
ESTIMATION OF COMMERCIAL AIRLINE TRAFFIC WITH ECONOMIC GROWTH INDICATORS

Erdal DURSUN¹, Cankut AYDIN², Ertan ÇINAR³, Cengiz SERTKAYA⁴

1- Dr, Nisantasi University, erdal.dursun@nisantasi.edu.tr

2- Dr, Southern University Institute of Management Business and Law,
cankut.aydin@suimbl.ru

3- Dr, Eskisehir Technical University, ecinar@eskisehir.edu.tr

4- Dr, OSTIM Technical University, cengiz.sertkaya@ostimteknik.edu.tr

Abstract

In recent days, it is crucial to calculate the volume of air traffic in line with the economic indicators of the countries and to make the necessary plans to increase efficiency and productivity according to this density type. Although commercial airline traffic is known to be associated with economic growth indicators, the relationship between them cannot be expressed numerically.

The purpose of this research is to form an Artificial Neural Network (ANN) -based model to reveal and estimate its relationship with commercial airline traffic, taking as reference economical growth parameters like; the country's Gross National Product (GDP), import and export data.

In the ANN model created in the study, gross domestic product, import and export volume values are used for the estimation of commercial airline traffic. Simulation results were analyzed using correlation coefficient (R) determination coefficient (R^2) and mean absolute percent error (MAPE) evaluation methods. It has been seen that the developed model is a successful model that can be used in the prediction of commercial airline traffic.

Key Words: Aviation, Air Traffic Management, ANN

INTRODUCTION

For commercial air transport, the Warsaw Agreement, which is still valid today, and the Chicago Agreement made afterwards are turning points. As a result of these agreements, both the principles of commercial air transportation and the rules of aviation have been determined at the global level. While the legal structure of air transport was drawn with international legal regulations, a more competitive commercial structure was introduced for aviation as a result of the deregulation process that first started in the USA in 1978 with the requirements of changing and developing world trade and competition. The impact of the deregulation process that started in the USA spread all over the world in a short time

and the industry was brought to a more dynamic and competitive level by reducing state intervention with the effect of release (Şengür, 2016).

When the airline passenger forecasts published by IATA are analyzed, it is predicted that the acceleration of airline traffic, especially in the Asia Pacific region, will be higher over the developing countries in the next twenty years (IATA, 2020).

When the studies in the literature are examined, there is no study that examines commercial airline traffic with economic growth indicators using the artificial neural network model. Yet, there are various studies using economic growth indicators, targeting air transport volume and using artificial neural network models in aviation field;

Air transport capacity has been revealed in many studies that it will generally increase economic performance and stimulate growth. According to Carbo and Graham (2019), a study has been conducted to examine the effects of air transport activity on efficiency in Chinese provinces, contributing to the empirical literature on aviation-economy. The causality effect of deregulation (liberalization policy) implemented by the state on air transport was estimated by increasing the GDP in Tibet and it was determined that there was a positive relationship between them. According to Kiracı (2018), using the causality analyzes of Toda, Yamamoto (1995) and Hatemi (2012) between 1960 and 2015, the relationship between airline demand and GDP has reached the conclusion that there is a positive causality relationship between airline demand and economic growth.

Dimitrios and Maria (2017), examined the contribution of the air transport industry to the economy and the impact on the performance of industries that trigger the country's economic growth. It has demonstrated that the aviation industry has strengthened the worldwide transportation network that is essential for global trade and tourism. According to Bal, Manga and Akar (2017), they examined the effect of airline passenger demand and cargo transportation on economic growth between 1967 and 2015. In this context, with Granger Causality analysis, they concluded that the aviation industry has a one-way and positive effect on economic growth. According to Çelik (2017); the benefits of airline transportation on the economy is as follows; directly, indirectly and catalytic. As a result of the study, solutions are offered for possible problems that may prevent the increase in value in the airline transportation sector.

Hakim, Merkert (2016) and Brida, Bukstein (2016) empirically proved the causality relationship and the correct rate of correlation between air transport and economic growth for South Asia and Italy in their analysis. Marazzo, Scherre, and Fernandes (2010); They investigated the relationship between air transport demand and economic growth (GDP) in Brazil between 1966 and 2006. Research findings show that there is a long-term relationship between GDP and air transport capacity. Huang, Wang, and Liu (2009); In their research papers, they associated GDP with air traffic flow for the Beijing region of China. According to Chang and Chang (2009), he worked on the relationship between air cargo transportation and economic growth in Taiwan in 1974-2006. The output of the study shows a two-way causality between air cargo expansion and economic growth.

Chen M. H. (2007) conducted a study examining the relationship between the stock prices of tourism enterprises (hotels, airlines and travel agencies) and economic development in Taiwan and China, and experimentally examines the tourism-economic growth link.

Drawing attention that the interactions between stock performance and GDP differ widely between companies, it reveals the likely existence of causal relationship patterns between GDP and individual tourism subsectors (hotels, airlines and travel agencies). Oktal and Küçükönel (2007), examining the development of air transportation in America and Europe, emphasized the importance of the implementation of regional air transportation in our country.

Xueni, Xuanxi, and Dongqing (2007); studied the causality between civil aviation transport and economic growth for Beijing, Tianjin, Hebei, Changjiang River delta and İnci River delta. As a result, it shows that although there is only one-way causality between aviation transport and economic growth at the national level, the relations at the regional level are different. The study analyzed the reason for this result and suggested some measures.

Air traffic complexity is often defined as the difficulty in monitoring and managing a particular air traffic situation. Because it is a psychological construct, the best measure of complexity is given by air traffic controllers. According to Andrasi et al., (2019), the possibility of using artificial neural networks for complexity estimation has been investigated. As a result, it has been determined that artificial neural networks perform better than linear models.

To Sakız B, Ünkaya G., (2018); In their study, they aimed to present the bankruptcy risk for THY with the Airscore model by including factors such as the 2008 crisis, which is the financial crisis model, the terrorist attack of September 11, the SARS disease epidemic in 2003 and the volcanic ash explosion in 2010, and to predict it with the artificial neural networks model. In this context, they determined that the period between 2002 and 2016, which was examined with the Airscore bankruptcy model, was in the area considered healthy.

According to Efendigil and Eminler, (2016); their studies on airline transportation volume between 1950 and 2015 were examined, and as a result, it was found that artificial intelligence techniques gave more consistent results compared to econometric models. In this context, regression analysis, which is an econometric model, and an artificial intelligence model, adaptive neural fuzzy inference system (ANFIS) and artificial neural networks were compared. ANN model was created as a back propagation model. The results obtained in the study were calculated over the mean square error (RMSE) value. Accordingly, the best result was obtained with the ANN model with a RMSE value of 0.01629.

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According to Kumar (2014), he determined that with Self-Organization Map (SOM), which is an unsupervised learning way of the artificial neural network, the collision risk can be reduced by using the self-organizing map neural network clustering algorithm. This

article presents automatic balanced sectoral calculation of airspace to reduce collision and increase air traffic control capacity in a high density air traffic area.

The aim of this study is to scrutinize the management philosophy of aviation in the recent past, the deregulation process in commercial practices and activities, and the instrument flight rules following the liberalization period; It is the development of a model that allows the estimation of commercial airline traffic by taking the country's gross domestic product and economic growth parameters such as import and export data as a reference. By means of the model to be created in this study, a model that allows for the estimation of air traffic will be added to the literature and it will enable studies based on traffic forecasting especially of regional airports.

1. CONCEPTUAL FRAME

1.1. Artificial Neural Network

Artificial neural networks, one of the artificial intelligence systems, are information processing systems that resemble neurons in the human brain. Artificial neural networks (ANN) based on simulating the working system of the human brain has been implemented in many areas (Civalek & Çatal, 2004). ANN has begun to replace the econometric models (Regression, ARIMA etc.), which were widely used until the 2000s, especially in the fields of banking, economy, logistics, aviation. The main reason for this is that ANN is successful in predicting situations that the system has not seen before, thanks to its memory, learnability and backward correction capabilities (Efendigil & Eminler, 2016).

ANN by imitating the working system of the human brain; It has capabilities such as learning from data, making generalizations and creating many examples by expanding its own data set. The basic unit used in the creation of ANN model is called "artificial neural cell" (Kaynar et al., 2011).

When artificial neural cells are scrutinized alone, they appear as very simple processors. A neural cell consists of synapses, collector and activation functions. Figure 1 contains the model of the artificial neural cell. In this context, the input of the neural cell is multiplied by the weights of the synaptic connections and the value obtained as a result of applying it to a collector is passed through the activation function of the neural cell and the outputs are calculated (Firat and Güngör, 2004).

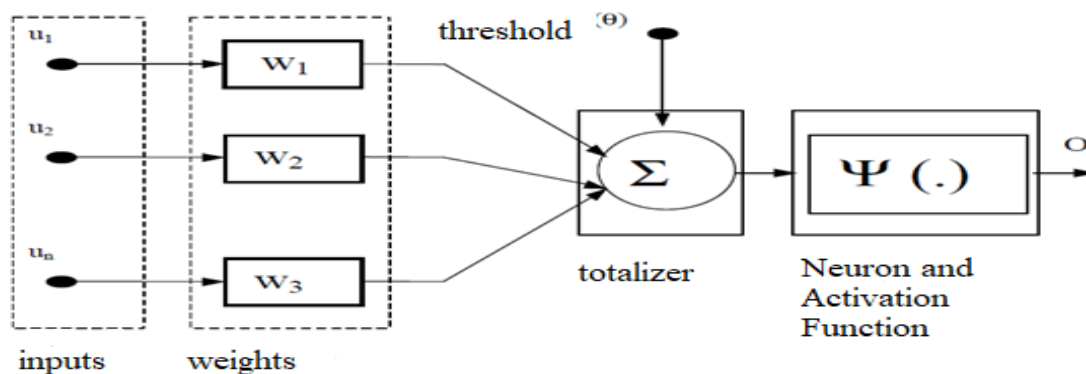


Figure 1. Mathematical Model of Artificial Neural Cell (Firat and Güngör, 2004)

The use of a feed forward back propagation network model from artificial neural network structures in the study is briefly explained below:

1.1.1. Feed-forward Networks

Feed forward networks consist of three parts: input layer, hidden layer(s), and output layer. In the input layer; the input data of the determined problem is taken into the artificial neural network. In the output layer, the result obtained from the data processed in the network is transferred. There is hidden layer(s) between input and result layers (Kaynar et al., 2011).

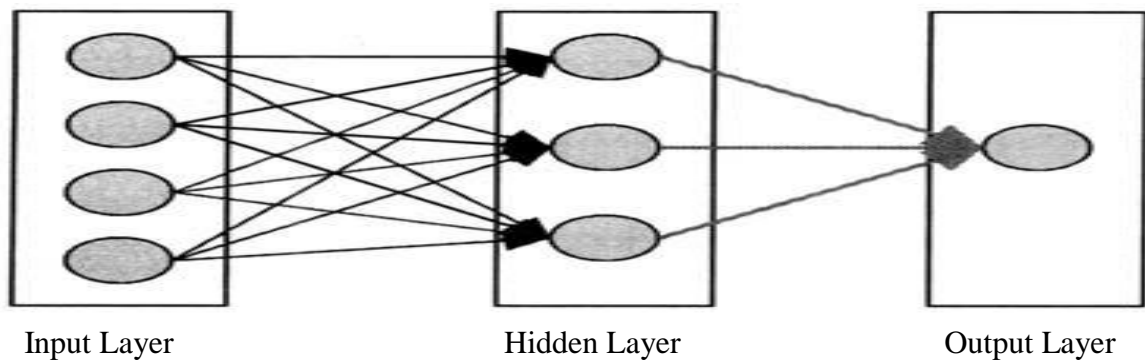


Figure 2. Feed Forward Artificial Neural Network Structure (Kaynar et al., 2011)

The most commonly used method in feed forward networks is the multi-layer perceptron model (MLP). The reason why the MLP model is preferred is that it is the most successful ANN model in estimation and classification.

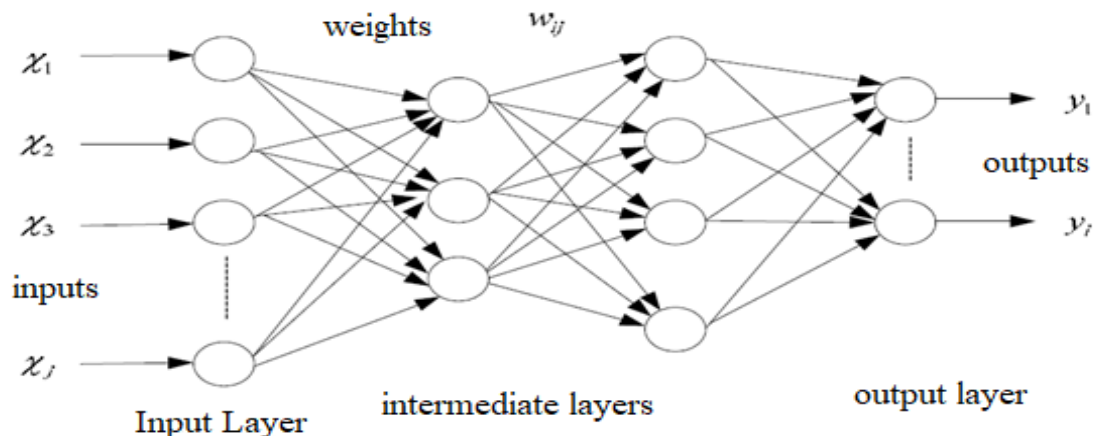


Figure 3. Multi-layer Perceptron Model (Karaali and Ülengin, 2008).

1.1.2. Feed Forward Backpropagation Algorithm

The back propagation algorithm is created with a feed forward, in which the output in the neural network is detected, and feedback stages formed by repetitive weights to minimize the gradient in the error occurring here.

In the feed-forward phase, training data is provided as an input to the input layer of the neural network. The input layer consists of neural cells that receive these inputs, and the input value must be equal in quantity. The neural cells in the input layer calculate the total value by adding the threshold value to the input values and transmit this value to the hidden layer directly to the output layer if there is no hidden layer by processing it with an activation function. The weights in the layers are mostly chosen randomly (Ari & Berberler, 2017).

The error rate between them is found by comparing the output value in the neural network with the actual output value. The formula used to find the error rate is as follows:

$$e_j(n) = d_j(n) - y_j(n) \tag{1.1}$$

Here, the "n" is training data for j output neuron, then; $d_j(n)$ is the predicted data.

The total error in the output layer is calculated by the following formula:

$$E(n) = \frac{1}{2} \sum_{j \in C} e_j^2(n) \tag{1.2}$$

Cluster C includes all of the neural cells in the output layer. Here, similar to the least squares algorithm rule, E (n) is aimed to be kept as low level as possible. The sum of input values reaching the output layer neural is explained by 2.3:

$$v_j(n) = \sum_{i=0}^m w_{ji}(n)x_i(n) \tag{1.3}$$

$X = (x_1, \dots, x_n), j$. The m input data which is applied on neural cell , w_j, x_i specifies the weigh and the f activating function. While w_{j0} shows deviation factor; according to this it is as follows: $x_0 = +1$

The resulting value produced by the neurons of the neural network is determined by passing through the activation function as in the follows:

$$y_j(n) = f(v_j(n)) \tag{1.4}$$

The gradient of the network can be determined by taking derivative of the falsification function according to the weights. According to chain rule the gradient:

$$\frac{\partial E(n)}{\partial w_{ji}(n)} = \frac{\partial E(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial d_{y_j}(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)} \tag{1.5}$$

When derivative of each of them is taken:

$$\frac{\partial E(n)}{\partial w_{ji}(n)} = -e_j(n)f(v_j(n))x_i(n) \quad (1.6)$$

Weigh correcting number, $\Delta W_{ji}(n)$ it is applied according to small squares rule.

$$\Delta W_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{ji}(n)} \quad (1.7)$$

The n is the learning prediction. Equation represents the steep drop in gravity space, which is meant to be expressed with - in 2.8. In this context, the weight correction ratio for the back propagation algorithm is:

$$\Delta W_{ji}(n) = \eta \delta_j(n)x_i(n) \quad (1.8)$$

Local gradient $\delta_j(n)$ is explained as follows:

$$\delta_j(n) = e_j(n)f'(v_j(n)) \quad (1.9)$$

The desired output value is not specified as for all j neural networks in the hidden layer, neural cells in the output layer. Therefore, the value of j neural cell in the latent layer is retroactively affected by the fallibility value of each neural cell that interacts with the relevant neural cell. In each j neural cell in the hidden layer; the local gradient $\delta_j(n)$ is expressed below:

$$\delta_j(n) = f'(v_j(n)) \sum_{j=0}^l \delta_j(n)w_{ji}(n) \quad (1.10)$$

In 1986, Rumelhart and McClelland added the term α speed to the weight updating formula found in the backpropagation algorithm, thereby reducing the possibility of the network stuck to the local minimum. The Weight updating formula following the addition of the concept of momentum: (Ari & Berberler, 2017).

$$w_{ji}(n + 1) = w_{ji}(n) + \Delta w_{ji}(n) \quad (1.11)$$

$$\Delta w_{ji}(n) = \eta \delta_j(n)x_i(n) + \alpha \Delta w_{ji}(n) \quad (1.12)$$

The back propagation algorithm, which provides the reduction of the error by going back to the above, refers to the part where the learning takes place for ANN. When the learning will be terminated should also be specified in the algorithm. The most used techniques to express where the learning will end; when a certain number of iterations reached, when the error falls below a certain level, or when an improvement over a certain value cannot be achieved in error correction, training stops.

Trained one is checked with ANN validation data set and it is ensured that they are trained correctly. After the ANN system completes the learning, the test data are given as an entry

to the system, the results obtained are compared and evaluated, and the success of the ANN is calculated.

2. METHOD

2.1. Forward Feed Back Propagation ANN Estimation Model

In this study, it is aimed to predict by applying feed forward back propagation algorithm by using data of GDP, import and export volumes, which are indicators of economic growth.

The steps of the methodology developed for this are shown in Figure 4:

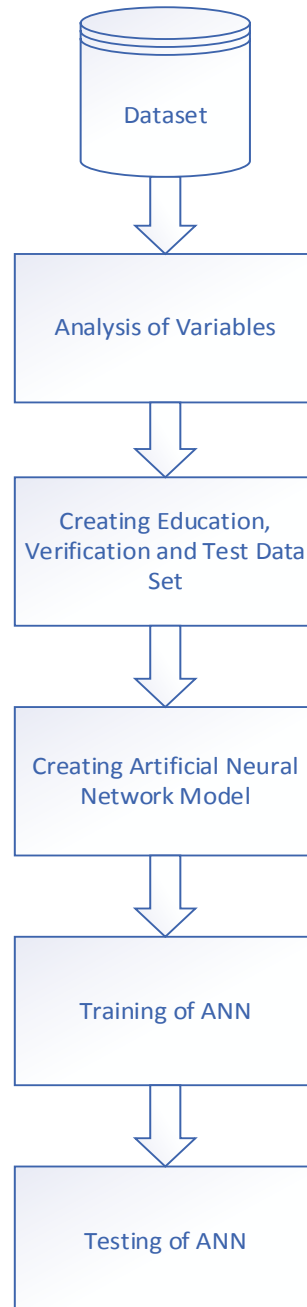


Figure 4. Estimating methodology with feed forward back propagation artificial neural networks using; GDP, Export and Import volumes of countries.

2.2. Data Set

In this study, in order to predict commercial airline traffic, a prediction model was created using the economic growth indicators data and the back propagation algorithm, which is a sub-branch of artificial neural networks. In this context, 19 of the EUROCONTROL member countries were selected between 2004 and 2017, and the data set for commercial airline traffic was prepared using EUROCONTROL documents (EUROCONTROL, 2008; EUROCONTROL, 2010; EUROCONTROL, 2018). Data set of variables used to predict commercial airline traffic; GDP (World Bank, 2018a), export (World Bank, 2018b) and import (World Bank, 2018c) volumes were obtained from the World Bank website. Within this data set, the following countries were examined:

Countries that Form the Data Set	
1	Turkey
2	Czech Republic
3	Hungary
4	Greece
5	Ireland
6	Denmark
7	Norway
8	Sweden
9	Romania
10	Bulgaria
11	Poland
12	Finland
13	Ukraine
14	Austria
15	Switzerland
16	Germany
17	France
18	Italy
19	Spain

Table 1. Table that belongs to Data Set Countries

The original aspect of our model proposal; Although different from the current study in terms of method and data set, the data sources entered were selected from previously unused parameters. Namely; the basic working logic of the model is based on artificial neural networks. The data feeding this structure and processed within the system consists of the export and import data of the country in addition to the gross national product.

The reason why the data set was determined between 2004-2017; In our country, it can be said that the liberalization process, which started in the field of aviation, which was founded with the Civil Aviation Law No. 2920 in 1983, with the regulations made in 2003, has made a rapid transition. So much so that while THY's fleet was limited to 65 aircraft in 2003, this number increased to 348 as of 2019 (THY, 2019).

2.3. Analysis of Variables

The graphics of the variables in the study are indicated in Figure 5,6,7,8. In conducting this analysis, commercial airline traffic movements, GDP, export and import volume data of 19 contracting states that are members of EUROCONTROL are evaluated in line with the model created for the years 2004-2017. The standard deviation values and average values determined by the minimum and maximum values of the graphics created for the analysis of the variables are given in table 2. In this section, firstly, after evaluating the changes of each variable by years for commercial airline traffic, GDP, Export, Import volumes, information will be given about the mean and standard deviation values of the aforementioned data.

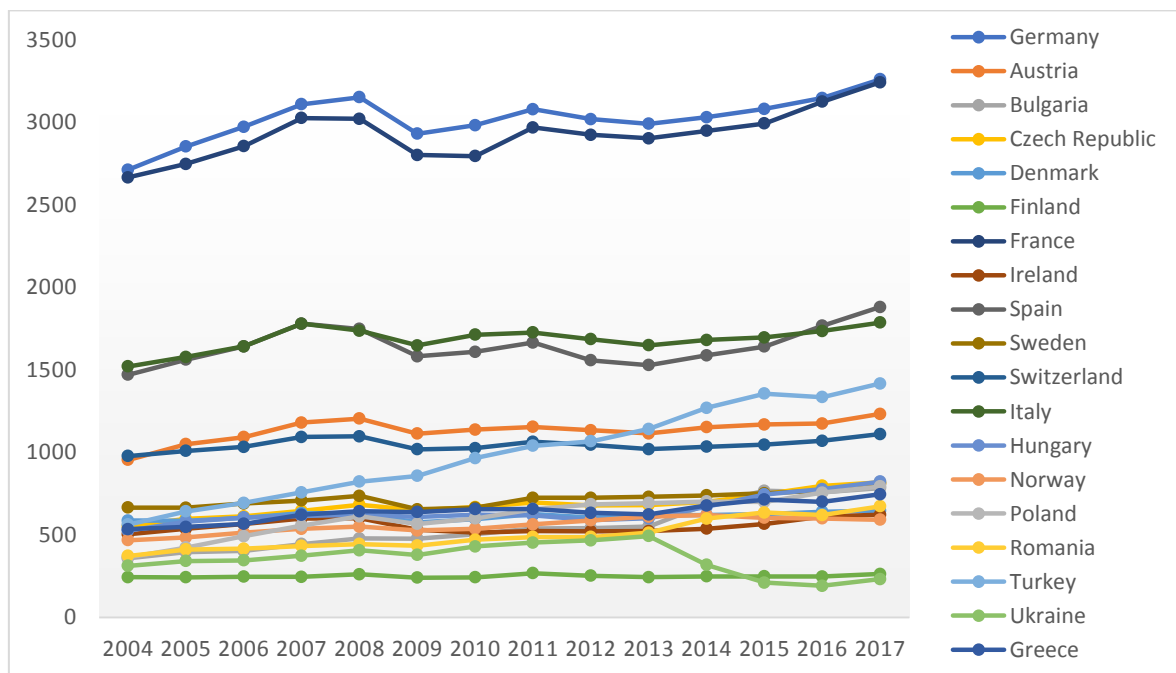


Figure 5. Change of commercial airline flight operations of countries by years.

When the changes in commercial airline flight movements in 19 countries are analyzed; First of all, it can be said that the commercial airline flight movements of Germany and France are quite high compared to other countries. The reason for this is that it is parallel to the ratios of GDP, Import and Export volumes of both countries. Therefore, it can be said that economic growth indicators directly affect the air traffic of countries even by interpreting these changes. When other countries are examined in commercial airline traffic changes, it is seen that Finland has the lowest traffic until 2013, but in 2013, Ukraine has become the country with the lowest commercial airline traffic among 19 countries used in the data set due to the internal crisis.

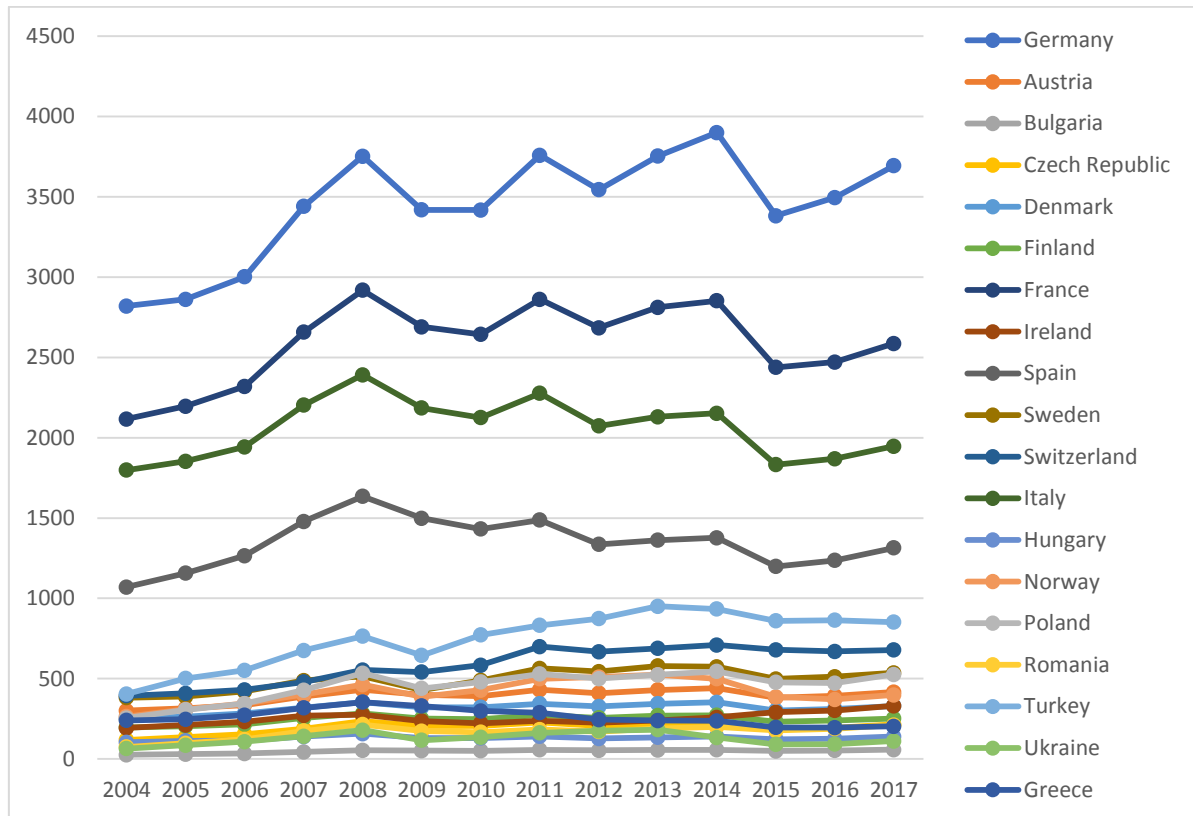


Figure 6. Change of GDP data of Countries

When the GDP values of the countries in the data set are examined, it is seen that Germany and France, the two countries with the highest density in commercial airline traffic, are at the top. When Italy and Spain, and Turkey said they have set aside each other quite a value in the GDP level of other countries. It is seen that Bulgaria has the lowest GDP values as from starting year.

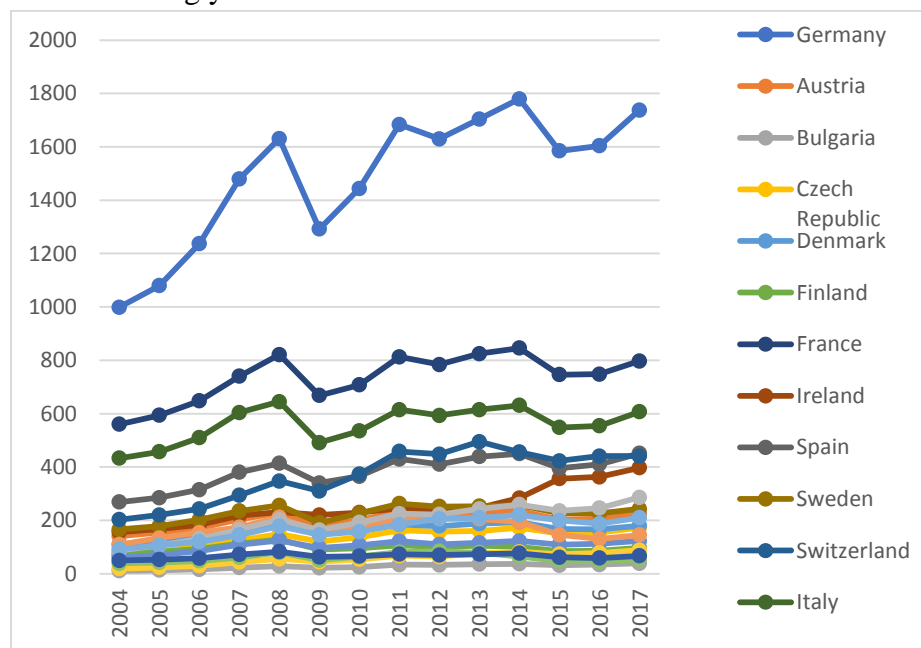


Figure 7. Change of Export Volume of Countries

Considering the export changes of countries, it is seen that Germany is at a very high level compared to other countries despite the serious decrease it experienced in 2009. France follows Germany as in the commercial airline traffic volume and GDP values. Considering the export volumes, it is observed that there has been a decrease in countries except Ireland as of 2015. Bulgaria has the lowest value in export values as well as in GDP values.

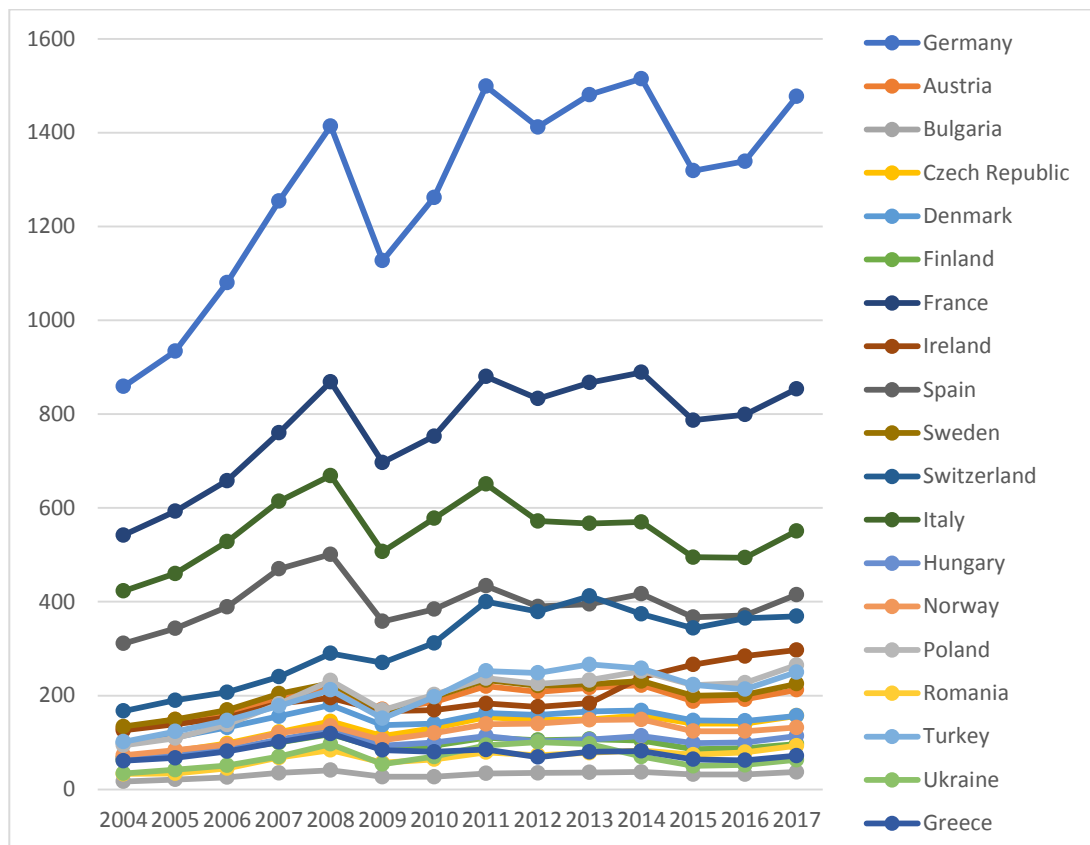


Figure 8. Change of Import Volume of Countries

When the import volumes considered, it is seen that Germany and France have the highest values as in the other 3 variables. Similar to the export volume in 2015, countries' import volumes decreased. In addition, the country with the lowest value is Bulgaria.

According to the study, the minimum, maximum, average and standard deviation values obtained from the analysis of system variables are given in Table 2:

	Minimum Value	Maximum Value	Mean	Standard Deviation
Commercial air traffic	191	3259	1006	2169,4
GDP	26	3899	751	2738,624564
IMPORT	11	1780	288	1250,871896

EXPORT	17	1515	270	1059,245958
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Table 2. Analysis table of system variables

Depending on the values specified in the above table, while the difference between the maximum and minimum values of the commercial airline traffic data set is 3068, it is 3873 for GDP, 998 for export volume and 1769 for import volume.

2.4. Creating Education, Verification and Test Data Set

Since the training data set encapsulates reference information used for the artificial neural network to learn the problem, it is extremely important to select it correctly. In this context, there is no standard method determined in the literature. For this reason, it is not known which data explains the problem in the best way and the data sets are randomly created. The purpose of the validation dataset is used to check if the neural network trained with the training dataset is properly trained. If the desired training has not taken place, the network is retrained.

In the literature, it is recommended to divide the data set as 60% education, 10% verification, 30% test or 70% education, 10% verification, and 20% test (Boyekin et al., 2019). As a result of the experiments in this study, the best success rate was obtained by dividing it into 70% training data set, 10% verification data set, and 20% test data set. Table 3 contains the table of training data to be used in training the model.

	Data Number
Training Data Set	186
Verification Data Set	27
Test Data Set	53

Table 3. Given Training, Verification and Test Data Numbers

2.5. Creating Artificial Neural Network Model

The artificial neural network model created in this study is a feed forward back propagation ANN (FFBP) model. In the model created for the forecast of commercial airline traffic, input parameters are GDP, export and import volumes. MATLAB R2018B program was used to create the FFBP ANN.

The view of the artificial neural network model flow created in this context is as in figure 9. Here, the ANN has 3 inputs, 1 intermediate layer, 10 neural cells in its intermediate layer, and one exit.



Figure 9. Feed Forward Back Propagation Artificial Neural Network Model

In Figure 10 below, the artificial neural tool (nntool) created as a result of entering the data belonging to the model created is specified.

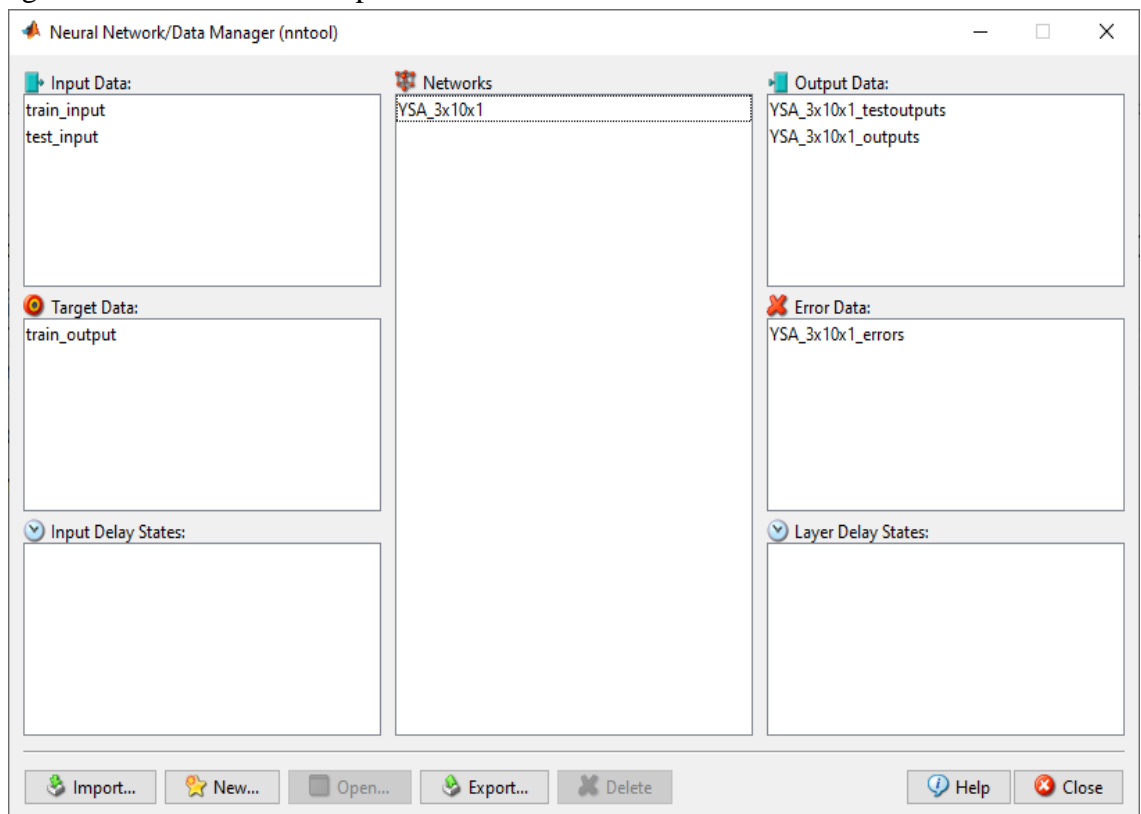


Figure 10. Artificial Neural Device

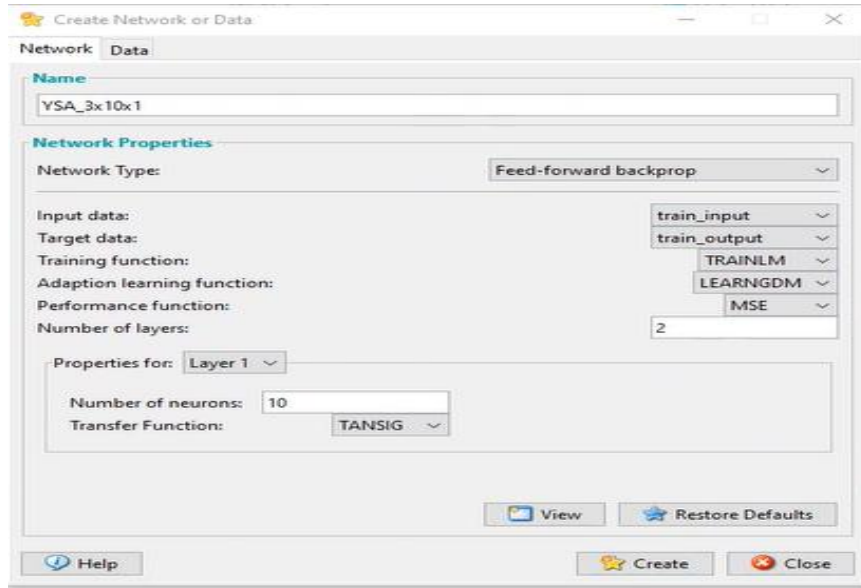


Figure 11. Neural Network

After the creation of neural network data management with the Artificial Neural Tool created in Figure 10, the artificial neural network model feed forward back propagation network model is selected in Figure 11. The reason for this is that it is the most preferred artificial neural network model in econometric data modeling and forecasting studies and its success in linear and nonlinear models (Bayır, 2006). Levenberg-Marquardt backpropagation algorithm was used to train the created artificial neural network. The reason for this is that the Hyperbolic Tangent (TANSIG) or Log-Sigmoid transfer function is preferred in the literature for models such as our model with linear or nonlinear characteristics (Dorofki et al., 2012). As a result of the experiments, the highest performance value has been reached with the TANSIG function in this study.

For the calculation of ANN performance, the Mean Square Error (MSE) method was chosen. In this context, it calculates the cumulative values of the difference between the desired output values and the values found by the network. As a result of these values, it is observed how close the data in the training set in the network to the requested result is observed and the weights of the links are changed using this information. For this reason, performance functions are one of the important factors that determine learning. The performance function used in feed forward networks is Mean Square Error (MSE).

$$MSE = \frac{1}{n} \sum_{i=1}^n [e(t)]^2 \quad (2.1)$$

Seçilen parametrelere göre oluşan YSA'nın MATLAB görünümü Şekil 12'de belirtilmektedir:

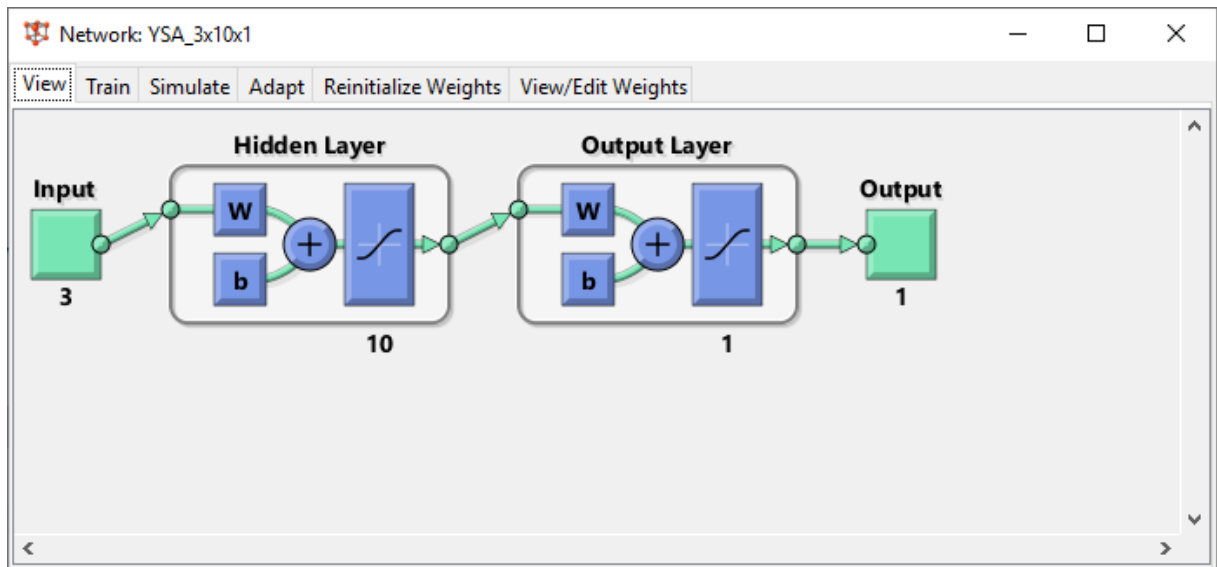


Figure 12: Artificial Neural Network Model Structure

2.6. Training of ANN

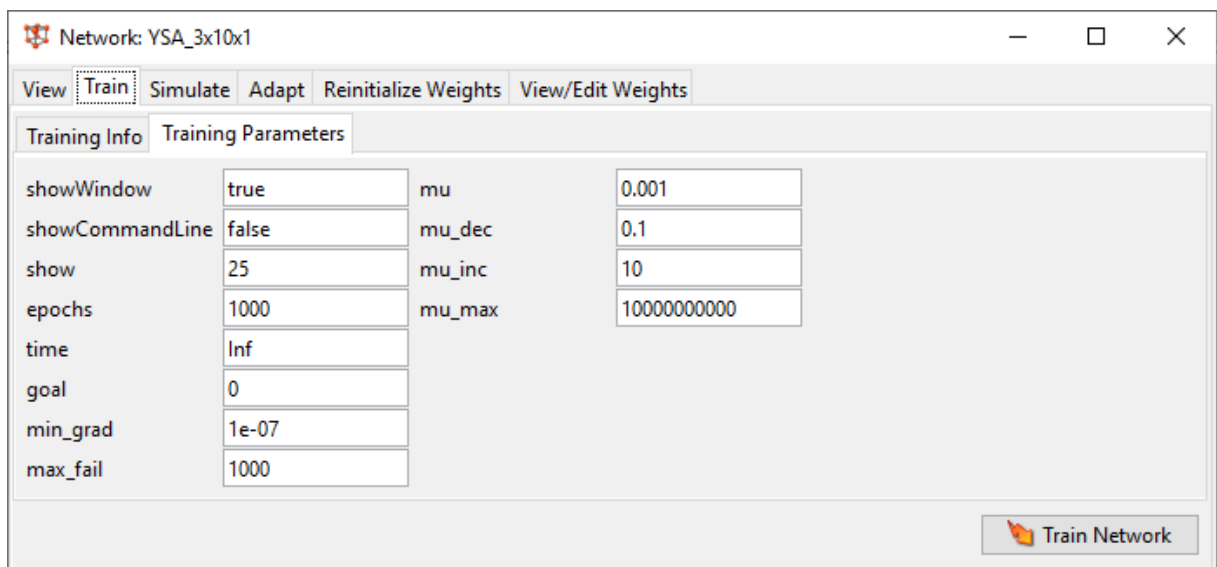


Figure 13. Iteration

Increasing the performance and keeping the error to a minimum in the model depends on the learning algorithm and iteration. The number of elements in the hidden layer is the strength of the network. For functions with low ups and downs; Few hidden layer elements are required for functions with hard fluctuations. In this context, an artificial neural network model consisting of 3 inputs, 1 hidden layer (with 10 neural cells) and 1 output layer was trained using 1000 cycles (iteration, epoch). Here; The reason for choosing 1000 loops; It gave the best result as a result of the experiments. Then the training of the network according to this rule was carried out according to the parameters in Figure 14.

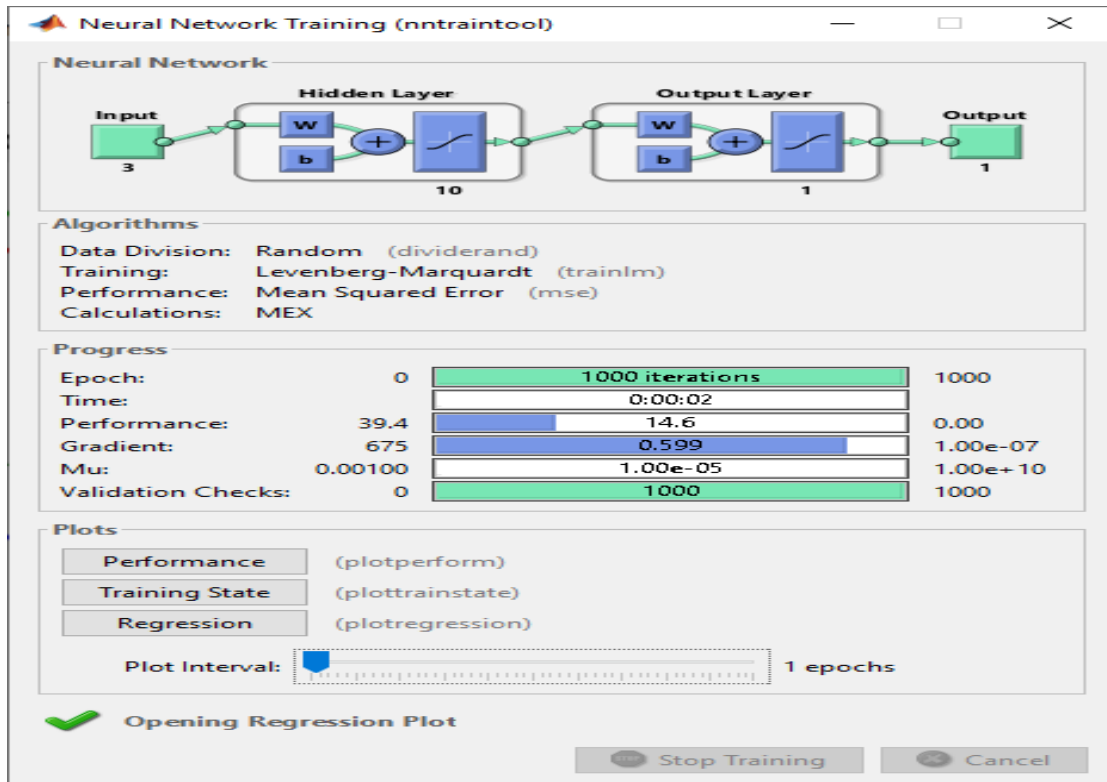


Figure 14. Training of Artificial Neural Network

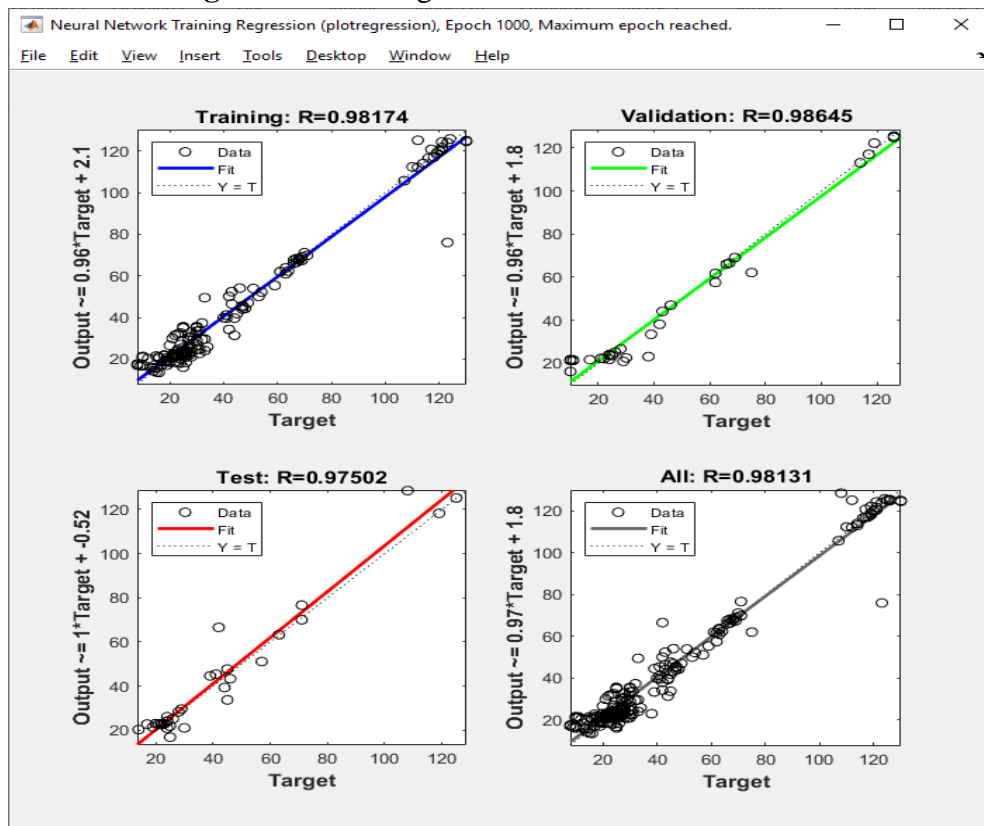


Figure 15. Regression Analysis of Model

In Figure 15, regression views of the model are given. Accordingly, correlation coefficients were determined as 0.987 for education, 0.986 for verification, 0.975 for testing and 0.981 for all data. When these results are evaluated, it indicates that the data in the model are in harmony with the actual data. In line with these values, the stage of testing the network has been started.

3. TESTING OF ANN

Trained ANN was tested with 53 test data. The results were obtained as shown in the graph below. The blue color actual value is the values predicted by the orange color model. As a result of the evaluation, it can be said that there was a high similarity and the network successfully completed its training.

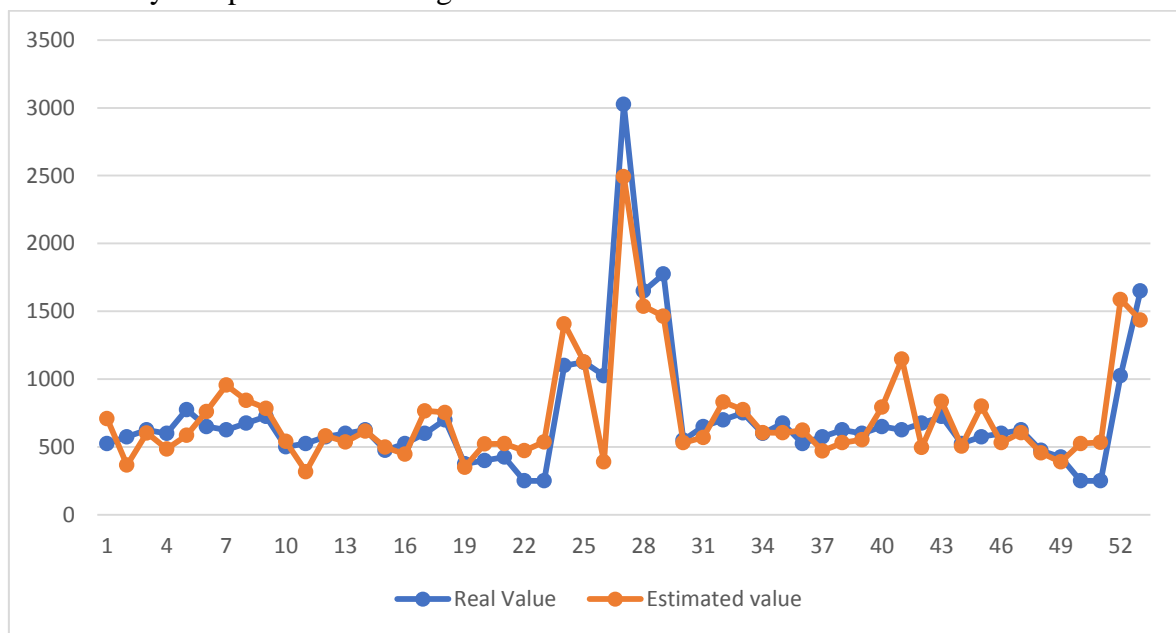


Figure 16. Comparison of Real and Estimated Result Values after Test

4. DISCUSSION AND RESULT

The most commonly used methods for evaluating ANN prediction errors in the literature are correlation coefficient (R), determination coefficient (R ^ 2), Mean Absolute Percent Error (MAPE) values (Sertkaya & Yurtay, 2018; Yiğit, 2016).

The applied R formula is as follows:

$$R = \frac{\sum(x_i - \bar{x}) - (y_i - \bar{y})}{(n-1)s_x s_y} \quad (4.1)$$

Here; $x_i, y_i, \bar{x}, \bar{y}$ sampling arithmetic averages are; s_x, s_y, x_i, y_i sampling standard deviations are; between $\sum i=1$ and n .

Implemented R^2 formula is as follow:

$$R^2 = \left\{ \frac{1}{r} \cdot \sum_{i=1}^r [(x_i - \bar{x}) \cdot (y_i - \bar{y})] / (\sigma_x \cdot \sigma_y) \right\}^2 \quad (4.2)$$

Here while r is the number of predictions, x_i is real value, \bar{x} envisaged x-value, y_i predicted value, \bar{y} envisaged y- value, σ_x x value standard deviation and σ_y standard deviation of “y”.

Applied *MAPE* formula is as follows:

$$MAPE = \frac{\sum_{i=1}^n \left| \frac{y_i}{\hat{y}_i} \right|}{n} \cdot 100 \quad (4.3)$$

Here n: recording number, y_i : monitored value, and \hat{y}_i : shows estimated value.

The Model’s acquired output values’; R, R^2 , MSEP and MAPE results given in the Table 4.

	R	R^2	MAPE
YSA	0,880	0,775	25,486

Table 4. Performance Indicators of Model

When the performance indicator results of the model are examined, the correlation value between the actual values and the predicted values of the developed ANN model was determined as 0.880. If the R value is greater than 0.8, it is understood that the predicted value of the model has a high similarity with the real value.

Similarly, when the R^2 value was examined (determination coefficient), it was found as 0.775. The fact that R^2 value is close to 1 indicates that the model prediction success is at a good level. The result of the model in interpreting the MAPE value; It is classified as "high accuracy" if it is below 10%, "true" if it is between 10% and 20%, "acceptable" if it is between 20% and 50%, "false" if it is above this range (Yiğit, 2016). According to these values, the model gave acceptable and consistent results. In this context, the ANN model, developed according to the performance values obtained, has been successful by learning the forecast of commercial airline traffic from GDP, import and export volume values.

In this study, a model for the prediction of commercial airline traffic is developed using FFBP, one of the artificial neural network models. In future studies, the data set can be expanded with input parameters such as population, tourism volume. Different Artificial Intelligence models can be created and hybrid models that use more than one Artificial Intelligence model together can also be tested to increase performance. In addition, it is considered that conducting new studies with data sets to be collected by considering a particular airport or airports in a certain region will contribute to the literature.

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