Predicting caloric and feed efficiency in turkeys using the group method of data handling-type neural networks

M. Mottaghitalab,*[1] A. Faridi,* H. Darmani-Kuhi,* J. France,† and H. Ahmadi‡

*Department of Animal Science, Faculty of Agricultural Science, University of Guilan, PO Box 41635-1314, Rasht, Iran; †Centre for Nutrition Modelling, Department of Animal and Poultry Science, University of Guelph, Guelph, Canada N1G 2W1; and ‡Center of Excellence in the Animal Sciences Department, Ferdowsi University of Mashhad, PO Box 91775-1163, Mashhad, Iran

ABSTRACT Neural networks (NN) are a relatively new option to model growth in animal production systems. One self-organizing submodel of artificial NN is the group method of data handling (GMDH)-type NN. The use of such self-organizing networks has led to successful application of the GMDH algorithm over a broad range of areas in engineering, science, and economics. The present study aimed to apply the GMDH-type NN to predict caloric efficiency (CE, g of gain/kcal of caloric intake) and feed efficiency (FE, kg of gain/kg of feed intake) in tom and hen turkeys fed diets containing different energy and amino acid levels. Involved effective input parameters in prediction of CE and FE were age, dietary ME, CP, Met, and Lys. Quantitative examination of the goodness of fit for the predictive models was made using R^2 and error measurement indices commonly used to evaluate forecasting models. Statistical performance of the developed GMDH-type NN models revealed close agreement between observed and predicted values of CE and FE. In conclusion, using such powerful models can enhance our ability to predict economic traits, make precise prediction of nutrition requirements, and achieve optimal performance in poultry production.

Key words: modeling, group method of data handling-type neural networks, caloric efficiency, feed efficiency, turkey

2010 Poultry Science 89:1325–1331
doi:10.3382/ps.2009-00490

INTRODUCTION

Selection pressure applied by industry geneticists has greatly reduced feed conversion ratio and age to slaughter as well as increased growth rate and yield of edible meat for commercial turkeys. These genetic improvements have occurred along with improvements in nutrition and management (Havenstein et al., 2007). The nutritional requirement of turkeys includes relatively high levels of protein and energy to achieve high market weight. Dietary energy plays a major role in the control of feed intake. This means that the intake of individual nutrients is strongly influenced by the nutrient:energy ratio (Ahmadi et al., 2008). It is therefore of utmost importance to determine dietary ME value for high performance in turkeys. Protein and amino acids have a major effect on performance as well as the overall cost of the finished product. In corn and soybean-based diets for turkeys, Met and Lys are the most limiting amino acids (Kidd and Kerr, 1996).

There has been extensive research conducted to clarify protein, essential amino acids, and energy requirements in poultry. Conventional laboratory and field-based techniques for determining nutrient requirements are expensive, cumbersome, and time-consuming. These disadvantages have prompted a search for alternative methods. In determining nutrient requirements, the potential benefits from modeling growth in poultry are considerable. This approach has the potential to provide information in several areas for poultry production, including prediction of growth rate and market weights, determination of factors that are truly of economic importance to the operation, general knowledge about the systems involved in production, and determination of more precise nutrient requirements based on sex, strain, protein versus fat accretion, parts yield, and feed intake.

Modeling of processes and system identification using input-output data has always attracted much research effort. System identification techniques are applied in many fields to model and predict behavior of unknown or very complex systems based on given input-output

Received October 3, 2009.
Accepted March 6, 2010.
[1]Corresponding author: mottaghi2002@yahoo.co.uk

Table 1. Ranges for the data used to develop the group method of data handling-type neural network model for feed and caloric efficiency in tom turkeys

	Input variable					Output variable[1]	
Range	Age (wk)	ME (kcal/g)	CP (% of diet)	Met (% of diet)	Lys (% of diet)	FE	CE
Minimum to maximum	3 to 20	2.6 to 3.5	6.5 to 29	0.25 to 0.75	0.76 to 1.76	0.34 to 0.8	0.111 to 0.285
Mean ± SD	11.3 ± 5.76	3.014 ± 0.2	22.22 ± 4.65	0.445 ± 0.123	1.268 ± 0.32	0.502 ± 0.132	0.172 ± 0.051

[1]CE = caloric efficiency (kg of gain/kcal of caloric intake); FE = feed efficiency (kg of gain/kg of feed).

data (Astrom and Eykhoff, 1971). However, very little research has been conducted on modeling animal growth using artificial neural networks (**NN**; Roush et al., 2006). Among these methodologies, the group method of data handling (**GMDH**) algorithm is a self-organizing approach by which gradually more complicated models are generated based on evaluation of their performance on a set of multi-input-single-output data pairs. In this way, GMDH has been used to circumvent the difficulty of having a priori knowledge of the mathematical model of the process being considered. In other words, GMDH can be used to model complex systems without having specific knowledge of the system. The main idea of GMDH is to build an analytical function in a feed-forward network based on a quadratic node transfer function (Farlow, 1984) whose coefficients are obtained using regression techniques. In most applications of the GMDH algorithm, coefficients are estimated by means of the least squares method. In recent years, the use of such self-organizing networks has lead to successful application of the GMDH algorithm over a broad range of areas in engineering, science, and economics (Farlow, 1984; Nariman-Zadeh et al., 2003, 2005).

Evolutionary methods such as genetic algorithms (**GA**) have been widely used in different aspects of design of NN because of their unique capability of finding a global optimum in a highly multimodal or nondifferentiable search space (Astrom and Eykhoff, 1971; Yao, 1999). Genetic algorithms have been used in feed-forward GMDH-type NN for each neuron searching its optimal set of connections with the preceding layer (Vasechkina and Yarin, 2001; Nariman-Zadeh et al., 2003). In this way, GA are deployed to design the whole architecture of GMDH-type NN, that is, the number of neurons in each hidden layer and their configuration of connectivities. Ahmadi et al. (2007, 2008) introduced GMDH-type NN as an effective tool for predicting performance of broilers based on dietary nutrients. The aim of this study was to model the effects of age, dietary ME (kcal/g), CP (% of diet), Met (% of diet), and Lys (% of diet) on caloric and feed efficiency (g of gain/kcal of caloric intake for caloric efficiency, **CE**, and kg of gain/kg of feed intake for feed efficiency, **FE**) in turkeys using GMDH-type NN.

MATERIALS AND METHODS

Data Source

The necessary information used in the present study was taken from results published by Noy and Sklan (2004). Ranges for the data used to develop and test the GMDH-type NN models for caloric and FE in turkeys are presented in Tables 1 and 2.

Model Development and Statistical Procedure

Using the GMDH algorithm, a model can be represented as a set of neurons in which different pairs in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used to map inputs to outputs. To demonstrate the predictive ability of the evolved GMDH-type NN, the input-output data (Tables 1 and 2) were divided into 2 different sets, namely training and testing sets. Input variables in both models were age (wk), dietary ME (kcal/g), CP (% of diet), Met (% of diet), and Lys (% of diet). Data sets used consisted of 77 lines in which 22 lines were randomly selected to test the GMDH-type NN for the CE model, whereas

Table 2. Ranges for the data used to test the developed group method of data handling-type neural network model for feed and caloric efficiency in hen turkeys

	Input variable					Output variable[1]	
Range	Age (wk)	ME (kcal/g)	CP (% of diet)	Met (% of diet)	Lys (% of diet)	FE	CE
Minimum to maximum	3 to 14	2.65 to 3.6	18.7 to 28.3	0.35 to 0.56	1 to 1.6	0.41 to 0.8	0.134 to 0.282
Mean ± SD	8.8 ± 6.05	2.98 ± 0.21	23.78 ± 3.33	0.448 ± 0.073	1.37 ± 0.22	0.56 ± 0.13	0.184 ± 0.046

[1]CE = caloric efficiency (kg of gain/kcal of caloric intake); FE = feed efficiency (kg of gain/kg of feed).

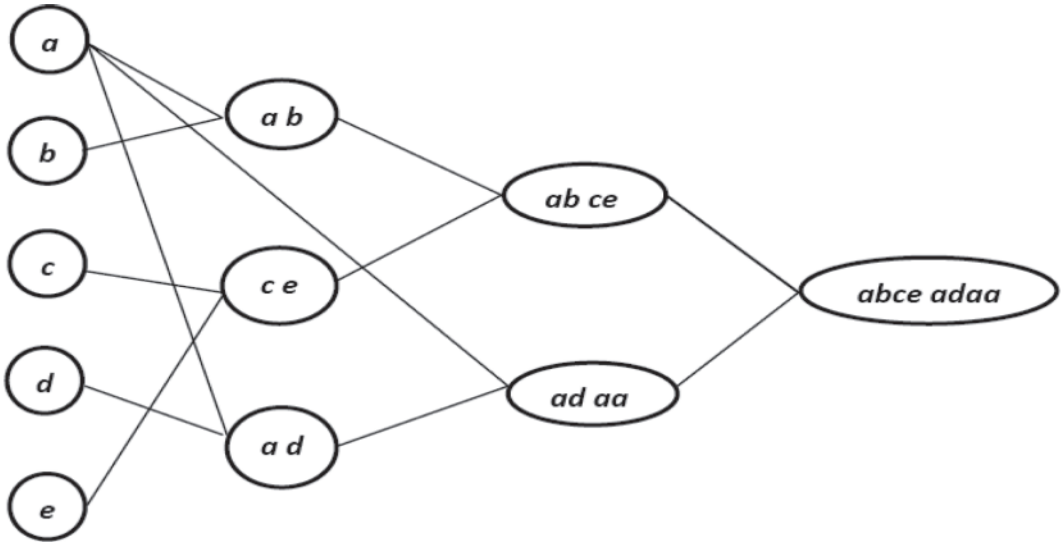

Figure 1. Evolved structure of the generalized group method of data handling-type neural networks for caloric efficiency in tom turkeys. The letters *a*, *b*, *c*, *d*, and *e* stand for input variables of age (wk), ME (kcal/g), CP (% of diet), Met (% of diet), and Lys (% of diet), respectively. This figure illustrates the generated relationship between input variables to reach output.

20 lines were randomly selected for testing for the FE model. The data set was imported into the GEvoM software for GMDH-type NN training (GEvoM, 2009). The best structures for both CE and FE were reached by 2 hidden layers with 600 generations, crossover probability of 0.85 and mutation probability of 0.01. It appeared that no further improvement could be achieved for such a population size. To evaluate the ability of GMDH-type NN to predict CE and FE in turkeys, a second test of the CE and FE polynomial equations was conducted using data on hen turkeys reported by Noy and Sklan (2004) (Table 2). Quantitative examination of the predictive ability of both models was made by common error measurement indices, including MS error, mean absolute deviation, mean absolute percentage error, mean relative error, and bias (Oberstone, 1990).

RESULTS AND DISCUSSION

The structures of the 2 hidden layer GMDH-type NN evolved for CE and FE are shown in Figures 1 and 2, respectively. These figures correspond to the genome representation of (*abceadaa*) and (*eeabacdd*) for the CE and FE models, respectively, and illustrate the gener-

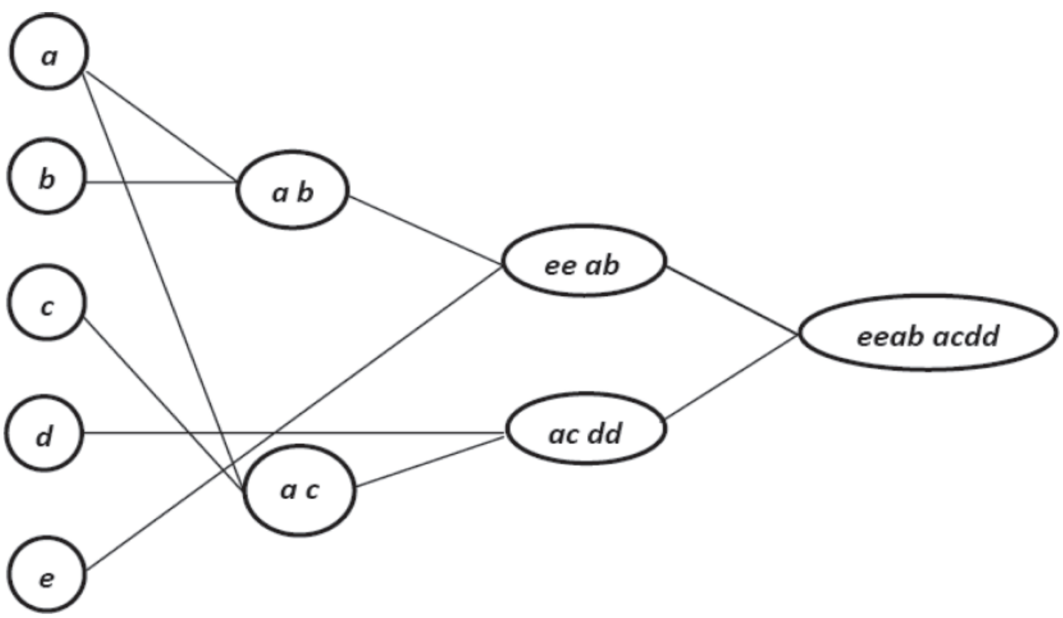

Figure 2. Evolved structure of the generalized group method of data handling-type neural networks for feed efficiency in tom turkeys. The letters *a*, *b*, *c*, *d*, and *e* stand for input variables of age (wk), ME (kcal/g), CP (% of diet), Met (% of diet), and Lys (% of diet), respectively. This figure illustrates the generated relationship between input variables to reach output.

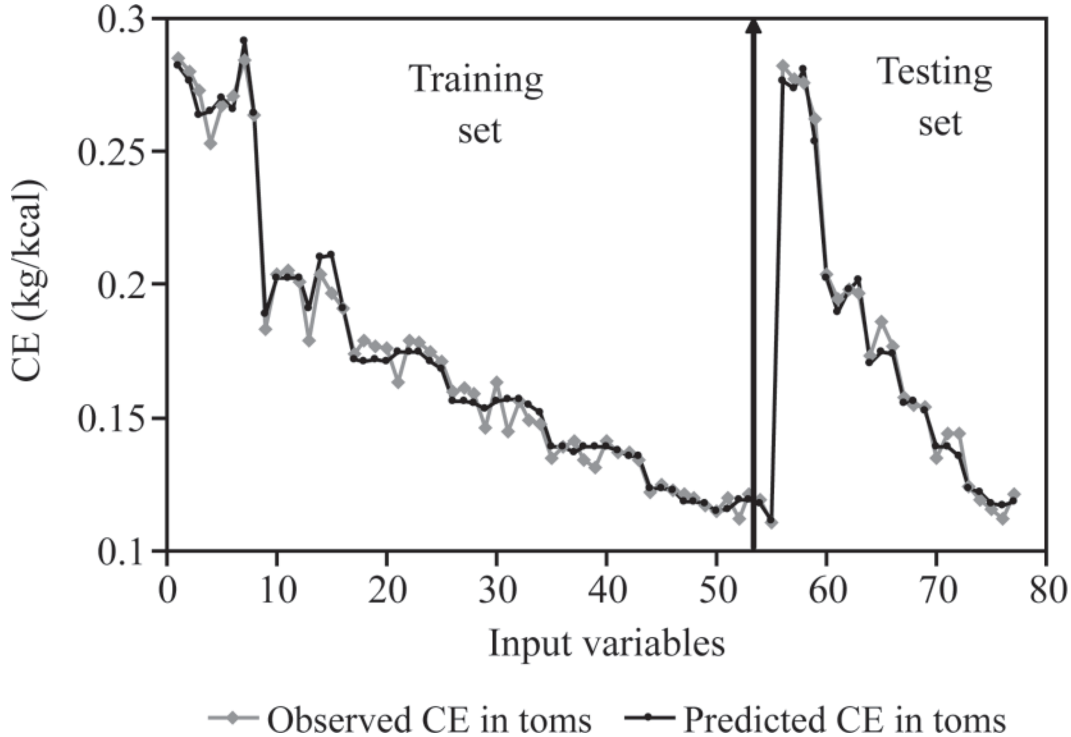

Figure 3. Comparison between actual and model-predicted values of caloric efficiency (CE) in tom turkeys.

ated relationship between input variables to reach the output. As Figures 1 and 2 show, the optimal structure of the evolved 2 hidden layer GMDH-type NN suggested by GA was found with 5 and 4 hidden neurons for CE and FE, respectively. In most GMDH-type NN, the neurons in each layer are only connected to neurons in the adjacent layer (Farlow, 1984), but for GMDH-type NN developed here, variable *a* of the input layer for CE is connected to *adaa* in the second hidden layer by directly passing through the first hidden layer. The same process happens for *d* and *e* input variables in the FE model. Such repetition occurs whenever a neu-

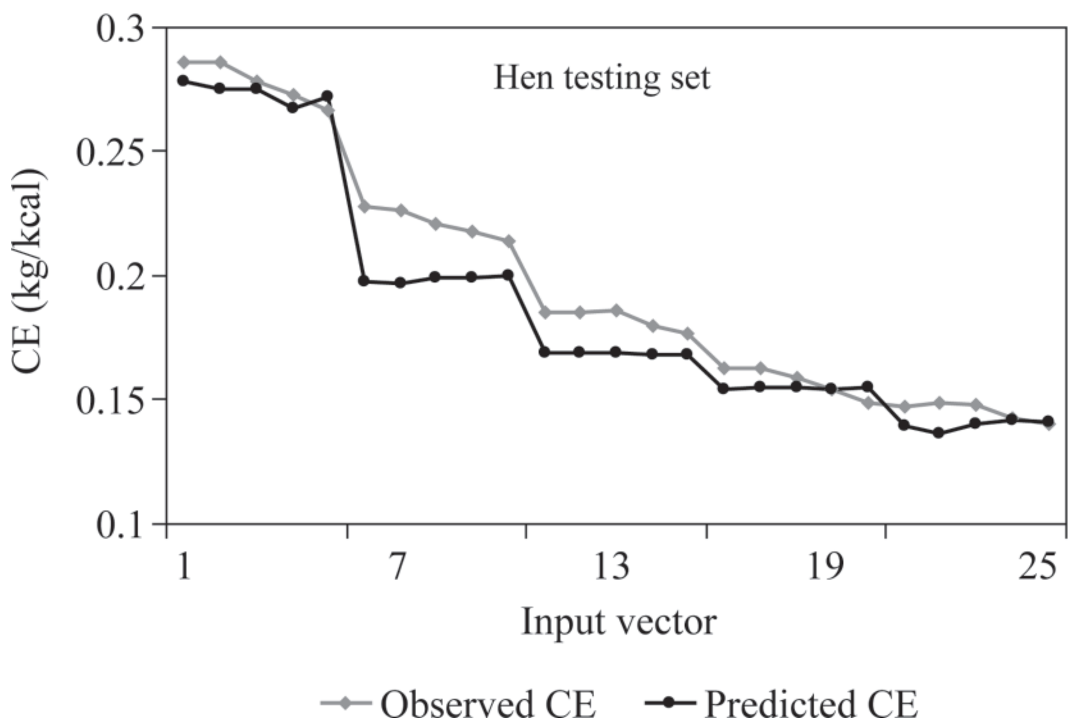

Figure 4. Comparison between actual and model-predicted values of caloric efficiency (CE) in hen turkeys.

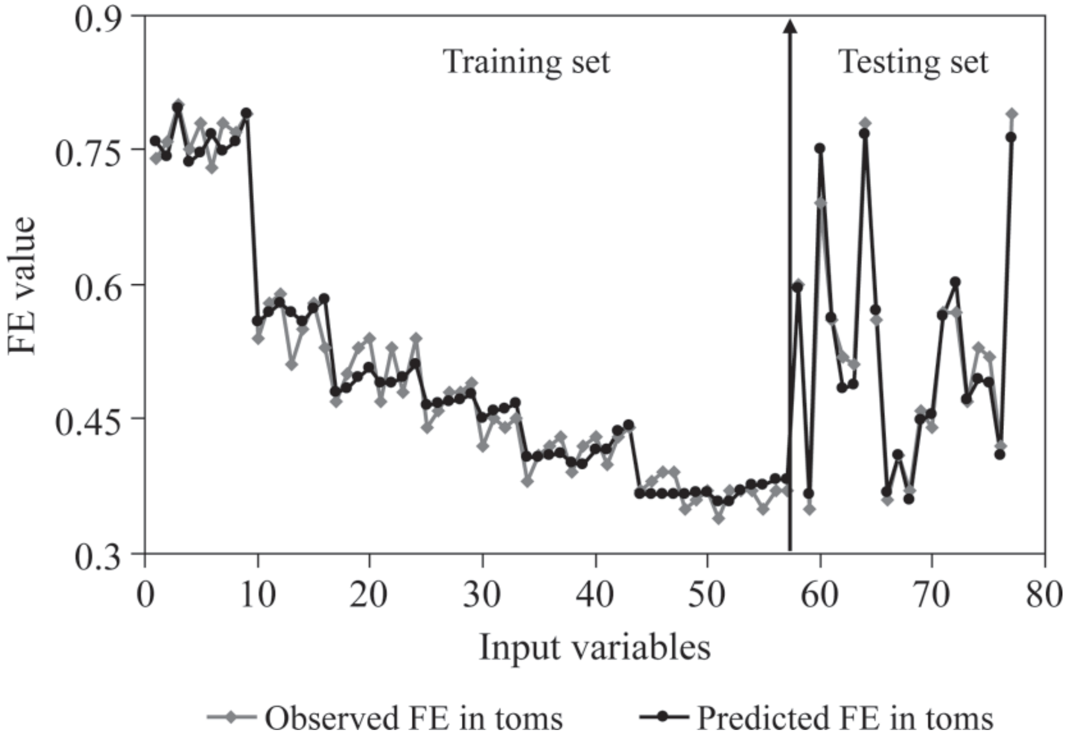

Figure 5. Comparison between actual and model-predicted values of feed efficiency (FE) in tom turkeys.

ron passes some adjacent hidden layer and connects to another neuron in the next following hidden layer. Polynomial equations [1] to [6] and [7] to [11] show the partial descriptions of GMDH-type NN for CE and FE in turkeys, respectively.

For CE:

$$y_1 = 0.19 - 0.025Age + 0.113ME + 0.0005Age^2 - 0.024ME^2 + 0.001Age \times ME \quad [1]$$

$$y_2 = 0.173 - 0.014CP + 0.037Lys + 0.0009CP^2 + 0.039Lys^2 - 0.0009CP \times Lys \quad [2]$$

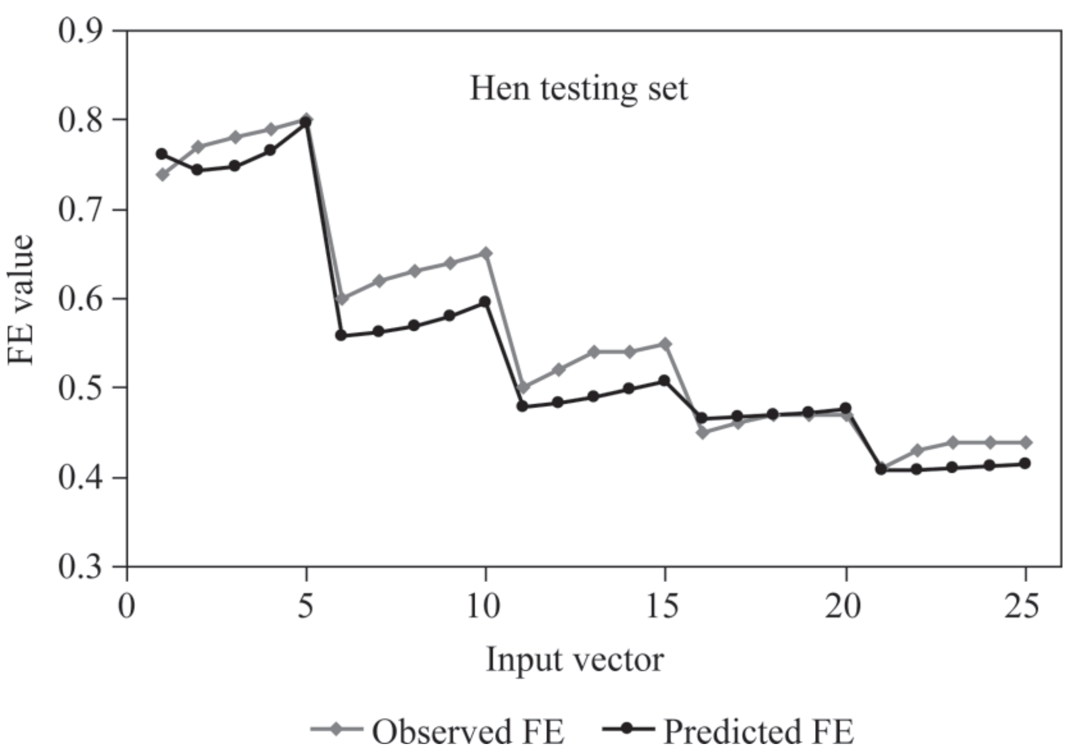

Figure 6. Comparison between actual and model-predicted values of feed efficiency (FE) in hen turkeys.

Table 3. Model statistics and information for caloric efficiency in tom and hen turkeys

	Tom data set		Hen data set
Statistic[1]	Neural training	Neural testing	Testing
MSE	3.04×10^{-5}	2.24×10^{-5}	2×10^{-4}
R^2	0.999	0.9993	0.995
MAD	0.0042	0.0039	0.01
MAPE	0.025	0.023	0.055
MRE	0.246	0.23	0.74
Bias	−0.0006	0.001	0.01
Hidden layer	2		2
Hidden neurons	5		5

[1]MSE = MS error; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MRE = mean relative error.

$$y_3 = -0.11 + 0.005Age + 1.26Met + 0.0001Age^2 - 0.9Met^2 - 0.04Age \times Met \quad [3]$$

$$y_4 = 0.028 - 2.23y_1 + 2.97y_2 + 16.56y_1^2 + 0.282y_2^2 - 16.46y_1 \times y_2 \quad [4]$$

$$y_5 = 1.41 - 11.47y_3 - 0.069Age + 26.3y_3^2 + 0.0007Age + 0.33Age \times y_3 \quad [5]$$

$$CE = 0.006 - 0.39y_4 + 1.33y_5 - 49.7y_4^2 - 52.64y_5^2 + 102.55y_4 \times y_5. \quad [6]$$

For FE:

$$y_1 = 0.65 - 0.042Age + 0.044ME + 0.0015Age^2 + 0.015ME^2 - 0.005Age \times ME \quad [7]$$

$$y_2 = 0.306 - 0.002Age + 0.044CP + 0.0009Age^2 - 0.0008CP^2 - 0.001Age \times CP \quad [8]$$

$$y_3 = 0.401 + 0.53Lys - 1.8y_1 - 0.06Lys^2 + 3.13y_1^2 - 0.586Lys \times y_1 \quad [9]$$

$$y_4 = 0.451 - 1.482y_2 + 0.834Met + 1.84y_2^2 - 0.852Met^2 + 0.472Met \times y_2 \quad [10]$$

$$FE = 0.055 + 2.71y_3 - 1.92y_4 + 15.28y_3^2 + 18.56y_4^2 - 33.66y_4 \times y_5. \quad [11]$$

Training and testing sets for CE of toms are shown in Figure 3, whereas actual and predicted CE values in hen turkeys are shown in Figure 4. Training and testing values of FE are shown in Figure 5 and actual and predicted FE values in hen turkeys are shown in Figure 6. It is clearly evident that the GMDH-type NN evolved in terms of simple polynomial equations could successfully model and predict the output of testing data. Statistical results for the training and testing sets of GMDH-type NN for CE and FE are summarized in Tables 3 and 4, respectively.

It appears that all selected input variables in both models had a strong effect on output prediction, which is in agreement with previous studies (Lemme et al., 2006 for amino acid; Noy and Sklan, 2004 for energy and amino acid; Potter et al., 1966 and Waibel et al., 1995 for Met and Lys; and Bowyer and Waldroup, 1986 for protein). Figure 1 shows a very strong effect of age on CE. This result is similar to previous studies aiming to describe the growth pattern of animals with age

Table 4. Model statistics and information for feed efficiency in tom and hen turkeys

	Tom data set		Hen data set
Statistic[1]	Neural training	Neural testing	Testing
MSE	4.5×10^{-4}	5×10^{-4}	0.001
R^2	0.9983	0.9981	0.996
MAD	0.0173	0.0173	0.03
MAPE	0.036	0.032	0.05
MRE	0.037	0.04	0.195
Bias	−0.001	0.003	0.025
Hidden layer	2		2
Hidden neurons	4		4

[1]MSE = MS error; MAD = mean absolute deviation; MAPE = mean absolute percentage error; MRE = mean relative error.

using growth functions (Darmani-Kuhi et al., 2003; Schulin-Zeuthen et al., 2008). The calculated values of CE model error measurement showed that the testing set for toms yielded lower values of MS error, mean absolute deviation, mean absolute percentage error, mean relative error, and higher values of R^2 compared with the training set. Similar findings were reported by Ahmadi et al. (2007) in predicting the performance of broiler chickens. Calculated values of model error measurement for prediction of CE and FE (Tables 3 and 4, respectively) in hen turkeys are higher than those in toms, but corresponding R^2 values for both models ($\geq$0.995) show the excellent prediction ability of GMDH-type NN. Calculated accuracy indices for the FE model revealed reverse results to those for the CE model and the training set provided higher accuracy compared with testing. Quantified values of bias show very little under- and overestimation for the training and testing data for both CE and FE. The overall computed value of bias in CE and FE prediction for hen turkeys shows slight overestimation by the models proposed by the GMDH-type NN. For both CE and FE, the training data had a smaller bias than the testing data, which is in contrast to the results of Roush et al. (2006) and Ahmadi et al. (2008). Based on the results of this study and those reported previously (Ahmadi et al., 2007, 2008), the GMDH-type NN appear as a promising method for modeling the relationship between dietary concentrations of nutrients and poultry performance, which can be used in choosing and developing special feeding programs to decrease production costs. Also, it can enhance our ability to predict other economic traits, make precise predictions of the nutrition requirements, and achieve optimal performance in poultry production systems.

REFERENCES

Ahmadi, H., M. Mottaghitalab, and N. Nariman-Zadeh. 2007. Group method of data handling-type neural networks prediction of broiler performance based on dietary metabolizable energy, methionine, and lysine. J. Appl. Poult. Res. 16:494–501.

Ahmadi, H., M. Mottaghitalab, N. Nariman-Zadeh, and A. Golian. 2008. Predicting performance of broiler chickens from dietary nutrients using group method of data handling-type neural networks. Br. Poult. Sci. 49:315–320.

Astrom, K. J., and P. Eykhoff. 1971. System identification. A survey. Automatica 7:123–162.

Bowyer, B. L., and P. W. Waldroup. 1986. Evaluation of minimal protein levels for growing turkeys and development of diets for estimating lysine requirements. Poult. Sci. 65(Suppl. 1):16. (Abstr.)

Darmani Kuhi, H., E. Kebreab, S. Lopez, and J. France. 2003. An evaluation of different growth functions for describing the profile of live weight with time (age) in meat and egg strains of chicken. Poult. Sci. 82:1536–1543.

Farlow, S. J. 1984. Self-Organizing Method in Modeling: GMDH Type Algorithm. Marcel Dekker Inc., New York, NY.

GEvoM. 2009. GMDH-type neural network designed by an evolutionary method of modelling. http://research.guilan.ac.ir/gevom/ Accessed Feb. 16, 2010.

Havenstein, G. B., P. R. Ferket, J. L. Grimes, M. A. Qureshi, and K. E. Nestor. 2007. Comparison of the performance of 1966- versus 2003-type turkeys when fed representative 1966 and 2003 turkey diets: Growth rate, livability, and feed conversion. Poult. Sci. 86:232–240.

Kidd, M. T., and B. J. Kerr. 1996. L-threonine for poultry . J. Appl. Poult. Res. 5:358–367.

Lemme, A., U. Frackenpohl, A. Petri, and H. Meyer. 2006. Response of male BUT Big 6 turkeys to varying amino acid feeding programs. Poult. Sci. 85:652–660.

Mueller, J. A., and F. Lemke. 2000. Self-Organizing Data Mining: An Intelligent Approach to Extract Knowledge from Data. Libri Publ. Co., Hamburg, Germany.

Nariman-Zadeh, N., A. Darvizeh, and R. Ahmad-Zadeh. 2003. Hybrid genetic design of GMDH-type neural networks using singular value decomposition for modeling and prediction of the explosive cutting process. J. Eng. Manuf. 217:779–790.

Nariman-Zadeh, N., A. Darvizeh, A. Jamali, and A. Moieni. 2005. Evolutionary design of generalized polynomial neural networks for modelling and prediction of explosive forming process. J. Mater. Process. Technol. 164–165:1561–1571.

Noy, Y., and D. Sklan. 2004. Effects of metabolizable energy and amino acid levels on turkey performance from hatch to marketing. J. Appl. Poult. Res. 13:241–252.

Oberstone, J. 1990. Management Science—Concept, Insights, and Applications. West Publ. Co., New York, NY.

Potter, L. M., A. T. Leighton Jr., and C. E. Howes. 1966. Methionine and lysine supplementation of turkey starting diets containing varying levels of protein. Poult. Sci. 45:1117–1118.

Roush, W. B., W. A. Dozier III, and S. L. Branton. 2006. Comparison of Gompertz and neural networks models of broiler growth. Poult. Sci. 85:794–797.

Schulin-Zeuthen, M., E. Kebreab, J. Dijkstra, S. Lopez, A. Bannink, H. Darmani Kuhi, and J. France. 2008. A comparison of the Schumacher with other functions for describing growth in pigs. Anim. Feed Sci. Technol. 143:314–327.

Vasechkina, E. F., and V. D. Yarin. 2001. Evolving polynomial neural network by means of genetic algorithm: Some application examples. Complex. Int. 9.

Waibel, P. E., C. W. Carlson, J. K. Liu, J. A. Brannon, and S. L. Noll. 1995. Replacing protein in corn-soybean turkey diets with methionine and lysine. Poult. Sci. 74:1143–1158.

Yao, X. 1999. Evolving artificial neural networks. Proc. IEEE 87:1423–1447.