Comparison of Gompertz and Neural Network Models of Broiler Growth

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ABSTRACT Neural networks offer an alternative to regression analysis for biological growth modeling. Very little research has been conducted to model animal growth using artificial neural networks. Twenty-five male chicks (Ross × Ross 308) were raised in an environmental chamber. Body weights were determined daily and feed and water were provided ad libitum. The birds were fed a starter diet (23% CP and 3,200 kcal of ME/kg) from 0 to 21 d, and a grower diet (20% CP and 3,200 kcal of ME/kg) from 22 to 70 d. Dead and female birds were not included in the study. Average BW of 18 birds were used as the data points for the growth curve to be modeled. Training data consisted of alternate-day weights starting with the first day. Validation data consisted of BW at all other age periods. Comparison was made between the modeling by the Gompertz nonlinear regression equation and neural network modeling. Neural network models were developed with the Neuroshell Predictor. Accuracy of the models was determined by mean square error (MSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE), and bias. The Gompertz equation was fit for the data. Forecasting error measurements were based on the difference between the model and the observed values. For the training data, the lowest MSE, MAD, MAPE, and bias were noted for the neural-developed neural network. For the validation data, the lowest MSE and MAD were noted with the genetic algorithm-developed neural network. Lowest bias was for the neural-developed network. As measured by bias, the Gompertz equation underestimated the values whereas the neural- and genetic-developed neural networks produced little or no overestimation of the observed BW responses. Past studies have attempted to interpret the biological significance of the estimates of the parameters of an equation. However, it may be more practical to ignore the relevance of parameter estimates and focus on the ability to predict responses.

Key words: growth equation, Gompertz, neural network

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INTRODUCTION

Neural networks offer an alternative to regression analysis for biological modeling. In relation to growth modeling, the difference between artificial neural networks and regression analysis is that an equation is not assumed, tighter fits of data are possible, and it is possible to work with "noisy" data. Very little research has been conducted to model animal growth using artificial neural networks. Yee et al. (1993) compared the modeling of a data set of Sprague-Dawley rats with traditional regression and a back-propagation neural network. They found that both methods produced models that adequately predicted the BW. However, the neural network was found to be superior in that it combined accuracy and precision. In this study, a comparison was made between the modeling by the Gompertz nonlinear regression equation and neural network modeling.

METHODS AND PROCEDURES

Animal Data

Twenty-five male chicks (Ross × Ross 308) were raised in an environmental chamber. Feed and water (via 4 nipple drinkers) were provided ad libitum. The birds were fed a starter diet (23% CP and 3,200 kcal of ME/kg) from 0 to 21 d, and a grower diet (20% CP and 3,200 kcal of ME/kg) from 22 to 70 d. Temperature started at 32.2°C and was reduced 2.8°C degrees each week until 21.1°C was attained. Dewpoint was constant at 10.0°C, and the lighting program was 23L:1D. The birds were individually weighed at 0800 h and BW were recorded on each day for 70 d. Four of the 25 birds died before the end of 70 d. Of the remaining birds, it was determined that 3 were females. The dead and female birds were not included in the study. The average BW of the remaining 18 birds were used as the data points for the growth curve to be modeled.

Model Development

Regression Model. The Gompertz nonlinear regression model (Rogers et al., 1987) was calculated using the

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SAS NLIN models of the SAS statistical package (SAS Institute Inc., 1999). The resulting equation was evaluated in an Excel spreadsheet. The form of the equation was:

$$W = A \exp[-\log(A/B)\exp(-Kt)]$$

where W is the weight to age (t) with 3 parameters: A = asymptotic or maximum growth response, B = intercept or weight when age (t) = 0, and K = rate constant.

Neural Network Models. The neural network models were developed with the Neuroshell Predictor and the Neuroshell Runtime Server of the AI Trilogy program package (Ward Systems Group, 2000). The developed neural networks were evaluated in an Excel spreadsheet using the Neuroshell runtime server program. The Neuroshell Predictor program was developed as an alternative to regression analysis for making predictions. The predictor model is based on 1 of 2 models called "neural" and "genetic." The neural method can be used to extrapolate. That is, it can produce output numbers above or below the examples on which it has been trained. The training procedure is based on the premise that the accuracy and precision of the model can be adjusted by inclusion or exclusion of the nodes in the hidden layer. The computer tries to define the optimal number of hidden layer nodes. The challenge for the program is to find the number of nodes in the hidden layer that will accurately reflect the data for a prediction while being able to generalize beyond the data set. The genetic approach was also evaluated. However, it should be noted that the genetic method is poor at extrapolation. It uses interpolation in its prediction approach.

A quantitative examination of the fit of the predictive models was made using error measurement indices commonly used to evaluate forecasting models (Oberstone, 1990). The accuracy of the models was determined by: 1) mean absolute deviation (**MAD**), computed as

$$\text{MAD} = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|}{n}$$

where y_t equals the observed value at time t, $\hat{y}_t$ equals the estimated value, and n equals the number of observations; 2) mean absolute percentage error (**MAPE**), computed as

$$\text{MAPE} = \frac{\sum \left|\frac{y_t - \hat{y}_t}{y_t}\right|}{n} \times 100, \ (y_t \neq 0)$$

where y_t equals the observed value at time t, $\hat{y}_t$ equals the estimated value, and n equals the number of observations; 3) mean square error (**MSE**), computed as

$$\text{MSE} = \frac{\sum_{t=1}^{n} |y_t - \hat{y}_t|^2}{n}$$

Table 1. Broiler BW data used for Gompertz regression modeling and neural network training and validation[1]

Training data		Validation data	
Age (d)	BW (g)	Age (d)	BW (g)
1	43	2	43
3	51	4	62
5	77	6	93
7	113	8	134
9	159	10	192
11	227	12	265
13	308	14	355
15	406	16	460
17	520	18	586
19	654	20	724
21	796	22	868
23	944	24	1,018
25	1,101	26	1,185
27	1,270	28	1,349
29	1,438	30	1,528
31	1,632	32	1,704
33	1,830	34	1,936
35	2,030	36	2,122
37	2,230	38	2,335
39	2,442	40	2,544
41	2,650	42	2,739
43	2,801	44	2,942
45	3,011	46	3,089
47	3,207	48	3,295
49	3,395	50	3,476
51	3,568	52	3,706
53	3,770	54	3,867
55	3,918	56	4,016
57	4,090	58	4,171
59	4,222	60	4,300
61	4,380	62	4,421
63	4,474	64	4,560
65	4,606	66	4,655
67	4,704	68	4,725
69	4,719	70	4,741

[1]BW responses used in modeling, training, and validation represent the mean of 18 birds.

where y_t equals the observed value at time t, $\hat{y}_t$ equals the estimated value, and n equals the number of observations; and 4) bias, computed as

$$\text{Bias} = \frac{\sum_{t=1}^{n} y_t - \hat{y}_t}{n}$$

where y_t equals the observed value at time t, $\hat{y}_t$ equals the estimated value, and n equals the number of observations.

RESULTS AND DISCUSSION

Table 1 lists the resulting training and validation data, and their associated days of collection. The following Gompertz equation was fit for the data:

$$W = 6066.5 \exp[-\log(6066.5/29.0568)\exp(-0.0454t)]$$

Table 2 shows the statistics for the Gompertz equation and the 2 developed neural networks. Table 3 shows the training and validation values for the observed and predicted BW for each mathematical modeling method. Forecasting error measurements based on the difference

Table 2. Model statistics and information for the mathematical and neural network models for predicting broiler BW

Statistic	Model: Gompertz fit	Genetic training	Neural training
R^2	0.999935	0.999883	0.999938
Correlation	0.999967	0.999964	0.999969
Mean square error	517.0	307.3272	163.109
RMSE[1]	22.7376	17.53075	12.77141
Hidden neurons[2]	—	—	32

[1]Root mean square error (standard deviation).

[3]Number of hidden neurons added by the algorithm to fit the neural network model.

between the model and the observed values are shown. For the training data, the lowest MSE, MAD, and bias were noted for the neural-developed neural network. For the validation data, the lowest MSE, MAD, and MAPE were observed with the genetic algorithm-developed neural network. However, the lowest bias was seen with the neural-developed neural network. As measured by bias, the Gompertz equation underestimated the values, whereas the neural- and genetic-developed neural networks produced little or no overestimation of the observed BW responses.

The advantage of neural networks is that there is no requirement for preselecting a model or basing the model entirely on the fit of the data. A disadvantage of artificial neural networks is that they take a "black box" approach, which does not give insight in to the internal workings of the neural network. In addition, the network does not provide estimates of parameters that may be useful for comparative and developmental purposes. Yee et al. (1993) suggests that although previous studies attempted

Table 3. Mathematical and neural network model predicted BW for training and validation data including model error evaluations[1]

Training data: BW (g)	Gompertz equation	Neural network genetic algorithm	Neural network neural algorithm	Validation data: BW (g)	Gompertz equation	Neural network genetic algorithm	Neural network neural algorithm
43	37	55	14	43	46	52	23
51	57	64	35	62	71	68	50
77	86	85	67	93	104	98	87
113	124	121	110	134	148	140	136
159	174	173	165	192	204	198	198
227	237	238	234	265	274	272	274
308	314	320	318	355	358	362	365
406	406	418	416	460	458	468	471
520	514	533	529	586	573	591	591
654	637	661	656	724	704	727	725
796	774	801	797	868	848	872	872
944	926	951	950	1,018	1,006	1,025	1,030
1,101	1,090	1,109	1,113	1,185	1,176	1,187	1,198
1,270	1,265	1,272	1,285	1,349	1,356	1,357	1,373
1,438	1,449	1,453	1,464	1,528	1,544	1,539	1,555
1,632	1,641	1,636	1,648	1,704	1,739	1,732	1,742
1,830	1,838	1,832	1,837	1,936	1,938	1,930	1,933
2,030	2,039	2,031	2,029	2,122	2,140	2,132	2,126
2,230	2,241	2,236	2,224	2,335	2,343	2,336	2,321
2,442	2,444	2,437	2,420	2,544	2,544	2,539	2,518
2,650	2,644	2,621	2,617	2,739	2,744	2,726	2,715
2,801	2,842	2,830	2,814	2,942	2,939	2,911	2,912
3,011	3,035	3,007	3,010	3,089	3,130	3,107	3,107
3,207	3,223	3,200	3,203	3,295	3,315	3,298	3,299
3,395	3,405	3,388	3,393	3,476	3,494	3,483	3,486
3,568	3,580	3,580	3,578	3,706	3,665	3,666	3,667
3,770	3,748	3,743	3,755	3,867	3,829	3,840	3,840
3,918	3,908	3,925	3,923	4,016	3,985	4,002	4,004
4,090	4,060	4,070	4,081	4,171	4,133	4,154	4,156
4,222	4,204	4,229	4,228	4,300	4,273	4,296	4,296
4,380	4,340	4,348	4,361	4,421	4,405	4,423	4,423
4,474	4,468	4,488	4,482	4,560	4,529	4,539	4,537
4,606	4,588	4,582	4,589	4,655	4,645	4,639	4,637
4,704	4,701	4,648	4,682	4,725	4,754	4,695	4,724
4,719	4,806	4,689	4,762	4,741	4,856	4,713	4,797
Forecast model error measurement[2]							
MSE	488.3	312.1	216.8		819.7	243.0	382.2
MAD	15.42	13.46	11.99		19.59	11.90	15.10
MAPE	2.473	3.089	4.070		2.295	1.830	2.983
Bias	–1.798	0.3477	0.000		–1.995	2.443	0.4365

[1]BW represent observed weights; the other training and validation values are predicted values.

[2]MSE = mean square error; MAD = mean absolute deviation; and MAPE = mean absolute percentage error.

to interpret the biological significance of the estimates of the parameters of an equation, it may be more practical to ignore the relevance of the parameter estimates and focus on the ability to predict responses.

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