

Modeling the number of horses in Turkey through Time Series Analysis and Artificial Neural Networks

Şenol Çelik

Bingol University, Faculty of Agriculture, Department of Animal Science, Biometry and Genetic Bingol, Turkey Correspondence: Şenol Çelik

Submitted: 30-08-2021	Revised: 03-09-2021	Accepted: 05-09-2021

ABSTRACT

The aim of this study is to make a production plan by using artificial neural networks (ANN) and time series analysis for establishing appropriate models and forecasting the mule population in Turkey over the years.

The years parameter was used as an input parameter in the development of time series analysis and artificial neural network, and the number of horses was used as an output parameter. Mean square error (MSE) and Mean Absolute Error (MAE) statistics were used to calculate the efficiency of the developed model. According to the results obtained, there will be a slow increase in the number of horses from 2021 to 2025.

It has been observed that ANN models outperform time series analysis in predicting horses population. **Keywords:** Artificial neural network, time series, forecasting, horses.

I. INTRODUCTION

Turkey, due to its climate and the important role of horse in our culture, has a large number of warm-blooded horses. Turkey has a considerable amount of Arabian and Thoroughbreds as well as at Haflinger. Irish Hunter, Anglo-Arabian, Hanoverian, Holstein, Akhal-Teke and Kabardin horses. In addition to these breeds, there are various types of horses such as Anadolu, Araba, Canik, Cirit, Çukurova, DoğuAnadolu, Hınıs, Karacabey, Karakaçan, Malakan (Ardahan), EgeMidillisi, Rahvan, Trakya and Uzunyayla that are used for many years in the different regions of Anatolia (Yildirim, 2014).

According to TSI (Turkish Statistical Institute) records of the year 2017, Kars, Erzurum, Van, Ağrı,Muşand Ardahanprovinces in Eastern Anatolia Region has the biggest share of the horse population in Turkey. The total number of horses in these 6 provinces are22149 and their total share (90007) is 24.61% in Turkey. Şanlıurfa province is in the first place in Turkey with 7347 horse presence. This province is followed by Kars with 6036 and Erzurum with 5226 (TSI, 2020).

The first scientific writing named "Hippike" regarding horses' body structure and military use was written by Xenophon (445-354 BC). The first quantitative approach in this topic was carried out by Bourgelat, who had been working on the body sizes of horses, in the 18th century. In the other scientific studies performed in the early 19th and early 20th centuries, joint angles in the legs have been taken into consideration (Bokor, 2011).

Body sizes are also a good indicator of reflecting horses' postnatal development and are closely related to the horse's performance. For this reason, body structure appropriateness and body sizes are of vital importance. In addition, the body structure determines the expected form of function from the animal (Arpacik, 1999, Akcapinar and Ozbeyaz, 1999).

Body sizes that reflect horses' body structure ideally are the general characteristics of appearance such as withers height, chest girth and cannon bone circumference measurements. The general appearance is one of the most important factors taken into account in selection studies (Bayram et al., 2005). The withers height of purebred British horses whose development has been completed is reported as between 160-170 cm (Demir, 1997; Arpacik, 1999). The average withers height values of the purebred British horses bred in America, Australia, England, India and New Zealand have been determined as follows respectively; 131.2-135.4 cm in 6 months; 144.2-147.8 cm in 12 months and 151.2-156.0 cm in 18 months (Brown-Douglas and Pagan, 2009).

There are some studies carried out with regards to the body sizes of the horses (Dogan et



al., 2002; Bayram et al., 2005; Kaygısız et al., 2011; Yilmaz and Ertugrul, 2014, Çelik et al., 2014; Çelik et al., 2015; Duru et al., 2017).

The present study goals to model the number of horses in Turkey using time series analysis and the artificial neural network method and to make predictions for the coming years.

II. MATERIALAND METHOD MATERIAL

The material of the study is 1961-2020 number of horses values supplied from the www.tuik.gov.tr web address of Turkish Statistical Institute (TSI, 2020) and Food and Agriculture Organization of the United Nations (FAO, 2019). The dependent variable was number of mule figures while the independent variable was year series. These variables were selected in order to be able to make reasonable estimations with the models to be performed using ANN and time series analysis methods.

METHOD

ARIMA Models

A pth-orderautoregressive modelAR(p) model is point out as (Cooray, 2008).

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} + e_t$$

AR(p) model uses a linear combination of past values of the target to make forecasts.

A qth-order moving average process, expressed MA(q), is indicated by (Cryer, 1986).

$$\mathbf{y}_{t} = -\theta_{1}\mathbf{e}_{t-1} - \theta_{2}\mathbf{e}_{t-2} - \dots - \theta_{q}\mathbf{e}_{t-q} + \mathbf{e}_{t}$$

ARMA(p,q) model composed of apth-order autoregressive andqth-order moving average process and it is showed by (Hamilton, 1994).

$$\begin{split} y_t &= \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \dots + \varphi_p y_{t-p} + e_t - \theta_1 e_{t-1} \\ &\quad - \theta_2 e_{t-2} - \dots - \theta_q e_{t-q} \end{split}$$

In order for time series models to be applied, series must be stationary and white noise (Kadılar and Çekim, 2020).

Artificial neural networks (ANN)

The artificial neural network (ANN) consists of numerous interrelated simple processing elements called neurons. These neurons take on input signals from the environment. The signals are transformed by connecting weights and through a process of training, the neurons get activated by

transfer functions to give a desired output (Pujol and Pinto, 2011; Schmidhuber, 2015).

ANN, which is a computational intelligence technique has been found to be more efficient than the standard empirical models. Neural networks have been very effective for modeling and for characterization of complex systems for a number of applications(Afrand et al., 2016; Meruelo et al., 2016).

One of the most common used type of ANN is the feedforward network. The architecture of a feedforward neural network is nonlinear. Therefore, the output is obtained from the input through a feedforward arrangement. The multilayer perceptron (MLP) is a type of feedforward neural network, consisting of input, hidden and output layers (Beale et al., 2011; Moghaddam et al., 2016).

The used activation function in configuration of ANNs in the study is Hyperbolic tangent sigmoid function (Bouabaz and Hamami, 2008).

$$f = \frac{2}{1 + e^{-net_j}} - 1$$

Normalization method standardizes the values of the input variables. Min Max normalization:Implements a linear transformation on the actual data. It normalizes the data in the range 0 to 1 by the formula (Öztemel, 2012):

$$\mathbf{X}^{'} = \frac{\mathbf{X}_{\mathrm{i}} - \mathbf{X}_{\mathrm{max}}}{\mathbf{X}_{\mathrm{max}} - \mathbf{X}_{\mathrm{min}}}$$

Where, X_i : Data value to be normalized, X': Normalized value of X_i , X_{min} : Minimum value, X_{max} : Maximum value.

To evaluate the precision of the predicted discharge volume, Square Mean Square Error (RMSE), Mean Square Error (MSE) and Mean Absolute Error (MAE) were used (Eyduranet al., 2019; Wangand Lu, 2018):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y_{ip})^2}{n}}$$
$$MSE = \frac{\sum_{i=1}^{n} (y_i - y_{ip})^2}{n}$$
$$MAE = \frac{1}{n} \sum_{i=1}^{n} |(y_i - y_{ip})|$$



Here, y_i is the real value of the dependent variable (number of pig), y_{ip} is the predicted value of the dependent variable (number of pig) and n is the number of samples.

III. RESULTS AND DISCUSSION

The artificial neural networks and ARIMA method goodness of fit statistics (RMSE, MSE and MAE) of number of mulebetween the years 1961-2020 in Turkey are demonstrated in Table 1. The time series graph is shown in Figure 1.

Table 1. Model performance values			
Fit Statistic	ARIMA(3,1,0)	ANN	
MSE	2941173.550	1210524.639	
RMSE	1714.985	1100.238	
MAE	1247.491	828.814	

Considering Table 1, when the time series analysis and artificial neural network methods are compared according to square mean square error (RMSE) values, MSE and MAE, artificial neural networks (ANN) with minimum RMSE, MSE and ME values (RMSE=1100.238, MSE=1210521.639 and MAE=828.814) are the most suitable model. The hyperbolic tangent function was used as activation function when creating a model with the ANN method. The number of neurons in the input layer, the hidden layer and the output layer was determined as 12-12-1 each. 1000 iterations were used for the ANN method in the data series consisting of 60 observations between 1961-2020.



Figure 1. Time series graph

The parameter coefficient of the time series model modeled as ARIMA (3,1,0) is $\phi_3 = -0.518$ and shown as;

$$(1 - B)(1 + 0.518B^3)X_t = e_t$$

 $(1 - B)(1.518B^3)X_t = e_t$

The model was found to be appropriate because its Ljung-Box statistics were 13.141 and p

= 0.727> 0.05. However, as the ARIMA and ANN methods compared, it has been observed that the ANN method had better results (Table 1). Since the MSE, RMSE, and MAE values are lower in the ANN method, it is much more appropriate.

The estimated and residual values are presented in Table 2 together with the real values of the ANN methodfor 2000-2020 period.

Table 2. Observed, predicted and residual values			
Years	Actual	Predicted	Residual
2000	3400	4993.590	-1593.590
2001	3000	5197.009	-2197.009
2002	2700	4444.876	-1744.876
2003	3595	4354.446	-759.446
2004	7090	3443.639	3646.361

Table 2. Observed, predicted and residual values

DOI: 10.35629/5252-0309268275 Impact Factor value 7.429 | ISO 9001: 2008 Certified Journal Page 270



2005	4399	3726.773	672.227
2006	1934	3212.175	-1278.175
2007	1362	2131.920	-769.920
2008	1813	2308.321	-495.321
2009	1717	2038.106	-321.106
2010	1896	1877.204	18.796
2011	1558	1722.817	-164.817
2012	1848	1801.737	46.263
2013	2986	2031.112	954.888
2014	3145	1883.979	1261.021
2015	2655	1729.842	925.158
2016	1642	1818.470	-176.470
2017	1299	1715.118	-416.118
2018	1361	1640.051	-279.051
2019	1636	1642.608	-6.608
2020	990	1561.826	-571.826

The graph of the observed and estimated values obtained with ANN method ispresented in Figure 2.



Figure 2. The combined graph of observed and estimated values for number of pig

In Figure 3, meantime the joint graph of observed and residual values was observed, residual and observed values were found to be

scattered free from each other and randomly. This situation shows that important hypotheses regarding the model are provided.





Figure 3. Joint graph of observed and residual values

The possible 2021-2025 number of pig forecasted with ANN and ARIMA(3,1,0) are given in Table 3.

Years	ARIMA(3,1,0)	ANN
2021	958	1533
2022	845	1557
2023	1150	1637
2024	1167	1537
2025	1241	1566

Table 3.	Number	of pig	fore	casting

Table 3 shows that the number of pigs will fluctuatebetween 2021-2025. The graph showing the actual and predicted values of the number of pig is shown in Figure 4.



Figure 4. The joint graph of observed and estimated values



In our study, we have obtained an appropriate model for predicting ARIMA (3,1,0) and ANN. Using these models, it is possible to predict that the number of pigs in the future will fluctuate.

There are some studies in the field of agriculture that employed artificial neural networks.

Eyduran et al. (2020), used exponential smoothing methods with ARIMA (0,1,1), ARIMA (1,1,0) and ARIMA (1,1,1) for the modeling of banana production forecast in Turkey. Brown's approach was selected as the most appropriate method in the study of authors. In another study, the modeling of Turkey's tobacco production has been made by employing artificial neural networks. In the said study, model suitability was tested according to MSE and ME, and a fluctuating course in tobacco production is predicted for the 2020-2025 period (Celik, 2020a). It is estimated that there will be a fluctuating course as suggested in this study. Another study used ARIMA models to analyze the production amount of some forage crops from 1969 to 2016, and a prediction was made between 2017 and 2025. The vetch plant was modeled as ARIMA (0,1,1) (Agirbas et al., 2019). As a result of time series analysis of the 1950-2010 period peanut production in Turkey, The ARIMA (0,1,1) model was obtained and the prediction between 2016-2030 was made according to this model. According to the prediction results, it was estimated that the amount of peanut production will increase in the period (Celik et al., 2017). ANN was used to model the production quantity of orange, tangerine, chickpea, and lentil plants (Celik, 2019a, Celik, 2019b, Celik, 2020b, Celik, 2020c).

IV. CONCLUSION

The number of pigs in Turkey was estimated by employing artificial neural networks and ARIMA models in this study. The input variables are the years (1961-2020), one independent variable, and the number of pigs as the output variable. For the next stage, the preparation, testing and verification processes of the network were carried out and the estimation process was carried out.

The results point out that the proven ANN method provides better estimates than ARIMA models. This is also supported by the low RMSE, MSE, and ME values in the preparation, testing, and verification phases.

Considering the prediction of the number of pigs, the said figure, which was 990 in 2020, is predicted to increase by 58.18% and reach 1566 in 2025. In the 2021-2025 period, there will be both an increase and a decrease. In other words, it is expected that the number of pigs would fluctuate.

In general, when compared to time series analysis, artificial neural networks are more effective in predicting available data. It is noted that good results in agriculture can be obtained by comparing artificial neural networks and alternative approaches in future prediction studies.

REFERENCES

- [1]. Afrand, M., Nadooshan, A.A., Hassani, M., Yarmand, H., Dahari, M. 2016. Predicting the viscosity of multi-walled carbon nanotubes/water nanofluid by developing an optimal artificial neural network based on experimental data, Int. Commun. Heat Mass Tran., 77: 49–53.
- [2]. Ağırbaş, N. C., Çelik, Ş., Sapmaz, K. 2019. Modeling forage crops production using the time series method. Fresenius Environmental Bulletin, 28(11):7763-7776.
- [3]. Akçapınar, H.,Özbeyaz, C. 1999.Hayvan Yetiştiriciliği Temel Bilgileri. Kariyer Matbaacılık Ltd. Şti., Ankara.
- [4]. Arpacık, R. 1999. At yetiştiriciliği. Şahin Matbaası, Ankara.
- [5]. Bayram, D., Öztürk, Y., Küçük, M. 2005.The Phenotypic Characteristics of Horses raised in Van Region. YYÜ Veteriner Fakültesi Dergisi 16(1):85-88, 2005.
- [6]. Beale, M. H., Hagan, M. T., Howard, B. D. 2011. Neural Network toolbox TM 7 User Guide.
- [7]. Bokor, A. 2011. Sport horse breeding. Agricultural and Food Science Non-profit Ltd. Kaposvar University.
- [8]. Bouabaz, M., Hamami, M. 2008. A cost estimation model for repair bridges based onartificial neural network. American Journal of Applied Science 5(4): 334–339.
- [9]. Brown-Douglas, C. G., Pagan, J.D. 2009. Body Weight, Wither Height and Growth Rates in Thoroughbreds Raised in America, England, Australia, New Zealand andIndia. Advances in Equine Nutrition Vol. IV, P. 213-220.
- [10]. Cooray, T. M.J.A. 2008. Applied Time Series. Analysis and Forecasting. NarosaPublishing House Pvt. Ltd., New Delhi.
- [11]. Cryer, J. D. 1986. Time Series Analysis. PWS Publishing, USA.
- [12]. Çelik, Ş. 2019a. Estimation of the orange production in Turkey by means of artificial



neural Networks. Global Journal of Engineering Science and Researches, 6(9): 10-16.

- [13]. Çelik, Ş. 2019b. Prediction of Mandarin Production in Turkey through Artificial Neural Networks and Time-Series Analysis. International Journal of Trend in Research and Development, 6(5):85-90.
- [14]. Çelik, 2020a. Estimation modelling of tobacco production in Turkey: Comparative Analysis of Artificial Neural Networks and MultiplicativeDecomposition Methods. International Journal of Trend in Research and Development, 7(4):154-187.
- [15]. Çelik, 2020b. Modelling and estimation of chickpea production in Turkey using Artificial Neural Networks and Time Series Analysis. Research Inventy: International Journal of Engineering and Science, 10(11):1–7.
- [16]. Çelik, 2020c. Artificial Neural Network and Time Series Modeling of predicted future production with lentil production in Turkey and Analysis. Journal of Multidisciplinary Engineering Science Studies (JMESS), 6(11):3564–3568.
- [17]. Çelik, Ş., Coşkun, F., Yılmaz, O. 2014. Çeşitli donlardaki Türk Alaca atlarının vücut ölçülerinin parametrik olmayan istatistik yöntemler ile incelenmesi. Bitlis Eren Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 3(2):133–141
- [18]. Çelik, Ş., Coşkun, F., Yılmaz, O. 2015. Türk Alaca atlarda yaş grubuna göre vücut ölçülerinin farklı ortogonal karşılaştırma yöntemleriyle incelenmesi. Çanakkale Onsekiz Mart Üniversitesi Ziraat Fakültesi Dergisi, 3(1):81–87
- [19]. Çelik, S.,Karadas, K., Eyduran, E. 2017. Forecasting the production of groundnut in Turkey using ARIMA model. The Journal of Animal and Plant Sciences, 27(3):920-928.
- [20]. Demir, H. 1997. At Yetiştiriciliği. İstanbul Üniversitesi Veteriner Fakültesi Zootekni Anabilim Dalı, İstanbul.
- [21]. Doğan, İ., Akcan, A., Koç, M. 2002. Investigation of Important Body Measurements in Pure- Bred Arabian Colts and Fillies.Turkish Journal of Veterinary and Animal Science 26:55-60.
- [22]. Duru, S.,Baycan, S. C., Ozhelvaci, N., Gundogan, B.,Akgun, H. 2017. Estimation

of variance components and genetic parameters for the various body measurements in Turkish Arabian horse. Yüzüncü Yıl Üniversitesi Tarım Bilimleri Dergisi 27(3):378-386.

- [23]. Eyduran, S. P., Akın, M., Eyduran, E., Çelik, Ş., Ertürk, Y. E., Ercişli, S. 2020. Forecasting BananaHarvest Area and Production in Turkey Using Time Series Analysis. Erwerbs- Obstbau, https://doi.org/10.1007/s10341-020-00490-1
- [24]. Eyduran, E., Akın, M., Eyduran, S. P. 2019. Application of Multivariate Adaptive RegressionSplines in Agricultural Sciences through R Software. Yayın Yeri:Nobel Akademik Yayıncılık, Basım sayısı:1, Sayfa sayısı:112, ISBN:978-605-2149-81-2.
- [25]. FAO, 2019. Food and Agriculture Organization of the United Nations. Live animal.

http://www.fao.org/faostat/en/#data/TP

- [26]. Hamilton, J. D. 1994. Time Series Analysis. Princeton University Press Princeton, New Jersey.
- [27]. Kadılar, C., Çekim, H. Ö. 2020. SPSS ve R Uygulamalı Zaman Serileri Analizine Giriş. Seçkin Yayıncılık San. ve Tic. A. Ş., Ankara.
- [28]. Kaygisiz, A.,Orhan, H., Vanli, Y., Guler, A., Gokdere, M. A. 2011.Phenotypic and Genetic Parameter Estimations of Body Measurements of Turkish Arabian Horses Raised in Sultansuyu State Farm. Iğdır University Journal Institute Science and Technology1(1):69-74.
- [29]. Khan, M. A., Tariq, M. M., Eyduran, E., Tatliyer, A., Rafeeq, M., Abbas, F., Rashid, N., Awan, M. A., Javed, K. 2014. Estimating body weight from several body measurements in Harnai sheep without multicollinearity problem. The Journal Animal Plant Science 24: 120-126.
- [30]. Meruelo, A. C., Simpson, D. M., Veres, S. M., Newland, P. L. 2016. Improved system identification using artificial neural networks and analysis of individual differences in responses of an identified neuron, Neural Network, 75:56–65.
- [31]. Moghaddam, A. H., Moghaddam, M. H., Esfandyari, M. 2016. Stock market index prediction using artificial neural network, J. Econ., Fin. and Admin. Sci., 21:89–93.
- [32]. Öztemel, E. 2003. Yapay sinir ağları. PapatyaYayıncılık, İstanbul.



- [33]. Pujol, J. C. F.,Pinto, J. M. A. 2011. A neural network approach to fatigue life prediction, Int. J.Fatig.33:313–322.
- [34]. Schmidhuber, J. 2015. Deep learning in neural networks: an overview, Neural Network. 61:85- 117.
- [35]. TSI, 2020. Turkey Statistics Institute. Hayvancılık istatistikleri. Canlı hayvan sayısı (baş) https://biruni.tuik.gov.tr/medas/?kn=101&lo cale=tr (Accessed to16.06.2021)
- [36]. Wang, W., Lu, Y. 2018. Analysis of the Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) in Assessing Rounding Model. ICMEMSCE, IOP Conf. Series: Materials Science and Engineering 324 (2018) 012049, doi:10.1088/1757-899X/324/1/012049.
- [37]. Yildirim, G. 2014. Atlarda vücut yapısının değerlendirilmesi. Nobel Tıp Kitabevleri Tic. Ltd. Şti.,Istanbul, p. 101. ISBN: 978-605-335-044-6.
- [38]. Yilmaz, O.,Ertugrul, M. 2014. Some Morphological Traits of Odd–Toed Ungulates RaisedinTurkey.COMU Journal of Agriculture Faculty 2(2):9-16.