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Forecasting the Tourism Demand of Türkiye Using Artificial Neural Network (ANN) Approach

Dr. Cagatay Tuncsiper

Ph.D., Centrade Fulfillment Services co-founder.

ORCID: 0000-0002-0445-3686

ABSTRACT **Published Online: March 31, 2023**

Modelling and forecasting the tourism demand is an important research area for both public and private sectors for planning the travel and accommodation facilities in advance. Therefore, modelling the tourism demand in terms of the number of tourists is an active research area for both tourism, economics and financial studies. In this work, the tourism demand of Türkiye is modelled using artificial neural network methods. The tourism demand represented by the number of tourists is taken as the dependent variable while the past values of the number of tourists is considered as the inputs. Furthermore, the tourism revenue is also modelled employing the same autoregressive artificial neural network approach. Monthly data in the period of 2008-2022 which are taken from the official sources are used as the research material. The multilayer perceptron type artificial neural networks with nonlinear neural activation functions is selected for the accurate modelling of the highly seasonal tourism demand data. The modelling and forecasting results show that the developed artificial neural network reaches high accuracy for modelling both the tourism demand and the tourism revenue such that the coefficient of determination of the developed artificial neural network models have the values of R^2=0.949 and R^2=0.840 for the tourism demand and tourism revenue, respectively, providing an objective assessment of the accuracy of the developed models. It is concluded that the multilayer perceptron based artificial neural network methods can be used to model the tourism demand therefore this type of modelling is expected to be helpful for tourism planners by providing them the tourism demand forecast in advance.

Keywords:
Tourism demand; artificial neural networks; forecasting; modelling; number of tourists.

1. INTRODUCTION

Tourism has become a significant income component for all countries The tourism revenue provides fiscal support, trade balance, foreign currency inflow into the country therefore contributes to the economic development. In addition to the economic development support, tourism also provides the increase of employment. Besides the economic and social contributions, tourism also strengthens social and cultural communication among nations. Tourism is not only an income-generating field of activity but also an important industry with many aspects that support the economic and production factors to interact with each other and this interactions support the economy to accelerate. The tourism sector which is an important income source also support to eliminate interregional economic imbalances and contributes to the constitute new employment areas. Therefore, tourism activities reduce unemployment, and support and increase other activities such as the agriculture, transportation and service sector.

According to the World Travel and Tourism Council (WTTC), travel and tourism's contribution to the gross domestic product (GDP) around the World has increased to 5.8 trillion USD in 2021 (WTTC, 2023). This translates to the contribution of 6.1% to the global GDP. In 2021, 9.2% of all jobs around the globe which is 289 million people, are employed in the tourism sector. According to the WTTC, 126 million new jobs are expected to be created by 2023 in the tourism activities. In order to increase the regional share from the potential of the tourism sector, the tourism activities obviously should be planned in a systematic way. From this viewpoint, tourism management, making the right investment decisions, turning opportunities into benefits and the requires

Corresponding Author: Dr. Cagatay Tuncsiper

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moves have to be planned properly. These planning activities demand the business managers to estimate the near future more clearly. In this sense, one of the most important tools is the artificial learning assisted tourism demand forecasting methods.

Modelling and forecasting the tourism activities enable the tourism manager and planners to make right decisions for proper and effective resource planning and make the tourism planning more efficient. Estimation of the tourism activities supports the effective utilization of the investment resources such as accommodation, travel and tourism services investments. Reliable and accurate demand forecasts are necessary for the effective management of all activities related to the tourism sector, especially accommodation, transportation and travel businesses (Cuhadar et al., 2009). Accurate forecasting the tourism demand also play an important role for making long-term tourism development planning. Therefore, making accurate estimations of the tourism demand with advanced methods is an important component for the management of the tourism development programs for both the central and local administrations and the private sectors. Therefore, researchers and decision makers put great efforts to predict the tourism activity of countries and regions in order to determine correct objectives based on these estimates. However, tourism is a socio-cultural activity hence the tourism activity is easily affected by several factors such as global economic shocks, pandemics, regional conflicts and natural disasters. These factors have the potential to slow down the tourism demands therefore the tourism demand modelling and forecasting studies have to be performed utilizing advanced methods for achieving high accuracy.

Türkiye has great international tourism potential with its historical, cultural and natural background, hospitality tradition, unique historical and archaeological sites, mild climate and developed tourism infrastructure. Türkiye is like an open air museum with various advanced tourism and airport facilities. The tourism attractions of Türkiye makes it one of the most preferred tourism destinations in the world. According to the WTTC website, the tourism revenue of Türkiye was 59.3 billion USD in 2021 making it 7.3% of its annual GDP. The 8.4% of the total jobs created in Türkiye was utilized in the tourism sector which is 2.42 million people (WTTC Türkiye report, 2022). Considering these numerical values, it can easily be argued that the tourism sector which provides an important source of foreign currency has an important place in reducing unemployment and improving the balance of payments by creating new employment. The tourism sector in Turkey has become one of the leading sectors of the economic structure. In addition to its contribution to the GDP, tourism sector plays an important role in the reduction of the payment deficit and contributes to reducing unemployment by providing job opportunities to the unemployed.

On the other hand, artificial neural networks (ANN) are algorithms and programs that imitate biological neural networks by providing parallel and distributed information processing, which are developed by mimicking the physiology of the brain. ANNs consist of processing elements called neurons which are connected to each other through weighted connections. ANNs are formed by the distributed connection of the neurons where the neurons utilize nonlinear activation functions for processing data. ANNs are trained by a set of data called the training data, where the weights of the neuron connections are optimized and then the results of the ANN is tested using the test data. ANNs have applications in various scientific and technical areas mainly in classification and regression problems. The utilization of ANNs as regression networks enable to model data which have high nonlinearity or seasonality as in tourism data.

In this study, the tourism demand of Türkiye is modelled using monthly data for the period of 2008-2022 for the aim of forecasting using ANN methods. The tourism demand is described by the number of tourists and this data is taken as the dependent variable while the previous values of the tourism revenue and the number of tourists are selected as the independent variables. The multilayer perceptron (MLP) network structure with nonlinear activation functions is developed for the accurate modelling of the highly seasonal tourism demand data in Python programming language. The modelling results show that the developed ANN results have the coefficient of determination values of R^2=0.949 and R^2=0.840 for the tourism demand and the tourism revenue data, respectively, indicating the accuracy of the developed ANN model.

II. LITERATURE ANALYSIS

There are vast number of studies existing in the literature regarding the tourism demand of various countries and regions. Some of these studies utilize the linear regression methods and the ANN methods together. For example, the number of Japanese tourists arriving to Hong Kong for the 1967-1996 period is investigated using both linear regression and feedforward ANN methods where the service prices, hotel prices, population, marketing costs and the exchange rate are taken as input variables and the number of tourists is considered as the output variable and they have concluded that the feedforward ANN performs better than the linear regression model (Law and Au, 1999). In another work, the Taiwanese tourists arriving to Hong Kong for the period of 1967-1996 is modelled using linear multiple regression, backpropagation and feedforward ANNs in which expenditure per person, exchange rate, hotel prices, service prices and marketing expenses are taken as input variables and the number of tourists is the output variable and it is shown that the backpropagation ANN is shown to have the best accuracy compared to the linear multiple regression and the feedforward ANN structure (Law, 2000). In another study, the number of tourists arriving to Spain for the period of 2001-2012 is modelled employing a multiple input ANN model and it is demonstrated that multiple input ANNs can be used to increase the accuracy of the tourism demand model (Claveria et al., 2015). A hybrid method consisting of the ANN structure combined with experimental data is used in another work in which the number of tourists arriving to Taiwan from Japan, Hong Kong and Macao for the 1971-2009 period is estimated and it is concluded that hybrid ANN methods have more accuracy compared to classical autoregressive integrated moving average (ARIMA) method (Chen et al., 2012). Similarly, the number of tourists arriving from the mainland China to Macao is modelled in another work for the 2011-2018 period using deep learning, ANN and support vector machines in which the prices of accommodation, food, tours, and transportation are utilized as the input variables and it is concluded that the deep learning method achieves the best accuracy (Law et al., 2019). The tourism demand of the Turkish Republic of Northern Cyprus (TRNC) is studied in another work where the number of tourists are modelled for the 1998-2010 period using trend analysis method in which the ratio of the price index of the originating country and the price index of TRNC is used as the input variable and the number of tourists is the output variable and they have demonstrated that the trend analysis method is successful for the modelling of the tourism demand (Ertek et al., 2002). In another study, the tourists arriving in Hong Kong for the 2012-2018 period is modelled employing ANN methods in which it is shown that the ANN method provides better accuracy compared to the support vector regression and ARIMA methods (Zhang et al., 2021).

The tourism demand for Türkiye is modelled in another work for the period of 1984-2014 using a seemingly unrelated regression model where the price index of the originating country and Türkiye are used as the input data and it is shown that the tourism demand can be modelled employing the seemingly unrelated regression method (Keskin, 2019). In another study, the tourism revenue of Türkiye for the 2003-2020 period is modelled employing the Box-Jenkins, ANN and exponential smoothing approaches and it is concluded that the ANN method provides the best accuracy (Cuhadar, 2020). The tourism demand for Türkiye for the 1984-2008 period is studies in another work in which ARMA, ARIMA, ANN and supervised learning methods are compared and it is demonstrated that the ANN method has the best performance (Zorlutuna and Bircan, 2019). The number of tourists visited Türkiye in 2016 is modelled dependent on various parameters such as the GDP of the originating country, and the distance of the originating country in another work and it is shown that the utilized panel gravity model can be used to forecast the tourism demand (Buluk and Duran, 2018). The factors affecting the tourism demand of Türkiye for the 1999-2003 period is investigated in another work where Hylleberg, Engle, Granger and Yoo (HEGY) test is used to assess the impact of the GDP, travel costs and the exchange rate on the tourism demand where it is concluded that the GDP impacts the tourism demand (Zortuk and Bayrak, 2013). The tourism demand for the Mugla province of Türkiye for the 2013-2014 period is studied in another study where Holtz-Winters, exponential smoothing and the Box-Jenkins methods are utilized and it is concluded that the exponential smoothing method has the best results (Cuhadar, 2014). Similarly, the tourism demand of Türkiye for the year 2006 is considered in another work where the gravity model approach is utilized with the input data of the economic size, distance, cultural and historical ties and adjacency are used and it is shown that the gravity model is useful for the modelling of the tourism demand data (Karagoz, 2008). In another study, the tourism demand of Türkiye is modelled employing the tourism data of 1986-2007 period for the forecasting the tourism demand for the 2007-2010 period with the exponential smoothing, seasonal smoothing, Box-Jenkins methodology and the ANN methods where it is shown that the ANN method can be used to model the tourism demand (Onder and Kuvat, 2009). The number of tourists arriving to Antalya, Türkiye for the period of 1991-2014 is modelled in another study using ANN, multiple regression, and nonlinear regression and it is shown that ANN model provides the best accuracy (Gungor and Cuhadar, 2005). Similarly, the tourism demand of Türkiye for the period of 1990-2002 is modelled by ANN methods in which the number of accommodation facilities, and the number of foreign tourists are used as inputs and it is shown that ANN gives results close to the real data (Cuhadar and Kayacan, 2005). In another work, the tourism demand for the Northeast region of Türkiye for the period of 1985-2000 is modelled using linear models where the number of beds, GDP of the country of tourists, exchange rates and the consumer price index and it is concluded that the number of beds has the greatest impact on the tourism demand (Emir, 2010). Similarly, in another work the tourism demand for Türkiye for the 1984-1999 period is modelled using ANNs, multiple regressions and moving averages when the service prices, average expenditure per tourist, exchange rate, the population of the originating countries, GDP of the originating countries and the marketing expenditure are taken as the independent variables and they have shown that the ANN method gives the best results for the forecasting of the tourism demand (Baldemir and Bahar, 2003). The impact of various macroeconomic parameters on the tourism demand is investigated in another study where Engle-Granger causality, Johansen VAR analysis, impact analysis and variance decomposition methods are utilized and it is shown that the economic growth and the exchange rate affects the tourism demand (Kara et al., 2012). Similarly, the tourism demand for Denizli province of Türkiye for the period of 2010-2013 is modelled employing feedforward ANN methods where the average temperature, tourism revenue, exchange rate and consumer price index are used as input data and it is concluded that the ANN methods can be utilized for the forecasting of the tourism demand (Karahan, 2015). In another study, the number of tourists arriving in Türkiye from Germany for the 1998-2009 period is modelled employing multiple linear regression, ANN and support vector regression in which the macroeconomic and population data of Germany are used as the input variables and it is concluded that the ANN method gives the best results among the used methods (Erdogan et al., 2021).

The number of tourists visiting the national parks in the United States is modelled using backpropagation ANN methods in another work in which it is concluded that the ANN methods provide better accuracy compared to the conventional linear methods (Pattie and Snyder, 1996). In another study, the tourism demand of Hong Kong for the 1974-2000 period has been modelled and it is shown that Elman ANN methods give accurate results for the number of tourists (Cho, 2003). The tourism demand from Canada to the United States is modelled in another work using multiple regression and ANN methods where it is concluded that the two methods give comparable results (Uysal and El Roubi, 1999). In another study, the tourism demand of Balearic Islands of Spain for the period of 1986-2000 is modelled using ANN methods with 28 different structures and they have shown that ANN methods has the advantages of providing nonlinearity, low error tolerance and no need for statistical assumptions (Palmer et al., 2005). The tourism demand of the South Portugal for the 1987-2005 period is modelled in another work employing the backpropagation ANNs and it is concluded that the backpropagation ANNs successfully models the tourism demand (Fernandes and Teixeira, 2008). Similarly, the tourism demand of Singapore originating from Australia, India, China, Japan, United Kingdom and the United States for the period of 1985-2001 is modelled in another work utilizing basic structural model, ANN model and exponential smoothing method in which it is concluded that ANN methods give the most accurate results (Kon and Turner, 2005). In another study, the tourism demand of Türkiye is modelled using the traditional time series analysis such as the Holt-Winters method and the ANN method and they have concluded that ANN models can be used as alternatives to the traditional models (Onder and Hasgul, 2009). The tourism demand of Türkiye for the 1977-2008 period is modelled in another work using learning algorithms of momentum update backpropagation, resilient backpropagation, Quasi-Newton backpropagation and Levenberg-Marquards update and it is shown that the ANN with the resilient backpropagation algorithm gives the best results (Aladag, 2010). On the other hand, it is argued in the literature that the ANN methods can be used to model time series with high seasonality without the need for seasonal component elimination process (Sharda and Patil, 1992; Franses and Diarisma, 1997; Alon et al. 2001; Hamzacebi, 2008; Cuhadar, 2013).

The number of tourists arriving into South Africa from the United States is modelled in a study where moving averages, exponential smoothing, genetic regression, autoregressive integrated moving averages and ANN methods are applied for the estimation of the number of tourists and it is shown that the ANN method has the most accurate results (Burger et al., 2001). Similarly, the tourism demand of Taiwan was modelled in another work with autoregressive integrated moving averages method, ANN and the multivariable regression and it is concluded that the ANN method provides accurate estimations (Chang-Jui et al., 2011). The tourism demand of Taiwan is modelled also in another work where autoregressive integrated moving averages, exponential smoothing, regression and ANN with backpropagation structure are used in combination and it is concluded that the combined utilization of these methods gives the best results (Kuan-Yu, 2011). The usage of the autoregressive integrated moving averages and the ANN with backpropagation structure for the estimation of the tourism demand of Taiwan are compared in another study and it is shown that the ANN method gives better results (Chun-Fu et al., 2012). The number of tourists arriving in Taiwan is modelled in another work employing the multivariable regression and the ANN methods and it is concluded that ANN method gives best results (Chang-Jui and Tian-Shyug, 2013). The tourism demand for the Guangdong province of China is modelled in another work employing the ANN with backpropagation where it is shown that ANN with the backpropagation method can be used to model and forecast the tourism demand (Yang et al., 2013). In another work, the tourism demand of Türkiye for the 1987-2012 period is modelled employing with multilayer perceptron network, radial based function and time delay ANNs where it is concluded that the multilayer perceptron network has the lowest mean absolute percentage error providing the best accuracy (Cuhadar, 2013).

As it can be seen from the literature analysis, there are vast number of studies regarding the modelling and forecasting the tourism demand of various countries for different periods and the common result of these studies is that the ANN models provide better results compared to the conventional linear models. Considering this, the tourism demand of Türkiye for the 2008-2022 period is modelled using a new autoregressive ANN structure such that the past values of the tourism demand are taken as the input data of the developed ANN model. The ANN structure is developed in Python programming language and the results of the ANN model shows that the developed model can be used to model and forecast the tourism demand. In addition, the tourism revenue is also modelled employing the autoregressive ANN model. The employed data and the details of the developed model are given in the Materials and Method section and the graphical and quantitative assessment of the developed ANN models are presented in the Results and Discussion section. Finally, the opportunities on the utilization of the developed model in other areas of econometrics is discussed in the Conclusions section.

III. MATERIALS AND METHOD

The tourism demand and the tourism revenue data of Türkiye is gathered from the Electronic Data Distribution System of the Central Bank of Türkiye for the period of 2008M01-2022M12 as monthly data (EVDS, 2023). The number of tourists and the tourism revenue data are originated from the Ministry of Culture and Tourism and the Turkish Statistical Institute, respectively (MCT, 2023; Turkstat, 2023). The obtained number of tourists data and the tourism revenue data are plotted in Fig. 1 and Fig. 2, respectively. As it can be observed from Fig. 1 and Fig. 2, both the tourism demand and the tourism revenue data are highly seasonal and nonlinear data as expected according to the studies existing in the literature.

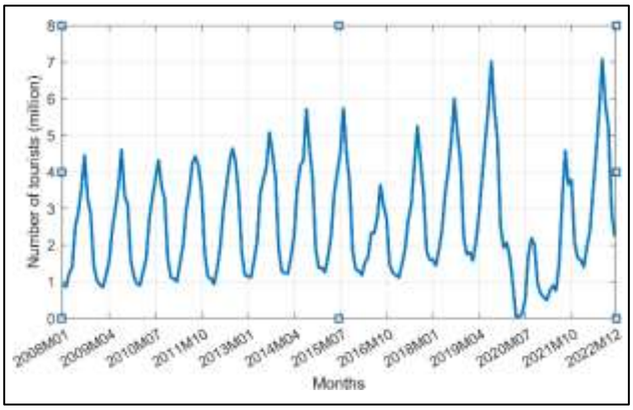

Fig. 1. The number of tourists arriving in Türkiye in the period of 2008-2022

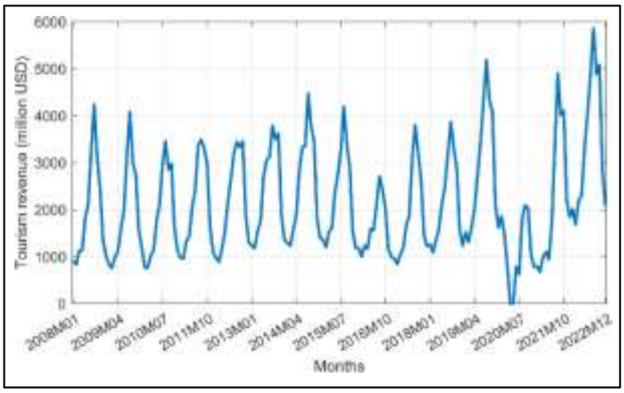

Fig. 2. The tourism revenue of Türkiye in the period of 2008-2022

In order to observe the seasonality and nonlinearity of the tourism demand and the tourism revenue data, the seasonal-trend decomposition using Loess method is applied in Eviews software on the data (Cleveland et al., 1990; Bhaumik, 2015). The resulting seasonal and trend components of the tourism demand and the tourism revenue data are shown in Fig. 3 and Fig. 4, respectively. Both the tourism demand and the tourism revenue data have high seasonal components as can be seen from Fig. 3 and Fig. 4, respectively. The linear modelling methods require the elimination of the seasonal components before the modelling phase however removal of the seasonal components are not mandatory for the ANN modelling as explained in various studies in the literature (Sharda and Patil, 1992; Franses and Diarisma, 1997; Alon et al. 2001; Hamzacebi, 2008; Cuhadar, 2013). Therefore, the seasonal components are not removed in this study to provide a complete picture of the modelled tourism demand and revenue data.

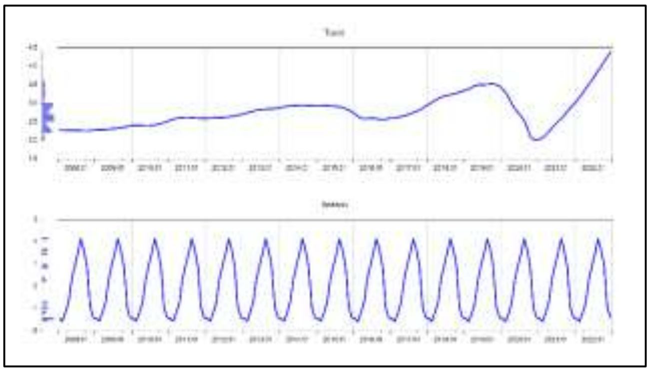

Fig. 3. Trend and seasonal components of the tourism demand data

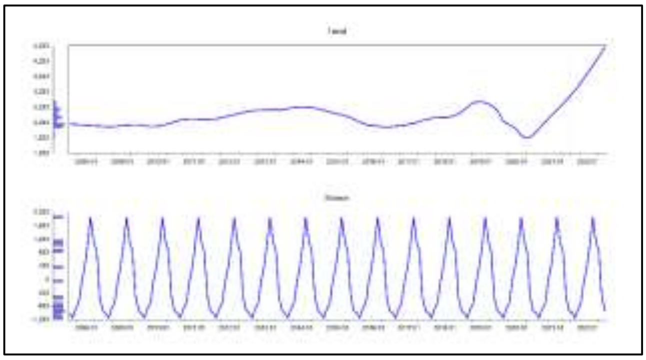

Fig. 4. Trend and seasonal components of the tourism revenue data

An autoregressive multilayer perceptron type ANN model is utilized for the modelling of the tourism demand and the tourism revenue data in this study. An ANN consists of neurons with nonlinear activation functions for the modelling of the data in which the weights of the neuron connections are optimized using the training data in the training phase.

The structure of the developed ANN model is shown in Fig. 5. The inputs of the ANN is the past four values of the modelled tourism demand or the tourism revenue data denoted as y_{n-1}, y_{n-2} and y_{n-3} and y_{n-4}. The output of the ANN is the tourism demand or the tourism revenue data shown by y_n. The ANN structure employs one hidden layer containing fifty neurons.

In an ANN, the neurons operate as nonlinear processing units therefore the input-output relationship of the neurons can be expressed as in Eq. (1).

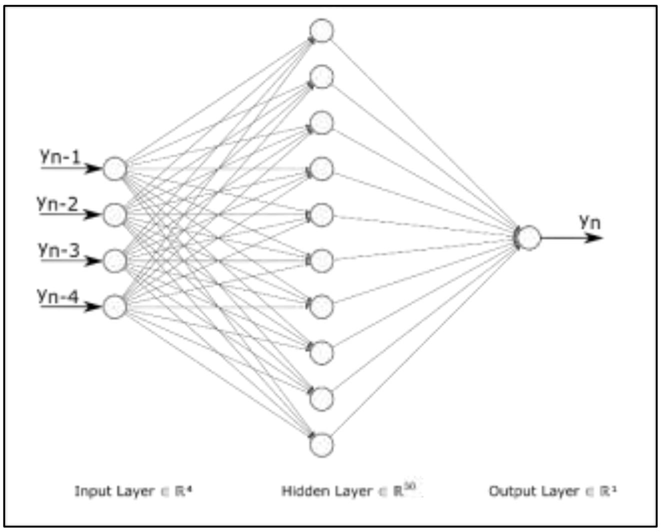

Fig. 5. The structure of the developed ANN for modelling the tourism demand and the tourism revenue data

$$y = f(b + \sum_{i=1}^{n} x_i w_i) \quad (1)$$

In Eq. (1), y is the output of the neuron, b is the bias, w_i are the weights and x_i are the input data of the neuron (Ahmad et al., 2014; Ghritlare and Prasad, 2018; Aggarwal, 2018). The selection of the activation function *f()* is crucial for the performance of the ANN. In this study, the tourism demand and the tourism revenue are modelled which are highly seasonal and nonlinear data as shown at the beginning of this section therefore hyperbolic tangent functions are used as the activation functions of the neurons for the accurate description of the nonlinearity of the tourism demand and the tourism revenue data. The hyperbolic tangent function has the form shown in Eq. (2).

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (2)$$

The hyperbolic tangent function shown in Eq. (2) accurately represents the nonlinearity of the data (Kadry, 2014; Viera-Martin et al., 2022; Shakiba and Zhou, 2021).

The proposed ANN structure is developed in Python programming language using the SciKit-Learn (SKLearn) library in conjunction with the NumPy and Pandas libraries for the data management activities (Bisong, 2019; Ziogas et al., 2021; Lemenkova, 2019). The 70% of the available data are taken as the training data while the remaining 30% is used as the test data which is a standard application in the literature (Yeole et al., 2022; Chauhan et al., 2019; Sarkar et al., 2021). The results of the modelling and forecasting of the tourism demand and the tourism revenue data using the developed ANN model and their objective assessment using performance metrics are given in the next section.

IV. RESULTS AND DISCUSSION

The developed artificial neural network, whose details are given in the previous section, is trained using the 70% of the available data as the first step. The test_train_split function is utilized for an objective splitting the data as the training and the test data in Python programming language (Shah et al., 2022; Raschka et al., 2022). The training performances of the developed ANN model for the tourism demand and the tourism revenue data are given in Fig.6 and Fig. 7, respectively.

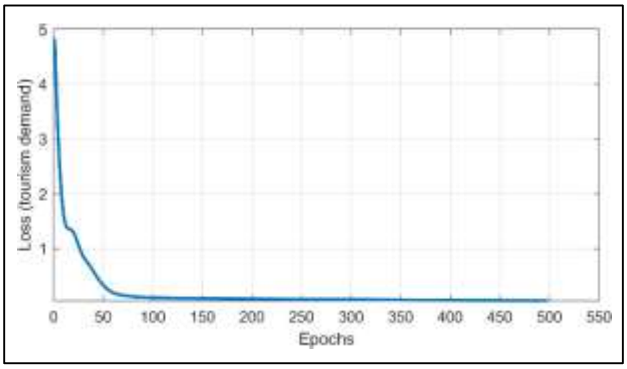

Fig. 6. The training performance of the developed ANN for the tourism demand data

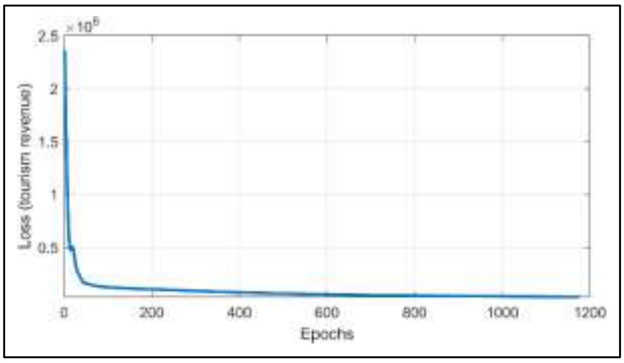

Fig. 7. The training performance of the developed ANN for the tourism revenue data

As it can be observed from Fig. 6 and Fig. 7, the developed ANN model is successfully trained for the tourism demand and the tourism revenue data. The convergence steps of the training phase for the tourism demand and the tourism revenue data are 520 and 1176, respectively.

The results of the developed ANN model for the tourism demand and the tourism revenue data are plotted as the next step. The matplotlib library of Python is utilized for the plotting activities (Schafer, 2021). The actual and the ANN model results of the tourism demand data are given in Fig. 8. Similarly, the actual and predicted values of the tourism revenue data are plotted in Fig. 9. As it can be observed from Fig. 8 and Fig. 9, the developed autoregressive ANN structure successfully models the tourism demand and the tourism revenue data.

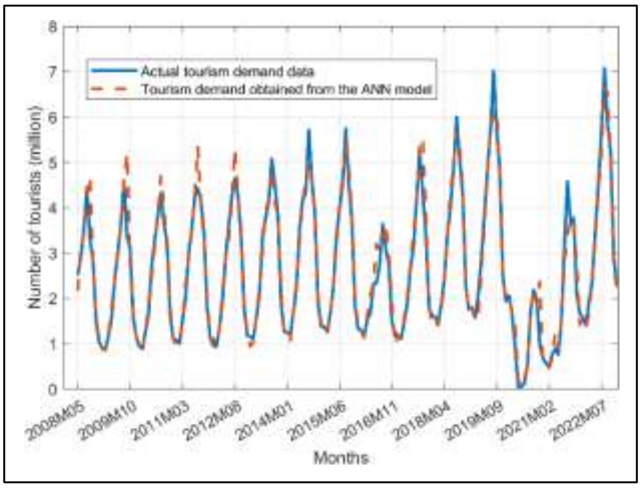

Fig. 8. The actual tourism demand and the tourism demand obtained from the ANN model

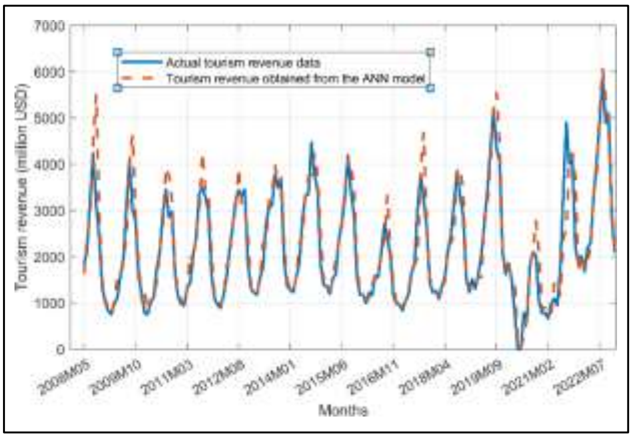

Fig. 9. The actual tourism revenue and the tourism revenue obtained from the ANN model

As it can be observed from Fig. 8 and Fig. 9, the developed ANN successfully models both the tourism demand and the tourism revenue. Furthermore, performance metrics namely the coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) of the developed model for the tourism demand and the tourism revenue cases are calculated in Python programming language and shown in Table 1.

Table 1. Performance metrics of the developed models

Model	R^2	RMSE	MAE	MAPE
Tourism demand	0.949	0.339	0.198	10.387%
Tourism revenue	0.840	462.735	281.229	14.152%

The performance metric given in Table 1 show that the developed ANN structure models both the tourism demand and the tourism revenue data successfully.

V. CONCLUSIONS

In this study, the tourism demand and the tourism revenue of Türkiye are modelled using an autoregressive artificial neural network (ANN) structure. The tourism demand is described by the number of foreign tourists and the past values of the number of tourists is considered as the inputs of the developed ANN making it effectively an autoregressive ANN model. The tourism revenue is also modelled employing the same autoregressive ANN approach. The tourism demand and the tourism revenue data are gathered from the official resources for the period of 2008-2022. The multilayer perceptron (MLP) type ANN with hyperbolic tangent activation functions is selected for the representation of the tourism demand and the tourism revenue data which are highly seasonal and nonlinear. The modelling results show that the developed autoregressive ANN provides coefficient of determination values of R^2=0.949 and R^2=0.840 for the tourism demand and tourism revenue data, respectively. It is worth noting that the developed autoregressive ANN structure can also be used to model other seasonal and nonlinear econometric data.

VI. DISCLOSURE

The author reports no conflicts of interest in this work.

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