

Performance Comparison of Holt-Winters and SARIMA Models for Tourism Forecasting in Turkey

Türkiye’de Turizm Tahmini İçin Holt-Winters ve SARIMA Modellerinin Performanslarının Karşılaştırılması

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ABSTRACT: Forecasting the number of tourists coming to Turkey can play a vital role in strategic planning for both private and public sectors. In this study, monthly data of foreigners visiting Turkey were collected between the years 2007 and 2018. The data showed a seasonal behavior with an increasing trend; consequently, two methods were chosen for the study: Holt-Winters (HW) and Seasonal Autoregressive Integrated Moving Average (SARIMA). The objective of the study is to determine the most appropriate forecasting model to achieve a good level of forecasting accuracy. The findings showed that all models provided accurate forecast values according to error measures. However, multiplicative model of HW achieved the highest forecasting accuracy followed by SARIMA and additive HW respectively.

Keywords: Holt-Winters, SARIMA, Exponential smoothing, Time-series, Tourism forecasting.

Öz: Türkiye’ye gelen turist sayısını tahmin etmek hem özel sektör hem de kamu sektörü için stratejik planlamada çok önemli bir rol oynayabilir. Bu çalışmada, Türkiye’yi ziyaret eden yabancıların sayısı 2007 ve 2018 yılları arasında aylık olarak alınmıştır. Veri artan bir eğilim ile mevsimsel davranış göstermektedir, bu nedenle çalışma için iki metod seçilmiştir: Holt-Winters (HW) and Seasonal Autoregressive Integrated Moving Average (SARIMA). Çalışmanın amacı iyi bir seviyede tahmin doğruluğu elde etmek için en uygun tahmin modelini belirlemektir. Sonuçlar bütün modellerin hata ölçümlerine göre doğru tahmin değerleri verdiğini göstermiştir. Bununla birlikte, HW çarpımsal modeli en yüksek tahmin doğruluğuna erişmiş, bunu sırasıyla SARIMA ve HW toplamsal modeli takip etmiştir.

Anahtar Kelimeler: Holt-Winters, SARIMA, Üstel düzeltme, Zaman serileri, Turizm tahmini.

JEL Classifications: C53

1. Introduction

Time series is a set of values that are taken with equal time intervals. Based on the behavior of data over time, a model can be chosen, and a prediction can be processed. In order to choose the proper forecasting model for any time series, the forecaster must look at a graphical representation of the data. As soon as the representation is understood, one can determine the main characteristics of this time series including the trend, seasonality, and business cycles. Another two important points the analyst should understand is how strong

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Geliş/Received: 12-03-2019; Kabul/Accepted: 28-06-2019

the relationship among the variables is, and the reason behind any data that doesn't follow the tested pattern. Next step is selecting a model for forecasting. A model can be tested by one of the error measures such as Root Mean Square Error (RMSE) or Mean Absolute Error (MAE) or other error measures. Then forecasting on time series can be done. Common time series analysis methods are Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, simple linear regression, multiple linear regression, moving average, etc.

This research focuses on tourism forecasting in Turkey. Tourism forecasting can be helpful to managers, planners and marketers in determining the number of customers which enables them to make better decisions with minimum risk. This can take place in small as well as big businesses such as hotels, tourism companies, aircraft allocations, transportations, and more.

Many researchers forecasted the number of tourists using different methods. Perhaps ARIMA is the most popular model in this field and it's been used effectively in the literature (Close et al., 2012; Athanasopoulou, Hyndman, & Song, 2010; Change & Liao, 2010; Dhahri & Chabchoub, 2007). ARIMA also has many varieties. For instance, Akal (2004) forecasted Turkey's tourists' arrivals for the 2002-2007 period using Autoregressive Integrated Moving Average Cause Effect (ARIMAX) where X stands for exogenous variables. His proposed model showed a good quality performance where Mean Absolute Percentage Error (MAPE) fluctuated between 0.64 and 3.11. Neural network is another important method in tourism forecasting. Çuhadar, Cogurcu & Kukre (2014) compared different neural network models in forecasting the cruise tourism demand in Izmir, Turkey. Authors found that in terms of forecasting accuracy, radial basis function (RBF) neural network outperforms multi-layer perceptron (MLP) and the generalized regression neural networks (GRNN). Oktavianus, Andriyana, & Chadidjah (2018) developed another method used for tourism forecasting in Bali. Their model used Support Vector Machine (SVM) technique, followed by filtering forecasted data using Singular Spectrum Analysis (SSA). Their combination (SVM-SSA) was compared to moving average (MA) technique of forecasting as well as non-filtered SVM. Authors' results showed that SVM-SSA technique was superior to the other techniques with a set of MAPE values rising gradually from 1.74 at 3 months to 11.57 at 12 months.

Furthermore, many researchers compared between Seasonal ARIMA (SARIMA) and Holt-Winters (HW) in other fields. Omane-Adjepong, Oduro, & Oduro (2013) tried to examine the most appropriate short-term forecasting method for Ghana's inflation. Authors compared four SARIMA models with both additive and multiplicative HW models. Their results show that SARIMA gave the best outcomes according to their studied data with MAPE equals to 1.91. Veiga, Da Veiga, Catapan, Tortato, & Silva (2014) also compared between ARIMA and HW for demand forecasting in food retail. In their study, HW obtained better results with MAPE equals to 4.97 in HW and to 5.66 in ARIMA.

As a result of the literature, the proper model depends typically on the examined data. For this reason, it is important to investigate many forecasting methods in order to determine the most appropriate one for the data so that the most appropriate forecasting model can

be determined to achieve a good level of forecasting accuracy. In this study, SARIMA model is compared with HW method of exponential smoothing in forecasting the future values of the time series which represents the number of foreigners who are targeting Turkey for tourism purposes each year.

The rest of the paper is organized as follows: In section 2 and 3, exponential smoothing and SARIMA methods are introduced. In section 4, error measures are presented. Section 5 gives the framework of forecasting. In section 6, the results of applying HW and SARIMA are presented and forecasting accuracy was computed. Finally, section 7 gives an overall conclusion with a further direction for future works.

2. Exponential Smoothing

Exponential smoothing methods are well-known for forecasting discrete time series. The popularity of exponential smoothing is a consequence of its effectiveness, simplicity, adaptation to change, as well as reasonable accuracy (Montgomery, Johnson, & Gardiner, 1990). The idea behind exponential smoothing is that recent observations have higher predictive value than older ones, hence they are more valued when calculating the forecast data. For that, usually these methods give accurate results and therefore they are widely used. It should be mentioned here that all kinds of exponential smoothing are usually used for short term forecasts. Adversely, long term forecasts using exponential smoothing can be quite unreliable.

2.1. Simple Exponential Smoothing (SES)

The first exponential smoothing model was created by Brown & Meyer (1961). The idea was to assign a weight (α) for the new observation of the time series and decreasing the value of this weight for older observations exponentially. Which basically means that the new observations are more important to the forecast than old ones, hence assigned with more weight. The forecast equation in its general form is:

$$\hat{y}_{i+1} = \alpha y_i + \alpha(1 - \alpha) y_{i-1} + \alpha(1 - \alpha)^2 y_{i-2} + \dots + \alpha(1 - \alpha)^{i-2} y_2 + \alpha(1 - \alpha)^{i-1} y_1 = \alpha \sum_{k=0}^{i-1} (1 - \alpha)^k y_{i-k} \quad (1)$$

where $0 \leq \alpha \leq 1$, and \hat{y}_{i+1} represents the forecast value of Y at time period $i + 1$ which is calculated based on the previous observations of the actual series values y_i, y_{i-1}, y_{i-2} and so on back to the first known value of the time series, y_1 .

Simple exponential smoothing is one of the most popular forecasting methods when a time series doesn't have any pronounced trend or seasonality.

2.2. Trend Adjusted Exponential Smoothing (Holt's method)

Holt (1957) expanded the previous model to involve the trend. His work is also reprinted on 2004 (Holt, 2004) for smoothing time series with trend and seasonality. This model is also called double exponential smoothing because the forecast is calculated based on two smoothing equations: one for the level and the other is for the trend.

Forecast equation:
$$\hat{y}_{t+h|t} = \ell_t + hb_t \quad (2)$$

$$\text{Level equation: } \ell_t = \alpha y_t + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad (3)$$

$$\text{Trend equation: } b_t = \beta(\ell_t - \ell_{t-1}) + (1 - \beta)b_{t-1} \quad (4)$$

where $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, and ℓ_t denotes an estimate of the level at time t , b_t is the trend or the slope of the series at time t .

The forecast function isn't flat anymore, but rather trending. The h -step-ahead forecast is equal to the last calculated level added by h multiplied by the last estimated trend value. Therefore, the forecasts are a linear function of h (Hyndman & Athanasopoulos, 2018).

2.3. Seasonal Adjusted Exponential Smoothing (Holt-Winters' Method)

Probably the most popular forecasting technique for seasonal patterns is the one presented by Winters (1960). One version of this technique is designated for additive seasonality and the other is for multiplicative seasonality. A seasonality is considered multiplicative when the seasonal variation increases over time, while additive model is the one where the seasonal variation is relatively constant over time.

The model includes main forecast equations with three smoothing equations, the first one is for the level ℓ_t , the second is for the trend b_t , and the last one is for the seasonality s_t . We also have three smoothing parameters to define α , β and γ with values between 0 and 1. Whereas m is used to denote the frequency of the seasonality, it can be four as the number of seasons per a year or 12 for the number of months and so on.

2.3.1. Additive Model

$$\text{Forecast equation: } \hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m} \quad (5)$$

$$\text{Level equation: } \ell_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad (6)$$

$$\text{Trend equation: } b_t = \beta(\ell_t - \ell_{t-1}) + (1 - \beta)b_{t-1} \quad (7)$$

$$\text{Seasonality equation: } s_t = \gamma(y_t - \ell_t) + (1 - \gamma)s_{t-m} \quad (8)$$

2.3.2. Multiplicative Model

$$\text{Forecast equation: } \hat{y}_{t+h|t} = (\ell_t + hb_t)s_{t+h-m} \quad (9)$$

$$\text{Level equation: } \ell_t = \gamma \frac{y_t}{s_{t-m}} + (1 - \alpha)(\ell_{t-1} + b_{t-1}) \quad (10)$$

$$\text{Trend equation: } b_t = \beta(\ell_t - \ell_{t-1}) + (1 - \beta)b_{t-1} \quad (11)$$

$$\text{Seasonality equation: } s_t = \gamma \frac{y_t}{\ell_t} + (1 - \gamma)s_{t-m} \quad (12)$$

When applying any exponential smoothing model, we need to determine the initial values for the level, trend, and seasonality. Also, we need to define the smoothing parameters α , β and γ . Bermúdeza, Segurab & Verchera (2006) suggested to calculate the initial parameters based on a heuristic approach such as the one used by (Wheelwright, Makridakis & Hyndman, 1998). This suggestion is proposed to make a better estimation to the smoothing parameters since these parameters are very sensitive to the initial values of the level, trend, and seasonal factor of the time series (Segura & Vercher, 2001). The estimation of smoothing parameters is often done with an objective to minimize one of the forecasting errors (Hyndman, Koehler, Snyder & Grose, 2002; Ord, Koehler & Snyder,

1997). (Wheelwright, Makridakis & Hyndman, 1998) proposed the following initialization:

$$\ell_m = (y_1 + y_2 + \dots + y_m)/m \quad (13)$$

$$b_m = [(y_{m+1} + y_{m+2} + \dots + y_{m+m}) - (y_1 + y_2 + \dots + y_m)]/m^2 \quad (14)$$

The level is set to be the average data in the first year, where the slope is the average of the slopes for each period in the first two years:

$$(y_{m+1} - y_1)/m, (y_{m+2} - y_2)/m, \dots, (y_{m+m} - y_m)/m \quad (15)$$

For additive seasonality $s_i = y_i - \ell_m$, whereas for multiplicative seasonality we can set $s_i = y_i/\ell_m$ where $i = 1, 2, \dots, m$. This method is easy to apply; however, it can't be used when the series is noisy or short as it gives unreliable results occasionally. Another disadvantage is that the model provides an estimation for period m . As a result, first forecast is calculated for period $m + 1$ rather than first period.

3. Seasonal Autoregressive Integrated Moving Average (SARIMA)

ARIMA was first introduced by Box & Jenkins (1970) as a statistical model for forecasting and analysis. Box & Jenkins also suggested a process for identifying the right model for a specific dataset, this process is known as Box-Jenkins method.

In order to fit a SARIMA model, first the time series must be stationary in its mean and variance. In case we have a multiplicative seasonality, variance is stabilized through logarithm transformation (S Moss, Liu & J Moss, 2013), followed by a process of differencing to maintain a stationary dataset in the mean. SARIMA model is referred to as SARIMA $(p, d, q)(P, D, Q)_S$ and is written as (Pankratz, 1983):

$$\varphi_p(B)\phi_p(B^S)\nabla^d\nabla_S^D y_t = \theta_q(B)\Theta_q(B^S)\tau_t \quad (16)$$

where,

y_t denotes dataset values

∇^d = non-seasonal differencing operator

$\varphi_p(B)$ = non-seasonal autoregressive operator $(1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p)$

$\theta_q(B)$ = non-seasonal moving average operator $(1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q)$

B = backshift operator which is defined so that $y_t B^S = y_{t-S}$

p, P = order of the autoregressive non-seasonal and seasonal part respectively

q, Q = order of the moving average non-seasonal and seasonal part respectively

d, D = degree of non-seasonal and seasonal differencing respectively

∇_S^D = seasonal differencing operator

$\phi_P(B^S)$ = parameters of seasonal autoregressive part ($1 - \phi_S B^S - \phi_{2S} B^{2S} - \dots - \phi_{PS} B^{PS}$)

$\theta_Q(B^S)$ = parameters of seasonal moving average part ($1 - \theta_S B^S - \theta_{2S} B^{2S} - \dots - \theta_{QS} B^{QS}$)

The popularity of this model comes from its ability to adapt very well with different patterns of time series.

4. Forecasting Errors

When dealing with practical problems, forecast accuracy or forecast error measures can be essential (Yokuma & Armstrong, 1995). Commonly used forecast error measures can indicate the quality of forecasting methods. Also, in the case of multiple objects, error measures can detect the best forecasting mechanism (Shcherbakov, Brebels & Shcherbakova, 2013). Consequently, it is the key element to determine optimum values of smoothing parameters, which will be demonstrated later on in this paper. Based on Shcherbakov, Brebels & Shcherbakova (2013) and Wallström (2009) we can use over 30 error measures to choose from depending on the time series we are forecasting. Fundamentally, to evaluate the performance of a model, it is logical to use absolute forecasting error group. One of the main drawbacks of these measurements is that they are greatly influenced by any outliers in data which impact the forecast performance evaluation. When the predicted data have seasonal or cyclical patterns, it's preferred to use the normalized error measures. Also, if time series is subjected to any kind of transformation, for example logarithm transformation, it becomes necessary to use percentage error measures such as MAPE to compare with other models that use different kind of transformation.

Basically, all errors measures include estimates based on calculating the value of e_t

$$e_t = (y_t - f_t) \quad (17)$$

where y_t represents the observation at time t , and f_t is the predicted value.

Here are the main error measures that are to be used in our article:

- **Mean Absolute Error:** $MAE = \frac{1}{n} \sum_{i=1}^n |e_i| = \text{mean } |e_i|$ (18)

where n represents forecast horizon.

- **Mean Square Error:** $MSE = \frac{1}{n} \sum_{i=1}^n (e_i^2) = \text{mean } (e_i^2)$ (19)

- **Root Mean Square Error:** $RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (e_i^2)} = \sqrt{\text{mean } (e_i^2)}$ (20)

- **Mean Absolute Percentage Error:**

$$MAPE = \frac{1}{n} \sum_{i=1}^n 100 \cdot |e_i/y_i| = \text{mean } 100 \cdot |e_i/y_i| \quad (21)$$

- **Normalized Root Mean Square Error:** $nRMSE = \frac{1}{y} \sqrt{\text{mean}(e_i^2)}$ (22)

where y denotes the normalization factor, which is usually equals the maximum observation in the time series, or the range of observations (the difference between the maximum and minimum values in observations).

5. Forecasting Framework

The process of forecasting is presented as follows: Firstly, historical data are collected, plotted and analyzed in order to identify any patterns. According to patterns, appropriate forecasting methods are selected. The data is then divided into two sets: a training set and a test set. Next, appropriate forecasting models are selected based on the evaluation of their fitting errors over the training set. After that, forecasts are calculated over a timeframe including the test set and the future time. Test set is used for evaluating the forecasting performance of the models based on forecasting errors. Forecasting accuracy for both model fitting using training set, and model performance evaluation using test set, is computed with some of the main absolute forecasting error group.

5.1. Data Collection

Studied data represented the number of foreigners targeting Turkey for tourism on monthly basis between January 2007 and January 2019. The data was divided into a training set from January 2007 to July 2018, and a test set from August 2018 to January 2019. Data were collected from the official website of ministry of culture and tourism of Turkey (Number of Arriving-Departing Foreigners and Citizens). Figure 1 shows the graphical representation the training part of the data.

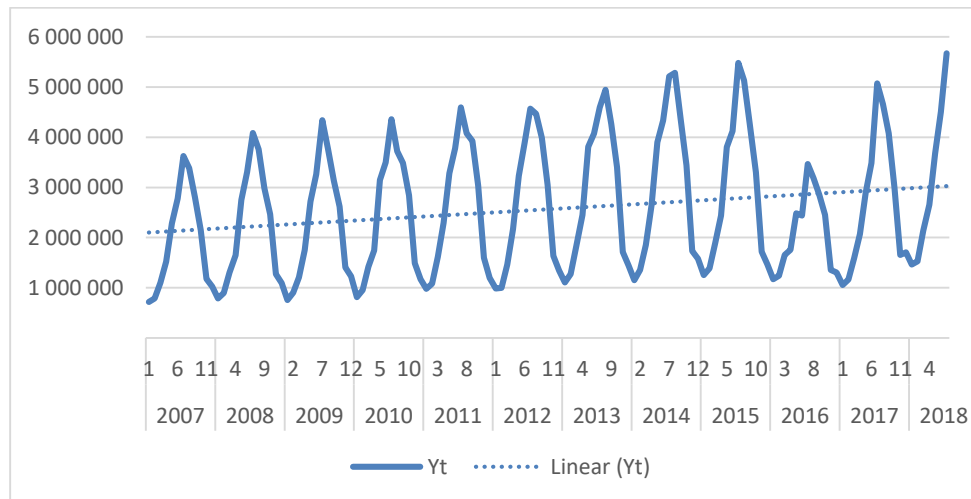


Figure 1. Number of Arriving-Departing Foreigners to Turkey between the years 2007 and 2018

Looking at Figure 1, we can directly identify two main patterns: First is the obvious uprising trend, and second is the seasonal pattern which seems multiplicative. In 2016, we can easily deduce that an event has affected the tourism movement, although later on the growing of the amplitude has continued until its peak in June 2018.

5.2. HW Model

As discussed before, in case we have seasonality patterns the recommended model is the one developed by HW. Since there are two HW models, the appropriate one will be determined based on the forecasting accuracy.

The initializations were used based on Hyndman model. Smoothing operators were optimized to get the minimum values of the errors, consequently a better forecasting quality. For this, Generalized Reduced Gradient optimization (GRG) was used which is a very robust method introduced by MS Excel solver to deal with large sets of data. Table 1 shows models' accuracy for both additive and multiplicative models.

Table 1. Error Measures for Multiplicative and Additive Models of HW

Parameter	Multiplicative HW	Additive HW
MAE	128997.918	182699.139
MSE	33308551391	65917191205
RMSE	182506.305	256743.435
MAPE	5.101	9.264
nRMSE	0.037	0.051

The results from error measures indicate that the multiplicative model has better fitted values than the additive model. Also, MAPE values were less than 10 in both models which indicates a high performance according to Change & Liao (2010). Figures 2 and 3 show the fitness of both models.

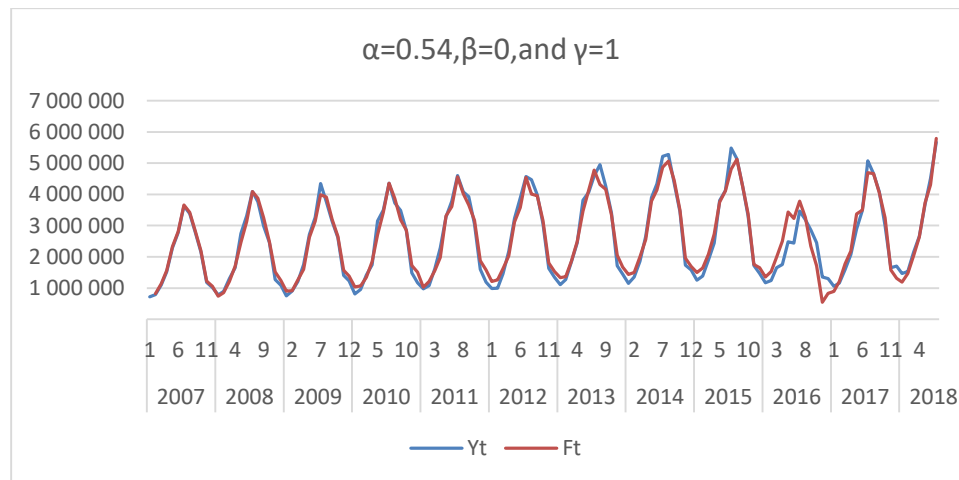


Figure 2. HW Additive Model

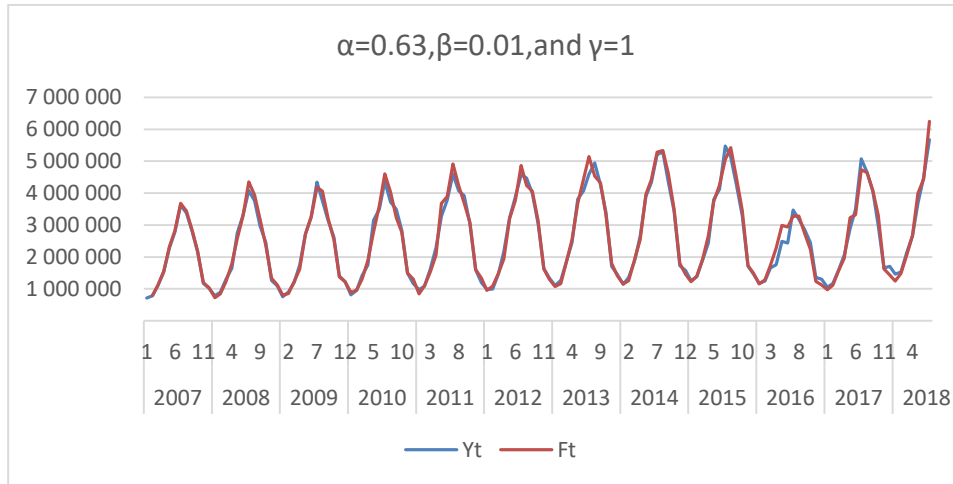


Figure 3. HW Multiplicative Model

Both models shared great fitness with the actual values of time series observations with some outliers in the period between 2016 and 2017.

The time span of a forecast depends on the purpose of forecasting in the first place. Procedures are the same whether forecast is being computed for one period ahead or ten, although usually, exponential smoothing methods provide a better-quality estimation when it's applied for short term forecasts. For this study, forecasts are calculated for 36 months ahead (three years) starting from August 2018 until July 2021.

5.3 SARIMA Model:

As mentioned before, time series needs to be stationary on the variance and constant mean before fitting SARIMA. To stabilize the variance, a logarithm transformation is performed. After some experiments, SARIMA (2,2,1)(1,1,1)₁₂ was suggested due to its high accuracy according to error measures. The SARIMA model can be illustrated with backshift notations as follows:

$$(1 - \phi_1 B - \phi_2 B^2)(1 - \phi_{12} B^{12})(1 - B)^2(1 - B^{12})y_t = (1 - \theta_{12} B^{12})(1 - \theta_1 B)\tau_t \quad (23)$$

Table 2 presents the estimated coefficients associated to the best obtained model:

Table 2. Estimated coefficients

Parameter	Value	Standard error
ar1	-0.01649	0.0956
ar2	-0.1302	0.0920
ma1	-0.9997	0.0337
sar1	0.4878	0.3179
sma1	-0.9302	0.6261

As for the training set, error measures are shown in Table 3.

Table 3. SARIMA(2, 2, 1)(1, 1, 1)₁₂ Error measures

Measure	ME	RMSE	MAE	MPE	MAPE	MASE
Value	-0.00023	0.06257	0.04695	-0.00142	0.32122	0.18692

Although most of the results from error measures are relatively small, a check of residuals should always be performed in order to make sure that residuals are white noise without any remained patterns. This check is usually done by computing Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF). Also, histogram could also be plotted to make sure that most of the residuals are distributed around zero. Figure 4 presents residuals along with ACF and PACF.

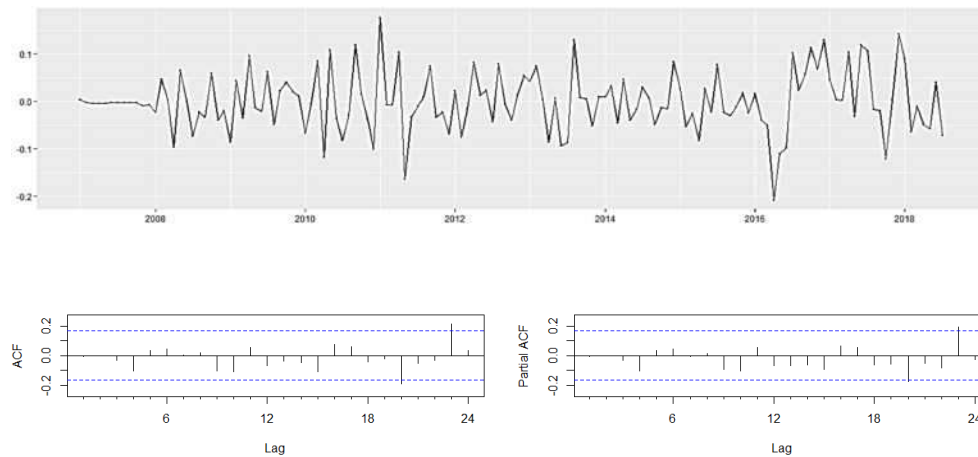


Figure 4. SARIMA Residuals Series with ACF and PACF

Clearly there aren't any noticeable patterns in residuals. There are two values that crossed the bounds, however these outliers are caused by mere chance. It is concluded that there is not any correlation among residuals.

Histogram is also plotted (Figure 5) to show the distribution of residuals.

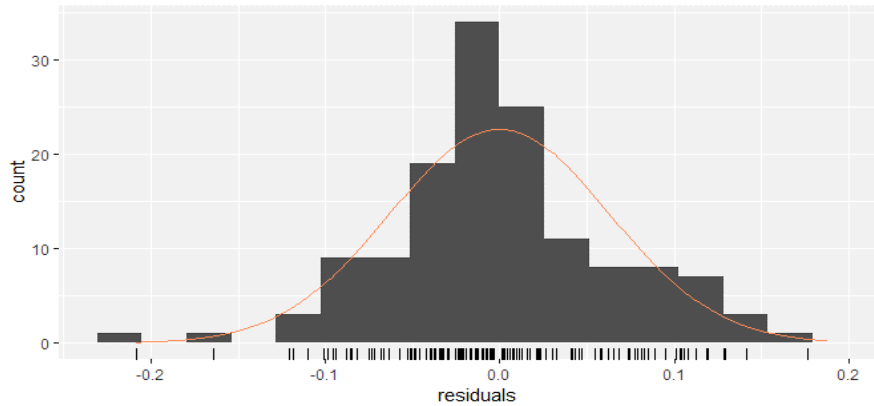


Figure 5. SARIMA Residuals Histogram

It is seen that the residuals are approximately normally distributed around zero. Consequently, the model is suitable for forecasting.

6. Results

Table 4 shows the forecast values for additive, multiplicative, and SARIMA models for 36 periods ahead starting from August 2018 until July 2021.

Table 4. Forecasted Values for 36 Periods Ahead

Period	Month	Additive HW	Multiplicative HW	SARIMA
1	August	5308716	5397565	5352745
2	September	4711444	4731288	4585089
3	October	3769988	3703358	3499883
4	November	2387134	2025360	1890194
5	December	2222483	1873344	1802238
6	January	1831481	1444639	1483463
7	February	1865412	1478988	1593510
8	March	2419043	2019129	2235309
9	April	2924114	2509488	2849802
10	May	3974524	3650982	4102430
11	June	4689682	4432364	4870514
12	July	5921448	5923404	6171670
13	August	5558363	5636120	5799777
14	September	4961092	4939629	4980496
15	October	4019635	3865838	3856961
16	November	2636781	2113896	2065391
17	December	2472131	1954938	1893675
18	January	2081128	1507333	1528229
19	February	2115059	1542941	1663443

20	March	2668691	2106126	2334667
21	April	3173761	2617226	3015391
22	May	4224171	3807167	4422740
23	June	4939329	4621302	5170966
24	July	6171095	6175006	6572928
25	August	5808010	5874676	6163405
26	September	5210739	5147970	5298795
27	October	4269283	4028318	4132033
28	November	2886428	2202432	2203329
29	December	2721778	2036531	1981748
30	January	2330775	1570027	1583820
31	February	2364706	1606895	1734951
32	March	2918338	2193122	2435445
33	April	3423408	2724963	3165242
34	May	4473818	3963352	4684689
35	June	5188976	4810240	5435924
36	July	6420743	6426609	6919610

Most of the forecasted values were higher in the additive HW compared with multiplicative HW whereas SARIMA model had a relatively larger amplitude as shown in Figure 6.

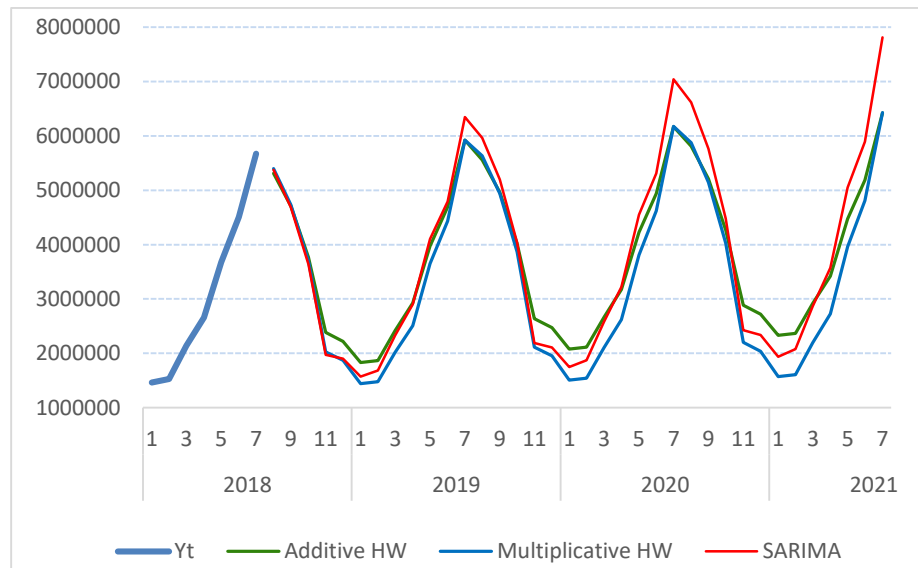


Figure 6. Forecasts from Models for 36 Periods Ahead

All models provided forecasts with high accuracy that were not affected considerably by the unexpected fall of the number tourists during the 2016. Table 5 shows the forecasting accuracy of the three models which is computed based on the test set of data.

Table 5. Forecasting Accuracy

	Additive HW	Multiplicative HW	SARIMA
MSE	58106545121.83	4196207121.50	23396808855.50
MAE	192521.83	59862.17	129080.50
MAPE	9.63	2.68	4.47
RMSE	241052.99	64778.14	152960.15
nRMSE	0.07	0.02	0.04

Based on the information in Table 5, multiplicative model of HW outperformed the models of SARIMA and additive HW with MAPE equals to 2.68 which indicates the high accuracy of the forecasted values.

Regarding the future status of tourists, this analysis clearly highlights the yearly expansion of the tourism movement in Turkey especially around the summer period. This uprising trend should be met with long-term plans and strategies to maintain and support this movement and utilize the needed accommodations accordingly.

7. Conclusions and Recommendations

This study examines the forecasting accuracy of three models: two models of HW and SARIMA model, based on using these models for forecasting the number of tourists coming to Turkey every month. Models were fitted with the time series by tuning the operators in HW and SARIMA with an objective of minimizing the error measures. Also, a test of residuals was performed for SARIMA model in order to check any remaining patterns. After that, forecasts have been obtained for 36 months ahead and forecasting accuracy was computed. All models had good fit with the time series data; however, the multiplicative model of HW presented a better model than additive HW and SARIMA according to the error measures.

MAPE was used to compare the three models as an error measure since SARIMA was performed based on a transformed form of the timeseries. Although, SARIMA had the lowest value of MAPE as a fitted model, multiplicative HW attained the highest accuracy as a forecasting model.

Exponential Smoothing is one of the most widely used forecasting methods and this study shows that a good level of forecasting accuracy can be achieved by this method for tourism forecasting. It is found that the multiplicative model of HW outperforms the additive model of HW and SARIMA model for tourism forecasting, since the data has seasonal pattern with nonstationary variance and increasing trend. These findings suggest that the multiplicative model of HW can be applied successfully to any time series data that have similar patterns.

The limitation of this research is the small size of the test set which included the last 6 months of the timeseries whereas the training set included 139 months. Usually test set is around 20-30% of the data, but in this case the forecast couldn't start until the unexpected turbulence which occurred between the years 2016-2018 has ended.

Finally, for a further direction, more researches should be performed in the field of forecasting in Turkey as one of the most targeted countries for tourism around the world. Some of the models that should be tested are neural networks and SVM to determine the most compatible model with the studied time series.

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