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MODELLING AND FORECASTING INBOUND TOURISM DEMAND TO ISTANBUL: A COMPARATIVE ANALYSIS

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ABSTRACT

In an increasingly completive industry, government bodies, managers and practitioners in tourism sector are faced with the necessity of forecasting future tourism demand for effective planning. In this study, it is aimed to determine the forecasting model that provides the best performance when compared the ex post forecast accuracy of different exponential smoothing and Box-Jenkins models which were to forecast the monthly inbound tourism demand to Istanbul by the model giving best results. As a conclusion of the assessment of experimental results, it has been observed that forecasts by the seasonal exponential smoothing models have provided quite good results. On the other hand, SARIMA (2,0,0)(1,1,0)12 model has showed best forecast accuracy with lowest deviation (MAPE % 3,42) among the all applied models. By the means of this model, it has been generated the monthly inbound tourism demand forecast to Istanbul years 2014 and 2015.

Keywords: *Tourism Demand, Forecasting, Time Series Methods, Istanbul*

1. Introduction

In recent decades cities have fought hard to insert themselves into the “space of flows” of global tourism. Their history, natural and architectural heritage, inimitable cultural assets and qualities, and clusters of amenities give older central cities built-in advantages as tourist destinations. Even within resort areas where travellers may be seeking beauty and solitude, major agglomerations boasting multiple sites for shopping and dining typically spring up. Tourism, as well as comprising a major economic sector within cities, carries important symbolic weight (Fainstein at al. 2003). Turkey’s Istanbul is a spectacularly picturesque city, located at a historically strategic point that bridges two continents, Europe and Asia, divided by the Bosphorus. Great importance has been placed on Istanbul, or Constantinople as it was previously known, because it served as the capital of the Rome Empire first, then as the capital of the Byzantine and Ottoman Empires, in that order. The cultural remains of many ancient civilizations are in harmony with both Turkish culture and modernism. It was this wealth of culture in Istanbul that led the Council of Ministers of the European Union to select Istanbul as the European Capital of Culture for the year 2010, along with two other cities in Europe (Özdemir, 2010: 169). Istanbul’s special attractiveness is related to its particular combination of historic and modern, in which architecture, accessible public space, and sociability are the elements of attraction.

Forecasting tourism demand is important for tourism planning at all levels in the tourism industry from the government to a single tourist business. Effective forecasting provides credible and timely information for tourism managers to balance the market demand with the tourism supply. Strategic planners, policymakers, financing officers, and market analysts for tourism products are all required to monitor and project the changing tourism demand (Hu, 2002). The value of forecasting lies in its ability to reduce the loss caused by disparities between demand and supply. In order to provide satisfactory services to tourists, destinations need to acquire reliable forecasts of future demand for accommodation, transportation, service staff and other related travel services (Wang & Lim, 2005). Louw & Saayman (2013) stated that a lack of knowledge of future tourist arrivals may lead to missed opportunities or an overestimation of tourism demand. Overestimating tourism demand may, for example, lead to excessive investment. Thus, forecasting is an integral part of the overall strategic planning process in the tourism industry.

Quantitative tourism demand forecasting methods can be classified into two sub-categories: causal econometric and time series methods. Econometric models identify the independent variables that could affect the values of a dependent variable and then estimate the relationship between the dependent and independent variables. The most common difficulty of applying the econometric methods is identifying the independent variables that affect the forecast variables. The data of many of these variables, such as price capacity and transportation costs, are not easily accessible and are often unavailable. Furthermore, the reliability of final forecast outputs will depend on the quality of other variables (Uysal & Crompton, 1985; Yeung & Law, 2005; Chen, 2006; Cang, 2013). Time series methods use past patterns in data to extrapolate future values, whilst time series approaches are useful tools for tourism demand forecasting, cyclical and seasonal effects can distinctly be seen in time series as well as long-term upward or downward trends. Most widely used procedures in time series forecasting are the exponential smoothing and the autoregressive integrated moving average (ARIMA) models known as Box–Jenkins methodology (Burger et al., 2001; Lim & McAleer, 2001; Lim, 2002; Goh & Law, 2002; Cho, 2003; Smeral & Wüger, 2005; Wang & Lim, 2005; Coshall, 2005; Oh & Morzuch, 2005; Huarng et al. 2006; Chu, 2009; Min, 2008; Goh & Law, 2011; Lin et al. 2011). Prior studies have shown that these methods are commonly used by tourism forecasters. In testing the accuracy of different forecasting models for tourist arrivals, researchers had found that time series models often generate acceptable forecasts at low cost with reasonable benefits (Law & Au, 1999; Burger et al. 2001; Goh & Law, 2002; Tseng et al. 2002; Kulendran & Shan, 2002; Yeung & Law, 2005; Chen, 2006; Chu, 2008; Lee et al. 2008; Claveira & Torra, 2014). Thus, the time-series models are selected to forecast the tourism demand in this research.

The main objective of this study is to determine the forecasting method that provides the best performance when compared the ex post forecasting accuracy of different exponential smoothing and Box-Jenkins models as time series methods which were to forecast the monthly inbound tourism demand to Istanbul for years 2014 and 2015 by the method giving best results. A review of existing literature shows that although there are some prior studies on modelling and forecasting tourism demand to some tourism destinations of Turkey such as Muğla and Antalya, no research is available on forecasting tourism demand to Istanbul, and this paper will fill this gap. Having introduced the significance of demand forecasting in tourism and research objectives, the remainder of this paper is structured as follows. The next section provides a brief overview of Istanbul tourism. Following section provides a review of the related literature with a critical approach and the subsequent section describes the data and methodology employed. The penultimate section presents the results of estimations along with an analysis of the forecasting performance of the estimated models and generated future inbound tourism demand to Istanbul. Conclusion and suggestions for future researches are presented in the last section.

2. Brief Overview of Istanbul Tourism

Istanbul, once known as the capital of capital cities, has many unique features. It is the only city in the world to straddle two continents, and the only one to have been a capital during two consecutive empires - Christian and Islamic. Once was capital of the Ottoman Empire, Istanbul still remains the commercial, historical and cultural pulse of Turkey, and its beauty lies in its ability to embrace its contradictions. Ancient and modern, religious and secular, Asia and Europe, mystical and earthly all co-exist here (Ministry of Culture and Tourism of Turkey, 2014). The number of visitors has grown annually, making Istanbul one of the most popular European cities for tourism. Istanbul has been voted the European Best Destination in a poll organized online by European Consumers Choice, one of the continent's leading NGO's giving voices to consumers' opinions. The award was created in 2010 to allow European travellers to vote on their favourite European destination from a choice of 20 iconic cities. According to "European Consumers Choice", Istanbul took the first line after three-week voting, and was followed by Lisbon, Vienna, Barcelona, Amsterdam, Madrid, Valletta, Nice, Milan and Stockholm. "European Consumers Choice" had selected Lisbon in 2010, Copenhagen in 2011 and Porto in 2012 as the best destinations (Hurriyet Daily News, 2013). Being the second destination of Turkey that attracts the highest number of tourists after Antalya, Istanbul maintains its increasing trend in recent years. Achieving an increase of more than 5 million in terms of foreign visitors in the last decade, the city experienced an increase in the number of foreign visitors especially thanks to the developments after the Arab Spring. The increasing penetrations of low-cost airlines, as well as cruise ships, contribute to the growing arrival numbers as well. The recent incidents in "Gezi Park" and the ongoing protests since the end of May, led to some reservation cancellations, particularly in the neighbouring area. By the end of these events, the trend of fast growth which had been experienced since the beginning of the year in Istanbul was interrupted. Istanbul hosted 10 474 867 visitors according to the yearend figures even though the number of visitors was temporarily affected by the Gezi Park protests (TUROFED, 2013). Table 1 presents the Europe's top 10 destination cities by international overnight visitors. London ranks first in Europe in international visitor arrivals, followed by Paris, Istanbul, Barcelona, and Milan. In fact, the line-up of the top 10 in Europe, shown in Table 1, is unchanged 2013 from 2012.

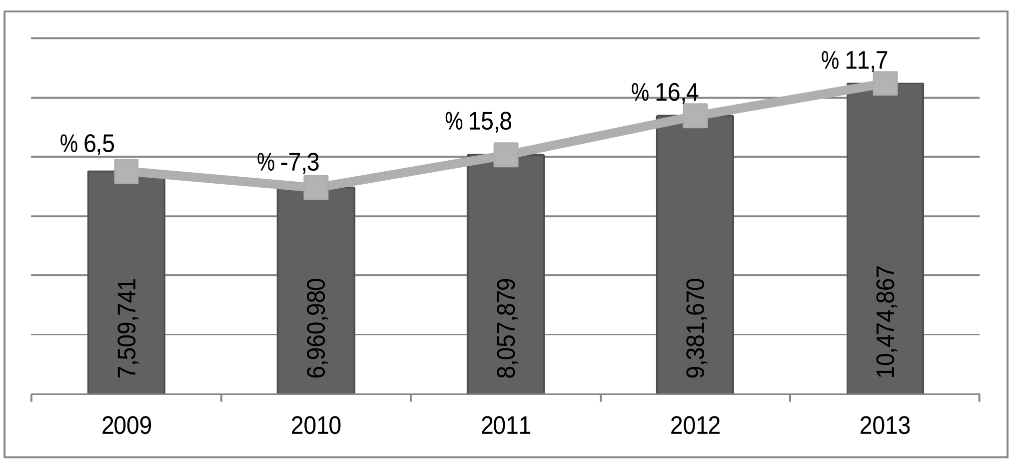
Table 1: Europe Top 10 Destination Cities by International Overnight Visitors (2013)

Rank	Cities	International Overnight Visitors (Million)
1	London	15,96
2	Paris	13,9
3	Istanbul	10,4
4	Barcelona	8,4
5	Milan	6,8
6	Rome	6,7
7	Amsterdam	6,3
8	Vienna	5,4
9	Madrid	4,7
10	Prague	4,4

Source: MasterCard Global Destination Cities Index 2013

The number of international tourist arrivals to Istanbul between the years 2009 and 2013 is given in the Fig. 1. The number of foreign tourists visiting Istanbul increased 11.7 percent in 2013 compared to 2012. The most of the tourists arrived in Istanbul are from Germany with 1 179 397 tourists which is followed by Russia with 573 528, USA with 503 019 tourists is in 3rd, and France with 478 258 tourists in fourth and UK with 456 172 tourists made the 5th place.

Fig 1: The number of international tourist arrivals to Istanbul (2009-2013)



Source: Istanbul Culture and Tourism Directorate (2013)

3. Literature Review

In the past two decades, there have been an increasing number of studies on tourism demand modelling and forecasting. While some scholars use a single type of method, either the time-series method, the econometric method to model tourism demand and forecasting, others have simultaneously analyzed tourism demand by different types of methods in order to understand which method models forecasting the best (Lin et al. 2011). Chen (2000) examined different forecasting techniques for domestic tourism demand forecasting. The author concluded that the ARIMA method was more accurate than other approaches to predict the future visitation figures in both annual and seasonal data forms. Burger, et al. (2001) have used the monthly data and ARIMA, genetic regression group method of data handling, and the ANN method to model tourism demand and forecasting in South African. It was found that the error rate established by ANN model is the lowest. Burger et al. (2001) compared various time series methods including naive, moving average (MA), ARIMA, decomposition, and exponential smoothing models in forecasting the US tourism demand to Durban. They stated that in terms of accuracy, exponential smoothing model performed best, followed by naive, ARIMA, and MA models. Kulendran & Shan (2002) have analyzed the demand for tourists in Mainland China using ARIMA model. In this study, in order to select the best forecasting model, both seasonal ARIMA models were compared with the AR model with fourth differences, the basic structural model (BSM) and the naïve "No Change" model. Their results revealed that the conventional seasonal ARIMA model with non-seasonal and seasonal differences is the best forecasting model to forecasts both China foreign visitor arrivals and total visitor arrivals. Lim (2002) used Box-Jenkins methodology for forecasting inbound tourism demand to Australia. Her results revealed that the ARIMA models outperformed the seasonal ARIMA models for forecasting demand from Hong Kong and Malaysia tourists, but demand from Singapore tourists was better forecasted using the seasonal ARIMA model. Huarng et al. (2006) have used the have used the model for neural-based fuzzy time-series and ARIMA method for forecasting the demand for tourists. In their study, ARIMA, neural networks and cloud-shaped regression (MARS) methods were used to investigate the forecasts for the demand for tourists to establish the tourism demand model and forecast as well as to compare the forecasting effects established by different methods. Chaitip et al. (2008), analysed forecasting performances of SARIMA, ARIMA, Holt-Winter- Additive, Holt-Winter-Multiplicative, Holt-Winter-No seasonal, Neural network, VAR, GMM methods to forecast international tourism arrivals to Thailand during 2006-2010. The results confirm that the best forecasting method based on first concept is SARIMA (0,1,1)(0,1,4) and the best forecasting method based on second concept is VAR model. Saayman & Saayman (2010) aimed to model and forecast tourism to South Africa from the country's main intercontinental tourism markets by naive, exponential smoothing and ARIMA models. Their results show that seasonal ARIMA models deliver the most accurate predictions of arrivals over three time horizons, namely three months, six months and 12 months. Lin et al. (2011) tried to build the forecasting model of visitors to Taiwan using three commonly adopted ARIMA, artificial neural networks (ANNs), and multivariate adaptive regression splines (MARS) methods. Their experimental results demonstrated that ARIMA outperformed ANNs and MARS approaches in terms of RMSE, MAD, and MAPE and provided effective alternatives for forecasting tourism demand. Cuhadar (2014) modelled inbound tourism demand for Mugla as a major tourism destination in Turkey by Exponential Smoothing and Box-Jenkins methods and forecasted monthly tourism demand of Muğla for years 2012 and 2013.

Review of prior studies has indicated that most studies in tourism demand forecasting focus on building and evaluating forecasting models. A large portion of these have yielded empirical information and a considerable majority have reported the accuracy of forecasts (Song & Li, 2008; Goh & Law, 2011). Song & Li (2008) reported that in the post 2000 empirical studies, 30 of 71 studies concentrated on the identification of the relationships between tourism demand and its influencing factors while 41 evaluated the forecasting performance of the econometric models in addition to the identification of the casual relationship. Amongst these 71 studies that employed econometric models, more than 30 of them applied both the time-series and econometric approaches in estimating the tourism demand models and compared the forecasting performance of these models. A lack of effort in providing actual forecasts is evident in tourism demand research. From a practitioner's point of view, tourism managers and administrators will not be able to (1) evaluate how reliable these forecasting models are, and (2) utilize these research findings directly for tourism planning or marketing purposes if the tourism research only aims to build demand models without producing forecasts. According to Hu (2002) a forecasting model should generate useful and reliable information (i.e., forecasts) for practical uses. Chu (2008) states that choosing a method should mainly be based on the accuracy of the forecast generated, the ease of use of the method, the cost of producing it and the speed at which it can be produced. From the perspective of practical forecasting in the tourism industry under uncertainty, the greatest need is for short term tourist arrival forecast. Industry's needs in the hospitality, transport and accommodation sectors have become more short-term in focus, and can change rapidly with changing market demand. Partly in consequence of this, longer-term econometric modelling (as opposed the short-term processes) has become less relevant to industry (Kon & Turner, 2005). For example for tour operators, the most useful forecasts concern tourism demand for the following season or year; because such short forecasting horizons tend to provide the most accurate results (Kollwitz & Papathanassis, 2011). In addition, a review of the existing literature shows that most of tourism demand modelling and forecasting studies are applied to country based and yearly data sets instead of applying to a specific region or destination (Hu, 2002; Song & Li, 2008; Goh & Law, 2011). Annual data only provide limited information for tourism decision making. Calling for the use of higher data frequencies (monthly and quarterly data) in tourism demand forecasting is necessary. It is also observed that there has been no published study in academic journals concerning the forecasting tourism demand to Istanbul. All this has led the author to focus on modelling and forecasting future inbound tourism demand for Istanbul, which is one of the main tourism destinations in Europe.

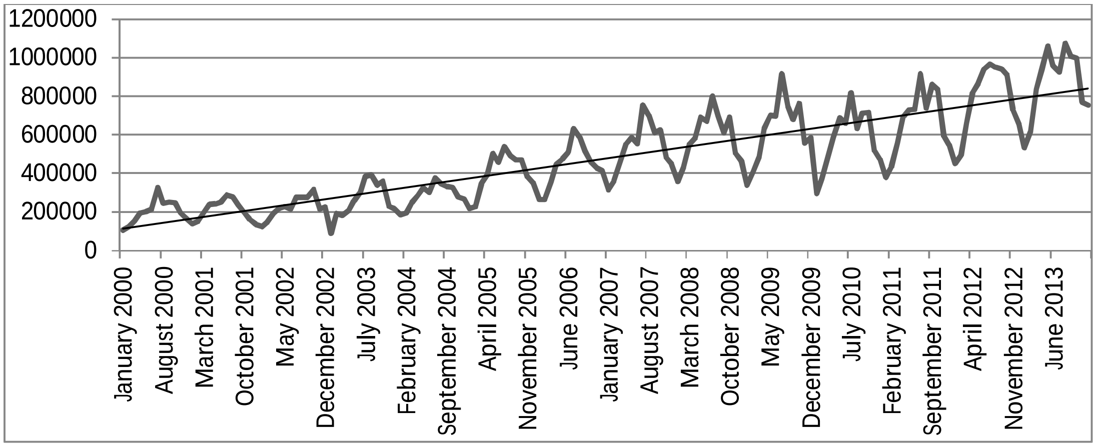
4. Data and Methodology

Tourism demand is usually regarded as a measure of visitors' use of a good or service. It can be measured in terms of tourist arrivals and/or departures, tourist expenditures and/or receipts, travel exports and/or imports, tourist length of stay, nights spent at tourist accommodation, and other. Tourist arrivals are the most frequently used measure of tourism demand, followed by tourist expenditure and tourist nights in registered accommodation (Fretchling, 2001; Lim, 2006; Song et al. 2009). This study considers foreign tourist arrivals as a measure of international tourism demand. The number of monthly foreign tourist arrivals to Istanbul cover the period between January 2000 – December 2013 data were used to build appropriate time series models. Monthly tourist arrival data were provided by Istanbul Culture and Tourism Directorate. The monthly data was preferred to be able to more detailed analyze by taking into account of seasonal and trend components. Statistical and econometric software packages (EViews 7, Minitab 16) are used to estimate the exponential smoothing and seasonal ARIMA models.

4.1.Patterns and Characteristics of The Data

Fig. 2 exhibits the time plot of international tourist arrivals data to Istanbul between January 2000 and December 2013, corresponding to 168 monthly observations. The key features of the data are growing trend and seasonal fluctuations.

Fig. 2: Time Series Plot of International Tourist Arrivals in Istanbul (2000:1 - 2013:12)



As a result of trend analysis applied to the data, growing and linear trend of the series has been found to have the structure. The validity of the F-test for testing trend equations and t-tests coefficients of the equation were found statistically significant at the significance level of 0,00. Parameter estimates and model summary of trend analysis are given in Table 2.

Table 2: Model Summary of Trend Analysis

Equation	**Model Summary**					**Parameter Estimates**		
	R Square	**F**	**df1**	**df2**	**Sig.**	**Constant**	**b1**	**b2**
Linear	0,752	502,100	1	166	,000	109072,101	4366,491	

To identify seasonality in the data, seasonal decomposition process was applied by the method of ratio-to-moving average. Weights of moving average were computed span equal to the periodicity plus one and endpoints weighted by 0.5. As a result of the analysis, obtained seasonal factor values show that the influence of seasonal fluctuations on the data periodically. Seasonal factor values are given in the Table 3.

Table 3: Seasonal Factor Values of the Data

Period	**Seasonal Factor Values (%)**	**Period**	**Seasonal Factor Values (%)**
January	60,7	July	136,7
February	68,7	August	121,5
March	88,1	September	115,4
April	103,3	October	114,9
May	112,8	November	86,8
June	111,4	December	79,9

4.2.Evaluation Forecasting Accuracy

The accuracy of a forecasting model depends on how close the forecast values of y ($\hat{y}$) are to the actual values of y. The accuracy measurement reflects how well a quantitative forecasting model can predict the future. The differences between the actual and forecast values are known as the forecasting errors, which are defined by (Song et al. 2009)

$$e_t = y_t - \hat{y}_t$$

Where,

y_t = Value of the observation at time t in the time series,
$\hat{y}_t$ = Fitted value for the observation at time t, and
n is the length of forecasting horizon.
The magnitude of the forecasting error allows the analyst to evaluate the performance of the forecasting procedures across time periods in the series. Different measures of forecasting error magnitudes are available for tourism demand forecasting evaluations such as mean square error (MSE), root mean square error (RMSE), mean absolute deviation (MAD), mean absolute error (MAE), mean percent error (MPE) and mean absolute percentage error (MAPE). The predominant measure is MAPE, commonly used in most forecasting studies (Goh & Law, 2002; Yeung & Law, 2005; Chen et al. 2003; Song et al. 2009). Some error measures can be problematic. For example, MSE and MPE may give misleading measures due to the cancellation of positive and negative errors. In this study, MAPE was used to evaluate the forecasting performance of tourism demand models because it is not prone to changes in the magnitude of the data to be forecasted defined as;

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{y_t}}{n} 100(\%)$$

As a rule, the lower the MAPE percentage errors, the more accurate the forecasts. Lewis's (1982) interpretation of MAPE results is a means to judge the accuracy of the forecast-less than 10 % is a highly accurate forecast, 11 % to 20 % is a good forecast, 21 % to 50 % is a reasonable forecast, 51 % or more is an inaccurate forecast.

4.3.Methodologies Used

This paper mainly focuses on the modelling and forecasting future tourism demand. Given the monthly inbound tourism demand data exhibit both trend and seasonal patterns, the forecasting methods used in this study incorporates trend and seasonal components in the data. Five time series forecasting models which handle seasonality are took into account in this study. They include the simple seasonal, multicaptive and additive Holt-Winters' exponential smoothing, multicaptive and additive seasonal ARIMA (SARIMA) models. The following sections briefly describe each of these methods.

4.3.1. Exponential Smoothing

Exponential smoothing methods summarize each value of a time series with an average of recent values. In many time series, recent values of the series are more relevant for modelling than older ones. So a weighted moving average that weights the more recent values more heavily than the older ones makes sense. Exponential smoothing does just that. Exponential smoothing is a weighted moving average with weights that decline exponentially into the past. The most recent data are weighted the most and the most distant data are weighted the least (Sharpe et al. 2010). The main difference among the various exponential smoothing methods is the way they treat the trend and seasonality. To accommodate trend and seasonality, Holt-Winters' method is based on three smoothing equations—one for the level (α), one for trend (β), and one for seasonality (γ). It is similar to Holt's linear method, with one additional equation for dealing with seasonality. In fact, there are two different Holt-Winters' methods, depending on whether seasonality is modelled in an additive or multiplicative way (Hyndman et al. 2008).

The basic equations for Holt-Winters' multiplicative method are as follows:

Level: $L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1})$

Growth: $b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1}$

Seasonal: $S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s}$

Forecast: $F_{t+m} = (L_t + b_t m)S_{t-s+m}$

The seasonal component in Holt-Winters' method may also be treated additively, although in practice this seems to be less commonly used. The basic equations for Holt-Winters' additive method are as follows:

Level: $L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1})$

Growth: $b_t = \beta(L_t - L_t) + (1-\beta)b_{t-1}$

Seasonal: $S_t = \gamma_t(Y_t - L_t) + (1-\gamma)S_{t-s}$

Forecast: $F_{t+m} = L_t + b_t m + S_{t-s+m}$

Simple seasonal exponential smoothing has level and season parameters and can be described by the following equations:

Level: $L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1})$

Seasonal: $S_t = \gamma_t(Y_t - L_t) + (1-\gamma)S_{t-s}$

Foreacst: $F_{t+m} = L_t + S_{t-s+m}$

where *m* is the length of seasonality (e.g., number of months or quarters in a year), L_t represents the level of the series, b_t denotes the growth, S_t is the seasonal component, F_{t+m} is the forecast for *m* periods ahead, α is the smoothing constant for the level, β is the smoothing constant for the trend estimate and γ is the smoothing constant for the trend estimate. Each of the three smoothing constants is updated with its own exponential smoothing equation. Together, these smoothing equations adjust and combine the component parts of the prediction equation from the values of the previous components. In order to find the optimal values for a; g; and d; the value that provides the smallest sum of square errors (SSE) by grid search is selected. The grid search chooses a combination for the three parameters by employing a method of trial and error. The grid values start with zero and end with one, incrementing by 0.01 (Cho, 2003).

4.3.2. ARIMA (Box-Jenkins) Methodology

Time-series models have been widely used for tourism demand forecasting in the past four decades with the dominance of the ARIMA models (Song & Li, 2008; Goh & Law, 2011). ARIMA models depend on a statistical modelling theory known as the Box–Jenkins methodology. The ARIMA model building method is an empirically driven methodology of systematically identifying, estimating, and diagnosing and forecasting time series. This methodology is concerned with iteratively building a parsimonious model that accurately represents the past and future patterns of a time series (Louvieris, 2002). The ARIMA modelling approach expresses the current time series value as a linear function of past time series values (AR) and current lagged values of a white noise process (MA). The seasonal ARIMA model, which can be fitted to seasonal time series (quarterly or monthly observations), consists of seasonal and non seasonal parts; the seasonal part of the model has its own autoregressive and moving average parameters with orders P and Q while the non seasonal part has orders p and q (Kulendran & Shan, 2002). The AR, MA, or ARMA models are often viewed as stationary processes, that is, their means and covariances are stationary with respect to time. Therefore, while the process is nonstationary, it is necessarily transformed to a stationary series before conducting their modelling processes. Differencing process is employed to transform a nonstationary series into a stationary one. The order of a differencing process is the number of times of differenced before achieving stationarity. Differencing processes for AR, MA, or ARMA models are also the so-called integrated processes and are named as ARI, IMA, and ARIMA, respectively (Hong, 2013). The general form of the ARIMA models is written as the following formulas (Aslanargun et al. 2007):

ARIMA $(p, d, q)(P,D,Q)_s$

where p is the number of parameters in the autoregressive (AR) model, d the differencing degree, q the number of parameters in MA model, P the number of parameters in AR seasonal model, D the seasonal differencing degree, Q the number of parameters in MA seasonal model, and s the period of seasonality, or

$$\phi_p(B)\Phi_{Ps}(B^S)\nabla^d\nabla^{DS}X_t = \theta_q(B)\Theta_{Qs}(B^s)a_t,$$

where X_t is the observed value at time point t (or transformed value); $\phi_p(B)$ the AR operator, $[(1-\phi_1 B-\phi_2 B^2-\cdots-\phi_2 B^p)]$; B the backshift operator, $[BX_t = X_{t-1}]$; $\Phi_{Ps}(B^S)$ the seasonal AR operator, $[(1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps})]$; B^s the seasonal backshift operator, $[B^S X_t = X_{t-s}]$; ∇^d the differencing operator, $[\nabla^d X_t = (1-B)^d X_t$; ∇^{DS} the seasonal differencing operator, $[\nabla^{DS}X_t = (1-B^S)^D X_t]$; a_t the random error at time point t, $[a_t \sim N(0,\sigma_a^2)]$; $\theta_q(B)$ the MA operator, $[(1-\theta_1 B-\theta_2 B^2-\cdots-\theta_1 B^q)]$; and the $\Theta_{Qs}(B^s)$ seasonal MA operator, $\left[\left(1-\Theta_1(B^s)-\Theta_2 B^{2S}-\cdots-\Theta_Q B^{Qs}\right)\right]$. Box-Jenkins methodology is normally implemented in four steps as indicated below (Louvieris, 2002).

- *Model Identification*. Autocorrelation functions (ACF), partial correlation functions, (PACF) and descriptive statistics are the tools used to identify a tentative ARIMA model. According to the PACFs we can identify the seasonal pattern and difference the series to achieve stationarity in standard practice of ARIMA modelling.
- *Parameter Estimation*. Initial and final estimates are computed, so that the equation for the tentative model can be specified.
- *Model Diagnostics*. This stage involves checking the model for adequacy and goodness of fit. Residual analysis, which tests whether the model has white noise residuals that satisfy homo-scedasticity conditions is the most important diagnostic check. If the tests are not statistically valid then the model has to be re-specified.
- *Forecasting*. If the model is satisfactory then the trend and seasonality are re-introduced into the model and forecasts can be made.

Since more than one tentative model may be identified and satisfactorily estimated, certain criteria must be imposed to select the final ARIMA or SARIMA model. Common criteria model selection step include: (1) statistical significance of estimated parameters, (2) adjusted residual sum of squares, (3) Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC or BIC) (Hu, 2002). The Akaike Information Criterion is calculated as;

AIC = n ln (residual sum of squares) + $2k$

Where n is the number of observations, ln is the natural logarithm, and k is the number of parameters being estimated. The Schwarz Bayesian Information Criterion is calculated as;

SBC = n ln (residual sum of squares) + k ln(n)

In an ARIMA model, k = the number of autoregressive parameters + the number of moving averages parameters + a possible intercept term When AIC is computed for two competing models, the model with smaller AIC is selected. The same applies to SBC. (Oh & Morzuch, 2005).

4.4.Application of Exponential Smoothing Models

Due to the data used in this study is the influence of growing trend and the seasonal component all seasonal exponential smoothing models (simple, Holt-Winters' additive and multiplicative) are applied. The Holt-Winters' additive method is appropriate if the magnitude of the seasonal effects in the series do not change. If the amplitude of the seasonal pattern changes over the time, then the Holt-Winter's multicaptive method would be suitable (Lim, et al. 2009). The smoothing constants are estimated by minimizing the sum of squared error (SSE) of the forecast. In order to find optimal values for α , β and γ, the value that provides the smallest SSE by grid search is selected. The grid search chooses a combination for the three parameters by employing a method of trial and error. The grid values start with zero and end with one, incrementing by 0.01. Parameter estimates of the three different models are given in Table 4.

Table 4: Parameter estimates of Exponential Smoothing Models

Model	α **(Level)**	β **(Growth)**	γ **(Seasonal)**	**SSE**
Simple Seasonal	0,5000	_	0,0000	4E+011
Holt-Winter's Multicaptive-Seasonal	0,3100	0,0000	0,0000	3,06E+011
Holt-Winter's Additive-Seasonal Linear Trend	0,7100	0,0000	0,0000	4,92E+011

The ex-post forecasting performances of three different models, as presented in Table 3, indicated that Winter's multicaptive-seasonal model outperformed the other models in terms of sum of squared errors. Model smoothing parameters which provide the smallest SSE were determined as follows.

α = 0,3100

β = 0,0000

γ = 0,0000

The mean of initial observations is used to start the iterative calculations by the software. Using time series decomposition method, a linear trend equation is first estimated using least square method, which minimizes the SSE. After removing trend component from the series, the seasonal index is estimated. These smoothing estimates are subsequently used in the Holt-Winters' multicaptive model to generate forecasts. Model equations are as follows;

$L_t = 0{,}365 \frac{Y_t}{S_{t-s}} + (0{,}365)(L_t + b_{t-1})$

$b_t = 0{,}001(L_t - L_{t-1})(1 - 0{,}001)b_{t-1}$

$S_t = 0{,}355 \frac{Y_t}{L_t} + (1 - 0{,}355)S_{t-s}$

Initial values of the model are calculated as follows;

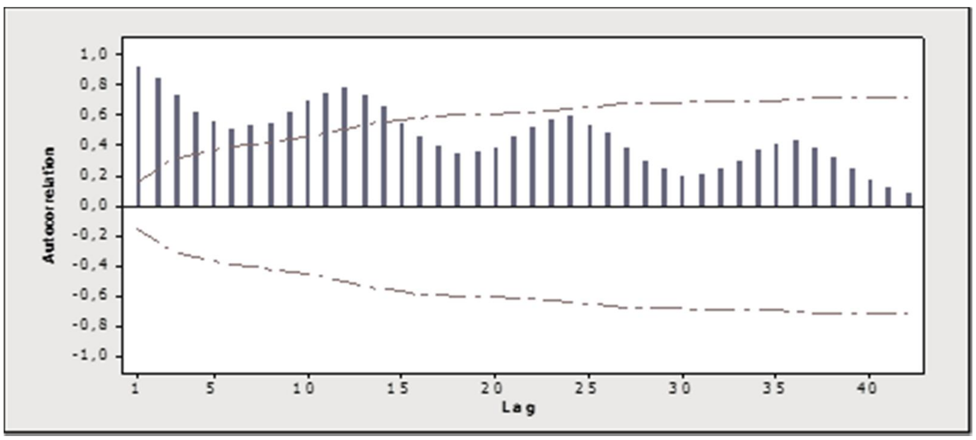
$L_s = 175904{,}78$ (Level)

$b_s = 4301{,}1624$ (Growth)

4.5.Application of ARIMA Models

As stated earlier, primarily in the implementation of the Box-Jenkins methodology is required to ensure the stationarity of the series. The data used in the study during the review phase of the components of the time series, the series exhibits a typical seasonal structure; the seasonal component is not constant over time and linear trend was determined. Correlogram belonging to the data is given in Fig. 3.

Fig. 3: Correlogram of Monthly International Tourist Arrivals Data



Examining the correlogram it is seen that structure of seasonal lags similar to each other. For example, ACF (1), ACF (13) and ACF (25) values show similar structures and systematically continued in other lags. In the case of a time series is completely random, sample autocorrelation value has a normal distribution, variance of $\frac{1}{T}$ (T= number of observations) and zero mean. Calculated seasonally lagged autocorrelations, standard errors and t statistics are given in Table 5. As can be seen in table, the t statistics calculated for different seasonally lagged autocorrelations ACF(12), ACF(24), ACF(36) are out of the confidence interval.

Table 5: Seasonally lagged Autocorrelations (ACF)

Lag	**(ACF)**	**SE**	$\mathbf{t_{ACF(k)}}$
1	0,920953	0,077	11,9369
12	0,790652	0,074	3,07024
24	0,595709	0,071	1,81833
36	0,432626	0,068	1,21210

These results revealed that series used in this study is not stationary. As a result of the analysis, stationarity of the series is provided using first order seasonal differencing. It is conducted seasonal Augmented Dickey-Fuller (ADF) test for the series at first-order seasonally differenced series. The ADF test is used to test against the hypothesis that there exists a unit root in the series.

The hypothesis $H = \begin{cases} H_0 : \gamma = 0 \\ H_0 : \gamma < 0 \end{cases}$ (H_0: the time series exhibits a lag unit root)

The t-statistic of the parameter γ is evaluated against a critical value at 5% significance level in MacKinnon distribution. If the absolute ADF test statistic is less than the absolute critical value, the series has unit root and is said to be non-stationary. The ADF test statistic for the international tourist arrivals to Istanbul is greater than the critical value and the null hypothesis of a unit root is rejected. The results revealed that series does not exhibit a unit root after seasonal differencing. The seasonal ADF test results are given in Table 6.

Table 6: Results of Seasonal ADF tests for unit roots

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.182572	0.0010
Test critical values:	1% level	-3.473096	
	5% level	-2.880211	
	10% level	-2.576805	

*MacKinnon (1996) one-sided p-values.

In applying ARIMA modelling, several mixed seasonal models were identified Two criteria are used in initial selection of the appropriate model. First one is the seasonal and nonseasonal AR an MA coefficients' statistical significance. Second, the absence of correlation in the error terms of models. Only models with all significant parameter estimates at the % 5 level and with no serial correlation selected. The selected models are compared using Akaike Information Criterion (AIC) Shwarz Bayes Criterion (SBC) and the residual correlogram. Examining the autocorrelation and partial autocorrelation functions of the series, model was identified as SARIMA $(2,0,0)(1,1,0)_{12}$. Final parameter estimates of the model are given in Table 7.

Table 7: Estimated Seasonal ARIMA Model

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	9161.565	4380.714	2.091341	0.0382
AR(1)	0.413006	0.081212	5.085506	0.0000
AR(2)	0.246922	0.081523	3.028872	0.0029
SAR(12)	0.911270	0.046487	19.60267	0.0000
MA(1)	-0.988767	0.009799	-100.9062	0.0000
R-squared	0.721552	Mean dependent var.		3618.516
Adjusted R-squared	0.714027	S.D. dependent var.		93779.63
S.E. of regression	50150.05	Akaike info criterion		24.51556
Sum squared resid	3.72E+11	Schwarz criterion		24.61459
Log likelihood	-1870.440	Hannan-Quinn criter.		24.55579
F-statistic	95.87948	Durbin-Watson stat.		1.990562
Prob(F-statistic)	0.000000	Seasonal Differencing		1

Apart from the constant term (C), all other model coefficients of the SARIMA $(2,0,0)(1,1,0)_{12}$ model in Table 6, are significant at the 5 % level of significance (α=0.05). Having estimated the parameters of model, the validity of the model's goodness of fit is assessed using diagnostic test. If the correct model is fitted to the data, the expected values of the residuals will be statistically equal to zero according to ACF (Louvieris, 2002). The Ljung-Box (Q^*) statistics were computed for checking residuals in seasonal lags of 12, 24, 36 and results were given in Table 8. The Ljung-Box Q^* statistics is a diagnostic measure of white noise for a time series, assessing whether there are patterns in a group of autocorrelations under the hypotheses with (k-p-q-P-Q) degree of freedom;

H_0: ACFs are not significantly different than white noise ACFs (i.e., ACFs = 0).

H_1: ACFs are statistically different than white noise ACFs (i.e., ACFs $\neq$ 0).

Table 8: Ljung-Box (Q^*) Statistics for Residual ACFs

Lag	**ACF(k)**	**SE**	χ^2 ($\alpha = 0{,}05$)	**Ljung-Box Statistics**		
				df	Q^*	Sig.
12	-,033	,076	18,31	9	2,673	,976
24	-,099	,073	33,92	21	11,351	,956
36	-,018	,070	43,77	$33 \cong 30$	24,373	,831

Examining the Table 9, since $Q^* < \chi^2$ at the seasonal lags (12, 24 and 36) the null hypothesis was accepted at the 5 % level of significance. The Ljung-Box (Q^*) statistics for diagnosing white noise confirmed that the residual ACFs are not significantly different than white noise ACFs.

4.6.Forecast Evaluation and Generating Future Forecasts

The empirical results of the forecasting performance of all examined exponential smoothing and ARIMA models are given in Table 9. The ranking of each model is provided in the first column. Based on the criteria established by Lewis (1982), it can be said that the all applied models successfully produced highly accurate forecasts since the MAPE values of each model is lower than 10 %. The low MAPE indicates that the deviations between the predicted values derived by the model and the actual values are very small. The ex-post forecasting performances of four different models indicated that SARIMA $(2,0,0)(1,1,0)_{12}$ model outperforms the other models with the smallest MAPE of 3,42 %. In other words, the number of international tourist arrivals to Istanbul estimated by Box-Jenkins method is very close to actual values.

Table 9: Forecast Performances of Models

Rank	**Forecast Model**	**MAPE (%)**
1	SARIMA$(2,0,0)(1,1,0)_{12}$	3,42
2	Holt-Winter's Multicaptive-	5,40
3	Holt-Winter's Additive-Seasonal	5,59
4	Simple Seasonal	9,78

Having confirmed the validity of the SARIMA $(2,0,0)(1,1,0)_{12}$ model through various diagnostic checks (AIC, BIC, ADF, Ljung-Box tests) and its highest ex post forecasting accuracy, the model is used to generate the monthly international tourist arrivals to Istanbul for years 2014 and 2015. Forecasts are presented in Table 10.

Table 10: Monthly Inbound Tourism Demand Forecast to Istanbul

Months (2014)	**Number of Tourists**	**Months (2015)**	**Number of Tourists**
January	617 915	January	676 010
February	688 006	February	750 214
March	884 379	March	954 341
April	999 787	April	1 063 776
May	1 093 852	May	1 166 730
June	1 008 763	June	1 076 086
July	1 153 633	July	1 221 926
August	1 125 369	August	1 192 393
September	1 074 546	September	1 135 366
October	1 059 204	October	1 122 472
November	844 234	November	902 992
December	808 025	December	873 585

5. Conclusion and Future Research

Proper forecasts of tourism demand are of great matter not only for the private sector, such as accommodation establishments, airline companies and travel agencies, in terms of their business planning and investment, but also for destination administration in terms of tourism planning and application. Tourism demand forecasts have a key role in the identification of the destination stages and for the planning of the economic and social facilities that are related to tourism. Given the limited number of tourism publications on tourism demand modelling to Istanbul which is one of the main tourism destinations in Europe, a time series modelling and forecasting tourism demand to Istanbul are presented. In this study, it is aimed to determine the forecasting model that provides the best performance when compared the ex post forecast accuracy of different exponential smoothing and Box-Jenkins models as time series methods which were to forecast the monthly inbound tourism demand to Istanbul by the model giving best results. The performances of the various models were evaluated by analysing their post forecasting accuracy using MAPE measurement. As a conclusion of the assessment of experimental results, it has been observed that forecasts by the seasonal exponential smoothing models have provided quite good results and on the other hand SARIMA $(2,0,0)(1,1,0)_{12}$ model has showed best forecast accuracy with lowest deviation (MAPE % 3,42) among the all applied models. By the means of this model, it has been generated the monthly inbound tourism demand forecast to Istanbul years 2014 and 2015. The use of ARIMA model building method for short to medium term forecasting has been long acknowledged for its versatility and accuracy.

The main challenges faced by tourism forecasters are defined by problems such as the incidence of missing information, the volatility of demand, the lack of consistent data series, the need of a rather complex set of indicators explaining tourists' behaviour and the sensitivity of demand to external events such as war, terrorism and catastrophes. In addition, the performance of forecasting models applied to tourism varies consistently according to the destination–origin pair. Under these conditions, any sophistication of the forecasting model has not yet proven to bring any benefit to the accuracy of the forecast. Large consensus has been achieved about the fact that no model outperforms others on all occasions and that the environment-specific conditions determine which approach is the most suitable for a forecasting task (Croce & Wöber, 2011). So, future research may include the more complex artificial intelligence based forecasting methods such as; support vector machines (SVMs), rough sets, fuzzy time series analysis, genetic algorithms and adaptive neuro-fuzzy inference system (ANFIS). Future research of this study may be extended to focus on comparisons between international and domestic tourism demand in order to advance the tourism demand forecasting. This study modelled and forecasted only inbound tourism demand. Witt et al. (1992) argued that domestic tourism demand is less susceptible than international tourism demand to external factors such as exchange rate fluctuations and international political events, and therefore is likely to be less volatile. Additional extensions of study may also be assumed by considering the econometric methods to investigate the tourist arrivals data as well as its relationships with other variables. Considering the limited number of studies on modelling and forecasting tourism demand in Turkey, suggested studies may contribute to government bodies and practitioners in tourism sector for effective tourism development and planning.

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