**Gaziosmanpaşa Üniversitesi Ziraat Fakültesi Dergisi**
*Journal of Agricultural Faculty of Gaziosmanpasa University*
http://ziraatdergi.gop.edu.tr/

Araştırma Makalesi/*Research Article*

JAFAG
ISSN: 1300-2910
E-ISSN: 2147-8848
(2020) 37 (2), 68-76
doi:10.13002/jafag4696

# Estimation and Comparison of Growth Curve in Broilers Through the Artificial Neural Networks and Gompertz Models

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Alındığı tarih (Received): 06.02.2020 Kabul tarihi (Accepted): 30.03.2020
Online Baskı tarihi (Printed Online): 09.07.2020 Yazılı baskı tarihi (Printed): 30.08.2020

**Abstract:** Mathematical models offer great convenience in estimating the variation in the growth of the living. The time-dependent change in weight and body sizes of the organism can be estimated easily via mathematical models. In this study, the growth curves of Ross 308 broilers compared through the Gompertz model, which explains growth best and the ANN model, which is assumed to be an alternative to this model. The model with high-estimated $R^2$ and low-estimated MSE, MAD, and MAPE values considered as the best model. The criteria obtained from the ANN and Gompertz models are 5625 and 2950 for MSE; 0.27, and 0.17 for MAPE; 0.5 and 1.2 for MAD, respectively while $R^2$ values were observed as 0.99 in both models. MSE and MAPE values were observed lower compared to the Gompertz model.

**Keywords:** Artificial neural networks, broiler, Gompertz model, growth curve live weight.

### Etlik Piliçlerde Büyüme Eğrisinin Yapay Sinir Ağları ve Gompertz Modeli ile Tahmin Edilmesi ve Karşılaştırılması

**Öz:** Canlının büyümesindeki değişimin tahminlenmesinde matematiksel modeller büyük kolaylıklar sağlamaktadır. Canlının ağırlık ve vücut ölçülerindeki zamana bağlı değişiminin tahmini matematiksel modeller ile kolay şekilde yapılabilmektedir. Çalışmada Ross 308 etlik piliçlerinin büyüme eğrileri, büyümeyi en iyi açıklayan Gompertz modeli ile bu modele alternatif olabileceği düşünülen YSA modeli karşılaştırılmıştır. $R^2$'sı yüksek; HKO, OMS ve OMYH değerleri düşük tahminlenen model en iyi model olarak dikkate alınmıştır. YSA ve Gompertz modelinden elde edilen kriterler sırasıyla HKO için 5625ve 2950; OMYH için 0.27 ve 0.17; OMS değerleri ise 0.5 ve 1.2; $R^2$ değerleri ise her iki model için de 0.99 olarak gözlenmiştir. HKO ve OMYH değerleri Gompertz modeline göre daha düşük olarak gözlenmiştir.

**Anahtar Kelimeler:** Yapay sinir ağları, Gompertz modeli, etlik piliç, canlı ağırlık, büyüme eğrisi

## 1. Introduction

Growth refers to the increase in the weight and body size of the living over a particular time. Physiological growth begins with the formation of zygote after sperm fertilizes the egg (Çolak et al., 2006). Despite being a hereditary feature, growth can vary by race, species, and individuals, and these differences can be explained by mathematics (Emsen et al., 2004). In the interpretation of growth parameters, there may be differences according to the characteristics analyzed and the mathematical model used. Besides, in cases where different models explain the same characteristics, the obtained parameters can better explain the same characteristics in one model, while not in another model (Köyceyiz, 2003).

In studies using nonlinear models, growth curve models serve a guide for further breeding research, and thus desired genetic and phenotypic characters can be achieved in selections to be done in breeding studies. Furthermore, the studies also reveal what sort of interaction can be possible between the obtained genotypes and environmental factors, which can be explained by growth curves (Yıldız et al., 2009).

The purposes of the use of growth curves in breeding can be summarized as follows; to show the change of measures of certain properties over time, to decide whether there are differences in terms of the researched properties, to determine the effects of different forms of care and feeding on the development of animals, to estimate the variable that could not be measured in some periods, to be able to make forward-looking decisions based on the data obtained to determine the optimal slaughter age, to ground a basis for the selection studies on growth curves and growth rate, to determine the general health conditions of animals (Yakupoğlu, 1999; Doğan, 2003; Lambe et al., 2006; Yıldız et al., 2009; Çelikoğlu et al., 2014).

With the advancement in computer technology, interest in artificial neural networks (ANN) has increased in recent years. The use of ANN, which is widely used in many areas, has also increased in agriculture. ANN is also often preferred because this model produces easy solutions to complex and nonlinear problems (Gevrekçi et al., 2011).

ANN has been used in various studies conducted on animal production. ANN refers to computer software created by the imitation and development of the information processing system in the human brain to find solutions to various problems. Created through the sampling of an existing biological neural network in the human brain, ANN has the skills to memorize, learn, reveal the relationships between variables, produce new information about what they have learned and generalize. There are significant relationships between statistical methods and ANN technology, which can be successfully applied in many fields (Yazıcı et al., 2007).

In this study, the growth curves of live weight in broilers were modeled with the Gompertz model and ANN, and these two models were compared.

## 2. Materials and Methods

Gaziosmanpaşa University Agricultural Application and Research Center for 0-6 weeks of live weights obtained from 121 Ross 308 broiler chicks fed in individual cages data. The study was approved by the Animal Experiments Local Ethics Committee of Tokat Gaziosmanpaşa University (2018-HADYEK-23).

The Gompertz model used to model the growth curve, which is one of the methods in this study, was calculated with the following equation:

$$Y = Ae^{-\beta e^{-kt}} \quad (1)$$

where;

**Y** 6th week live weight in the equation, **A** asymptotic weight, **β** integration constant, **exp** natural logarithm base, **t** refers to the time, and **k** the rate of growth. Parameter A is the highest live weight that the animal can reach (Şahin et al., 2014). The initial values of $\beta_1$ and $\beta_2$ were calculated based on the following equations.

$$\beta_1 = \frac{(y_2 - y_1)/(t_1 - t_2)}{b_0} \quad 2)$$

$$\beta_2 = -\log_e y(0) + \log_e \beta_0 \quad (3)$$

where y1 and y2 are the highest and lowest values of the weight variable corresponding to the broadest time interval of t1 and t2; b0 is the initial value of the parameter β0 (Narinç et al., 2009).

ANN used in this study is the networks formed by interconnecting neurons in various ways through the sampling of the way the biological nervous system works. These networks can store information, learn, and specify the relationship between data (Öztemel, 2003). ANN has general characteristics such as being nonlinear, learning, generalization, applicability, and fault tolerance. As ANN is modeling of biological neural networks, it is necessary to analyze the structure of the biological nervous system initially to understand its structure. Neurons, which are the building blocks of the biological nervous system, consist of four main parts. Figure 1 shows these parts as nucleus, axon, dendrites, and synapses (Çayıroğlu, 2003).

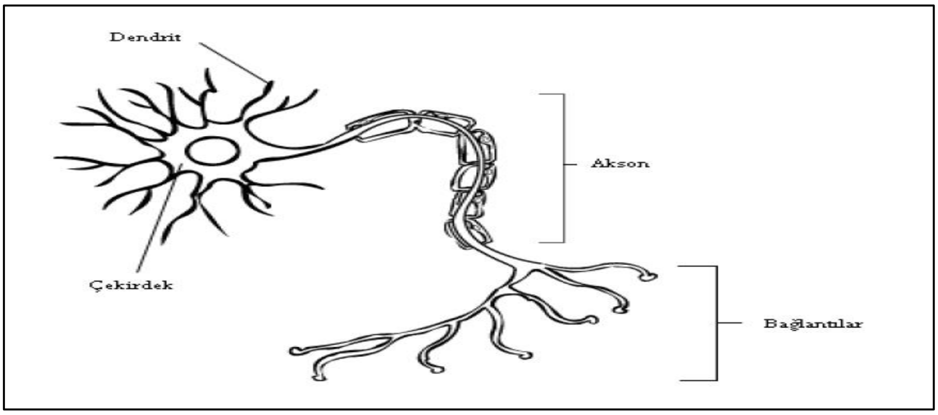


**Figure** 1. Biological nerve cell structure
***Şekil 1.*** *Biyolojik sinir hücre yapısı*

The smallest units, which constitute the basis of the working system of ANN, are called operational elements or artificial nerve cells. In the simplest form, as presented in Figure 2, the artificial nerve cell structure consists of five main components, being inputs (weights$X_i$)($W_i$), aggregate function (NET), activation function (F (NET)) and output.

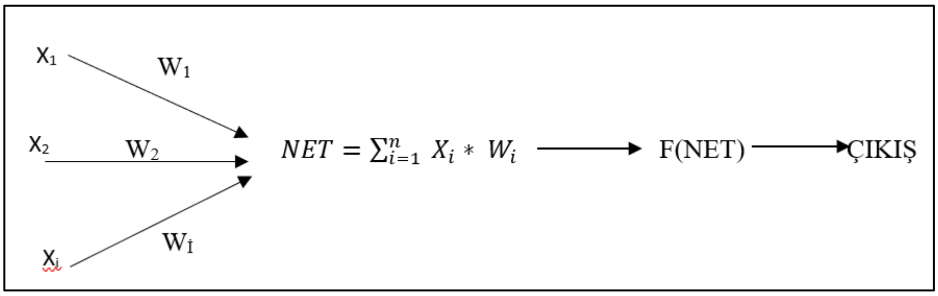


**Figure 2.** Artificial nerve cell structure
***Şekil 2.*** *Yapay sinir hücre yapısı*

The sigmoid function is generally used as an activation function that minimizes error in the multi-layer sensor model, which is widely used nowadays (Öztemel, 2003). The backpropagation algorithm also uses the sigmoid function that produces real values between 0 and 1 as the activation function. Due to the sigmoid function in the backpropagation algorithm, actual outputs can be provided, even between two close values. Thus the right decision can be made. Therefore, reverse learning is inevitable in solving nonlinear problems (Nabiyev, 2003).

f (x) = $\frac{1}{1+e^{-NET}}$, here refers to the NET input value of the element is under the NET process. This value is determined through the aggregate function (Öztemel, 2003).

As presented in Figure 4, ANN is the structure formed as a result of the interconnection of the artificial nerve cells and consists of three layers. These are the input layer, interlayer, and the output layer (Öztemel, 2003).

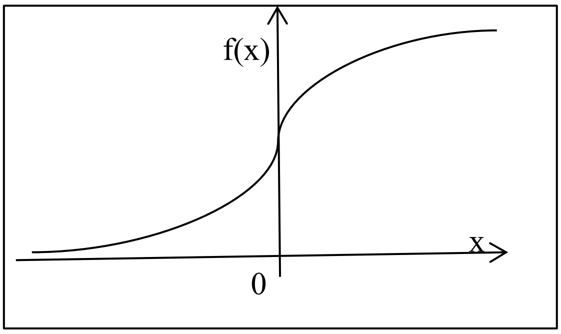


**Figure 3.** Sigmoid activation function model
***Şekil 3.*** *Sigmoid aktivasyon fonksiyon modeli*

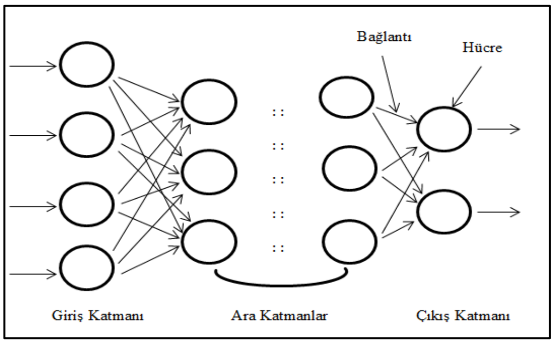


**Figure 4.** Artificial neural network structure
***Şekil 4.*** *Yapay sinir ağı yapısı*

A large number of connections can be established between cells in separate layers while no connection is established between cells in the same layer (Yılmaz, 2015). The data from the outside is taken by nerve cells placed in the input layer and transmitted to the input layer, interlayer, and output layer, respectively (Yılmaz, 2015). The network itself is responsible for the operation that occurs in the interlayer. This layer is, in a sense, the intelligence part of the network, and a large number of neurons in that layer leads the network to memorization. . The network is expected to learn rather than memorizing. In this way, the network will be able to tolerate any changes made through the learning process; otherwise, it will not be able to solve a knowledge-based problem in small change (Nabiyev, 2003).

Learning systems in ANN are of three types; supervised, unsupervised, and reinforcement learning systems (Takma et al., 2012). In a supervised learning system, output values corresponding to the input values also give to the network. In the unsupervised learning system, only input data is displayed to the network, while the expected output data is not displayed. In a reinforcement learning system, information gives to the network according to the results obtained at the end of each iteration (Çayıroğlu, 2003; Öztemel, 2003).

In this study, the feed-forward backpropagation supervised algorithm selected as a network type. The reason for preferring the algorithm was that during the training of the network when a forward connection is first established, the network obtained outputs corresponding to the input values by using its weights, and reverse propagation algorithm ensures backward rearrangement of the weights to mitigate error that occurs in the output layer. Furthermore, the Levenberg-Marquardt algorithm was preferred as the training function of the network since it significantly increases the learning speed. According to Kaastra et al. (1996), networks with an interlayer generally found to be successful in solving ANN problems (Aksu et al., 2016). The number of interlayers used in the network was taken as one because the over-preferred number of interlayers increases the complexity of calculation and extends the time. The number of neurons in the interlayer was determined by the method of trial and error (Takma, 2012; Yılmaz, 2015). The percentage (%) values used to determine the number of sampling during the training of the network were taken as 5 -10 -15 -20 -30 -35%, respectively within the limits of the program. Training, validation, and test set percentages were tried as 50 -60 -70 -80 -90%, respectively in order to determine the most accurate network model. Afterward, the network was trained. The network updated its weight to determine the desired output in response to the given inputs so that the error between the outputs of the network and the output observed by the network was calculated by the network, and the new weights of the network were regulated by this margin of error.

In practice, 21 different percentage distributions were used within the limitations of the program. Table 1 presents these percentage distributions and sampling numbers corresponding to percentages. The number of neurons in the interlayer was determined in 5 different ways, being the number of neurons (10), minus two (9-8), and two (11-12), which is automatically assigned by the program. For achieving the most accurate result, a total of 105 network models, including five different neurons (21x5), were tested in 21 applications. As a result of the analysis, the model with the highest $R^2$ value in all sets, including training, testing, and validation set, was chosen as the best model

(Şahin et al., 2014). Besides, the MSE and $R^2$ values in the training, validation, and test sets were examined to determine whether the network completed the training by learning or memorizing. - The network calculated low MSE in the training set and high MSE in test set; high $R^2$ in the training set and low $R^2$ in the test set, however, the network model only memorized (Aka et al., 2018).

**Table 1.** ANN data set distribution
***Çizelge 1.*** *YSA veri seti dağılımı*

| Training set (%) | Validation set (%) | Test set (%) | Training set (%) | Validation set (%) | Test set (%) | Training set (%) | Validation set (%) | Test set (%) |
|---|---|---|---|---|---|---|---|---|
| 50 | 15 | 35 | 60 | 15 | 25 | 70 | 15 | 15 |
| 50 | 20 | 30 | 60 | 20 | 20 | 70 | 20 | 10 |
| 50 | 25 | 25 | 60 | 25 | 15 | 70 | 25 | 5 |
| 50 | 30 | 20 | 60 | 30 | 10 | 80 | 5 | 15 |
| 50 | 35 | 15 | 60 | 35 | 5 | 80 | 10 | 10 |
| 60 | 5 | 35 | 70 | 5 | 25 | 80 | 15 | 5 |
| 60 | 10 | 30 | 70 | 10 | 20 | 90 | 5 | 5 |

In this study, SPSS 17.0 for Windows was used for parameter estimation of the Gompertz model, and MATLAB statistical package programs for model estimation with ANN. Comparing the two models, the coefficient of determination ($R^2$), mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean squared error (MSE) criteria were used. $R^2$ values were used to determine the best estimating ANN model. (Asilkan et al., 2009; Yavuz et al., 2013). The equations of these criteria are presented below.

$$R^2 = \frac{\sum(\hat{y}_t-\bar{y})^2}{\sum(y_t-\bar{y})^2} \quad (4)$$

$$MAD = \frac{\sum_{t=1}^{n}|y_t-\hat{y}_t|}{n} \quad (5)$$

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right|}{n} * 100 \;\; (y_t \neq 0) \quad (6)$$

$$MSE = \frac{\sum_{t=1}^{n}(\hat{y}_t-y_t)^2}{n} \quad (7)$$

In the equations, $y_t$ is the value observed in t period, $\hat{y}_t$ is the value estimated through the model for t period, n is the total number of observations.

MAPE statistics are recognized to be superior to similar methods as it is expressed as a percentage (Çuhadar et al., 2009; Yavuz et al., 2013). According to the MAPE categorization made by Witt and Witt (1992) and Levis (1982); models detected below 10% are considered "very good," those between 10-20% as "good," those between 20 -50%. As "acceptable" and those above 50% as "faulty" (Çuhadar et al., 2009).

## 3. Results and Discussion

In ANN analysis based on MSE, R2, and scatter plots among 105 models, the model with 12 neurons, 80% training, 15% validation, and 5% test set detected as the best model. Table 2 presents MSE and $R^2$ values for this model, and Figure 5 shows the scatter plot of the model. The $R^2$ values obtained from the model were found as 0.97, 0.97, 0.99 for training, validation, and test sets, respectively. These R2values are the highest R2values, among other models. Therefore, this model selected as the best among all the models. 0.99 R2 value detected for the test set also indicates that the model is a good one. Considering the MSE value of the sets, it can be observed that the MSE in the training set was low, and the $R^2$ value was high, which indicates that the selected model did not memorize but completed the training successfully.

**Table 2.** MSE and $R^2$ values of the best model determined by ANN analysis
***Çizelge 2.*** *YSA analizi ile belirlenen en iyi modele ait HKO ve R² değerleri*

| **Data Set** | **(%)** | **MSE** | **$R^2$** |
|---|---|---|---|
| Training Set | **80** | **7 005** | **0.97** |
| Validation Set | **15** | **11 457** | **0.97** |
| Test Set | **5** | **5 625** | **0.99** |

The distribution of two variables together is examined through scatter plots. According to the distribution of points on the scatter plot, it can be determined whether there is a weak, strong, and complete relationship between variables (Alpar, 2013). The best result in the plot showing the overlap of the network's output and target values is possible with the maximum stack on the 45-degree curve (Kubat, 2015).

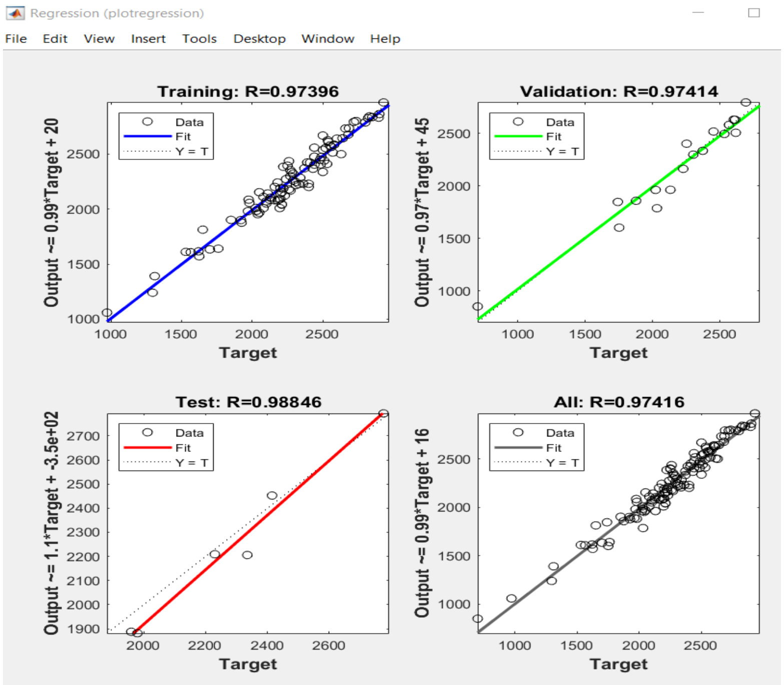


**Figure 5.** Regression scatter plots of the twentieth application.
***Şekil 5.*** *Yirminci uygulamaya ait regresyon saçılım grafikleri*

The regression line drawn in the training and validation sets in the plots of the model determined by ANN analysis in Figure 5 coincides with the 45-degree line and the test set is very close to this value. Other applications do not have such a close overlap. No other network models were preferred along with scatter plots and $R^2$ values since some networks only memorize.

The estimated $R^2$ value for the ANN reported by Ahmadi et al., (2007) and Roush et al., (2006) is 0.99. These values reported in the literature are in line with the estimated value of the model.

**Table 3**. Parameters of the Gompertz model
***Çizelge 3***. *Gompertz modeline ait parametreler*

| **Model** | **A** | $S_{\bar{x}a}$ | **β** | $S_{\bar{x}b}$ | **k** | $S_{\bar{x}k}$ |
|---|---|---|---|---|---|---|
| **Gompertz** | 3999 | 585.7 | 4.6 | 0.39 | 0.05 | 0.008 |

The reason why estimated values were found different from other studies was the fact that the live weight values were taken at different periods, maintenance and feeding conditions and trial periods were different. Live weight increase continues over time and changes the initial value of parameter A.

The parameters of the Gompertz model used in the study are given in Table 3. The parameters A, β, and k were found as 3999, 4.6, and 0.05, respectively. Parameter A was found lower than the studies of Narinç et al. (2007) and Eleroğlu et al. (2016) and higher than Mohammed (2015). Parameter β was found similar to the studies of Şekeroğlu et al. (2013), Eleroğlu et al. (2016) and Mohammed (2015); lower than Narinç et al. (2007) Parameter k was found in line with the studies of Mohammed (2015) and Şekeroğlu et al. (2013); and lower than Narinç et al. (2007) and Eleroğlu et al. (2016).

Growth curve graphs for the weekly live weight values estimated and observed from the specified models are presented in Figures 6 and

7. The growth curve estimated by the Gompertz model shows that the shape of the growth curves coincided with the ANN through which a deviation between the 21-42 days was estimated.

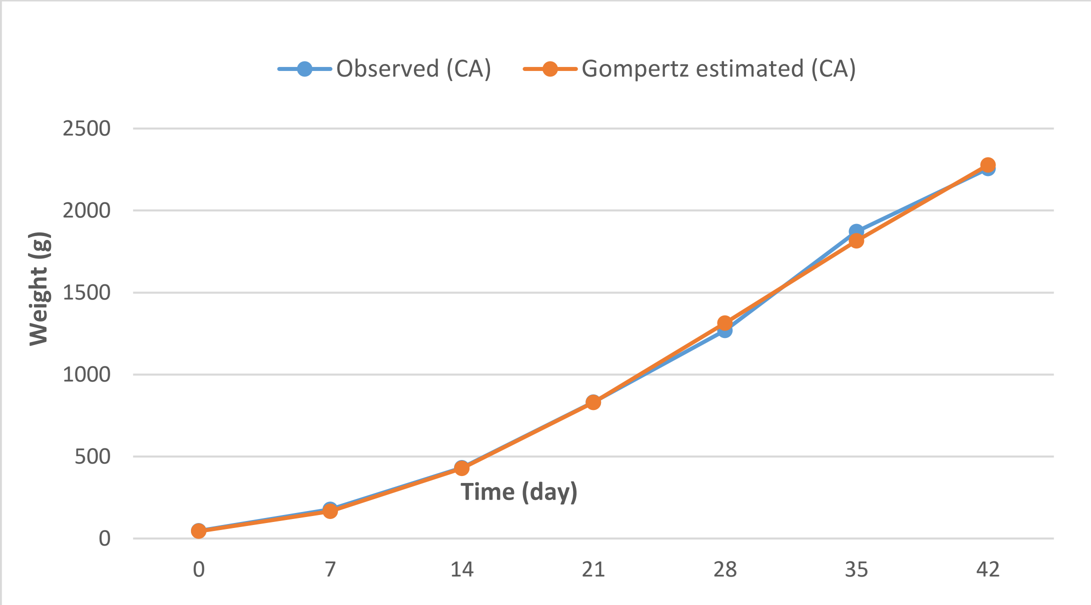


**Figure 6.** Change of observed and estimated values through the Gompertz model
***Şekil 6.*** *Gompertz modeli ile tahminlenen ve gözlenen değerlerin değişimi*

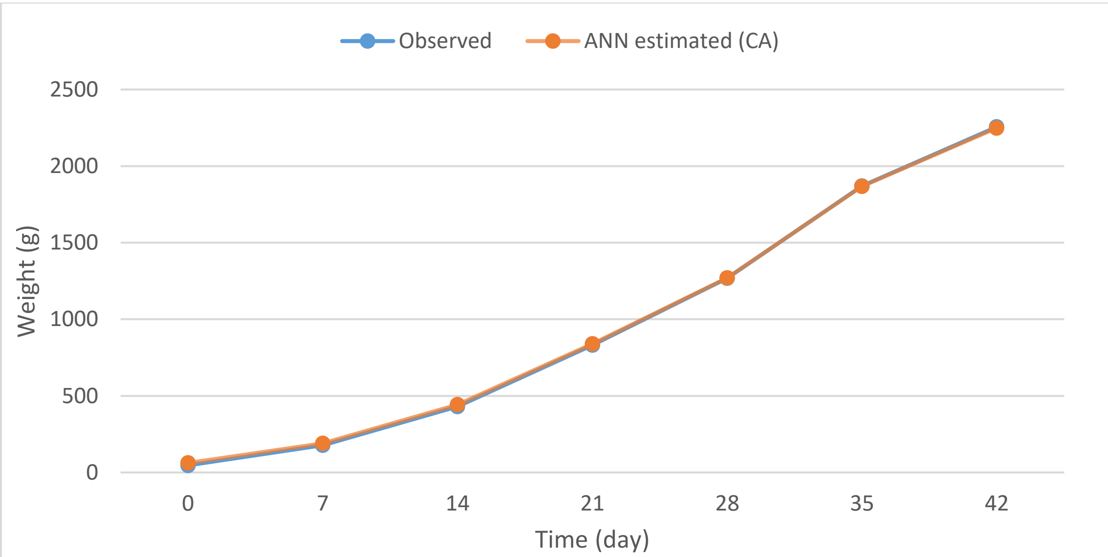


**Figure 7.** Change of observed and estimated values through the ANN model
***Şekil 7.*** *YSA modeli ile tahminlenen ve gözlenen değerlerin değişimi*

Comparison criteria for Gompertz and ANN model are presented in Table 4. In Table 4, MSE, MAPE, MAD, and $R^2$ were 2950, 1.2, 0.2, and 0.99 for the Gompertz model, respectively, and 5625, 0.5, 0.27, and 0.99 for ANN. In both models, $R^2$ was found equal, while the MAD was high in Gompertz while the other criteria were low. According to the results of the study, despite the high difference in MSE, both models made very good estimations considering $R^2$, MAD, and MAPE values according to the classification of Witt and Witt (1992) on MAPE values.

**Table 4**. Estimation criteria of Gompertz and ANN models

***Çizelge 4.*** *Gompertz ve YSA modele ait tahmin kriterleri*

| Model | MSE | MAD | MAPE (%) | $R^2$ |
|---|---|---|---|---|
| **Gompertz** | 2950 | 1.2 | 0.17 | 0.99 |
| **ANN** | 5625 | 0.5 | 0.274 | 0.98 |

Comparing the estimations with other studies, MSE was found higher than the studies of Eleroğlu et al. (2016) Mohammed (2015), higher than the first stocking density of Şekeroğlu et al. (2013) and similar with the other studies. $R^2$ values reported by Şekeroğlu et al. (2013), Adenaike et al. (2017), Roush et al. (2006), Mohammed (2015), Eleroğlu et al. (2016) and Topal et al. (2008) coincide with the value of the R value in the present study. The high $R^2$ value indicates a very good estimation. MAPE and MAD values were lower than Roush et al. (2006). MAPE and MAD values of ANN were found lower than Roush et al. (2006) and Ahmadi et al. (2007).

## 4. Conclusion

In the study, it was observed that ANN and Gompertz models gave close results. The $R^2$ value is the same in both models; MAPE and MAD values were close to MSE, whereas Gompertz model was lower However, ANN estimated the live weight at the end of fattening, which is important in stockbreeding, with small errors than the Gompertz model.

In Gompertz model, individual parameters are estimated and averaged for each animal. It causes loss of time and raw data loss when the parameters are averaged. ANN is an easy method. A single model is obtained from the data of all animals. It prevents loss of time and data. Also, since ANN is not affected by the changes in the data set, it can be retrained even when new information occurs or when changes occur

As a result, ANN can be used as an alternative to classic growth curve models since it yields close results to the Gompertz model, prevents data loss, adapts to changes, and can be retrained.

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