Estimation Modelling Of The Amount Of Fodder Beet Production In Turkey: Comparative Analysis Of Artificial Neural Networks And Trend Analysis Methods

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***Abstract*—The aim of this study is to show that production planning may be performed using artificial neural networks (ANN) and trend analysis in the establishment of fodder beet production amount model and in forecasting in Turkey by years.**
In the development of ANN and trend analysis, parameter of years was used as an input parameter and production amount was used as an output parameter. The efficiency of the model developed was determined using statistical parameters such as Mean Squared Error (MSE) and determination coefficient (R^2). The results foresee that fodder beet production will be in a decline in 2025 over the year 2019.
ANN is a useful tool in terms of determining the results found in case of any changes that may occur in variables and in terms of improving the processes accordingly. It has been noted that ANN models yield better results than trend analysis in production modelling.

Keywords*— *Artificial neural network, trend analysis, production, beets for fodder.

I. INTRODUCTION (*Heading 1*)

Fodder beet is raised everywhere in Turkey. Fodder beet being from the *Chenopodiaceae* family is a two-year plant. Fodder beet generally found in mild climate is more cold-resistant compared to sugar beet. However, it needs more moisture. Fodder beet does not develop well in stony soil as clayed, heavy and poor in lime because it is found in sandy and loamy soil with adequate lime [1].
When fodder beet is compared to other fodder plants, it is found to be an important fodder plant providing the highest amount of nutrients and energy from unit area and has a high ratio of being ingestible in 80-90 % [2]. Fodder beet burls especially used for dairy farming provide a source of feed with very delicious burls and high nutritional value [3].
It has been stated that dairy cattle could be fed with fodder beet up to 20-30 kg and feeder cattle up to 50 kg daily and that fodder beet has 10% dry matter, 1.0 % crude protein and 7.1 % elementary substances without nitrogen in its root-stem. The same author noted that fodder beet leaf dried artificially included 13.6 % crude protein, 10.4% crude cellulose and 42.6% elementary substances without nitrogen [4].
Studies in which production amount modelling and forecasting were made in the field of agriculture with artificial neural networks (ANN) and other statistical estimation methods were available [5-7].
For instance, banana production modelling [8] and forage plants production amount modelling and forecasting [9] were performed with Box-Jenkins and exponential straightening methods. Potato production modelling [10] and peanut production model [11], orange production [12] modelling and forecasting with artificial neural networks were studied using ARIMA models. Mandarin production was modelled with time series and artificial neural networks [13], and cotton production [14] and sunflower production [15] were modelled using exponential smoothing methods.
The aim of the present study is to perform the modelling of fodder beet production amount in Turkey through ANN and trend analysis and to present its prospective forecasting.

II. MARERIAL AND METHOD

A. Material

The material of the study is 1988-2019 fodder beet production amount values provided from the www.tuik.gov.tr web address of Turkish Statistical Institute [16]. The dependent variable was fodder beet production figures whereas the independent variable was year series. These variables were selected in order to be able to make reasonable estimations with the models to be selected with ANN and trend analysis methods.

B. Method

Artificial neural networks (ANN)

Artificial neural networks (ANN) are computational models, which consist of a set of interconnected neurons and evaluate outputs from inputs by feeding information through the network and adjusting the weights. These techniques have been successfully used in several applications such as time series prediction, pattern recognition, function approximation and classification [17]. Using a neural network as a

forward model involves two stages, including, a learning (training) stage and a recalling stage [18].
ANN has got such as input layer, a hidden layer and an output layer. Input layer, a hidden layer and an output layer, respectively for input data, data processing, and output data, constitute layers of Multilayer Perceptron network (MLP). Each layer is comprised of several knots or artificial neurons. All neurons, save for those located in a layer, are connected to one another. For the problems that involve prediction, each knot of the input layer equals one of the impact factors prepared as data layers for various dates. Hidden layers are used for categorizing and transferring the results to output layer. The output layer also shows the predicted values of the target variable [19].
The training process of MLP involves Back Propagation method. According to, the definition of this algorithm, the initial weights are defined first and then allocated to the knots. Next the learning samples are introduced into the model. The output is then generated and compared with trial samples. In cases of inconsequence larger than the specified threshold value, the weights are changed up to the point the discrepancy between the desired and real outputs generated by the network are minimized [20].
MLP classifier makes use of the following algorithm for calculating the inputs receiving an individual knot [20]:

$$net_j = \sum_i w_{ij} I_i$$

where net_j is the input parameter that receives the individual neuron j, W_{ij} shows the weights between neurons i and j, and I_i stands for the output of neuron i belonging to the sender, input or hidden layer. The output value resulting from neuron j is computed through following [20]:

$$O_j = f(net_j)$$

where the f function is usually a nonlinear sigmoid function. Namely, it is activation function. The utilized activation functions in configuration of ANNs in the case of this study were:
Hyperbolic tangent sigmoid transfer function (tansig):

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

purlin function generates outputs in the range of -∞ to +∞, logsig function produces outputs in the range of 0 to 1, and tansig function produces outputs in the range of -1 to +1 [21].
To evaluate the precision of the predicted discharge volume, Mean Square Error (MSE) was used [22]:

$$MSE = \frac{\sum_{i=1}^{N}(\widehat{I_i} - I_i)^2}{N}$$

where $\widehat{I_i}$ is the estimated discharge for sample i, I_i is the discharge volume obtained from reference data, and N is the number of samples.
Trend analysis

Linear regression model

$$y = a + bx + \varepsilon$$

Quadratic regression model

$$y = a + bx + cx^2 + \varepsilon$$

Cubic regression model

$$y = a + bx + cx^2 + dx^3 + \varepsilon$$

it shaped [23].
Exponential regression model

$$y = e^{\alpha + \beta x}\varepsilon$$

it shaped [24].

III. RESULT AND DISCUSSION

The artificial neural networks and trend analysis method goodness of fit statistics and model equations of fodder beet production between the years 1988-2019 in Turkey are presented in Table 1.

Table 1. ANN and trend analysis models for production amount

Model	MSE	MAE	R^2	Equation
ANN	19 416 873	3 604		
Linear	815 714 446		0.138	Y_t = 100040 +1200.3*t
Quadratic	80 820 001		0.917	Y_t = 35454 +12598*t -345.38*t^2
Cubic	74 583 691		0.926	Y_t = 44474 +9549.7*t - 117.98*t^2 -4.5938*t^3
Exponential model			0.179	Y_t = 94237 * (1.0125**t)

When Table 1 is examined, cubic regression model is found to be the model with the highest R^2 value among trend analysis methods. However, when the mean squared error (MSE) values were considered, artificial neural networks with minimum MSE value were found as the best model. The estimated and residual values are presented in Table 2 together with the real values of the ANN method.

Table 2. Observed, estimated and residual values

Years	Actual	Predicted	Residual
2000	140000	144941.962	-4941.96
2001	150000	146644.245	3355.756
2002	160000	154770.042	5229.958
2003	160000	162433.736	-2433.74
2004	160000	162242.503	-2242.5
2005	165000	163085.608	1914.392
2006	158771	160433.379	-1662.38
2007	151611	152604.736	-993.736
2008	157541	147237.795	10303.2
2009	145628	147469.829	-1841.83

2010	132970	141020.404	-8050.4
2011	127114	128912.391	-1798.39
2012	125610	127249.987	-1639.99
2013	131289	124803.02	6485.98
2014	127300	125367.762	1932.238
2015	114165	118481.52	-4316.52
2016	111974	107121.592	4852.408
2017	98537	104585.948	-6048.95
2018	92069	91120.6857	948.3143
2019	88446	87358.2429	1087.757

The graph of the observed and estimated values obtained with ANN method are shown in Figure 1.

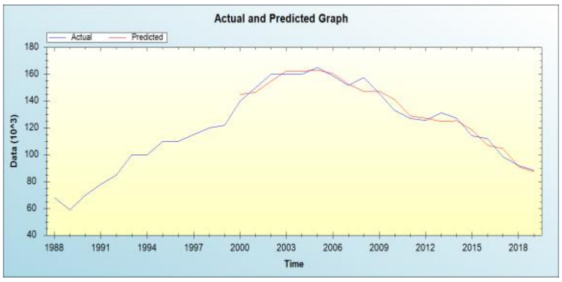

Figure 1. The combined graph of observed and estimated values

The possible 2020-2025 values of fodder beet production forecasted with ANN are presented in Table 3.

Table 3. Fodder beet production amount estimation

Years	Forecasted
2020	87019
2021	82204
2022	75996
2023	70070
2024	71834
2025	77605

According to Table 3, while a decrease is expected between the years 2020-2024 in fodder beet production amount, it is expected to see an increase in 2025. Thus, the graph showing fodder beet production amount observed values and estimated values is given in Figure 2.

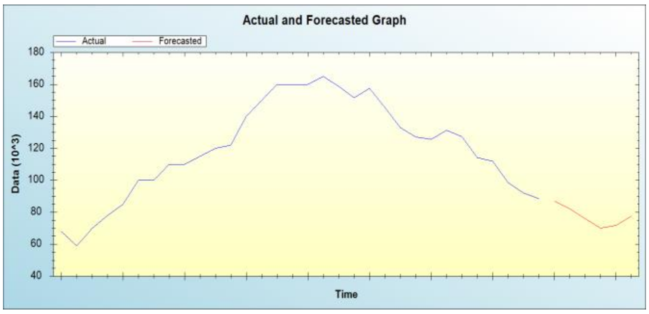

Figure 2. The joint graph of observed and estimated values

As is seen in Figure 2, it is estimated that the amount of fodder beet production decreasing in 2019 will slightly increase in 2025. In Figure 3, when 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 proved.

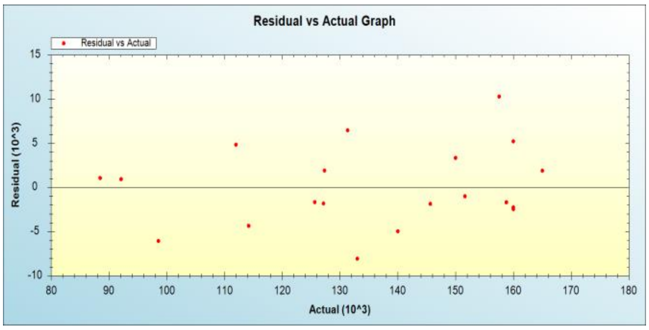

Figure 3. Joint graph of observed and residual values

[7] in the study of (2019), artificial neural networks gave better results than regression models for prediction of body weight in Raini Cashmere goat. In another study, artificial neural networks and multiple regression models were examined comparatively and artificial neural networks gave better results [25]. In this respect, this study is in line with the results.

IV. CONCLUSION

Fodder beet production amount in Turkey was estimated through artificial neural networks and trend analysis (linear, quadratic, cubic and exponential regression) in the study. The years (1988-2019) were used as the input variable, as 1 independent variable and fodder beet production values were used as the output variable. Then, the training, test and verification processes of the network were performed and estimation was made.

The results obtained have revealed that the ANN model established has given better results than trend analysis methods. Low MSE (Mean Squared Error) values in the training, test and verification phases also support the results.

When the fodder beet production estimations were considered, it was foreseen that the production, which was 88 446 tons in 2019 would decrease by 12.26%

and be 77 605 in 2025. This situation is a loss for this plant being important in animal nutrition. It may also be considered that it will have significant negative effect on husbandry. Precautions in order to overcome such problems could be taken in the country production planning.

When compared to trend analysis in general, artificial neural networks were found to be more successful in estimating the present data. It is believed that forming a production estimation model by comparing with artificial neural networks and alternative techniques in estimation studies regarding the future will present good results.

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