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Predicting performance of broiler chickens from dietary nutrients using group method of data handling-type neural networks

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Abstract 1. Successful artificial neural network (ANN) applications have been found for many areas. One sub-model of ANNs is the group method of data handling-type neural networks (GMDH-type NNs). The use of self-organising networks leads to successful application in a broad range of areas. However, the use of such methods is not common in poultry science.

2. Broiler chicken nutrition is recognised as a biological system consisting of a complex set of interconnected variables. The adequate information on nutrients (variables), such as metabolisable energy (ME) and amino acid requirements, can help to establish specific feeding programmes, defining optimal performance and reducing production costs.

3. This study addressed the question of whether GMDH-type NNs can be used to estimate the performance of broiler chickens (output) based on specified variables—inputs (dietary crude protein (CP), ME, ME/CP, methionine (Met), lysine (Lys), ME/Met and ME/Lys)—for a commercial broiler chicken farm. The recorded data from 10 broiler chicken flocks were obtained, from March 2003 to April 2005, corresponding to 52 data lines.

4. The results suggested that the GMDH-type NNs may provide an effective means of recognising the patterns in data and accurately predicting the performance of broiler chickens based on investigating inputs. In addition the polynomial equations obtained can be used to optimise the performance of broilers.

INTRODUCTION

Responses of broiler chickens to dietary crude protein (CP) and amino acids (AA) depend on dietary energy content obtained. There are biological reasons for treating energy as a special case (MacLeod, 2000): firstly, dietary energy has a major role in the control of food intake since the intake of individual nutrients is strongly influenced by the nutrient:energy ratio; secondly, the biological systems of the chicken's control mechanisms may, in effect, perceive the substrates as contributors to energy supply rather than identifying them as specific chemicals. Hence, when considering the effects of nutrition on performance of broiler chickens, several dietary nutrients may influence the breast meat yield, feed:gain ratio, mortality and number of days required to reach market weight; among them, metabolisable energy (ME), CP and AA, such as methionine (Met) and lysine (Lys), are more important (Gous, 1998).

Although various systems are used to describe the energy and essential AA requirements of broiler chickens, predicting the performance from the dietary energy and AA patterns in practice and useful terms is still difficult. This difficulty is partly due to the nonlinearity of growth responses related to changes in dietary nutrients (Hruby *et al.*, 1996; Leeson *et al.*, 1996; MacLeod, 2000). A more useful method is to model the nutrition system, which in turn requires an explicit mathematical input–output relationship.

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Such explicit mathematical modelling is, however, very difficult and is not readily tractable in poorly understood systems. Alternatively, soft-computing methods, which concern computation in an imprecise environment, have gained significant attention. One of the soft-computing methods is artificial neural networks (ANNs), which have shown a great ability for solving complex nonlinear system identification and control problems. Artificial neural networks are applied in many fields to model and predict the behaviours of unknown systems, very complex systems or both, based on given input–output data. Several studies have been conducted to examine the potential use of ANNs in various poultry subjects, such as in the prediction of ascites in broilers (Roush *et al.*, 1996; Roush and Wideman, 2000), the estimation of production variables in the production phase of broiler breeders (Salle *et al.*, 2003), and the comparison of Gompertz and neural network models of broiler growth (Roush *et al.*, 2006). One sub-model of ANNs is the group method of data handling-type neural networks (GMDH-type NNs), which is a self-organising approach by which gradually more complicated models are generated based on the evaluation of their performance on a set of multi-input, single-output data pairs. The GMDH was first developed by Ivakhnenko (1971) as a multivariate analysis method for modelling and identification of complex systems. The group method of data handling-type neural networks was used to circumvent the difficulty of obtaining prior 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 systems. The main idea of GMDH is to build an analytical function in a feed-forward network based on a quadratic node transfer function whose coefficients are obtained by using a regression technique (Farlow, 1984). The use of such self-organising networks has led to successful application of the GMDH-type algorithm in a broad range of areas in engineering, science and economics. Recently, Ahmadi *et al.* (2007) reported that the GMDH-type NNs may provide an effective tool for predicting performance of broiler chickens based on dietary ME, Met and Lys.

This study addressed the question of whether GMDH-type NNs can be used to estimate the performance of broiler chickens (output) based on specified variables—inputs CP, ME, ME/CP, Met, Lys, ME/Met and ME/Lys—from a broiler chicken farm.

MATERIALS AND METHODS

Database

Data were collected from 10 commercial broiler farms of a single genetic line (Lohmann: from Niko Poultry Breeding Co., distributor for Aviagen Group Ltd) during the period between March 2003 and April 2005. Over this period, 10 flocks produced 52 data lines (input–output data). The collected data consisted of ME (kJ/kg), CP (% of dry matter), Met (% of dry matter), Lys (% of dry matter), ME/CP, ME/Met and ME/Lys as the input variables and data related to the feed conversion ratio, length of production (d), mortality and live weight were used to calculate the performance of broiler chickens in terms of European efficiency factor (EEF) as the system output. The EEF is an indicator of poultry performance assessment (Lemme *et al.*, 2006) and was calculated as

$$\mathrm{EEF} = [(\text{Live weight, kg} \times \text{Liveability, \%}) / (\text{Age, d} \times \text{Feed conversion ratio})] \times 100$$

where Liveability $= 100 - (\%\,\text{dead} + \%\,\text{rejected})$.

Data were collected from three separate growing periods of 0 to 21 d, 21 to 42 d and 42 d to market which referred to starting, growing and finishing periods, respectively. Diets were formulated based on maize and soybean meal and supplemented with fishmeal, sodium chloride, calcium, phosphorus and vitamin and mineral premixes to meet the nutrient requirements of broilers during every period. A training set of 42 data lines and a validation set of 10 data lines were randomly extracted from the database to train and calibrate the GMDH-type NNs. Samples as well as ranges of data patterns collected from three growing periods to develop the GMDH-type NN model for an EEF are shown in Tables 1 and 2.

Model development

A detailed description of GMDH-type NN terminology, development and application is beyond the scope of this paper. Suggested references include Farlow (1984) and Nariman-Zadeh *et al.* (2002, 2005). The GMDH-type NN models were developed with 'GMDH-type NNs designed by an evolutionary method of modelling' (GEvoM), which is a program based on GMDH-type NNs which generates polynomial neural networks to model either simulation or experimental data of any kind (Ahmadi *et al.*, 2007). Such a neural network identification process, in turn, needs some optimisation methods to find the best network architecture. In this way, genetic algorithms (GA) are deployed in a new approach to design the whole architecture of the

Table 1. *Data sample lines (10 lines) used to develop the group method of data handling-type neural network model for the performance of broiler chickens*[1]

Growing period (d)	Inputs							Output
	CP (%)	ME (kJ/kg)	ME/CP	Met (%)	Lys (%)	ME/Met	ME/Lys	EEF
Starting (0 to 21)	20	11 297	565	0·6	1·28	18 828	8826	141
	22	12 008	546	0·71	1·39	16 913	8639	128
	22	12 050	548	0·71	1·36	16 972	8860	179
	21	12 125	577	0·77	1·44	15 747	8420	151
	21	11 715	558	0·47	0·91	24 926	12 874	115
	21·1	11 975	566	0·54	1·22	22 175	9815	140
	22	12 050	548	0·71	1·36	16 972	8860	164
	21·5	11 786	546	0·42	1	28 063	11 786	132
	21·5	12 506	581	0·63	1·17	19 851	10 689	190
	23	13 389	582	0·63	1·16	21 252	11 542	111
Growing (21 to 42)	19·3	13 389	694	0·52	1·08	25 748	12 397	203
	20	11 924	596	0·55	1·11	21 681	10 743	209
	20·2	12 092	599	0·56	1·12	21 592	10 796	187
	19·8	12 113	610	0·5	1·08	24 225	11 215	180
	19	11 841	623	0·54	1·13	21 927	10 479	175
	18·7	12 531	670	0·48	0·98	26 106	12 787	213
	20·5	11 749	573	0·68	1·27	17 277	9251	223
	20	12 175	609	0·37	1·14	32 907	10 680	156
	20	12 088	604	0·52	1·12	23 245	10 792	184
	20	11 577	579	0·53	1	21 844	11 577	157
Finishing (42 to market)	16·1	12 155	755	0·51	0·83	23 832	14 644	154
	16·4	12 255	746	0·49	0·89	25 010	13 770	169
	16·7	12 393	739	0·43	0·86	28 821	14 410	150
	17·15	12 761	744	0·3	0·89	42 537	14 338	220
	17·2	12 259	713	0·39	0·9	31 434	13 621	155
	17·7	13 389	754	0·28	0·85	47 817	15 752	172
	17·7	13 389	754	0·31	0·85	43 190	15 752	190
	16·8	12 531	744	0·4	0·84	31 328	14 918	195
	17·7	13 389	755	0·269	0·85	49 772	15 752	191
	17·5	12 079	690	0·57	1·05	21 192	11 504	209

[1]CP = crude protein; ME = metabolisable energy; Met = methionine; Lys = lysine; EEF = European efficiency factor.

Table 2. *Ranges of data (minimum-maximum (mean ± SD)) patterns (input-output) from the database used to develop the group method of data handling-type neural network model for the performance of broiler chickens*[1]

		Growing period (d)		
		0 to 21	21 to 42	42 to market
Inputs	CP (%)	20–23 (21·5 ± 0·6)	17·9–22 (19·6 ± 0·8)	16–19·4 (17·4 ± 0·84)
	ME (kJ/kg)	11 297–13 389 (12 182 ± 340)	11 577–13 389 (12 145 ± 400)	11 933–13 389 (12 657 ± 473)
	ME/CP	514–610 (568 ± 19)	574–698 (620 ± 36)	663–791 (728 ± 34)
	Met (%)	0·42–0·77 (0·61 ± 0·1)	0·35–0·68 (0·52 ± 0·07)	0·27–0·57 (0·38 ± 0·09)
	Lys (%)	0·91–1·44 (1·25 ± 0·13)	0·98–1·27 (1·1 ± 0·08)	0·74–1·1 (0·9 ± 0·08)
	ME/Met	15 078–28 480 (20 339 ± 3464)	17 265–35 683 (23 701 ± 3583)	21 192–49 872 (34 827 ± 8757)
	ME/Lys	8063–12 874 (9893 ± 1113)	9224–12 970 (11 141 ± 1000)	11 504–17 199 (14 133 ± 1444)
Output	EEF	105–198 (154 ± 25)	155–225 (189 ± 21)	150–220 (182 ± 21)

[1]CP = crude protein; ME = metabolisable energy; Met = methionine; Lys = lysine; EEF = European efficiency factor.

GMDH-type NNs, that is, the number of neurons in each hidden layer and their configuration of connectivities, in combination with singular value decomposition to find the optimal set of appropriate coefficients of quadratic expressions to model a broiler EEF. The parameters of interest in this multi-input, single-output system that affect the EEF are dietary ME (kJ/kg), CP (% of dry matter), Met (% of dry matter), Lys (% of dry matter), ME/CP, ME/Met and ME/Lys. Forty-two input–output actual data lines obtained from three rearing periods were used to train the GMDH-type NN models. The validation set, which consisted of 10 unforeseen input–output data lines during the training process, was used merely for validation to show the predictive ability of such evolved neural networks during the training process. Databases were imported into GEvoM for GMDH-type NN training. Two hidden layers were considered for each model. To design such neural networks genetically, a population of 10 individuals with a crossover probability of 0·7, mutation probability of 0·07 and 600 generations was used; it appeared that no further improvement could be achieved for such a population size. All procedures were applied for three growing periods as three separate models, and all results were recorded.

A quantitative examination of the fit of the predictive models was made by using error measurement indices, which are commonly used to evaluate forecasting models (Roush *et al*., 2006). The accuracy of the models was determined by using determination coefficient (R^2), mean square error (MSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) as well as bias.

RESULTS AND DISCUSSION

The optimal structures of the evolved two-hidden-layer GMDH-type NNs that were suggested by GA for EEF modelling were found with 6 hidden neurons for all three growing periods. Because of genetical design, these structures have least complexity (in terms of number of neurons). All models constructed from this data-set were characterised by an excellent response for all input variables from the learning set. The partial descriptions of the GMDH-type NNs were found with two hidden layers and 6 hidden neurons for the starter period (which are shown as polynomial Equations (1) to (7)), two (polynomial Equations (8) to (14)) and three (polynomial Equations (15) to (21)). In fact, these equations revealed the quantitative relation between inputs (dietary nutrients) and output (EEF) variables under investigation. Because of limitation on space, in the following polynomial equations the letters *a*, *b*, *c*, *d*, *e*, *f* and *g* stand for input variables of CP, ME, ME/CP, Met, Lys, ME/Met and ME/Lys, respectively.

The corresponding polynomial equation representations of using the GMDH-type NN model for the starter period were obtained as:

$$y_1 = 0{\cdot}00000079 + 0{\cdot}0000037d - 0{\cdot}00334f + 0{\cdot}0000049d^2 + 0{\cdot}0000003f^2 + 0{\cdot}0083df \quad (1)$$

$$y_2 = 2{\cdot}02 + 77{\cdot}86a - 12{\cdot}49c - 2{\cdot}29a^2 + 0{\cdot}034c^2 + 0{\cdot}158ac \quad (2)$$

$$y_3 = -0{\cdot}0000015 - 0{\cdot}0022b - 0{\cdot}00000081e + 0{\cdot}0000025b^2 - 0{\cdot}000000059e^2 + 0{\cdot}00013be \quad (3)$$

$$y_4 = -0{\cdot}008 - 6{\cdot}83b + 8{\cdot}43g + 0{\cdot}001b^2 - 0{\cdot}00092g^2 - 0{\cdot}0013bg \quad (4)$$

$$y_5 = -103{\cdot}46 + 20{\cdot}90y_1 - 7{\cdot}07y_2 - 0{\cdot}71y_1^2 + 0{\cdot}21y_2^2 + 0{\cdot}098y_1y_2 \quad (5)$$

$$y_6 = 13{\cdot}76 + 17{\cdot}19y_3 - 18{\cdot}21y_4 - 2{\cdot}43y_3^2 - 1{\cdot}3y_4^2 + 3{\cdot}82y_3y_4 \quad (6)$$

$$\mathrm{EEF} = -63{\cdot}15 - 5{\cdot}03y_5 + 14{\cdot}74y_6 + 0{\cdot}86y_5^2 + 0{\cdot}075y_6^2 - 1{\cdot}23y_5y_6. \quad (7)$$

Polynomial equations for the grower period were obtained as:

$$y_1 = 0{\cdot}000003 + 0{\cdot}0045b + 0{\cdot}0000015e + 0{\cdot}00000078b^2 - 0{\cdot}00000046e^2 - 0{\cdot}00025be \quad (8)$$

$$y_2 = 0{\cdot}0046 + 0{\cdot}393c - 0{\cdot}0137g + 0{\cdot}0009c^2 + 0{\cdot}0000076g^2 - 0{\cdot}00019cg \quad (9)$$

$$y_3 = -13{\cdot}33 + 8{\cdot}06a - 65{\cdot}39e + 0{\cdot}035a^2 + 114{\cdot}93e^2 - 9{\cdot}58ae \quad (10)$$

$$y_4 = 0{\cdot}0000021 + 0{\cdot}0000044d - 0{\cdot}0032f + 0{\cdot}0000051d^2 + 0{\cdot}00000019f^2 + 0.01df \quad (11)$$

$$y_5 = 167{\cdot}16 + 17{\cdot}04y_1 - 33{\cdot}49y_2 - 1{\cdot}88y_1^2 - 0{\cdot}56y_2^2 + 2{\cdot}9y_1y_2 \quad (12)$$

$$y_6 = -84{\cdot}88 - 3{\cdot}63y_3 + 12{\cdot}53y_4 - 0{\cdot}11y_3^2 - 0{\cdot}52y_4^2 + 0{\cdot}45y_3y_4 \quad (13)$$

$$\mathrm{EEF} = 0{\cdot}91 - 4{\cdot}69y_5 + 5{\cdot}51y_6 + 0{\cdot}049y_5^2 - 0{\cdot}2y_6^2 + 0{\cdot}16y_5y_6. \quad (14)$$

Polynomial equations for the finisher period were developed as:

$$y_1 = 0{\cdot}0000024 + 0{\cdot}0037b + 0{\cdot}00000095d + 0{\cdot}00000054b^2 + 0{\cdot}00000022d^2 + 0{\cdot}0017bd \quad (15)$$

$$y_2 = 96{\cdot}8 - 0{\cdot}66c - 49{\cdot}93d + 0{\cdot}0017c^2 + 85{\cdot}08d^2 - 0{\cdot}15cd \quad (16)$$

$$y_3 = 0{\cdot}00000063 + 0{\cdot}00000047e + 0{\cdot}0025f + 0{\cdot}00000033e^2 - 0{\cdot}0000002f^2 + 0{\cdot}00161ef \quad (17)$$

$$y_4 = 0{\cdot}000066 + 0{\cdot}0017a + 0{\cdot}0065g + 0{\cdot}045a^2 - 0{\cdot}00000053g^2 - 0{\cdot}00019ag \quad (18)$$

$$y_5 = -1836{\cdot}29 + 156{\cdot}57y_1 + 42{\cdot}70y_2 - 3{\cdot}41y_1^2 - 0{\cdot}34y_2^2 - 1{\cdot}58y_1y_2 \quad (19)$$

$$y_6 = 11{\cdot}24 + 6{\cdot}28y_3 - 6{\cdot}38y_4 + 0{\cdot}83y_3^2 + 1{\cdot}15y_4^2 - 1{\cdot}95y_3y_4 \quad (20)$$

$$\mathrm{EEF} = 110{\cdot}46 - 2{\cdot}11y_5 - 9{\cdot}04y_6 - 0{\cdot}13y_5^2 + 0{\cdot}05y_6^2 + 0{\cdot}41y_5y_6. \quad (21)$$

As described earlier, the validation of results was tested by using 10 lines of data (validation set) that were extracted from the database. The neural networks were trained with only 42 lines, and 10 lines were omitted. After the training process, the predicted values of neural networks were compared with those of actual values (the remaining 10 lines). The findings are demonstrated in Figures 1, 2 and 3. Results (training and validation values) revealed a very good agreement with actual and predicted EEF with GMDH-type NNs for three growing periods. The comparison of training and validation values showed the behaviour of such neural network models in predicting EEF. All of the 6 dietary nutrients introduced as input variables were accepted by the network, and models predicting the EEF were based on all inputs. These results suggested that the magnitudes of 6 selected variables had strong effects on the performance of broiler chickens, which is similar to other reports that used a lower number of variables such as AA, energy and protein levels (Summers *et al.*, 1992), energy levels (Leeson *et al.*, 1996), and CP and Met levels (Morris *et al.*, 1992). The statistical results for the training and validation set of GMDH-type NN models are summarised in Table 3. The statistics showed the forecasting error measurements based on the differences between the model-predicted and actual values. By considering these training and validation data, the lowest MSE, MAD, MAPE and bias and the highest R^2 were calculated for the grower period. As measured by the bias, models produced relatively little over/under-estimation however, the validation data had a smaller bias than the training data. This is in agreement with Roush *et al.* (2006) who demonstrated the application of ANNs to model broiler chicken growth. The calculated statistics in this study indicated that the GMDH-type NNs may provide an effective

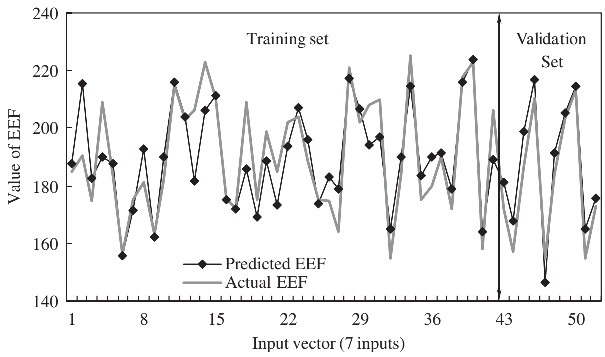

Figure 2. *The comparisons of neural network model-predicted European efficiency factor (EEF) obtained from training and validation sets and actual values for growing period.*

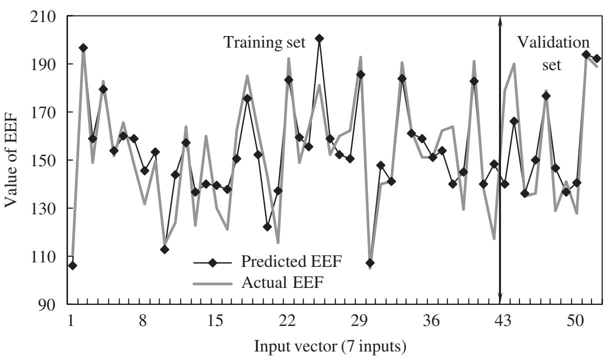

Figure 1. *The comparisons of neural network model-predicted European efficiency factor (EEF) obtained from training and validation sets and actual values for starting period.*

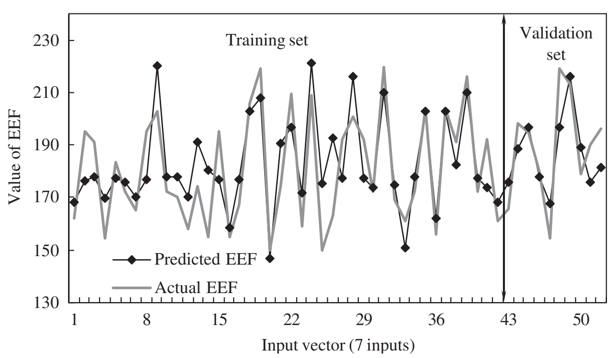

Figure 3. *The comparisons of neural network model-predicted European efficiency factor (EEF) obtained from training and validation sets and actual values for finishing period.*

Table 3. *Group method of data handling-type neural network model statistics and information for broiler chicken performance*

Statistic[1]	Growing period (d)					
	0 to 21		21 to 42		42 to market	
	Neural training	Neural validation	Neural training	Neural validation	Neural training	Neural validation
R^2	0·9939	0·9889	0·9970	0·9983	0·9950	0·9960
MSE	146·7	281·0	109·5	61·1	166·2	140·3
RMSE	12·1	16·8	10·5	7·8	12·9	11·9
MAD	9·8	12·0	8·0	6·9	10·9	10·1
MAPE	6·8	7·6	4·2	4·0	6·1	5·4
Bias	−0·9	2·1	0·8	−5·3	−1·9	2·3
Number of hidden layers	2		2		2	
Hidden neurons	6		6		6	

[1]MSE = mean square error (standard deviation); RMSE = root mean square error; MAD = mean absolute deviation; MAPE = mean absolute percentage error; hidden neurons = number of hidden neurons suggested by the genetic algorithm to fit the group method of data handling-type neural network model.

means of recognising the patterns in data and predicting the EEF based on 7 inputs. Similarly, Ahmadi *et al*. (2007) predicted the performance of broiler chickens based on three variables (ME, Met and Lys) as inputs. The genetic approach was successfully used to provide optimal networks in terms of hidden layers, the number of neurons and their configuration of connectivities or both so that a polynomial expression for dependent variables of the process may consequently be achieved. The polynomial equations obtained could be used to optimise the performance of broiler chickens based on dietary nutrients by optimising methods such as the GA.

In conclusion, knowledge of an adequate description of nutrient requirements of poultry may help in establishing specific feeding programmes, defining optimal performance and reducing production costs. In this way, the use of new tools such as GMDH-type NNs may help to define a nutrition system. The advantage of GMDH-type NNs is that there is no requirement for pre-selecting a model or basing the model entirely on the fit of the data. This advantage produced a great use for GMDH-type NNs in the poultry science area. This study revealed that the GMDH-type NNs could be used to estimate the performance of broiler chickens (output) based on specified variables such as dietary nutrients. However, this area of research requires further investigation.

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