Sci.*, 69: 1467-1470.
- Cason, J.A., 1991. Egg production models for molted flocks. *Poult. Sci.*, 70: 2232-2236.
- Dayhoff, J.E. and J.M. DeLeo, 2001. Artificial neural networks: Opening the black box. *Cancer*, 15 (8): 1615-1635.
- Fairfull, R.W. and R.S. Gowe, 1990. Genetics of Egg Production in Chickens. *Poultry Breeding and Genetics*. In: Crawford, R.D. (Ed.) Elsevier Science Publishers B.V., The Netherlands, pp: 705-759.
- Grossman, M., T.N. Gossman and W.J. Koops, 2000. A model for persistency of egg production. *Poult. Sci.*, 79: 1715-1724.
- JMP, 2007. JMP User's Guide. Version 7.0. SAS Institute Inc., Cary, NC.
- Koops, W.J. and M. Grossman, 1992. Characterization of poultry egg production using a multiphasic approach. *Poult. Sci.*, 71: 399-405.
- Oberstone, J., 1990. *Management Science-Concepts, Insights and Applications*. West Publ. Co., New York.
- Roush, W.B., W.A. Dozier III and S.L. Branton, 2006. Comparison of Gompertz and neural network models of broiler growth. *Poult. Sci.*, 85: 794-797.
- Yee, D., M.G. Prior and L.Z. Florence, 1993. Development of predictive models of laboratory animal growth using artificial neural networks. *Comput. Applied Biosci.*, 9: 517-522.