International Journal of Agriculture and Wildlife Science (IJAWS) 2021, 7(3): 515 - 523
doi: 10.24180/ijaws.990297

International Journal of Agriculture and Wildlife Science

http://dergipark.org.tr/ijaws

Research Article

Comparative Analysis of Artificial Intelligence and Nonlinear Models for Broiler Growth Curve

Erdem Küçüktopcu*, Bilal Cemek

Department of Agricultural Structures and Irrigation, Faculty of Agriculture, Ondokuz Mayıs University, Samsun, Turkey

Received: 02.09.2021 Accepted: 20.10.2021

Keywords:
Growth curve, broiler, artificial intelligence, regression model

***Corresponding author**
erdem_kt@hotmail.com

Abstract. Numerous mathematical expressions for growth models have been developed, but each has its own characteristics and limitations. Therefore, this study has investigated whether artificial intelligence (AI) methods can be an alternative to these models. To this aim, four nonlinear (NL) models (logistic, Richards, Gompertz-Laird, and von Bertalanffy) and three AI techniques — artificial neural networks (ANN), integrated adaptive neuro-fuzzy inference systems with grid partitioning and subtractive clustering (ANFIS-GP and ANFIS-SC) — were used to analyze growth. Some statistical methods, including the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to evaluate the model performance. As a result of the study, it was determined that the ANFIS-SC model yielded a better fit with the broiler data due to its low MAE, RMSE, and MAPE values (7.68 g, 11.93 g, and 1.06%, respectively). The overall recommendation of this study is that the AI models could be used as an alternative to determine a broiler growth curve.

Etlik Piliç Büyüme Eğrisinin Tahmininde Yapay Zeka ve Doğrusal Olmayan Modellerin Karşılaştırmalı Analizi

Anahtar kelimeler:
Büyüme eğrisi, etlik piliç, yapay zeka, regresyon modeli

Özet. Büyüme modelleri için çok sayıda matematiksel ifade geliştirilmiştir, ancak her birinin kendine has özellikleri ve sınırlamaları bulunmaktadır. Dolayısıyla bu çalışmada yapay zeka (YZ) yöntemlerinin bu modellere alternatif olup olamayacağı araştırılmıştır. Bu amaçla büyümeyi analiz etmek için dört farklı doğrusal olmayan model (NL) (lojistik, Richards, Gompertz-Laird ve von Bertalanffy) ve üç farklı YZ tekniği - yapay sinir ağları (YSA) ve uyarlamalı sinirsel bulanık çıkarım sisteminin farklı yöntemleri (ızgara bölümleme (ANFIS-GP) ve eksiltici kümeleme (ANFIS-SC)) kullanılmıştır. Modellerin performansını değerlendirmek için ortalama mutlak hata (MAE), ortalama karekök hata (RMSE) ve ortalama mutlak yüzde hata (MAPE) gibi bazı istatistiksel yöntemler ele alınmıştır. Çalışma sonucunda ANFIS-SC modelinin en düşük MAE, RMSE ve MAPE değerleri (sırasıyla 7.68 g, 11.93 g ve %1.06) ile gerçek ağırlık verileriyle daha iyi uyum sağladığı tespit edilmiştir. Sonuç olarak YZ modellerinin etlik piliç büyüme eğrisini belirlemek için alternatif olarak kullanılabileceği belirlenmiştir.

INTRODUCTION

Broiler industry requires birds that can grow faster and produce a high-quality carcass in the shortest time. It is important for broiler businesses to have sufficient information about the growth of the chickens in terms of profitability and continuity (Chang, 2007; Abdurofi *et al*., 2017).

Growth curves, an economically important feature of the broiler industry, are used to describe the changes in weight and body size per unit of time or age. Modeling growth curves is advantageous because it enables visualization of growth patterns over time, and the resulting equations can be used to predict the expected weight of chickens at a given age (Eleroğlu *et al*., 2014; Koushandeh *et al*., 2019).

Some nonlinear (NL) models (e.g., logistic, Richards, Gompertz-Laird, and von Bertalanffy) have been used widely to describe poultry growth curves, and the comparison of NL models was generally recommended to determine the best model based on different assessment criteria for species, strains, and even different lines. Numerous researchers have used NL models to investigate and characterize the growth curves of various poultry species, including Cetin *et al*. (2007), Balcioğlu *et al*. (2009), and Sariyel *et al*. (2017) in partridge, Raji *et al*. (2014), and Narinc *et al*. (2014) in quail, Vitezica *et al*. (2010) and Tang *et al*. (2010) in duck, Şengül and Kiraz (2005) and Porter *et al*. (2010) in turkey, van der Klein *et al*. (2020) in laying hens, and Roush *et al*. (2006), Topal and Bolukbasi (2008), Ahmad (2009), Şekeroğlu *et al*. (2013), Demuner *et al*. (2017) and Koushandeh *et al*. (2019) in broiler. These NL models can describe the growth of chickens, but each one has unique characteristics and shortcomings (Norris *et al*., 2007).

Recently, artificial intelligence (AI) techniques offer an alternative to complicated NL models. A significant advantage of using AI compared to NL models is that AI modeling could only be performed on a dependent variable, and it is also possible to design various types of the variable in AI modeling. This results in less time and resource waste, a more accurate error estimation, and less variability in data collection under various conditions. Another important advantage of AI models is that they could effectively handle the nonlinearity and complexity of a system and overcome the limitations of NL models (Haykin, 2010; Shanmuganathan, 2016). In recent years, several studies have been performed to compare the performance of artificial neural networks (ANN) and NL models in broiler growth estimation (Roush *et al*., 2006; Ahmad, 2009; Koushandeh *et al*., 2019).

These studies have contributed significantly to the knowledge base regarding the ANN technique in poultry houses. However, to our knowledge, no comprehensive study has been conducted to compare different NL models, neuro-fuzzy, and neural networks techniques for broiler growth curve.

Therefore, the main objective of the present study is to compare the different AI techniques and NL growth models to identify which is most suitable for the data of the "Ross 308" chickens.

MATERIAL AND METHOD

The research was conducted in Samsun, Turkey (41°70' N, 36°30' E), at a commercial broiler farm. The farm had a length of 90.00 m, a width of 14.00 m, and a height of 3.80 m (Figure 1).

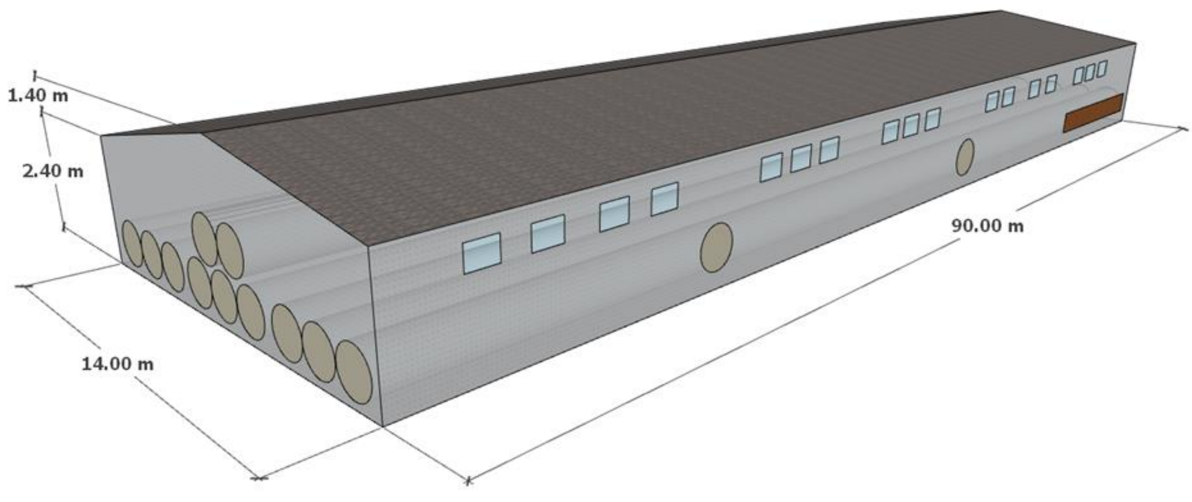

Figure 1. The dimensions of the broiler house**.**
Şekil 1. Kümesin boyutları.

Chickens from the "Ross 308" breeding stock were reared until 40-42 days old. Ventilation, heating, lighting, feeding, and watering were all controlled by an automatic control system. Chicken weights were recorded daily at eight rearing seasons (Table 1) using an electronic poultry weighing scale. The average of eight rearing seasons was used as the body weight of chickens for the growth curve to be modeled.

Table 1. Broiler rearing seasons and dates.
Çizelge 1. Etlik piliç yetiştirme dönemleri ve tarihleri.

Seasons	Dates	Number of birds
S1	03.02.2018-16.03.2018	20,035
S2	09.04.2018-20.05.2018	19,840
S3	12.06.2018-22.07.2018	24,000
S4	09.11.2018-19.12.2018	19,440
S5	09.01.2019-18.02.2019	17,760
S6	14.03.2019-24.04.2019	18,000
S7	16.07.2019-26.08.2019	18,240
S8	11.09.2019-23.10.2019	18,384

Nonlinear (NL) Model

Four growth models were selected to characterize the growth pattern of "Ross 308" chickens: Logistic (Eq. 1), Richards (Eq. 2), Gompertz-Laird (Eq. 3), and von Bertalanffy (Eq. 4). Mathematical equations were as follows:

$$\text{Logistic} \rightarrow \quad W_t = W_A / \left[1 + \exp{-K(t - t_i)}\right] \tag{1}$$

$$\text{Richards} \rightarrow \quad W_t = W_A \left[1 - (1-m)\exp\left[-K(t - t_i) / m^{m/(1-m)}\right]\right]^{1/(1-m)} \tag{2}$$

$$\text{Gompertz-Laird} \rightarrow \quad W_t = W_0 \exp\left[\left(L/K\right)\left(1 - \exp{-Kt}\right)\right] \tag{3}$$

$$\text{Von Bertalanffy} \rightarrow \quad W_t = W_A \left[1 - B\exp^{(-Kt)})\right]^3 \tag{4}$$

where, W_t is the bird weight at time t (g), W_0 is the initial (hatch) weight (g), K is the maximum relative growth (g D^{-1}), L is the instantaneous growth rate (g D^{-1}), t_i is the age at the maximum rate of growth (D), and m is a shape parameter and B is the integration constant. The asymptotic weight (W_A) (g) and age of maximum growth (t_i) (D) were estimated using the following formulas:

$$t_i = \left(1/K\right)\log\left(L/K\right) \tag{5}$$

$$W_A = W_0 \exp\left(L/K\right) \tag{6}$$

Artificial Neural Networks (ANN)

This paper employed multi-layered feedforward back-propagation (MLP) during network training due to its speed and power. The tangent sigmoid (*tansig*) and linear transfer functions (*purelin*) were used in the hidden and output layers, respectively. The MLP can have multiple hidden layers; however, studies have shown that a single layer is sufficient for any neural network to approximate complex nonlinear functions. Therefore, one hidden layer was tested, and the number of neurons changed from 7 to 15 to achieve the optimal training network.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

This system combines the fuzzy inference system's decision-making process (FIS) with the learning capability of ANN. As is the case with ANN, ANFIS learns with samples from a training set. This method yields the optimal network structure for resolving the problem at hand. The test procedure is carried out on previously unobserved samples, which enables the identification of the effect. The smaller error values attest to the conformity of the ANFIS model. One of ANN's primary drawbacks is its inability to justify the weight values acquired. This problem is addressed by the FIS, which is incorporated into the ANFIS structure. Different identifications such as subtractive clustering (SC) and grid partitioning (GP) can be applied in the ANFIS model. It is necessary to define the appropriate cluster radius in ANFIS-SC to apply fuzzy rules. The cluster radius denotes a cluster's sphere of influence, assuming that the data space is a unit hypercube, with a range of zero to one. The smaller the cluster radius, the more rules are generated, while the larger the cluster radius, the fewer rules are generated. Suitable values for radii usually fall between 0.2 and 0.5. To determine the best estimation model, the cluster radius in this study ranged between 0.1 and 1. In ANFIS-GP models, three methods, including Gaussian, triangular, trapezoidal, and three membership functions (MFs) (3, 4, and 5), were considered in the data processing.

Model Performance Evaluation Criteria

The mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to evaluate model performance. The equations are expressed as follows (Waller, 2003):

$$MAE = \frac{\sum_{i=1}^{n}\left(\left|X_{mea,i} - X_{est,i}\right|\right)}{n} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{mea,i} - X_{est,i})^2}{n}} \tag{8}$$

$$MAPE = \frac{\sum_{i=1}^{n}\left(\left|\frac{X_{mea,i} - X_{est,i}}{X_{mea,i}}\right|\right)}{n} \times 100 \tag{9}$$

where $X_{mea,i}$ is the measured value of variable, $X_{est,i}$ is the estimated value of variable, and n is the data number.

RESULTS AND DISCUSSION

The studied training and testing data for the estimation of chicken weight are presented in Table 2. Starting from day 0, the even numbers of data were used as training, while the odd numbers of data were used as testing.

Table 2. Broiler weight data used for modeling in training and testing.
Çizelge 2. Eğitim ve test için modellemede kullanılan piliç ağırlık verileri.

Training		**Testing**	
Age (D)	**Weight (g)**	**Age (D)**	**Weight (g)**
0	46	1	55
2	70	3	85
4	103	5	125
6	146	7	170
8	201	9	236
10	275	11	315
12	364	13	423
14	482	15	536
16	599	17	673
18	740	19	797
20	876	21	978
22	1044	23	1118
24	1204	25	1294
26	1361	27	1388
28	1505	29	1585
30	1662	31	1762
32	1881	33	1959
34	2008	35	2118
36	2187	37	2260
38	2353	39	2408
40	2449	41	2485

Four NL models, including logistic, Richards, Gompertz-Laird, and Von Bertalanffy, and three AI models, namely ANN, ANFIS-GP, and ANFIS-SC, were used to explore the "Ross 308" chickens growth patterns. The developed equations for four NL models for growth are presented in Table 3.

Table 3. Developed NL model equations for growth.
Çizelge 3. Büyüme modelleri için geliştirilmiş NL eşitlikleri.

Model	Equation
Logistic	$W_t = 2878.01 / \left[1 + \exp - 0.13(t - 26.90)\right]$
Richards	$W_t = 4057.52\left[1 + 0.03\exp\left[-0.02(t - 27.83) / 1.03^{-34.33}\right]\right]^{-33.34}$
Gompertz-Laird	$W_t = 4143.98\exp\left[-\log(4143.98 / 0.09)\exp(-0.05t)\right]$
von Bertalanffy	$W_t = 6217.74\left[1 - 0.87\exp^{(-0.03t)}\right]^3$

A developed ANN model can be represented as:

$$BroilerWeight = \sum_{k=1}^{m}\left(\left[\left[\frac{2}{1+\exp\left(-2\left(\sum_{j=1}^{m}\sum_{l=1}^{n}\left((w_1(i,j)x(i))+b_1(j)\right)\right)\right)}-1\right]\right]w_2(k)b_2\right) \quad (10)$$

w_1, w_2 and b_1, b_2, are the weight and bias values of the network, respectively, x symbolizes the input data, m and n are the number of neurons in hidden and input layers, respectively. The w_1, w_2, b_1, and b_2 values of the developed model are given in Table 4.

Table 4. Weight and bias values of the network.
Çizelge 4. Ağın ağırlık ve bias değerleri.

Weights		Biases	
$w_1 = \begin{bmatrix} 32.002 \\ 26.414 \\ 0.077 \\ 3.110 \\ -1.201 \\ 0.139 \\ -7.459 \\ -11.897 \\ -29.796 \\ -17.098 \end{bmatrix}$	$w_2 = \begin{bmatrix} 640.544 \\ 75.914 \\ 946.895 \\ 48.784 \\ 117.264 \\ 425.393 \\ -100.590 \\ 2.324 \\ 1.457 \\ 1.164 \end{bmatrix}^T$	$b_1 = \begin{bmatrix} 32.657 \\ 42.047 \\ -1.565 \\ 10.923 \\ -19.147 \\ -4.834 \\ -29.137 \\ 51.763 \\ 4.719 \\ 43.657 \end{bmatrix}$	$b_2 = \left[585.33\right]$

ANFIS-GP model with Gauss method (3 MF) was selected as the best model, whereas ANFIS-SC with the cluster radius of 0.234 yielded the best results for estimating BW.

In the training period, it is obvious from Table 5 that the MAE values were 31.41, 20.67, 10.53, 16.78, 6.70, 4.53, and 5.39 g for logistic, Richards, Gompertz-Laird, von Bertalanffy, ANN, ANFIS-GP, and ANFIS-SC, respectively. The results indicate that the ANFIS-GP model had the lowest MAE (4.53 g), whereas the logistic model had the highest value (31.41 g). Similarly, the RMSE value for ANFIS-GP was 6.36 g, while it was 35.05 g for logistic. Additionally, MAPE values for AI models ranged between 0.59 and 0.81%, whereas they varied between 2.22 and 12.34% for NL models.

In the testing period, the MAE values varied between 14.47-32.23 g and 7.68-8.99 g for NL and AI models, respectively. As with the MAE criterion, the ANFIS-SC model had the lowest RMSE value (11.93 g), while the logistic model produced the highest RMSE value (36.28 g). Similarly, MAPE values varied between 1.06 and 10.64%, depending on the model under consideration (Table 6).

Table 5. Error values of NL models and AI techniques used to predict weights for training dataset.
Çizelge 5. Eğitim veri seti için ağırlık tahmininde kullanılan NL ve YZ tekniklerinin hata değerleri.

Weight (g)	Logistic	Richards	Gompertz-Laird	von Bertalanffy	ANN	ANFIS-GP	ANFIS-SC
46	84.61	52.46	39.42	14.92	46.00	45.34	45.89
70	108.78	80.54	63.99	38.77	70.00	71.88	70.49
103	139.51	118.79	98.76	76.96	103.00	100.44	102.04
146	178.37	168.89	145.69	130.51	144.21	147.29	146.71
201	227.16	232.19	206.40	199.56	202.86	202.78	201.94
275	287.86	309.58	282.01	283.65	276.51	270.95	272.10
364	362.57	401.40	373.00	381.88	366.86	368.47	368.69
482	453.27	507.39	479.20	493.04	474.68	478.98	477.23
599	561.59	626.74	599.80	615.77	599.21	600.26	600.71
740	688.46	758.12	733.41	748.61	737.99	738.69	739.92
876	833.67	899.83	878.22	890.05	887.03	880.14	879.11
1044	995.58	1049.86	1032.09	1038.64	1041.70	1036.42	1036.05
1204	1170.92	1206.07	1192.70	1192.96	1198.15	1212.19	1212.52
1361	1354.92	1366.26	1357.73	1351.65	1354.85	1359.24	1359.51
1505	1541.72	1528.29	1524.89	1513.47	1513.33	1495.58	1495.95
1662	1725.10	1690.18	1692.06	1677.28	1677.33	1677.84	1680.17
1881	1899.30	1850.14	1857.35	1842.04	1849.29	1865.90	1859.84
2008	2059.66	2006.61	2019.10	2006.80	2025.42	2016.37	2020.27
2187	2203.08	2158.30	2175.96	2170.75	2193.81	2185.17	2189.69
2353	2328.08	2304.16	2326.81	2333.15	2339.73	2352.78	2344.87
2449	2434.58	2443.39	2470.83	2493.37	2454.02	2449.29	2452.29
MAE	31.41	20.67	10.53	16.78	6.70	4.53	5.39
RMSE	35.05	24.30	13.56	20.26	10.08	6.36	7.87
MAPE	12.34	5.87	2.22	8.28	0.61	0.81	0.59

Table 6. Error values of NL models and AI techniques used to predict weights for testing dataset.
Çizelge 6. Test veri seti için ağırlık tahmininde kullanılan NL ve YZ tekniklerinin hata değerleri.

Weight (g)	Logistic	Richards	Gompertz-Laird	von Bertalanffy	ANN	ANFIS-GP	ANFIS-SC
55	95.96	65.34	50.56	25.15	55.61	59.43	57.99
85	123.23	98.28	79.97	55.98	84.16	84.42	84.76
125	157.82	142.27	120.59	101.79	119.82	121.84	122.81
170	201.40	198.83	174.24	163.11	171.79	174.53	173.13
236	255.89	269.09	242.30	239.78	237.69	233.71	234.15
315	323.33	353.69	325.58	331.07	319.52	316.61	317.57
423	405.80	452.66	424.24	435.92	418.59	423.04	422.00
536	505.15	565.46	537.78	553.05	534.97	537.36	536.36
673	622.69	691.02	665.09	681.02	667.04	668.20	669.49
797	758.83	827.81	804.55	818.35	811.52	809.17	809.46
978	912.70	973.94	954.16	963.55	963.94	954.76	953.46
1118	1081.84	1127.33	1111.70	1115.17	1119.87	1124.67	1124.84
1294	1262.19	1285.80	1274.81	1271.83	1276.45	1290.58	1291.41
1388	1448.36	1447.17	1441.18	1432.24	1433.66	1424.62	1423.67
1585	1634.22	1609.37	1608.60	1595.20	1594.40	1579.91	1583.33
1762	1813.67	1770.50	1775.05	1759.61	1762.36	1777.40	1774.36
1959	1981.44	1928.90	1938.76	1924.48	1937.41	1942.81	1939.76
2118	2133.61	2083.12	2098.22	2088.93	2111.54	2095.85	2104.23
2260	2267.91	2232.01	2252.19	2252.18	2270.36	2276.08	2271.66
2408	2383.60	2374.64	2399.72	2413.57	2401.04	2408.75	2405.61
2485	2481.19	2510.34	2540.08	2572.48	2498.94	2481.70	2485.16
MAE	32.23	24.51	14.47	20.42	8.99	8.76	7.68
RMSE	36.28	27.62	20.53	27.71	13.56	12.83	11.93
MAPE	10.64	5.98	2.11	6.78	1.99	1.32	1.06

After comparing the results of NL and AI models, model estimation ability (ANFIS-SC > ANFIS-GP > ANN > Gompertz-Laird > Richards > von Bertalanffy > logistic) was determined for chicken weight estimation. At an early age, von Bertalanffy and Gompertz-Laird models underestimated weights, whereas the logistic model overestimated weights. Richards model was consistently overestimated weights at all ages. Yakupoglu and Atil (2001) compared the Gompertz and von Bertalanffy models to weekly body weight values in broiler flocks, and they reported that Gompertz was better than von Bertalanffy. Adenaike *et al*. (2017) found that Gompertz and von Bertalanffy models performed equally well at predicting chicken growth curves. Mouffok *et al.* (2019) stated that the Gompertz model was the most suitable for estimating broiler weight before four weeks of age, and after one month of age, the von Bertalanffy model was the best predictor of light chicken weights.

The growth pattern for "Ross 308" chicken by actual broiler weight and ANFIS-SC model are presented in Figure 2. Comparing the estimations with other AI studies, the RMSE and MAPE values of developed model were found lower than the studies of Berberoğlu and Özkan (2020), Koushandeh *et al.* (2019), and Roush *et al.* (2006).

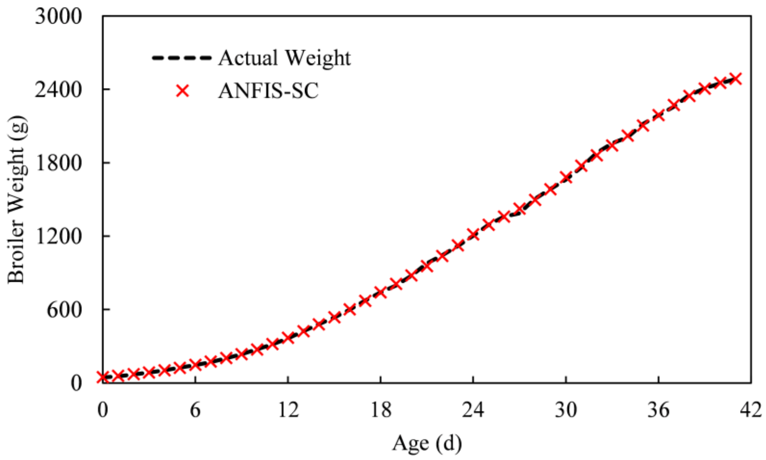

Figure 2. The weight of broilers used as testing data for the ANFIS-SC.
Şekil 2. ANFIS-SC modeli için test verisi olarak kullanılan etlik piliç ağırlığı.

Applying an AI model to make predictions for poultry growth, several advantages can be achieved, such as faster predictions using less time and resources. AI models are more accessible, require fewer variables, and perform more efficiently when determining poultry growth, but only if the data is appropriately handled.

CONCLUSION

In this research, the growth model of "Ross 308" chicken was compared using NL models and AI techniques. Based on the comparison of these results, AI techniques were superior to NL models for modeling broiler growth. Of all AI techniques studied in this research, the ANFIS-SC model best describes the growth pattern of "Ross 308" chicken based on MAE, RMSE, and MAPE (7.68 g, 11.93 g and 1.06%, respectively) for the testing data. In summary, this study demonstrates that AI techniques could be used effectively to identify broiler growth curves and is thus recommended as an alternative approach.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DECLARATION OF AUTHOR CONTRIBUTION

E.K. designed and performed the experiments, derived the models, and analyzed the data, B.C. was involved in planning and supervised the work. E.K. and B.C. wrote the manuscript.

ACKNOWLEDGMENT

This research was funded by the Ondokuz Mayıs University Scientific Research Projects Department (PYO.ZRT.1901.18.018).

REFERENCES

Abdurofi, I., Ismail, M. M., Kamal, H., & Gabdo, B. (2017). Economic analysis of broiler production in Peninsular Malaysia. *International Food Research Journal, 24*(2), 761-766.

Adenaike, A. S., Akpan, U., Udoh, J. E., Wheto, M., Durosaro, S. O., Sanda, A. J., & Ikeobi, C. O. N. (2017). Comparative evaluation of growth functions in three broiler strains of nigerian chickens. *Pertanika Journal of Tropical Agricultural Science*, *40*(4), 611-620.

Ahmad, H. (2009). Poultry growth modeling using neural networks and simulated data. *Journal of Applied Poultry Research, 18*(3), 440-446.

Balcioğlu, M. S., Kizilkaya, K., Karabağ, K., Alkan, S., Yolcu, H. İ., & Şahin, E. (2009). Comparison of growth characteristics of chukar partridges (Alectoris chukar) raised in captivity. *Journal of Applied Animal Research*, *35*(1), 21-24.

Berberoğlu, E., & Özkan, N. (2020). Estimation and comparison of growth curve in broilers through the artificial neural networks and gompertz models. *Journal of Agricultural Faculty of Gaziosmanpasa University*, *37*(2), 68-76.

Cetin, M., Sengul, T., Sogut, B., & Yurtseven, S. (2007). Comparison of growth models of male and female partridges. *Journal of Biological Sciences*, *7*(6), 964-968.

Chang, H.S. (2007). Overview of the world broiler industry: Implications for the Philippines. *Asian Journal of Agriculture and Development, 4*, 67-82.

Demuner, L. F., Suckeveris, D., Muñoz, J. A., Caetano, V. C., Lima, C. G. D., Faria, D. E. D., & Faria, D. E. D. (2017). Adjustment of growth models in broiler chickens. *Pesquisa Agropecuária Brasileira*, *52*, 1241-1252.

Eleroğlu, H., Yıldırım, A., Şekeroğlu, A., Çoksöyler, F. N., & 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*(3), 529-535.

Haykin, S. (2010). *Neural Networks and Learning Machines*. Pearson Education, New Jersey.

Koushandeh, A., Chamani, M., Yaghobfar, A., Sadeghi, A., & Baneh, H. (2019). Comparison of the accuracy of nonlinear models and artificial neural network in the performance prediction of Ross 308 broiler chickens. *Poultry Science Journal*, *7*(2), 151-161.

Narinc, D., Karaman, E., Aksoy, T., & Firat, M. Z. (2014). Genetic parameter estimates of growth curve and reproduction traits in Japanese quail. *Poultry Science*, *93*(1), 24-30.

Norris, D., Ngambi, J. W., Benyi, K., Makgahlele, M. L., Shimelis, H. A., & Nesamvuni, E. A. (2007). Analysis of growth curves of indigenous male Venda and Naked Neck chickens. *South African Journal of Animal Science*, *37*(1), 21-26.

Mouffok, C., Semara, L., Ghoualmi, N., & Belkasmi, F. (2019). Comparison of some nonlinear functions for describing broiler growth curves of Cobb500 strain. *Poultry Science Journal*, *7*(1), 51-61.

Porter, T., Kebreab, E., Kuhi, H. D., Lopez, S., Strathe, A. B., & France, J. (2010). Flexible alternatives to the Gompertz equation for describing growth with age in turkey hens. *Poultry Science*, *89*(2), 371-378.

Raji, A., Alade, N., & Duwa, H. (2014). Estimation of model parameters of the Japanese quail growth curve using Gompertz model. *Archivos de zootecnia*, *63*(243), 429-435.

Roush, W., Dozier, W., & Branton, S. (2006). Comparison of Gompertz and neural network models of broiler growth. *Poultry Science, 85*(4), 794-797.

Sariyel, V., Aygun, A., & Keskin, I. (2017). Comparison of growth curve models in partridge. *Poultry Science*, *96*(6), 1635-1640.

Shanmuganathan, S. (2016). Artificial neural network modelling: An introduction. In S. Shanmuganathan, & S. Samarasinghe (Eds.), *Artificial Neural Network Modelling. Studies in Computational Intelligence* (pp. 1-14). Cham, Germany: Springer.

Şekeroğlu, A., Tahtalı, Y., Sarıca, M., Gülay, M. Ş., Abacı, H. S., & Duman, M. (2013). Comparison of growth curves of broiler under different stocking densities by gompertz model. *Kafkas Universitesi Veteriner Fakültesi Dergisi*, *19*(4), 669-672.

Şengül, T., & Kiraz, S. (2005). Non-linear models for growth curves in large white turkeys. *Turkish Journal of Veterinary and Animal Sciences*, *29*(2), 331-337.

Tang, X., Li, J., Zhao, P., Liu, Z., & Chen, Q. (2010). Study on growth and development and fitting of growth curve of Huainan partridge duck. *Journal of Henan Agricultural Sciences*, *2*, 105-107.

Topal, M., & Bolukbasi, Ş. (2008). Comparison of nonlinear growth curve models in broiler chickens. *Journal of Applied Animal Research*, *34(*2), 149-152.

van der Klein, S., Kwakkel, R., Ducro, B., & Zuidhof, M. (2020). Multiphasic nonlinear mixed growth models for laying hens. *Poultry Science, 99*(11), 5615-5624.

Vitezica, Z., Marie-Etancelin, C., Bernadet, M.-D., Fernandez, X., & Robert-Granie, C. (2010). Comparison of nonlinear and spline regression models for describing mule duck growth curves. *Poultry Science*, *89*(8), 1778-1784.

Waller, D. L. (2003). *Operations management: A supply chain approach*. Cengage Learning Business Press, Boston.

Yakupoglu, C., & Atil, H. (2001). Comparison of growth curve models on broilers growth curve I: Parameters estimation. *Online Journal of Biological Sciences*, *1*(7), 680-681.