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FORECASTING TOURISM DEMAND: A COMPARATIVE MODEL ANALYSIS FOCUSING ON SPANISH TOURIST'S TRAVEL TO CAPPADOCIA

Ebrucan İSLAMOĞLU*, Nuri Özgür DOĞAN**

Abstract

This study has two purposes. Firstly, it aims to identify models that best estimate tourism demand. Secondly, it also aims to estimate the demand of Spanish tourists who visit Cappadocia, by using the identified proper models. As international tourism demand continually grows, the importance and magnitude of the tourism sector for the economies of the countries increase. In order to take into account the tourism demand, countries need to be prepared and therefore they want to know about the future demand. However, it is not always possible to know the actual demand and one can only make forecasts in such cases. This paper deals with forecasting international tourism demand, specifically focusing on the Spanish tourist visits in Cappadocia region of Turkey. In accordance with this aim, eight forecasting models are used. The results of the analyses for each model are obtained and the forecasting accuracy examined. It is seen that the Artificial Neural Networks and the Multiple Regression Model outperforms the other models. Finally, limitations of the study and future resarch directions are discussed.

Keywords: *Spanish Tourist Visits Artificial Neural Networks, Tourism Demand Forecasting, Cappadocia, Multiple Regression.*

JEL Codes: *Z32, Z30.*

TURİZM TALEP TAHMİNİ: İSPANYOL TURİSTLERİN KAPADOKYA'YA SEYAHATİNİ İNCELEYEN KARŞILAŞTIRMALI BİR MODEL ANALİZİ

Özet

Bu çalışmanın iki amacı vardır. İlki, turizm talebini en iyi tahmin eden modelleri tanımlamaktır. İkincisi, tespit edilen uygun modeller yardımıyla Kapadokya'ya gelen İspanyol turistlere ilişkin talebi tahmin etmektir. Uluslararası turizm talebi arttıkça, ülkelerin ekonomisi için turizm sektörünün önemi ve büyüklüğü de artmaktadır. Ülkelerin turizm talebini dikkate almaları için hazırlıklı olmaları gerekmekte ve bu nedenle ülkeler gelecekteki turizm talebi hakkında bilgi sahibi olmak istemektedir. Ancak, gerçek talebi tespit etmek her zaman mümkün değildir ve bu gibi durumlarda insanlar sadece tahmin yapabilmektedir. Bu makale uluslararası turizm talep tahmini üzerine, özellikle de Türkiye'nin Kapadokya bölgesindeki İspanyol turist ziyaretleri üzerine odaklanmaktadır. Bu amaca uygun olarak, sekiz tahmin modeli kullanılmıştır. Her model için analiz sonuçları elde edilmiş ve tahmin doğruluğu incelenmiştir. Yapay sinir ağları ve çok değişkenli regresyon modelinin çalışmada kullanılan diğer modellere göre daha iyi sonuçlar verdiği görülmüştür. Sonuç olarak, çalışmanın kısıtları ile gelecekte gerçekleştirilecek araştırmalar için birtakım önerilere yer verilmiştir.

Anahtar Kelimeler: *İspanyol Turist Varışları, Yapay Sinir Ağları, Turizm Talep Tahmini, Kapadokya, Çoklu Regresyon.*

JEL Sınıflandırması: *Z32, Z30.*

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1.INTRODUCTION

Cappadocia is among the most beautiful tourism regions in the world. It attracts about 2,5 or 3 million tourists each year (www.aa.com.tr). It is located within the borders of city of Nevşehir in the central Anatolian part of Turkey. Cappadocia is unique with its natural structure formed by the accumulation of old volcano's ashes and lavas. The region has site-specific natural beauties such as fairy chimneys, rock houses and churches, valleys, underground cities, open air museums and so on. While geographical events constituted fairy chimneys, people built houses and churches into fairy chimneys. They decorated them with frescoes. Thereby they carried the traces of civilization which lasts thousands of years to the present (Culture and Tourism Ministry, 2016). During the last 15 years, the Spanish economy has experienced substantial growth. The Gross Domestic Expenditure per capita, increased from 906,9 billion USD in July 2003 to 1,34 trillion USD in September 2012 (Banco Mundial, 2018). The global economic crisis broke out in 2008 and began to threaten the Eurozone. One of the outcomes of this threat in domestic income in Spain was the decreased number of departer tourists (Paksoy and Çolakoğlu, 2010). For this reason, in the period of July 2003 to September 2012, the number of Spanish visitants to Nevşehir did not change. Figure 1 shows the number of Spanish tourist destinations in Nevşehir during the period of July 2003 to September 2012. Data were attained from Turkish Statistical Institute, Nevşehir District Office. The number of tourists coming to Cappadocia was determined according to their nationality by using these data. As a result, the highest number of inbound tourists to this region come from Spain.

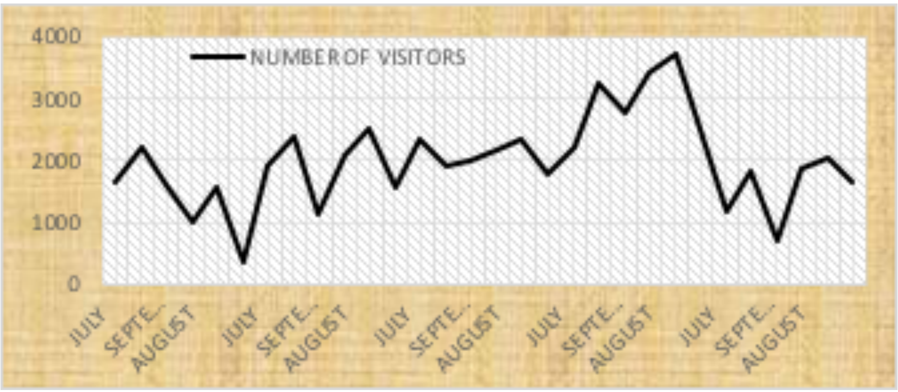

Figure 1. **The number of Spanish visitor in Nevşehir from July 2003 to September 2012**
(**Source:** Turkish Statistical Institute).

Inherently, the tourism related sectors in Nevşehir draw on dramatically from the visits of Spanish visitants. In 2012, total tourism receipts in Turkey attained US$ 25. 7 billions (UNWTO, 2013). World economy suffered from crisis in 2008 and it had also some effects on the Spanish economy. The crisis led to a decrease in national income and a raise in unemployment. These parameters were the indicators of the Spanish crisis. Spain's national income index was 100 in 2007 and it decreased to 90 in 2013 (EUROSTAT, 2018). In the same period, unemployment increased from 9 percent to 26 percent (Turkish Rebuplic Development Ministry International Economic Indicators, 2014). Spanish officials say that the Spanish economy has recovered due to structural reforms (Reinhart and Rogoff, 2008:339). The economic crisis lasted five years (2008-2012). Spain eventually emerged from this economic crisis in 2013. In accordance with this situation the number of inbound Spanish tourists to Nevşehir decreased between the years of 2008 and 2012. It is predicted that tourism will be one of the world's largest industry by 2050 (HSBC, 2050). Tourism attracts great attention of all developing and developed countries. It is not an unexpected situation because the tourism sector is directly and indirectly related to economic activities and this increases the importance of development of the sector. In order to benefit from the advantages of tourism, it is a big step to estimate accurate and reliable demand in both public and private sectors (Çuhadar and Kervankıran, 2016: 51). Accurate forecasts are substantial to make right decisions for managers and practitioners.

This study focused on tourism demand forecasting in a regional manner and dealt with inbound tourist visits to Cappadocia. Therewith, the aims of the research are to model and forecast Spanish tourist's demand for Cappadocia to determine the model that gives the highest accuracy, and to make a small additive to the related literature.

2. LITERATURE

Tourism demand modelling and/or forecasting is an interesting subject and has succeeded to arouse the interest of many researchers in past several years. For example; (Song and Li, 2008: 206-209) made an extensive literature review on tourism demand between 2000 and 2007 and analyzed the forecasting methods used in a detailed way. This study reviews the post-2008 literature on tourism demand forecasting. Table1 gives the abstract of this literature. Table1 includes some abbreviations and we benefit from the study of (Song and Li, 2008 : 206-209) while using this framework. The explanations of these abbreviations are given below the table.

Table1: The Abstract of Post-2008 Tourism Demand Studies.

Köse et al. (2008)	In this study, 1991 and 2006 period are examined. Quarterly data are used. Turkey tourism demand analysis are examined in the framework of structural time series models. Empirical findings have shown that income and price variables are significant. In addition, predictive performances of four alternative models are compared with the structural time series model. The most succesful forecast is achieved by combining seasonal ARIMA and structural time series model. **DF :** Monthly, **RF:** Turkey (D), **MFM :** AR(I)MA(X), ES, MA TCM, **FE :** FC, **RT :** FAC
Çeken (2008)	In this study, tourism' s regional development and the effect of tourism's underdevelopment is focused on. Impact on development of tourism in Turkey is discussed based on observations and scientific researches. Tourism sector has the highest added-value depending on the touristic supply data in the region. For this, the tourism sector of a country or region depends on its effectiveness in development. Its effectiveness in eliminating interregional imbalances depends on specified issues. This study focused on these issues. **RF:** Turkey (D), **MFM:** Qualitative technique, **FE:** Ex-post, **RT:** Tourism on Regional Development
Karagöz (2008)	In the study, demand-side factors are mentioned. These factors are affected the number of tourists coming to Turkey. Turkey' s tourism potential according to countries has been investigated by gravity model approach. According to results, countries' economic size, distance, cultural-historical links and neighborhood have an effect on tourist flow to Turkey. **DF:** Monthly, **RF:** Turkey (D), **MFM:** SR, **FE:** No, **RT:** Econometric analysis of tourism demand
Song and Li (2008)	In the study, the authors review the studies since 2000 about tourism demand. According to results, this study is more diverse than other review articles. Thanks to this study, a number of new techniques have come into view. **FE:** Ex-ante, **RT:** Related literature on tourism is examined
Bahar and Baldemir (2008)	In this study, the direction of the relationship between international tourism and international trade is determined. Between 1980 and 2005 years are used. From tourism to export a one way and positive relationship is found. **DF :** Monthly, **RF:** Turkey (D), **MFM:** SR, **FE:** Ex-post, **RT :** EM, FA
Önder et al. (2009)	İzmir is examined in this study. Factors affecting international tourism demand are determined. Data is used between 1980 and 2005 years. According to results, price and income are the main factors of tourism demand. **DF:** Yearly, **RF:** Turkey-İzmir (D), **MFM :** The double logarithmic model, **FE:** Ex-post, **RT:** Econometric analysis, FA
Çuhadar et al. (2009)	Exponential smoothing methods, Box-Jenkins methods and artificial neural network methods are used in the study. The period from January 1992 to December 2005 is examined. 12 delayed neural network model has been shown to provide the highest accuracy. Thanks to the model obtained, monthly foreign tourism demand forecasts for Antalya province are made for 2009 years. **DF :** Monthly, **RF:** Turkey-Antalya (D), **MFM :** ES, ANN, AR(I)MA(X) **FE :** Ex-ante, **RT :** FAC, FA
Wang (2009)	This work uses the auto-regression distributed lag model. This model is proposed by Pesaran, Smith, Shin [Pesaran et al. (2001)]. Incomes, foreign exchange rates, transportation costs and relative prices explore the influence of variables. All variables has a long-term equilibrium. Safety affects tourism demand negatively. The safety and health of tourists are important for inbound tourism. **DF :** Quarterly, **RF:** China-Taiwan (D), **MFM :** ARDL, **FE:** No, **RT :** EM

Aslan et al. (2009)	A dynamic model is used for tourism in Turkey. Nine major clients are used for 1995-2004. Arellano and Bond (1991) are proposed GMM-DIFF estimator. They used this estimator in this study. The significant value of the lagged dependent variable is the main conclusion of this study. **DF :** Monthly, **RF:** Turkey (D),**MFM :** PDR, **FE:** FC, **RT :** EM, FAC
Görmüş and Göçer (2010)	In this study, the data set consist of annual panel data for 32 countries for a period of 7 years (2000– 2006). Panel data techniques are used. Turkey is examined for tourism demand forecasting. The authors are made several diagnostic tests. They used tourist visits from 32 sending countries to Turkey between years 2000 and 2006. EGLS estimation method for panel data set is used. **DF:** Monthly, **RF:** Turkey (D), **MFM :** PDR , **FE :** FC, **RT :** FAC
Eryiğit et al. (2010)	The numbers of international tourists is examined in this study. A gravity-based modelling is used. The top 11 countries for 1995 and 2005 are used. The main important factors are negative distance effect. **DF :** Monthly, **RF :** Turkey, **MFM :** Gravity model, **FE :** No, **RT :** The Factors Affecting Tourism Demand
Soysal and Ömürgönülşen (2010)	A demand forecast has been made for the Turkish tourism industry. Domestic and foreign tourists are staying in the facilities with tourism operation certificate issued by the Ministry of Culture and Tourism were examined. The number of tourists is used as data in the study. The aim of the study is to find the most suitable numerical forecasting method for the available data set and making predictions. Traditional methods in time series are applied to the data set and then the performances of these methods are compared. Winter method is the most suitable method and predictions are made accordingly. **DF :** Monthly, **RF :** Turkey (D), **MFM:** MA, ES, Holt's Exponential Smoothing Method, Winters Exponential Smoothing Model, **FE :** FC, **RT :** EM, FAC
Kaya and Canlı (2011)	The factors of the international tourism demand to Turkey are studied. Panel data approach is used for the period of 1990-2010 and 1990- 2008. The effect of Portugal is positive and the effect of Greece is negative. At the same time the effect of Spain is insignificant. **DF :** Monthly, **RF :** Turkey (D), **MFM :** PDR, **FE :** Ex-post, **RT :** Econometric analysis of tourism demand
Tsaur and Kuo (2011)	Taiwan's tourism demand is predicted in this study. An adaptive fuzzy time series model is used. MAPE and RMSE is determined the prediction accuracy. The potential benefits of the new approach is mentioned. **DF:** Monthly, **RF:** China-Taiwan (D), **MFM:** FTS, **FE:** FC, **RT:** EM, FA
Huang and Lee (2011)	The authors combines the grey forecasting model (GM) and Fourier residual modification model. The new model is used to refine the forecasting effectiveness for the stochastic volatility data and to predict international visitors to Taiwan and improving the forecasting accuracy. **DF:** Monthly, **RF:** China-Taiwan (D), **MFM :** GM, FGM, **FE:** FC , **RT :** EM, FA
Athanasopoulos et al. (2011)	518 annual, 427 quarterly and 366 monthly series are used in this study. Econometric models, univariate and multivariate time series are used. Pure time series are gives good results. For seasonal data the authors are implemented three pure time series algorithms. For annual data the authors find that Naive forecasts are the best. **DF:** Monthly–Quarterly, **MFM:** AR(I)MA(X), ForePro, TS, Theta, Damped, **FE:** No, **RT:** EM, FA
Hong et al. (2011)	Barbados is examined in this study. Data is used from 1994 to 2003. Forecast the tourist visits are made by using SVRCGA-II and SVRCGA-I. These models are compared with SVMG-I and SVMG-II. According to results the proposed SVRCGA model is the best model. **DF:** Daily, **RF:** China-Taiwan (D), **MFM:** EMD, MLP, EMD-BPN, **FE:** FC, **RT:** FAC
Chen (2011)	Taiwanese is examined in this study. Real time series data sets are used. Outbound tourism demand is predicted. the linear and nonlinear models are combined. The empirical results show that the SVR combination models has a high forecasting accuracy and a change detect ability. **DF:** Monthly, **RF:** China-Taiwan (D), **MFM:** Naïve method, ES, AR(I)MA(X), Naïve BPNN, ES BPNN, ARIMA BPNN, Naïve SVR, ES SVR, ARIMA SV, **FE:** FC, **RT:** FAC
Song et al. (2011)	Hong Kong is examined in this study. Demand for hotel rooms is forecast. From the first quarter of 2009 to the fourth quarter of 2015 is used in this study. The main factors are the economic conditions in the origin markets, the price of the hotel rooms and the 'word of mouth' effect. **DF:** Quarterly, **RF:** China-Hong Kong (D), **MFM :** SE, **FE:** Ex-ante, **RT :** FAC

Wu et al. (2012)	The sparse GPR models are used in this study for tourism demand. Data of Hong Kong is used. Experimental results show that the sparse GPR model outperforms ARMA and other kernelbased models. **DF:** Monthly, **RF:** China-Hong Kong(D), **MFM :** SR, ARMA AR(I)MA(X) **FE :** FC, **RT :** EM, FA
Türkben et al. (2012)	They talked about agricultural tourism, viticulture and argo-tourism in their works. In our country, promotion of our cultural values, nature building, argo-tourism, winemaking, organizing tours etc. can apply. In terms of oenotourism potential lands are introduced. **DF:** Monthly, **RF:** Turkey (D), **FF:** No, **RT:** Importance of Argo-touris
Chen et al. (2012)	In this study, tourism demand is predicted. Neural network and empirical mode decomposition (EMD) is used. Taiwan is examined. According to results the proposed model outperforms the single BPN model without EMD preprocessing and the traditional autoregressive integrated moving average (ARIMA) models. **DF:** Monthly, **RF:** China-Taiwan (D), **MFM :** EMD-BPN, BPN, AR(I)MA(X), **FE:** FC, **RT :** FAC.
Wei and Chen (2012)	Passenger flow in metro systems is used as data in this study. A hybrid EMD–BPN forecasting approach is proposed. According to the results the hybrid approach performs well and stably. **DF:** Daily, **RF:** China-Taiwan (D), **MFM:** EMD, ANN, EMD- BPN, **FE:** FC **RT :** EM and FAC
Pan et al. (2012)	Query volume data in forecasting demand for hotel rooms is used in this study and sought to identify the best econometric forecasting model. They employed three ARMA family models and their ARMAX counterparts. The authors also evaluated ADL, TVP, and VAR for comparison. All three ARMAX models outperformed their ARMA counterparts of demand for hotel rooms. **DF:** Weekly, **RF:** USA-Charleston (D), **MFM:** ADLM, TVP, VAR, AR(I)MA(X), **FE:** FC, **RT:** FAC.
Huarng et al. (2012)	Taiwan's tourism demand forecasting is used for study. The authors are used a neural network based fuzzy time series model. This study outperforms previous studies undertaken during the SARS events of 2002-2003. **DF:** Monthly, **RF:** China-Taiwan (D), **MFM:** FTS, **FE:** Ex-post, **RT :** FAC
Azaklı (2012)	The main purpose of this thesis is to determine the problems of thermal tourism in Turkey. Assessments carried out in Nevsehir Kozaklı Thermal Tourism Center. This study offers some suggestions about the improvement of thermal tourism in Turkey. **DF:** Monthly, **RF:** Turkey (D), **MFM:** In-Depth Analysis, **RT:** EM and Improve of Thermal Tourism
Çuhadar (2013)	Inbound tourism demand to Turkey is examined in this study. Radial Basis Function (RBF), Feed Forward-Back Propagation (MLP) and Time Delay (TDNN) artificial neural network architectures are used. The authors made prediction for 2013. The period of January 1987 – December 2012 are utilized. It has been observed that MLP model has presented best forecasting performance. **DF:** Monthly, **RF:** Turkey (D), **MFM:** MLP, RBF, TDNN, **FE:** Ex-ante, **RT :** EM and FAC
Shahrabi et al. (2013)	Modular Genetic-Fuzzy Forecasting System (MGFFS) is used in this study. Results show that forecasting accuracy of MGFFS is better than other models. Powerful non-parametric statistical tests are also used for comparing the performance of MGFFS with others. **DF:** Monthly, **RF:** Japan (D), **MFM:** AR(I)MA(X), ANN, ANFİS, GFS, MGFFS, **FE:** FC, **RT:** EM, FA
Song et al. (2013)	The authors introduces tourism demand forecasting system (TDFS). The made forecasting for Hong Kong tourism. Quantitative and judgmental forecasts are combined. According to results, forecasting accuracy is improves by combination of quantitative and judgmental forecasts. **DF:** Quarterly, **RF:** China-Hong Kong (D), **MFM:** Quantitative forecasting methods, User intervention, Computer-based innovation **FE:** FC, **RT :** FAC
Çuhadar (2014)	Inbound tourism demand for Muğla is studied in this study. The authors are made prediction for 2012 and 2013 years. According to results, Holt-Winter's Exponential Smoothing model is made the best performance. **DF:** Monthly, **RF:** Turkey-Muğla (D), **MFM:** ES, AR(I)MA(X), **FE:** Ex-ante, **RT:** FAC

Cloveria and Torra (2014)	Catalonia is examined in this study. The autors are used overnight stays and tourist visits. ARIMA models outperform SETAR and ANN models **DF:** Monthly, **RF:** Spain-Catalonia (D), **MFM:** ANN, AR(I)MA(X), SETAR, **FE:** Ex-post, **RT:** Forecasting Tourism Demand
Pai et al. (2014)	Fuzzy c-means (FCM) with logarithm least-squares support vector regression (LLS-SVR) Technologies are combined in this study. Genetic algorithms (GA) are used. Tourist visits to Taiwan and Hong Kong are used in the study. Empirical results indicate that the proposed forecasting system demonstrates a superior performance to other methods. **DF:** Monthly, **RF:** China-Taiwan (D), China-Hong Kong (D), **MFM:** Hybrid Systems, **FE:** FC, **RT:** EM, FA
Claveria et al. (2015)	The multi-layer perceptron neural network, the radial basis function neural network and the Elman recursive neural network are used in this study. This study contributes to the tourism forecasting literature and to the tourism industry. This research also highlights radial basis function neural networks to improve forecasting accuracy. They find that the multivariate multiple-output approach does not outperform the forecasting accuracy of the networks. It improves the forecasting performance for total tourist visits. **DF:** Monthly, **RF:** Spain-Catalonia (D), **MFM:** ANN, AR(I)MA(X), SETAR, **FE:** Ex-post, **RT:** EM, FA
Peng et al. (2014)	65 studies are reviewed during the period 1980 and 2011. The relationship between forecast accuracy, data characteristics and study features is studied in this study. According to results, key study features and data characteristics influence forecasting accuracy. The meta-regression analysis is used. The results provide suggestions for the choice of appropriate forecasting methods in different forecasting settings. **DF:** Quarterly-Monthly, **RF:** Asia(OC-D), America(OC-D), Europe(OC-D), Australia(OC-D), Africa(OC-D), Other(OC-D), **MFM:** ANN, Time Series, DES, SES, **FE:** FC, **RT:** FAC
Çuhadar et al. (2014)	Forecasting cruise tourism demand to İzmir is examined in this study. It is aimed to find the best performance among the varios models. Generalized Regression neural network (GRNN), Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) are used. The period of January 2005 and December 2013 is examined. Experimental results showed that radial basis function (RBF) neural network outperforms multi-layer perceptron (MLP) and the generalised regression neural networks (GRNN) in terms of forecasting accuracy. **DF:** Monthly, **RF:** Turkey-İzmir(D), **MFM:** MLP, RBF, GRNN, FE**,** FC, **RT:** FAC
Gunter and Önder (2015)	The authors are forecasting international city tourism demand for Paris. Five most important foreign source markets (Germany, Italy, Japan, UK and US) are used. Classical VAR, EC-ADLM, ARMA, TVP, Bayesian VAR and ETS models are used. According to results, univariate models of ARMA(1,1) and ETS are more accurate for the US and UK source markets. Multivariate models are better predictors for the German and Italian source markets, in particular (Bayesian) VAR but for the Japanese source market, the results vary. **DF:** Monthly, **RF:** France-Paris(D), **MFM:** EC-ADLM, VAR, TVP AR(I)MA(X), ETS, **FE:** FC, **RT:** EM, FA
Aksakal et al. (2015)	In this study, the authors aimed to model the demand of tourism to Turkey for European countries. For this purpose, Visibly Unrelated Regression Models are used. Parameters are estimated based on these models. It has been compared with the Least Squares estimates. This study proposes using the GIR model as a decision method. **DF**: Monthly, **RF:** Turkey (D), **MFM:** SUR, **FE:** FC, **RT:** EM, FAC
Hazır et al. (2015)	Turkey furniture sales values estimated with a sample artificial intelligence application. In this study, demand forecast of furniture for 2023 is performed using artificial intelligence methodology and regression analysis with the basic indicators between the years 2004-2013. As the result of the research 24 billion dollars and 21 billion dollars demands are predicted by multiple variable regression analysis and artificial intelligence methodology respectively. These results may be evaluated as the possible retail values for Turkish furniture sector within the target of vision 2023. **DF:** Monthly, **RF:** Turkey(D), **MFM:** ANN, Multivariable Regression Analysis, **FE:** FC, **RT**: EM, FAC
Bangwayo-Skeete and Skeete (2015)	Google Trends data is used for improvingforecast accuracy. MIDAS models using Google data outperformed conventional time series models. The authors are used Autoregressive Mixed-Data Sampling (AR-MIDAS) models, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and autoregressive (AR) approach. Policymakers and business practitioners in the Caribbean can take advantage of the forecasting capability of Google search data. **DF:** Monthly-Weekly, **RF:** Caribbean(D), **MFM:** AR-MİDAS,SARIMA,AR, **FE:** Ex-post, **RT:** FAC

Daştan et al. (2016)	The Erzurum province and winter tourism is chosen in this study. The relationship between socio-economic and demographic factors is determined. In 2015, a questionnaire is applied to 531 tourists. Chi-square test and logit model are applied. Nationality, occupation, age and income variables are positively related. The education and spending variables are negatively related. **DF:** Monthly, **RF:** Turkey-Erzurum (D), **MFM:** Chi-square analysis-Logit Model, **FE:** Ex-post, **RT:** Winter tourism
Çuhadar and Kervankıran (2016)	It is aimed analyzing and modeling tourism demand for lodging properties operating in Nevşehir as a tourism destination of Turkey. They used Exponential Smoothing and Box-Jenkins (ARIMA) models and forecasting monthly tourism demand for year 2016 via the method providing the highest accuracy. The data is in the period of January 2010 – December 2015. Data are utilized to build appropriate model. As a result, it is seen that Holt-Winter's Multicaptive-Seasonal exponential smoothing model has presented the best performance. They made prediction in Nevşehir for year 2016. Forecasting performances of models used in the study are evaluated by "Mean Absolute Percentage Error (MAPE)" statistic. **DF:** Monthly, **RF:** Turkey-Nevşehir (D), **MFM:** AR(I)MA(X), ES, **FE:** FC, **RT:** FAC
Lyu et al. (2016)	For prediction the singular spectrum analysis (SSA) is used in this study. The acceleration signals of a historic Tibetan building is used for data. The SSA is outperforms the X-11-ARIMA model, the autoregressive integrated moving average model (ARIMA) and the cubic spline extrapolation. As a result, the SSA algorithm is appropriate for daily tourist number to protect an ancient building. **DF:** Daily, **RF:** Tibet-China(D), **FE:** SSA, AR(I)MA(X), **FE:** FC, **RT :** FAC
Abbreviations	
D	As a destination
OC	As a country/region of origin
AR(I)MA(X)	AutoRegressive (Integrated) Moving Average (cause effect) model
ES	Exponential Smoothing
MA	Moving Average
TCM	Trend Curve Model
FC	Forecasting Competition
FAC	Forecast Accuracy Comparison
SR	Static Regression
EM	Econometric Modelling
FA	Forecast Accuracy
ES	Exponential Smoothing
ANN	Artificial Neural Network
ARDL	Autoregressive Distributed Lag
PDR	Panel Data Regression
FTS	Fuzzy Time Series
GM	Grey Forecasting Model
FGM	Fourier Residual Modification Grey Forecasting Model
ForePro	Forecast Pro
ETS	ExponenTial Smoothing
Theta	Theta Method
Damped	Damped Trend Method
EMD	Empirical Mode Decomposition
MLP	Multilayer Perceptron
EMD-BPN	Empirical Mode Decomposition- Back Propagation Neural Network
Naive BPNN	Naive Back Propagation Neural Network
ES BPNN	Exponential Smoothing Back Propagation Neural Network,
ARIMA BPNN	AutoRegressive (Integrated) Moving Average (cause effect) model Back Propagation Neural Network Naïve

SVR	Naive Support Vector Regression
ES SVR	Exponential Smoothing Support Vector Regression
ARIMA SVR	AutoRegressive (Integrated) Moving Average (cause effect) model Support Vector Regression
ADLM	Autoregressive Distributed Lag Model
TVP	Time Varying Parameter Model
VAR	Vector AutoRegression
FTS	Fuzzy Time Series
RBF	Radial Bases Function
TDNN	Time Delay Artificial Neural Network
ANFIS	Adaptive Artificial Neural Network-Fuzzy Logic
GFS	Genetic Fuzzy Systems
MGFFS	Moment Generating Function Fuzzy Systems,
SETAR	Self-Exciting Threshold AutoRegressive Model
DES	Double Exponential Smoothing Model
SES	Single Exponential Smoothing Model
MLP	Multilayer Perception
GRNN	Generalized Regression Neural Network
EC-ADLM	Error-Correction Formulation of the ADLM
ETS	ExponenTial Smoothing
SUR	Seemingly Unrelated Regression Model
AR-MİDAS	AutoRegressive Mixed Data Sampling
AR	AutoRegressive process
SARIMA	Seasonal AutoRegressive Integrated Moving Average
ES	Exponential Smoothing,
MFM	MFM
DF	DF
RF	**RF**
FE	**FE**
RT	**RT**

As can be seen in Table1, there are many studies about tourism demand made with the aim of forecasting various aspects of tourism demand such as number of tourists, hotel occupancy rate, tourist visits/ departures, tourist expenditures/receipts, inbound tourism, hotel room, winter tourism, new destinations, golf tourism, agricultural tourism, cruise tourism and city tourism. The most of the studies about forecasting and modeling in Turkey are made in macro level and not dealt with a specific region or tourist attraction center. In other words they are made by focusing on the whole country. It is noteworthy that forecasting studies related with tourism demand of Cappadocia region are rather limited. It is believed that this work is important in terms of giving direction to the future work in this area in Turkey.

3. METHOD

3.1. Data Analysis and Procedure

The study is carried out using the data set of July 2003 and September 2012. The data set which consists of Spanish tourists' visits to Cappadocia region were attained from Turkish Statistical Institute, The Ministry of Culture and Tourism of the Republic of Turkey and The Provincial Directorate of Culture and Tourism of Nevşehir. Table2 shows the relevant data. As previously emphasised in the preceeding parts of the paper, this study aims to forecast the Spanish tourists' demand for travel to Cappadocia. This demand is restrained by the number of Spanish tourist visits (Y) and can be emphasised as follows:

"Y = f (NS,NHR,ET,PS,MEN,GDS)"

We largely utilise from (Law and Au, 1999) in determining this function. The dependent variable, Y, is the number of visitors, namely the number of Spanish tourists. The other variables are independent variables and listed as follows:

1) Service price in Nevşehir relative to Spain - (NS*)
2) Average hotel rate in Nevşehir (TL) - (NHR)
3) Foreign exchange rate (Euro/TL) - (ET)
4) Population in Spain (1000) - (PS)
5) Marketing expenses in promotional Nevşehir (TL) - (MEN)
6) Gross domestic expenditure per capita in Spain (US$) - (GDS)

*NS is calculated as follows :

$$NS_I = \frac{CPI_I^{(Nevşehir)} / CPI_{July\text{-}2007}^{(Nevşehir)}}{CPI_I^{(Spain)} / CPI_{July\text{-}2007}^{(Spain)}}$$

where CPI is Consumer Price Index, equation is based on 2007 prices.

$CPI_I^{(Nevşehir)}$: Consumer price index of Nevşehir Province
$CPI_I^{(Spain)}$: Consumer price index of Spain Province
$CPI_{July\text{-}2007}^{(Nevşehir)}$: Consumer price index of Nevşehir Province for July 2007
$CPI_{July\text{-}2007}^{(Spain)}$: Consumer price index of Spain Province for July 2007

Table 2: A Review of Spainish Tourist Visits in Nevşehir

Year	Month	Service fee in Nevşehir relative to Spain	Average hotel rate in Nevşehir (TL)	Exchange Rate (EURO/ TL)	Population in Spain (1,000)	Marketing (promotional) expenses in Nevşehir (TL)	Gross domestic expenditure per capita in Spain (US)	Number of Spainish visitors
2003	July	0,82	1,95	1.571	4272	194	2149571	1642
2003	August	0,82	1,94	1.582	4272	100	2149571	2221
2003	September	0,82	1,85	1.542	4272	95	2149571	1602
2004	July	0,85	2,24	1.765	432	316	2491865	1023
2004	August	0,86	2,22	1.789	432	149	2491865	1588
2004	September	0,86	2,33	1.829	432	466	2491865	375
2005	July	0,89	2,09	1.608	4411	163	2651072	1934
2005	August	0,89	2,11	1.675	4411	10	2651072	2382
2005	September	0,90	2,21	1.642	4411	183	2651072	1138
2006	July	0,96	2,79	2.016	4471	181	2848261	2076
2006	August	0,79	2,69	1.888	4471	102	2848261	2506
2006	September	0,96	2,66	1.877	4471	120	2848261	1549
2007	July	1,00	2,59	1.754	452	153	3270940	2358
2007	Augusr	1,00	2,59	1.796	452	129	3270940	1915
2007	September	1,01	2,62	1.729	452	101	3 270940	1989
2008	July	1,06	3,07	1.966	4616	155	3557874	2154
2008	August	1,06	2,82	1.747	4616	113	3557874	2328
2008	September	1,07	2,72	1.760	4616	109	3557874	1792
2009	July	1,14	3,61	2.136	4675	206	3233347	2231
2009	August	1,13	3,49	2.148	4675	10	3233347	3256
2009	September	1,14	3,61	2.169	4675	110	3233347	2786
2010	July	1,20	3,49	1.990	4702	157	3073783	3423
2010	August	1,20	3,48	1.938	4702	102	3073783	3734
2010	September	1,22	3,48	1.916	4702	154	3073783	2525
2011	July	1,24	4,25	2.353	4719	4	3183224	1160
2011	August	1,25	4,42	2.455	4719	176	3183224	1826
2011	September	1,25	4,52	2.457	4719	451	3183224	699
2012	July	1,32	4,40	2.211	4727	183	2864784	1885
2012	August	1,32	4,29	2.250	4727	156	2864784	2049
2012	September	1,32	4,45	2.354	4727	152	2864784	1669

3.2. Forecasting Models

Eight models are used in the study to predict the Spanish tourists' demand for Cappadocia. These models are Artificial Neural Network Model, Naive Model, Moving Average, Exponential Smoothing, Multiple Regression, Winter's Exponential Smoothing Method, Box-Jenkins Model (ARIMA) and Holt Exponential Smoothing Method. These methods are used within the scope of numerical prediction methods. As shown in Figure1, the number of Spanish visitants has an increasing trend and seasonal fluctuations. Due to the structure of the data these models are thought to be more appropriate and therewith choosen as the analyzing tools. Utilized models are explained respectively in the following paragraphs.

3.2.1. Artificial Neural Networks (ANNs)

ANNs form an thoroughly different non-linear approach (Chatfield, 2015 : 206). The single hidden layer feedforward network model is largely used for time series modelling and forecasting (Zhang et al., 1998). This model is qualified by a network. This network has three layers. The following mathematical representation is the relationship between the output (Z_i) and the inputs ($Z_{t-1,} Z_{t-2},...Z_{t-s}$)

$$z_t = \alpha_0 + \sum_{l=1}^{k} \alpha_l g(\beta_{ol} + \sum_{k=1}^{s} \beta_{kl} z_{t-i}) + \varepsilon_t \quad (1)$$

The model parameters are α_l *(l=0,1,2,3,...k)* and β_{kl}*(k=0,1,2,...s; l=1,2,...,k).* The connection weights; (*s)* is the number of input nodes and (*k)* is the number of hidden nodes (Zhang, 2003). The hidden layer transfer function is used. Therewith, the Artificial Neural Network model of (1) is as follow,

$$Z_t = f(Z_{t-1,} Z_{t-2},...Z_{t-s}, w) + e_t \quad (2)$$

where,

$Z_{t-1,} Z_{t-2},...Z_{t-s}$ the past observations,

Z_t the future value, *w* a vector of all parameters and *f* a function

specified by the network structure and connection weights (Zhang, 2003). Additively, another substantial task of Artificial Neural Network modeling is choosing a suitble number of hidden nodes (Zhang, 2003).

In a feedforward network, data leaks from the input layer to the final output layer (Cooper, 1999).

3.2.2. Naive Model

A naive method is equipotent to a random walk model. Here, future forecasts are equal to the ultimate existing value X_t, where *t* indicates the most novel time period. This model has trends and turning points.

$$F_t = X_{t-1} \quad (3)$$

where F_t is the forecasting value at time *t,* and X_t the observed value at time t.

3.2.3. Moving Average

In the moving average representation of a process, if only a quantifiable number of *ψ* weights are nonzero, i.e., $\psi_1=-\theta_1$, $\psi_2=-\theta_2$,..., $\psi_q=-\theta_q$ and $\psi_k=0$ for k>q, so the resulting process is occur and this is a moving average process. This is expressed as MA(q). It is given by (Wei, 2006),

$$\hat{Z}_t = a_t - \theta_1 a_{t-1} - ... - \theta_q a_{t-q} \quad (4)$$

or

$$\hat{Z}_t = \text{q}(B) a_t \quad (5)$$

where

$$\theta(B) = (1 - \theta_1 B - ... - \theta_q B^q) \quad (6)$$

Because $1 + \theta_1^2 + ... + \theta_q^2 < \infty,$ a finite moving average process is always constant. This process is rotatable if the bases of *θ(B)=0* lie outside of the unit circuit. Moving average processes are beneficial in specification incident in which events generate an urgent effect that only lasts for short periods of time. The process originated as a result of the study by Slutzky on the effect of the moving average of random events (Wei, 2006).

3.2.4. Exponential Smoothing

All exponential smoothing methods are average of the data. The averaging is done in an exponential attitude (Goh and Law, 2002).

3.2.5. Multiple Regression Analysis

Multiple regression analysis techniques use linear, relationship between a single dependent variable and several independent variables. The form of the equation is as follows:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_nX_n+u \quad (7)$$

where Y = the dependent variable,

X_i = a variable,

b_i = coefficient to be predicted

n = the number of variables included in the equation

u = the error term (Mark and Goldberg, 2001).

3.2.6. Winters Exponential Smoothing Method

Exponential smoothing models are linear estimators. They place larger weight on novel values. The weight on past values diminishes exponentially (Williams et al. 1998).

Holt-Winters or Winters exponential smoothing Seasonal exponential smoothing models are known as. Winters model has the following equations (Williams et al.,1998).

$$Y_t = M_t C_{t-d} + K_t \quad (8)$$

$$M_t = V_{t-1} + O_{t-1} \quad (9)$$

$$V_t = \alpha\left(\frac{Y_t}{C_{t-d}}\right) + (1-\alpha)(V_{t-1} + O_{t-1}) \quad (10)$$

$$O_t = \gamma(V_t + V_{t-1}) + (1-\gamma)O_{t-1} \quad (11)$$

$$C_t = \delta\left(\frac{Y_t}{V_t}\right) + (1-\delta)C_{t-d} \quad (12)$$

where,

$\{Y_t\}$ is a time series. It has seasonality and trend,

$\{V_t\}$ is the series level (deseasonalized) at time t,

$\{O_t\}$is slope at time t,

$\{C_t\}$is multiplicative seasonal factor at time t,

$\{K_t\}$= WN(0, s^2) and

α, γ and δ are smoothing parameters ∈ (0,1) (Williams et al., 1998).

3.2.7. Box-Jenkins Model

Box-Jenkins ARIMA linear models denoted as ARIMA(*p, d, q*) or expressed as (Ho et al., 2002),

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \varepsilon_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \quad (13)$$

where $\{\phi_t\}$ and $\{\theta_t\}$ are the coefficients, p and q are the orders of autoregressive and moving average polynomials, in turn. In the same way, a seasonal model can be represented as ARIMA(*p,d,q*)*(P,D,Q*) (Ho et al., 2002).

3.2.8. Holt's Exponential Smoothing Method

Holt's exponential smoothing method is an enlargement of simple exponential smoothing. Model can be expressed as follow (Goh and Law, 2002).

$$F_{t+1} = \alpha.X_t + (1-\alpha)(F_t + T_t)$$
$$T_{t+1} = \beta(F_{t+1} - F_t) + (1-\beta)T_t$$
$$H_{t+l} = F_{t+1} + l.T_{t+1} \quad (14)$$

α, β the smoothing constant (0<α<1), (0<β<1),

X_t the actual value in period t,

F_t the forecast value for period t,

T_{t+1} the trend estimate,

l the number of periods ahead to be forecast,

H_{t+l} the Holt's forecast value for period t+l (Goh and Law, 2002).

4. FINDINGS

Eight models are implemented to forecast Spanish tourist visits to Cappadocia. The data set in Table 2 is used. Results are shown in Table3.

Table 3: Results of Forecasting Spanish Demand for Travel to Nevşehir

Period	Actual number of visitors	Artificial Neural Network	Naive	Moving Average	Exponential Smoothing	Winter's Exponential Smoothing	Multiple Regression	ARIMA (0,1,1) (3,0,0)	Holt Exponential Smoothing
2004-July	1023	1417,7	1602	1893,9	1778	1778	725,79	1812	1810
2004-August	1588	1417,7	1023	1663,2	1460	1460	1313,03	1462	1516
2004-September	375	1417,7	1588	1691,6	1514	1514	919,2	1318	1566
2005-July	1934	1417,7	375	1942,1	1034	1034	1813,16	1108	1110
2005-August	1138	1417,8	1934	1715,4	1821	1413	1310,51	1778	1461
2007-August	1915	1866	1138	1748,1	2066	2066	1941,12	2191	2106
2009-September	2786	2314,7	1915	1753,5	2590	2590	2500,5	2357	2616
2010-July	3423	1866	2786	1763,9	2673	2673	3658,67	3110	2705
2011-September	699	2314,7	3423	2005,5	2048	2048	843,35	1651	2131
2012-July	1885	2314,7	699	2020,1	1480	1480	1740,68	1645	1579

At first glance, it can be seen that the number of Spanish tourist visits predicted by artificial neural network is closer to the actual values. SPSS software is used to prediction multiple regression analysis. In order to make a more robust judgement on the forecasting accuracy of these eight models, Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and the Coefficient of Determination (R-squared [(R^2)]), accepteble output percentage (Z_{op}) and normalized correlation coefficient (r_{ncc}) values are calculated. The parameters are given in Table 4. These parameters are used when applying forecasting models.

Table 4: Parameters used in models

Moving Average (k=3)
Exponential Smoothing ($\alpha = 0.3$)
Holt Exponential Smoothing (α=0.952716,β=0.881154)
Winter's Exponential Smoothing ($\alpha = 0.2, \beta = 0.3, \gamma = 0.4$)

This study has two purposes. Fristly, it aims to identify models that best estimate tourism demand. Table 5 gives the accuracy comparison of these eight models.

Table 5: An Accuracy Comparision of Eight Forecasting Model

FORECASTING MODEL	MAPE	RMSE	R-squared	MAE	r_{ncc}	Z_{op}
Neural Network Model	**0,014**	840,272	0,187	652,637	0,8984	20
Naive Model	0,176	1256,377	0,330	1090,700	0,7773	0
Multiple Regression Model	25,969	**261,506**	**0,912**	**224,569**	0,1015	**60**
Exponential Smoothing Model	42,835	716,237	0,063	570,306	0,9194	30
Moving Average Model	78,042	916,659	0,041	714,817	0,8792	40
Winters Exponential Smoothing Model	24, 486	467,695	0,628	318,046	**0,9721**	30
ARIMA (0,1,1)(3,0,0) Model	37,364	692,711	0,269	488,837	0,9504	10
Holt Exponential Smoothing Model	43, 376	730,356	0,059	562,395	0,9194	30

Forecasting accuracy is based on MAPE, RMSE, R-squared, MAE, r_{ncc} Z_{op} and .[1]The formulas are used given in footnote. The low MAPE values state that the deviations between the predicted values reproduced by the neural network and the actual values. This values are too small. In accordence with MAPE criterian, neural network model is preferable. The model with low RMSE criterian is prefered. R-squared is the coefficient of determination. R-squared range from 0 to 1. R-squared value is suitable for multiple regression model. This value indicates that the independent variable explains how many percent of the dependent variable. According to the performance criteria, the lower value of MAE is preferred. Multiple Regression Model gives good results according to R-squared and MAE values. r_{ncc} quantifies the closeness of the observed and predicted Spanish tourist visits. r_{ncc} is used as a relative measurement for acceptance level (Law and Au, 1999: 94-95). According to obtained results, Artificial Neural Networks and Multiple Regression Models are the most suitable models for prediction Spanish tourıst' s travel to Cappadocia. The models that provides the highest accuracy are artificial neural networks and multiple regression. Figure 2 and Figure 3 give a graph of the predicted values attained with the neural network model and multiple regression model.

1

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{Y}_i - Y_i\right| , \quad R^2 = \frac{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2}{\sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2 + \sum_{i=1}^{n}(\hat{Y}_i - Y)^2}$$

$$Z_{op} = \frac{\sum_{i=1}^{n} j}{n} * 100\% \text{ for } \begin{cases} j=1, & \text{if } \frac{|Y_i - \tilde{Y}_i|}{Y_i} \leq 0.15 \\ j=0, & \text{otherwise} \end{cases} , \quad r_{ncc} = \frac{\sum_{i=1}^{n}(Y_i * \hat{Y}_i)}{\sqrt{\sum_{i=1}^{n}(Y_i)^2 * \sum_{i=1}^{n}(\hat{Y}_i)^2}}$$

$$MAPE = \frac{\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| / Y_i}{n} * 100\% , \quad RMSE = \sqrt{\frac{\sum_{i=1}^{n}((Y_i - \hat{Y}_i)^2)}{n}}$$

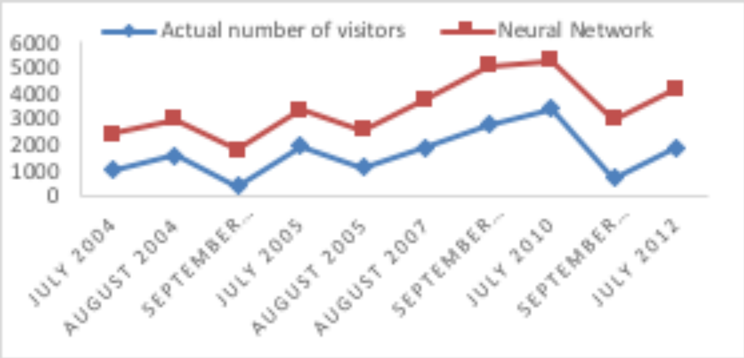

Figure 2: The graph of observations and the forecast

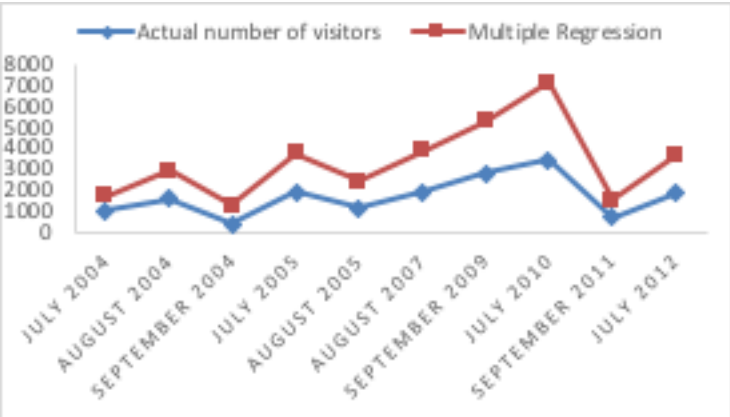

Figure 3: The graph of observations and the forecasts

This study aims to estimate the demand of Spanish tourists who are coming to Cappadocia with the help of identified prepare models. This prediction is shown in Table 6.

Table 6: Tourism Demand Forecasts for Nevşehir Province

Period	Actual number of visitors	Artificial Neural Network Model	Multiple Regression Model
July 2013	1 890	2 250	2 032
August 2013	2 150	2 038	2 025
September 2013	1 958	1 796	2 135

5.DISCUSSION AND CONCLUSIONS

This study is a comparative analysis study. Firstly it aims to identify models that best estimate tourism demand. According to obtained results, Artificial Neural Networks and Multiple Regression are the best models. Secondly, it also aims to estimate the demand of Spanish tourists who are coming to Cappadocia with the help of identified prepare models. According to these results, tourism demand forecasts for Nevşehir province are made for July 2013, August 2013 and September 2013. These results are shown in Table 6. The importance and economical magnitude of the tourism industry in the world increases as time passes. Due to the emerging role of the tourism industry, many countries depend more on the probable gains from tourism. However, transforming the tourism potential into the financial achievements requires to know the tourism demand. It is always not possible to exactly know the demand so one must rely on forecasting in such conditions. This study took a closer look at the tourism demand forecasting by focusing on a regional tourism center, Cappadocia and aimed to forecast the Spanish tourists' visits to Cappadocia. Predicted Spanish tourists' visits to Cappadocia are compared with the actual values. Eight models are used to forecast the number of visitants and it is seen that artificial neural network model and multiple regression model outperforms the other seven models in terms of forecasting accuracy. In the study, artificial neural networks and traditional methods are compared. Multiple regression method is preferred among traditional methods. Like other studies, this study has limitations. First, the findings of this study may not be generalized to entire tourism industry because it is focused on a local tourism center. Second limitation is concerned with the structure of the data. Although the data is not monthly and its period is not long enough it is the most current, consistent and the available one.

This study dealt with a demand forecasting problem in a regional and/or micro level. Analysis of similar subjects can be made in future studies. Additively, comparative studies of different tourism attractive countries can be the focus of other studies. Artificial neural networks have developed especially in the last 20 years. It consists of a simple modeling. These networks include the biological functions of the human brain. Limited studies are available on artificial neural networks and traditional time series forecasting methods in our country. This study is expected to provide important contributions to the literature of Turkey. It is also thought that it makes important contributions to future planning studies in the international area. There is no specific standart in artificial neural networks, in determining the structure of the network, in the selection of the parameters. However, artificial neural networks are still among the most substantial techniques.

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