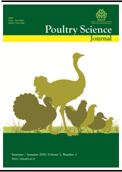

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Comparison of the Accuracy of Nonlinear Models and Artificial Neural Network in the Performance Prediction of Ross 308 Broiler Chickens

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Abstract
This study aimed to investigate and compare nonlinear growth models (NLMs) with the predicted performance of broilers using an artificial neural network (ANN). Six hundred forty broiler chicks were sexed and randomly reared in 32 separate pens as a factorial experiment with 4 treatments and 4 replicates including 20 birds per pen in a 42-day period. Treatments consisted of 2 metabolic energy levels (3000 and 3100 kcal/kg), 2 crude protein levels (22 and 24%) and two sexes. Ten birds in each pen tagged and their weekly BW records were collected individually to evaluate the accuracy of predicted BW by ANN as an alternative to nonlinear regression models (Logistic, Gompertz, Von Bertalanffy, and Brody). Based on the goodness of fit criteria and error measurement statistics, the NLMs fitted the age-weight data better than ANN. The findings indicated that the performance prediction of broiler chicks using the Gompertz model (R^2 = 0.9989) was more accurate than other NLMs (R^2 = 0.9628 to 0.9988) and ANN (R^2 = 0.95839). Therefore, the application of the Gompertz model is suggested to predict the BW changes of Ross 308 broiler chicks over time.

Introduction

Growth can be defined as a biological process resulting from changes in the body weight of an animal and has an economic significance in livestock breeding. Some researchers are interested in analyzing the relationship between weight and its changes over the lifespan of an animal (Eleroglu *et al*., 2014). Animal growth represents an event caused by complex metabolic reactions, which has led to extensive studies to describe the growth characteristics using appropriate math models (Sogut *et al*., 2016). The necessity of using the parameters of the growth curve and the relationship between them and other characteristics affecting the growth of an animal is considered to be the most essential determinants of the animal's growth curve (Saghi *et al*., 2012). The Growth curve in different animals is a good tool for describing body weight (BW) changes, which are directly related to the age of an animal (Prestes *et al*., 2012), and the side effects of the choice on the growth curve parameters are accepted (Tariq *et al*., 2013).

The Growth curve is important in describing the production of an animal since they can be estimated by using the number of daily feed requirements for growth, especially when the food intake includes various types of food additives, with reasonable accuracy (Abbas *et al*., 2014). The shape of the growth curve is also affected by the composition of the diet (Mohammed, 2015). The application of such estimates by predicting the nutritional requirements of animals is important in this regard, which can lead to restrictions on the level of ad libitum access to feed for animals (Lopez *et al*., 2000). Some nonlinear models (NLMs) such as Brody, Von Bertalanffy, Gompertz, Logistic, and Richards used to describe animal growth affected by nutritional and environmental factors (Kum *et al*., 2010) and the comparison of NLMs is usually recommended for selecting the best model using different assessment criteria for species, strains and even different lines (Narinc *et al*., 2010). Various researchers have used NLMs to study and describe the growth curve in different poultry species, including Narinc *et al*.

(2010) in quails, Nahashon *et al*. (2006) in gray pheasants, Aggrey (2002), Darmani Kuhi *et al*. (2003), Yang *et al*. (2006), Ahmadi and Mottaghitalab (2007), Norris *et al*. (2007) and Golian and Ahmadi (2008) in broiler chicks, Vitezica *et al*. (2010) in Ducks, Sengul and Kiraz (2005), Porter *et al*. (2010) in turkeys, and Sabbioni *et al*. (1999) in ostriches. The most important advantage of NLMs is the use of statistical software in the design of specific mathematical functions to estimate the growth curve and the effects of nutritional needs on it (Sengul and Kiraz, 2005).

Recently, the artificial neural network (ANN) has become commonplace in predicting animal performance in addition to mathematical models. The design and programming of ANN are like a human brain, has the ability to respond to different inputs through several layers, including millions of neurons, which ultimately leads to solving a small part of a big problem. One of the main advantages of using ANN in comparison with the classic statistical modeling is that ANN modeling can only be performed based on a dependent variable and designing various types of the variable is also possible. This fact reduces wasting time, resources, a better estimation of error and variability in data collection under different circumstances (Ahmad, 2009). Another important advantage of ANN in estimating the nutritional requirements of broiler chickens is the need to determine the best fitting model before simulating growth data (Kaewtapee *et al*., 2011). On the other hand, ANN models have been introduced in many breeding systems as an alternative to regression analysis for predicting broiler chicken growth performance (Ahmad, 2009; Roush *et al*., 2006).

This study was carried out to evaluate and describe the performance prediction of Ross 308 broiler chicks by comparing the fitting growth data set using ANN and NLMs.

Materials and methods

Six hundred forty Ross 308 broiler chicks were sexed and reared in 32 pens with separate dipping and drinking water. Ten chicks from each pen were randomly selected and tagged. The treatments were carried out in a factorial experiment using a completely randomized design with 2 levels of metabolic energy (3,000 and 3,100 kcal/kg), 2 levels of crude protein (22 and 24%) and two sexes which were repeated 4 times. The nutritional treatments used are shown in table 1.

Table 1. Composition percentage of experimental diets in starter, grower and finisher phases

Ingredients (%)	Starter (1-10 days)				Grower (11-25 days)				Finisher (26-42 days)			
	T1	T2	T3	T4	T1	T2	T3	T4	T1	T2	T3	T4
Corn	57.29	50.60	56.14	49.00	57.38	55.00	55.80	53.30	62.50	59.10	60.00	57.80
Soybean Meal (%48)	37.0	42.69	37.0	43.0	35.92	38.1	35.8	38.0	30.5	33.4	31.0	33.2
Soybean Oil	2.00	3.00	3.20	4.40	3.40	3.60	5.00	5.30	4.00	4.50	6.00	6.00
Oyster Shell	0.80	0.80	0.80	0.80	0.70	0.70	0.80	0.80	0.65	0.65	0.65	0.65
Defloured Phosphate	1.71	1.71	1.70	1.70	1.50	1.50	1.50	1.50	1.30	1.30	1.30	1.30
Salt	0.22	0.22	0.22	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Vitamin Premix[1]	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
Mineral Premix[2]	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
DL-Methionine	0.27	0.27	0.22	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20	0.20
L-Lysine HCL	0.21	0.21	0.22	0.20	0.20	0.20	0.20	0.20	0.15	0.15	0.15	0.15
Calculated composition												
ME (kcal/g)	3.00	3.00	3.06	3.07	3.10	3.09	3.18	3.18	3.19	3.19	3.29	3.27
Protein (%)	22.03	24.01	21.91	23.96	21.50	22.28	21.31	22.08	19.45	20.47	19.46	20.26
Ether Extract (%)	4.23	5.11	5.40	6.46	5.62	5.78	7.17	7.42	6.30	6.74	8.23	8.20
Crude Fiber (%)	4.65	4.81	4.61	4.78	4.58	4.65	4.52	4.58	4.39	4.47	4.33	4.41
Calcium (%)	0.96	0.98	0.96	0.97	0.86	0.86	0.89	0.90	0.76	0.77	0.76	0.76
Available Phosphorus (%)	0.45	0.46	0.45	0.46	0.41	0.42	0.41	0.41	0.37	0.37	0.37	0.37
Lys (%)	1.28	1.42	1.29	1.42	1.25	1.30	1.24	1.29	1.08	1.15	1.08	1.14
Met (%)	0.58	0.60	0.53	0.53	0.50	0.51	0.50	0.51	0.48	0.49	0.48	0.49
Cys (%)	0.32	0.34	0.31	0.34	0.31	0.32	0.31	0.32	0.28	0.30	0.28	0.29
TSAA (%)	0.90	0.94	0.84	0.87	0.81	0.83	0.81	0.83	0.77	0.79	0.76	0.78

[1]Provided per kg of diet: 44000 IU A, 17000 IU D3, 440 mg E, 40 mg K3, 70 mg B12, 65 mg B1, 32 mg B2, 49 mg Pantothenic acid, 122 mg Niacin, 65 mg B6, 22 mg Biotin and 27 mg Choline chloride.
[2]Provided per kg of diet: 99.2 mg Mn (MnO), 85 mg Zn (ZnO), 50 mg Fe ($FeSO_4$), 10 mg Cu ($CuSO_4$), 0.2 mg Se (Na_2SeO_3), 13 mg I (KI), and 250 mg Co

The breeding broiler management and ratio formulation were both based on the catalog of Ross 308 (2016). The guide for the care and use of laboratory animals was followed, and the project was approved by the CETEA of the Federal University of Minas Gerais (Protocol number 111/2009). Individual weight records of tagged birds and the group weight of other chicks were collected in each pen every week (Table 2).

Table 2. Statistical description of recorded body weight data for two sexes (Means ± SE (Range: Min - Max))

Age (wk)	Male				Female			
	T1	T2	T3	T4	T1	T2	T3	T4
1	50.96±0.54 (45.4 - 57.2)	50.34±0.67 (43.9 - 58.8)	49.7±0.63 (42.4 - 58.3)	49.35 ± 0.77 (39 - 59.1)	49.97 ± 0.77 (41.1 - 57.4)	49.63 ± 0.72 (42.6 - 57.7)	48.09± 0.79 (40.1 - 57.5)	49.26± 0.88 (39.3 - 61)
2	165.71±3.55 (100 - 200)	155±4.55 (110 - 200)	147.5±3.45 (115 - 185)	170.09 ± 3.04 (135 - 250)	163.38 ± 3.06 (125 - 195)	154.19 ± 4.49 (90 - 210)	140.47 ± 3.31 (85 - 180)	160.92 ± 4.15 (105 - 215)
3	415.51±14.05 (280 - 610)	339.44±10.85 (210 - 430)	342.18±7.5 (245 - 455)	403.91 ± 6.15 (315 - 475)	372.43 ± 7.43 (255 - 455)	327.57 ± 10.86 (185 - 420)	333.89 ± 8.23 (175 - 415)	355.51 ± 9.44 (250 - 480)
4	1315.95±20.64 (1020 - 1530)	1286.67±32.22 (925 - 1785)	1291.54±20.34 (1100 - 1585)	1414.57±28.82 (935 - 1780)	1173.71±22.55 (835 - 1450)	1132.16±26.62 (835 - 1495)	1168.34±24.43 (685 - 1460)	1204.21±24.63 (955 - 1630)
5	1787.64±32.9 (1345 - 2240)	1758.29±43.34 (1185 - 2240)	1808.82±36.56 (1270 - 2335)	1937.5 ± 44.96 (1290 - 2615)	1660.86±35.46 (1230 - 2130)	1609.81±33.5 (1225 - 2125)	1631.39±31.9 (1080 - 2025)	1699.61±38.96 (1165 - 2335)
6	2519.12±53.32 (1600 - 3000)	2433.33±61.49 (1700 - 3200)	2448.65±59.73 (1600 - 3200)	2693.33±62.15 (1500 - 3400)	2254.29±48.74 (1600 - 2700)	2148.57±47.52 (1400 - 2600)	2200±39.84 (1500 - 2600)	2318.42±48.86 (1800 - 3100)

The artificial neural network (ANN) used in this research was multi-layer perceptron (MLP), composed of three connected feed-forward layers of neurons named as input, hidden and output (Rumelhart *&* McClelland*,* 1986). The input layer consisted of ME, CP, sex, and age that were connected to three hidden layers and the output layer was predicted weight. The following functions used in this type of ANN were hyperbolic tangent in the hidden layers and the active linear function in the output layer.

Hyperbolic function in hidden layers:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

Active linear function in the output:

$$f(x) = x$$

Where, f(x) and x represent the output of the function from neurons and the weighted sum of inputs or the width of the basis function, respectively.

The ANN was designed by using the neuralnet package of the R software (2017). Age, sex, and different levels of ME and CP were considered as input layers of ANN along with three hidden layers and the predicted weight formed the output (Figure 1). Seventy-five percent of the weight record data was used as training data and other samples were used as test data for validating of the model and various states of the ANN structure including the number of neurons, intermediate layers, and learning periods were applied to describe the growth curve in broilers. To investigate the relationship between age, sex, ME and CP with BW of broilers, the NLMs including Logistic, Gompertz, Von Bertalanffy, and Brody were used to fit the growth data set by the NLIN procedure of SAS software (2013) as follows.

Logistic model: $W_t = A * [(1 + B * exp(-kt))^{-1}]$

Gompertz model: $W_t = A * \exp[-B * exp(-kt)]$

Von Bertalanffy model:

$$W_t = A * [(1 - B * exp(-kt))^3]$$

Brody Model: $W_t = A * [1 - B * exp(-kt)]$

Where, W_t represents the BW at age *t* and the parameters of A, B, and k, represents the maturity weight, initial weight and maturity rate, respectively. The estimated parameters (A, B and k) were analyzed by GLM procedure (SAS 2013), and Duncan's multiple range test (α=0.05) used for means comparison between sex and treatment levels (Duncan, 1955). The accuracy of the NLMs was measured by calculating the following criteria (Kaewtapee *et al*., 2011; Masoudi, 2017).

1. The Pearson correlation coefficient (PCC):

$$\rho y_t \hat{y}_t = \frac{cov(y_t, \hat{y}_t)}{\sigma_{y_t} . \sigma_{\hat{y}_t}} \quad \text{(Equation 1.)}$$

2. The coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n} \hat{y}_t{}^2 - \frac{\left(\sum_{t=1}^{n} \hat{y}_t\right)^2}{n}} \quad \text{(Equation 2.)}$$

3. The root of mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad \text{(Equation 3.)}$$

4. Mean absolute deviation (MAD):

$$MAD = \frac{\sum_{t=1}^{n}|y_t - \hat{y}_t|}{n} \quad \text{(Equation 4.)}$$

5. The Mean absolute percentage error (MAPE):

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right|}{n} \times 100 \ ; \ (y_t \neq 0) \quad \text{(Equation 5.)}$$

6. The Akaike information criterion (AIC):

$$AIC = 2k - 2lnL = n \times \ln\left(\frac{SSE}{n}\right) + 2P \quad \text{(Equation 6.)}$$

Where, y_t and $\hat{y}_t$ represent the observed and predicted weight, respectively and *n* is the number of observations, *k* is the number of parameters (P = k + 1) and L is the value of likelihood function.

Results and Discussion

All nonlinear models converged in terms of the individual weight of broiler chicks. The estimated values of the parameters of NLMs and ANN along with the statistics of estimation for each model are presented in table 3.

Table 3. Estimated parameters of non-linear models and artificial neural network

Model parameters	Nonlinear regression models				ANN
	Logistic	Gompertz	Von Bertalanffy	Brody	
A	3294.7703±819.6601	5797.182±1955.9871	15320.6709±9529.6648	9963.5049±433.3521	—
B	40.0051 ± 11.2784	5.0009 ± 0.4595	0.8873 ± 0.0303	1.0287 ± 0.0335	—
k	0.1137 ± 0.0178	0.0443 ± 0.0118	0.0196 ± 0.009	0.0439 ± 0.0152	—
CV	5.20043	4.29973	4.40472	22.42431	—
PCC	0.99816 (< 0.0001)	0.99878 (< 0.0001)	0.99872 (< 0.0001)	0.96281 (< 0.0001)	0.97962
R^2	0.99837	0.99895	0.99889	0.96719	0.95959
RMSE	50.9648	40.68236	42.53597	223.84191	166.02934
MAD	37.84551	27.97285	30.8842	183.54734	102.6055
MAPE	17.26078	8.61803	10.6297	103.29908	12.96117
AIC	16528.62987	13588.03117	11928.61241	42858821.6028	29325.36

A: Asymptotic or mature weight, B: Initial weight, k: Growth rate, CV: Coefficient of variance, PCC: Pearson correlation coefficients between predicted and actual BW, R^2: Coefficient of determination, RMSE: Root of mean square error, MAD: Mean absolute deviation, MAPE: Mean absolute percentage error, AIC: Akaike information criterion

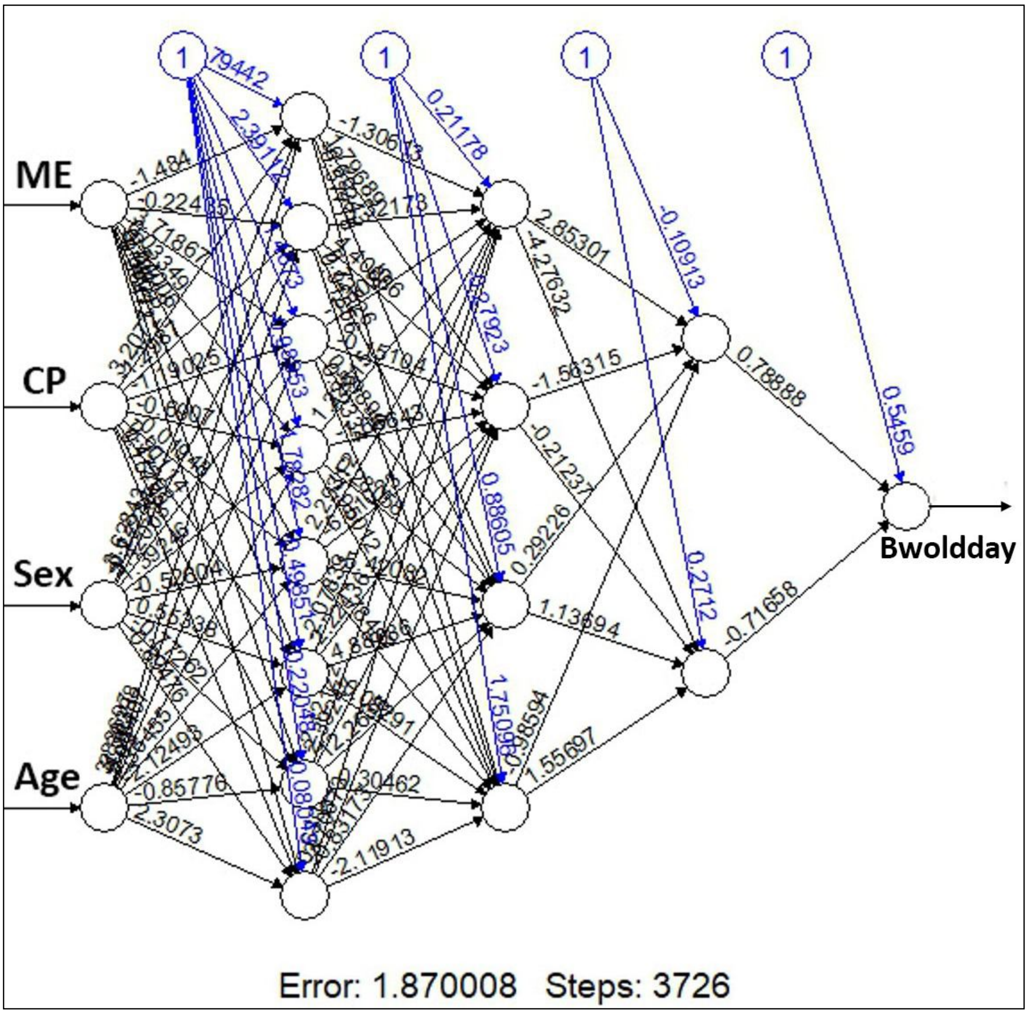


Figure 1. The graphical representation of the ANN model with the weights on each connection and the bias term in each step.

The Gompertz model was superior to the Von Bertalanffy, Logistic and Brody models with regard to R^2, RMSE, MAD, MAPE and PCC. However, the weakest amount of AIC belonged to the Von Bertalanffy model. The Gompertz equation comes as follows.

$$W_t = 5797.182 * exp[-5.0009 * exp(-0.0443t)]$$

In addition, the Gompertz model was determined for RMSE as the best nonlinear model, although the lowest R^2 value was unexpectedly observed in the ANN model (R^2 = 0.95959). The comparison of fitting plots and residual-age diagrams indicated that estimated BW by the Gompertz model had the best overall fit (Figures 2 and 3).

The shape of growth curves in the Logistic, Gompertz and ANN models were better fitted to the observed BW data set. The estimated value for the maturity weight (parameter A) of Logistic and Gompertz models were more symmetric than other NLMs to the observed BW data set. The most predicted value of initial weight (parameter B) belonged to the Logistic model. The Von Bertalanffy model had the highest slope of the growth curve which was directly affected by the maturity rate (parameter k). The comparison of NLMs in order to select the best fitting model was determined by measuring the error of each model using various criteria such as MAD and RMSE.

Table 4. Estimated parameters of non-linear models for male and female broilers

Model parameter	Nonlinear regression models			
	Logistic	Gompertz	Von Bertalanffy	Brody
Male:				
A	3535.07 ± 964.5813	5914.51 ± 2025.96	16201.95 ± 9827.47	9912.21 ± 681.2076
B	42.2461 ± 13.354	5.0977 ± 0.4796	0.8954 ± 0.0328	1.0349 ± 0.0526
k	0.1154 ± 0.0209	0.0462 ± 0.0131	0.0198 ± 0.0088	0.048 ± 0.0226
PCC	0.99782	0.99873	0.99864	0.96091
R^2	0.99807	0.99891	0.99882	0.96535
RMSE	58.55798	45.90971	46.79243	242.71306
MAD	43.65951	32.19886	34.45277	198.16451
MAPE	18.29051	9.21634	11.45374	109.10697
AIC	8760.53726	6653.11083	6909.3368	22257226.32124
Female:				
A	3036.42 ± 611.9564	5648.97 ± 1906.11	14453.8 ± 9256.33	10000 ± 0
B	37.8253 ± 9.4693	4.9136 ± 0.4351	0.8798 ± 0.0263	1.0244 ± 0.0119
k	0.1125 ± 0.015	0.0428 ± 0.0107	0.0196 ± 0.0092	0.0401 ± 0.0066
PCC	0.99859	0.99895	0.99880	0.965
R^2	0.99876	0.99911	0.99898	0.96962
RMSE	41.54597	35.31973	38.13825	202.18875
MAD	31.75383	24.16768	27.5544	168.23209
MAPE	16.18188	8.0793	9.86079	97.21382
AIC	7657.39451	6882.24382	6996.16192	20536108.1712

A: Asymptotic or mature weight, B: Initial weight, k: Growth rate, PCC: Pearson correlation coefficients between predicted and actual BW, R^2: Coefficient of determination, RMSE: Root of mean square error, MAD: Mean absolute deviation, MAPE: Mean absolute percentage error, AIC: Akaike information criterion

The statistical results of the estimated parameters of NLMs for male and female broilers are presented in table 4. The R2, RMSE, MAD and MAPE criteria for both males and females in the Gompertz model were better than other NLMs. Therefore, the following Gompertz models were selected as the best descriptive functions for predicting of BW in male and female broilers.

$$W_t = 5914.51 * exp[-5.0977 * exp(-0.0462t)]$$
(Male broilers)

$$W_t = 5648.97 * exp[-4.9136 * exp(-0.0428t)]$$
(Female broilers)

The estimated value of parameters A and k in Logistic, Gompertz and Von Bertalanffy models in male chicks were higher than females, which indicate that male chicks had better growth than females (Table 4). The growth curves of the most fitted NLMs and ANN are shown in Figure 4. The predicted BW by the Gompertz model from 2nd week to the end of breeding period (6th week) was more than the Logistic model, which was consistent with achieved results by Topal and Bolukbasi (2008) in Ross PM3 strain. The predicted BW of both male and female broilers for Logistic, ANN and Gompertz models were just fitted to the observed BW up to the 4th week, but then by the 6th week slightly overestimating of BW was recognizable. Though, this prediction for the Von Bertalanffy model was exaggerated due to the difference in the estimated value of the parameter A. The growth curve analysis and change-points detection revealed that the predicted weight up to 21 days of age were consistent with the actual values of body weight but then by the end of the breeding period in both sexes, the predicted values were slightly higher than the actual values in Logistic, Gompertz, and ANN models. The only observed exception was the Von Bertalanffy model which the predicted weight values were overestimated after 14 days of age.

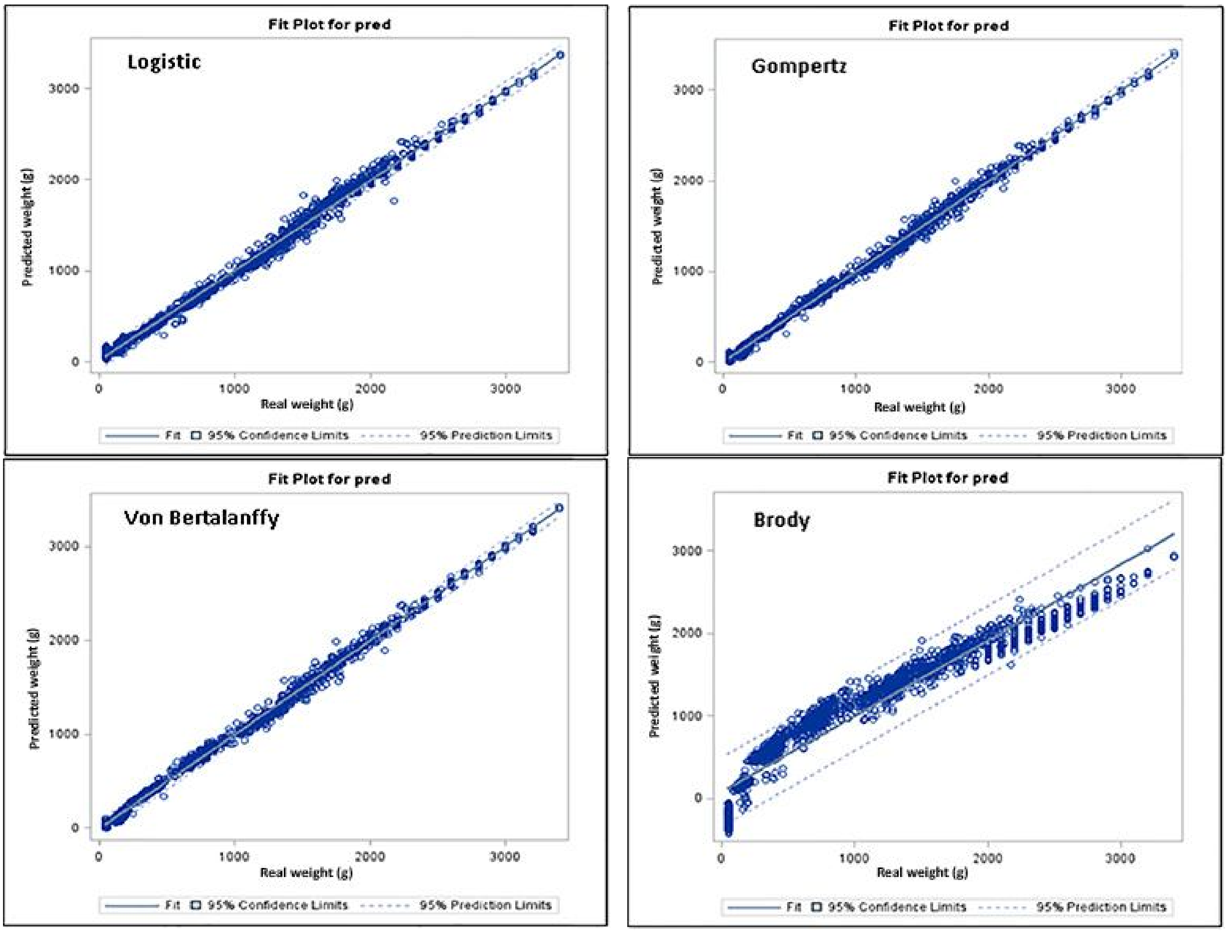


Figure 2. The fit plot for prediction of non-linear models

Table 5. Duncan's multiple range test for parameters of non-linear models of male and female broilers

Model parameters	Nonlinear regression models			
	Logistic	Gompertz	Von Bertalanffy	Brody
A				
Male	3535.07^{a}	5914.5	16202	9912.21
Female	3036.42^{b}	5649	14454	10000
SEM	48.4553	45.2442	628.7965	227.9611
F-value	28.59^{**}	1.11^{ns}	2.2^{ns}	2.43^{ns}
B				
Male	42.246^{a}	5.09767^{a}	0.895358^{a}	1.034863^{a}
Female	37.825^{b}	4.91359^{b}	0.879837^{b}	1.02443^{b}
SEM	0.6747	0.0285	0.002	0.0022
F-value	12.26^{**}	11.87^{**}	15.63^{**}	5.49^{*}
k				
Male	0.115375	0.046197^{a}	0.019766	0.048018^{a}
Female	0.112534	0.042818^{b}	0.019612	0.0401^{b}
SEM	0.001	0.0007	0.0006	0.001
F-value	2.2^{ns}	5.8^{*}	0.01^{ns}	16.5^{**}

SEM: Standard Error of the Mean
* The difference between two means is significant (α=0.05)
** The difference between two means is significant (α=0.01)
ns: The difference between two means is not significant

Table 6. Estimated parameters of non-linear models for different treatments of experimental diet

Model parameter	Nonlinear regression models			
	Logistic	Gompertz	Von Bertalanaffy	Brody
T1:				
A	3423.6 ± 872.9266	6015.51 ± 2133.38	16933.55 ± 10448.88	9964.55 ± 300.767
B	36.4901 ± 8.9886	4.8492 ± 0.5028	0.8746 ± 0.0264	1.0271 ± 0.0174
k	0.1086 ± 0.0167	0.0427 ± 0.0118	0.0186 ± 0.0094	0.0433 ± 0.0075
PCC	0.99775	0.99858	0.99854	0.96302
R^2	0.99805	0.99881	0.99877	0.96822
RMSE	55.42455	42.81293	43.96681	219.68438
MAD	41.70416	29.19256	31.07777	179.35564
MAPE	20.10765	8.39798	8.64069	97.36559
AIC	3968.81229	2992.93111	3507.06713	10021991.77646
T2:				
A	3146.99 ± 926.5408	5473.05 ± 2195.76	13830.02 ± 10066.68	10000 ± 0
B	42.9508 ± 11.7746	5.1594 ± 0.4997	0.8968 ± 0.035	1.0272 ± 0.0197
k	0.1177 ± 0.0191	0.0472 ± 0.0149	0.0222 ± 0.0107	0.0413 ± 0.0086
PCC	0.99826	0.99836	0.99815	0.96201
R^2	0.99846	0.99858	0.99839	0.96623
RMSE	47.21712	45.06019	49.34104	216.85828
MAD	34.60361	32.10665	37.67799	177.31964
MAPE	13.99179	10.4886	14.25828	101.46718
AIC	3857.04696	3353.42325	3684.54672	10119605.28756
T3:				
A	3103.4 ± 824.2826	5404.67 ± 1746.3	14302.58 ± 8805.46	9904.51 ± 837.9391
B	42.4719 ± 14.2784	5.0885 ± 0.4487	0.8961 ± 0.0292	1.0329 ± 0.0716
k	0.1185 ± 0.0173	0.0458 ± 0.0115	0.0203 ± 0.0094	0.045 ± 0.0311
PCC	0.99873	0.99914	0.99905	0.96255
R^2	0.99884	0.99925	0.99915	0.96641
RMSE	41.58302	33.57554	35.92302	219.53405
MAD	32.04429	23.45147	27.04793	181.70238
MAPE	15.51832	8.22197	11.61712	108.86291
AIC	3961.35352	3516.77025	3574.566	10772780.87055
T4:				
A	3479.71 ± 727.8659	6214.91 ± 1724.02	16185.91 ± 9136.89	9953.34 ± 398.0528
B	38.5626 ± 10.5722	4.897 ± 0.3501	0.8811 ± 0.0266	1.0315 ± 0.016
k	0.1113 ± 0.0184	0.042 ± 0.0091	0.018 ± 0.0062	0.0466 ± 0.0091
PCC	0.99792	0.99889	0.99889	0.96307
R^2	0.99817	0.99906	0.99906	0.96766
RMSE	57.49184	41.36731	42.00623	236.80391
MAD	42.66421	27.88674	29.46144	194.1725
MAPE	19.24909	7.53917	8.40006	104.83707
AIC	4701.80263	3710.15609	4478.69505	11934048.89649

Treatments: T1 (3000 kcal/kg ME, 22% CP); T2 (3000 kcal/kg, 24% CP); T3 (3100 kcal/kg, 22% CP); T4 (3100 kcal/kg, 24% CP), A: Asymptotic or mature weight, B: Initial weight, k: Growth rate, PCC: Pearson correlation coefficients between predicted and actual BW, R^2: Coefficient of determination, RMSE: Root of mean square error, MAD: Mean absolute deviation, MAPE: Mean absolute percentage error, AIC: Akaike information criterion

The ranking of NLMs based on PCC between observed and predicted BW of broilers indicated the superiority of the Gompertz model for male and female chicks. The statistical comparison of the fitting models to the observed BW in terms of the R^2 and RMSE described the accuracy of performance prediction for broilers as Gompertz > Von Bertalanffy > Logistic > Brody. Therefore, the Gompertz and Brody models were determined as the best and weakest NLMs for fitting BW data set of broilers. These findings were contrasted with the conclusion of Yang *et al.* (2006) that reported the

Von Bertalanffy as the best model for fitting data of Jinghai yellow chicken with reference to R^2. Furthermore, the Gompertz model had been introduced as the best fitting model by Yakuboglu and Atil (2001).

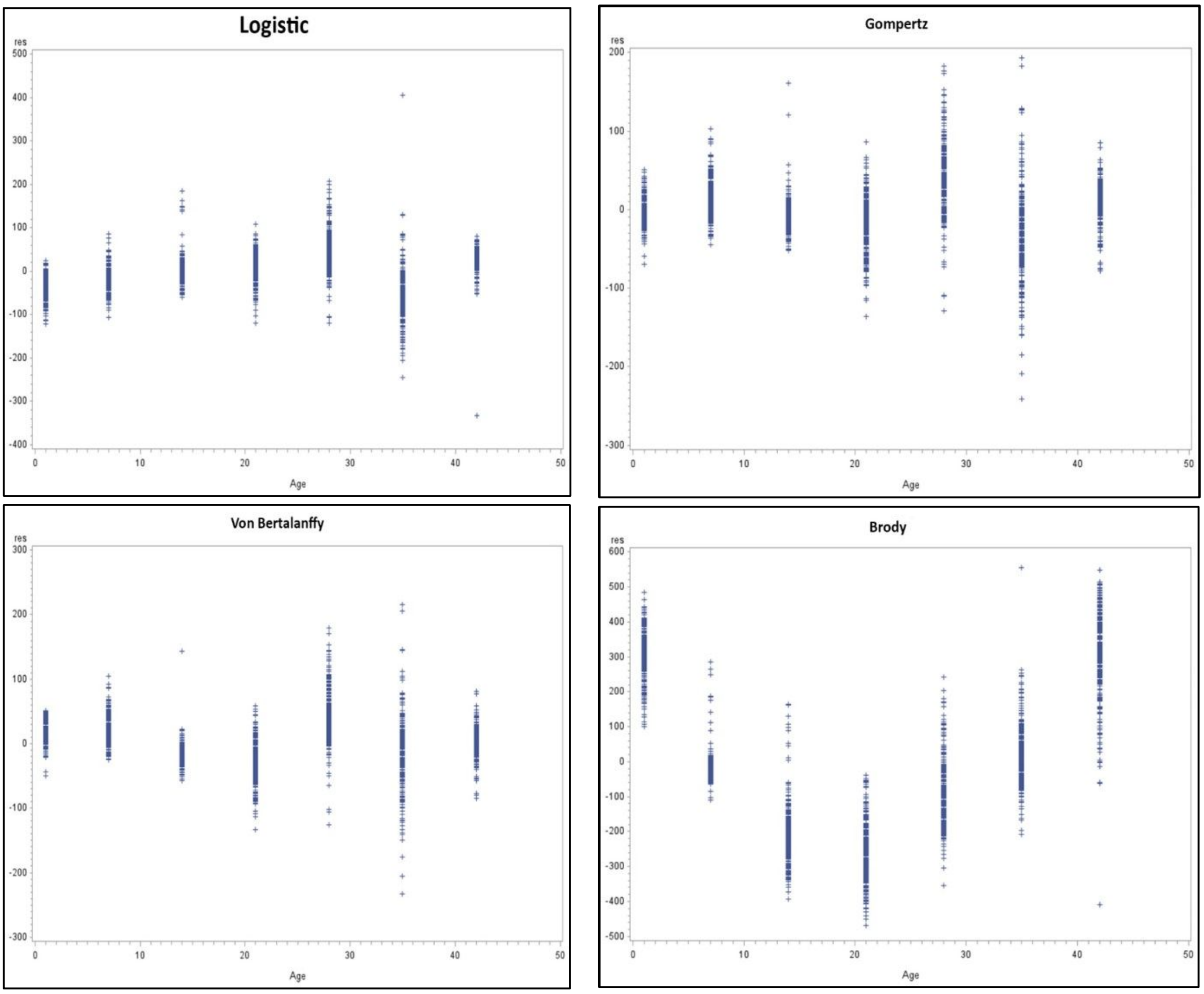


Figure 3. The residual-age diagram of non-linear models

The current conclusion was also consistent with the findings of Topal and Bolukbasi (2008), which reported the Gompertz as the best model for describing BW change over time. The result of NLM comparison in male and female broilers by Duncan's multiple range test (DMRT) is presented in table 5. In relation to maturity weight (parameter A), a significant difference ($P < 0.0001$) was only found in the Logistic model, while the differences in respect of initial weight (B) for all NLMs were significant. The maturity rate (parameter k) difference was significant in both of the Gompertz and Brody models which demonstrate the growth rate of males was better than females.

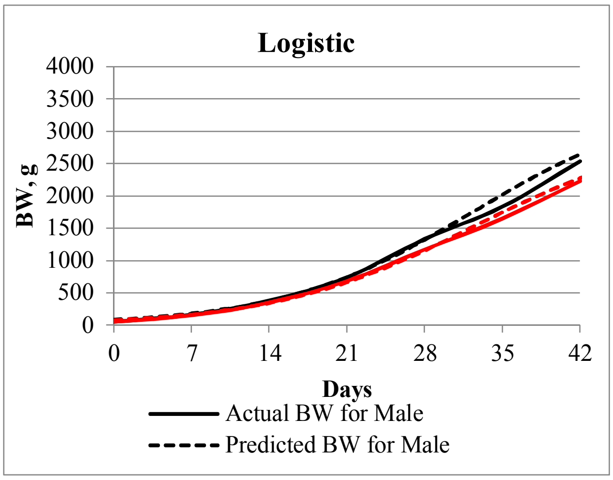
The effect of different treatments on the estimation of NLMs parameters is presented in table 6. The Gompertz model was better as regards PCC, R^2, RMSE, MAD, and MAPE in all treatments compared to the other NLMs. Hence, the Gompertz model seems to be the best model in terms of fitting data for all treatments. The parameters of NLMs for different treatments are compared by DMRT in table 7. However, increasing the protein level boosted the predicted maturity rate (parameter k) of the Logistic, Gompertz and Von Bertalanffy models but there was no significant difference with a simultaneous increase in protein and energy levels. Moreover, the high energy (3100 kcal/kg) or protein (24%) diets caused a significant reduction in the prediction of maturity weight (parameter A) of the Logistic model.

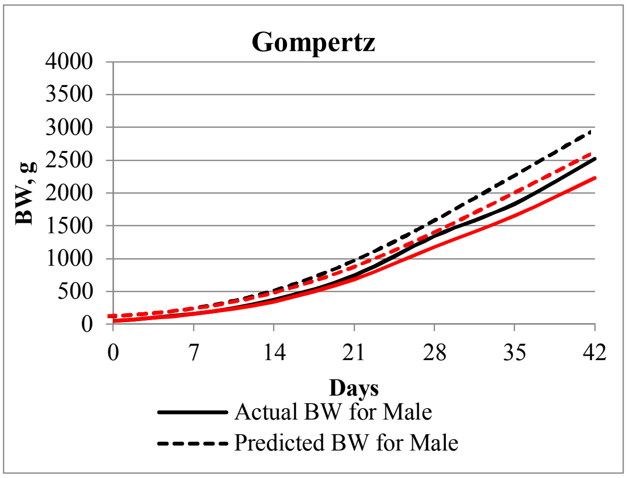
Table 7. Duncan's multiple range test for parameters of non-linear models for different treatments of experimental diet

Model parameters	Nonlinear regression models			
	Logistic	Gompertz	Von Bertalanffy	Brody
A				
T1	3423.6^{a}	6015.5^{ab}	16934	9964.55
T2	3147^{b}	5473^{b}	16186	10000
T3	3103.4^{b}	5404.7^{b}	14303	9904.51
T4	3479.7^{a}	6214.9^{a}	13830	9953.34
SEM	48.4553	45.2442	628.7965	227.9611
F-value	11.66**	7.98**	4.07^{ns}	0.03^{ns}
B				
T1	36.49^{b}	4.84916^{b}	0.874592^{b}	1.027114
T2	42.951^{a}	5.15943^{a}	0.896774^{a}	1.027235
T3	42.472^{a}	5.08846^{a}	0.896116^{a}	1.032873
T4	38.563^{b}	4.89702^{b}	0.881089^{b}	1.031492
SEM	0.6747	0.0285	0.002	0.0022
F-value	16.67**	21.6**	22.91**	0.05^{ns}
k				
T1	0.10859^{b}	0.042047^{b}	0.018569^{b}	0.043268
T2	0.117663^{a}	0.047218^{a}	0.022203^{a}	0.041346
T3	0.1185^{a}	0.045768^{ab}	0.020309^{ab}	0.044988
T4	0.111346^{b}	0.042047^{b}	0.018031^{b}	0.046637
SEM	0.001	0.0007	0.0006	0.001
F-value	16.04**	8.22**	6.13*	0.67^{ns}

Treatments: T1 (3000 kcal/kg ME, 22% CP); T2 (3000 kcal/kg, 24% CP); T3 (3100 kcal/kg, 22% CP); T4 (3100 kcal/kg, 24% CP)
SEM: Standard Error of the Mean
* The difference between two means is significant (α=0.05)
** The difference between two means is significant (α=0.01)
ns: The difference between two means is not significant

According to Kaewtapee, *et al*. (2011), the model of ANN was superior to other models with regard to R^2 and RMSE, which is consistent with Ahmad (2009) and Roush *et al*. (2006). However, other researchers, such as Cravener and Roush (2001) believed that ANNs based on back-propagation will not increase the potential for forecasting of the resulting models in comparison with NLMs which is consistent with the findings of this research.





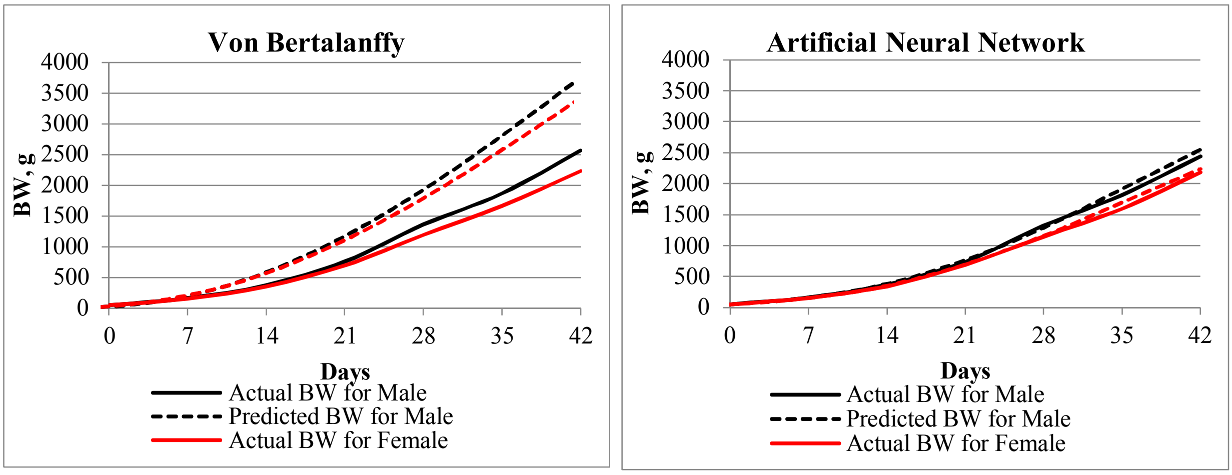


Figure 4. The growth curves for male and female BW prediction of non-linear models

Conclusion

The Gompertz model was better than other NLMs among the different experimental treatments in both sexes, indicating high flexibility of model in predicting the weight of broiler Ross 308 and due to the significant difference in the values of parameter k, it is recommended to separate the diets of male and female chicks. However, the goodness of fit was better in female than male chicks and was also slightly more favorable in the high-energy diets. Because of the significant increase in k and A parameters of the Gompertz model, it is suggested to use 24% CP with 3000 and 3100 kcal/kg ME for the grower and finisher diets.

References

Abbas AA, Yosif AA, Shukur AM & Ali FH. 2014. Effect of Genotypes, Storage Periods and Feed Additives in Broiler Breeder Diets on Embryonic and Hatching Indicators and Chicks Blood Parameters. Scientia Agriculturae, 7: 44-48. DOI: 10.15192/PSCP.SA.2014.3.1.4448

Aggrey SE. 2002. Comparison of Three Nonlinear and Spline Regression Models for Describing Chicken Growth Curves. Poultry Science, 81: 1782-1788. DOI: 10.1093/ps/81.12.1782

Ahmad, HA. 2009. Poultry Growth Modeling Using Neural Networks and Simulated Data. Journal of Applied Poultry Research, 18: 440-446. DOI: 10.3382/japr.2008-00064

Ahmadi H & Mottaghitalab M. 2007. Hyperbolastic Models as a New Powerful Tool to Describe Broiler Growth Kinetics. Poultry Science, 86: 2461-2465. DOI: 10.3382/ps.2007-00086

Cravener TL & Roush WB. 2001. Prediction of Amino Acid Profiles in Feed Ingredients: Genetic Algorithm Calibration of Artificial Neural Networks. Animal Feed Science and Technology, 90: 131-141. DOI: 10.1016/S0377-8401(01) 00219-X

Duncan, D. B. 1955. Multiple Range and Multiple F Tests. Biometrics, 11: 1-42. DOI: 10.2307/ 3001478

Darmani Kuhi H, Kebreab E, Lopez S & France J. 2003. An Evaluation of Different Growth Functions for Describing the Profile of Live Weight with Time Age in Meat and Egg Strains of Chicken. Poultry Science, 82: 1536-1543. DOI: 10.1093/ps/82.10.1536

Eleroglu H, Yildirim A, Şekeroğlu A, Çoksöyler FN & Duman M. 2014. Comparison of Growth Curves by Growth Models in Slow Growing Chicken Genotypes Raised the Organic System. International Journal of Agriculture and Biology, 16: 529-535

Golian A & Ahmadi H. 2008. Non-linear Hyperbolastic Growth Models for Describing Growth Curve in Classical Strain of Broiler Chicken. Research Journal of Biological Sciences, 3: 1300-1304.

Kaewtapee C, Khetchaturat C & Bunchasak C. 2011. Comparison of Growth Models between Artificial Neural Networks and Nonlinear Regression Analysis in Cherry Valley Ducks. Journal of Applied Poultry Research, 20: 421-428. DOI: 10.3382/japr.2010-00223

Kum D, Karakus K & Ozdemir T. 2010. The Best Nonlinear Function for Body Weight at Early Phase of Norduz Female Lambs. Trakia Journal of Sciences, 8: 62-67.

Lopez S, France J, Gerrits WJJ, Dhanoa MS, Humphries DJ & Dijkstra, J. 2000. A Generalized Michaelis-Menten Equation for the Analysis of Growth. Journal of Animal Science, 78: 1816-1828. DOI: 10.2527/2000.7871816x

Masoudi A & Azarfar A. 2017. Comparison of Nonlinear Models Describing Growth Curves of Broiler Chickens Fed on Different Levels of Corn Bran. International Journal of Avian &

Wildlife Biology, 2: 34-39, DOI: 10.15406/ ijawb.2017.02.00012

Mohammed FA. 2015. Comparison of Three Nonlinear Functions for Describing Chicken Growth Curves. Scientia Agriculturae, 9: 120-123. DOI: 10.15192/PSCP.SA.2015.9.3.120123

Nahashon SN, Aggrey SE, Adefope NA, Amenyenu A & Wright D. 2006. Growth Characteristics of Pearl Gray Guinea Fowl as Predicted by the Richards, Gompertz, and Logistic Models. Poultry Science, 85: 359-363. DOI: 10.1093/ps/85.2.359

Narinc D, Karaman E, Ziya Firat M & Aksoy T. 2010. Comparison of Nonlinear Growth Models to Describe the Growth in Japanese Quail. Journal of Animal and Veterinary Advances, 9: 1961-1966. DOI: 10.3923/javaa.2010.1961.1966

Norris D, Ngambi JW, Benyi K, Makgahlela ML, Shimelis HA & Nesamvuni EA. 2007. Analysis of Growth Curves of Indigenous Male Venda and Naked Neck Chickens. South African Journal of Animal Science, 37: 21-26. DOI: 10.4314/ sajas.v37i1.4021

Porter T, Kebreab E, Darmani Kuhi H, Lopez S & Strathe AB. 2010. Flexible Alternatives to the Gompertz Equation for Describing Growth with Age in Turkey Hens. Poultry Science, 89: 371-378. DOI: 10.3382/ps.2009-00141

Prestes AM, Garnero ADV, Marcondes CR, Damé MC, Janner EA & Rorato PRN. 2012. Estudo da Curva de Crescimento de Bubalinos da Raça Murrah Criados no Estado do Rio Grande do Sul. Anais do 9º Simpósio Brasileiro de Melhoramento Animal. João Pessoa: ABMA.

Roush WB, Dozier WA & Branton SL. 2006. Comparison of Gompertz and Neural Network Models of Broiler Growth. Poultry Science, 85: 794-797. DOI: 1093/ps/85.4.794

Rumelhart DE & McClelland JL. 1986. Parallel Distributed Processing: Explorations in the Microstructure of Cognition: Foundations. Vol. 1: MIT Press. Cambridge. UK.

Sabbioni A, Superchi P, Bonomi A, Summer A & Boidi G. 1999. Growth Curves of Intensively Reared Ostriches Struthio Camelus in Northern Italy. Proceedings of 50th EAAP Congress, July 2000.

Saghi DA, Aslaminejad A, Tahmoorespur M, Farhangfar H, Nassiri M, Dashab GR. 2012. Estimation of Genetic Parameters for Growth Traits in Baluchi Sheep Using Gompertz Growth Curve Function. Indian Journal of Animal Science, 82: 889-892.

SAS (Statistical Packages for the Social Sciences). 2013. SAS/STAT® 9.4. User's Guide. SAS Institute Inc. Cary, North Carolina.

Sengul T & Kiraz S. 2005. Non-linear Models of Growth Curves in Large White Turkeys. Journal of Veterinary and Animal Science, 29: 331-337.

Sogut B, Celik S, Ayasan T & Inci H. 2016. Analyzing Growth Curves of Turkeys Reared in Different Breeding Systems Intensive and Free-Range with Some Nonlinear Models. Brazilian Journal of Poultry Science, 18: 619-628. DOI: 10.1590/1806-9061-2016-0263

Tariq MM, Iqbal F, Eyduran E, Bajwa MA, Huma ZE & Waheed A. 2013. Comparison of Non-Linear Functions to Describe the Growth in Mengali Sheep Breed of Balochistan. Pakistani Journal of Zoology, 45: 661-665.

The R Foundation for Statistical Computing. 2017. Training of Neural Network: Package 'neuralnet'. https://cran.r-project.org/web/packages/neuralnet/ neuralnet.pdf. Accessed on February 7. 2019.

The Ross 308 Broiler: Nutrition Specification. 2014. Aviagen Publications. http://tmea.staging. aviagen. com /assets/ Tech_Center/Ross_Broiler/ Ross-308-Broiler-Nutrition-Specs-2014r17-EN. pdf

Topal M & Bolukbasi SC. 2008. Comparison of Nonlinear Growth Curve Models in Broiler Chickens. Journal of Applied Animal Research, 34: 149-152. DOI: 10.1080/09712119.2008. 9706960

Vitezica ZG, Marie-Etancelin C, Bernadet MD, Fernandez X & Granie RC. 2010. Comparison of Nonlinear and Spline Regression Models for Describing Mule Duck Growth Curves. Poultry Science, 89: 1778-1784. DOI: 10.3382/ps.2009-00581

Yakuboglu C & Atil H. 2001. Comparison of Growth Curve Models on Broilers Growth Curves I: Parameters Estimations. Online Journal of Biological Science, 1: 680-681. DOI: 10.3923/jbs.2001.682.684

Yang Y, Mekki DM, Lv SJ, Wang LY & Wang JY. 2006. Analysis of Fitting Growth Models in Jinghai Mixed-Sex Yellow Chicken. International Journal of Poultry Science, 5: 517-521. DOI: 10.3923/ijps.2006.517.521