

Air Traffic Forecasting using Time Series Models



Manohar Dingari, D. Mallikarjuna Reddy, V. Sumalatha

Abstract: In this paper, Holt-Winters' Additive model is fitted to the data regarding Domestic Air traffic in Air India flights. The investigation was done using dataset on number of passengers travelling by Air India domestic flights during January 2012 to November 2018. To prepare a tool to analyze the traffic flow monthly wise this helps Air India to revise their services. ARIMA model also has been fitted to the data, and compared with Holt-Winters' Additive model. Finally, the results, findings and analysis proved that the Holt-Winters' Additive model is superior to the ARIMA model for this data. This kind of analysis is very useful for forecasting the Air traffic.

Keywords: Holt-Winters' Additive, ARIMA, Air Traffic, Time series analysis, Forecasts.

I. INTRODUCTION

Air transport is presently one of the fastest growing service sectors in India. People continuously travel for various reasons (tourism, business) to different locations within country and worldwide. As a result, analyses and forecasts of data regarding air passengers is of great importance in designing development strategies for air service providers. Air transport improves the growth of local economy, arriving to the development of companies, and thus developing the competitiveness of business. For this it is important to analyze the future air traffic and its changes with time properly which helps the air service providers to design their services adequately.

Forecasting traffic intensity using air traffic models involves finding the future demand for air transport in the service. Another important thing is the seasonality of air traffic. Seasonal variations make it essential to observe traffic intensity in every month of the year, and on every day of the month. The main output of a traffic forecast includes number of air passengers. The main purpose of this study is to prepare a tool to analyze and forecast the traffic flow month wise which helps Air India to revise their services.

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Air India is the flag carrier airline of India headquartered at New Delhi. It is owned by Air India Limited, a government owned enterprise, and operates a fleet of Airbus and Boeing aircraft serving 94 domestic and international destinations. The airline has its hub at Indira Gandhi International Airport, New Delhi, alongside several focus cities across India. The subject of the analysis is Air India with number of passengers travelled by Domestic flights being the focus. The research period covers the years from 2012 to 2018. Data were presented in monthly cycles. Two research methods were compared for analyzing the data: Holt-Winters' Additive model and ARIMA model.

II. TIME SERIES MODELS

A. Holt-Winters method

Holt-Winter's (HW) method originated from 1950's. As the famous experimenters had received a request from Planning and control of Industrial Operations, the Naval Research office US. They were asked to develop a low cost, high accuracy forecasting model [6]. Holt created a new model which could control additive and multiplicative trend as well as additive and multiplicative seasonality and standard errors. The proposed new system by Holt required less data storage, it was quick and easy to program and used robust parameters and simple basic conditions and permitted automatic adaptation. A graduate student P.R.Winters tested this model in various time series [6]. Winters found these prediction formulas were accurately and then in 1960s he published his results. From then this new approach was termed Holt-Winters [7] model. The applications Holt and Holt-Winters models were rapidly spread in to software system to analyze and forecast and they have been used even now in researches [5].

Holt-Winters smoothing method removes seasonality and leaves that time series with clear long time fluctuations. This method is generally called method of Holt-Winters or Seasonal Exponential Smoothing method or Winters method. It is the generalization of Double Exponential Smoothing technique, it deals with Level, Trend and Seasonality. This method considers three parameters α , β and γ [7].

Holt-Winters techniques are classified in to two methods based on the modeling of seasonality. They are multiplicative approach and additive approach. If the data set has approximately constant seasonal fluctuations the additive approach is preferable otherwise if the dataset has seasonal fluctuations deviating in proportion with the level of dataset multiplicative approach is preferable. In additive approach the seasonal factor is presented in absolute values of the actual dataset with the same scale, and to get the level, seasonal adjustments are done to the dataset by taking the difference of the seasonal



factor. The seasonal factor sum up to roughly zero within every year. In multiplicative technique the seasonal factor is presented as percentages, the seasonal adjustments of the dataset are obtained by dividing the entire dataset with seasonal factor. The seasonal factor will add to roughly m within every year.

In this paper Holt-Winters' Additive model has been applied.

❖ Holt-Winters' Additive method

The Holt-Winters technique consists an expression for forecast and three equations for smoothing- one level equation l_t , one trend equation b_t , and one more for seasonal factor s_t , and the relating smoothing parameters are α , β and γ . m is used to denote the seasonal frequency, which indicates total seasons per year.

The component form for the additive method is:

Level $l_t = \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1})$

Trend $b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$

Seasonal $s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}$

Forecast $\hat{y}_{t+h/t} = l_t + hb_t + s_{t+h-m(k+1)}$

Where m is the seasonal frequency, for $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$ and $0 \leq \gamma \leq 1$. The seasonal equation picks up differences between the current level and the data at that time in the seasonal cycle. This is then added to a forecast at the same point in the cycle. Where k is the truncation of $(h-1)/m$ that makes clear that the seasonal factor estimates applied for forecasting belong to the last year of the dataset. The equation of level can be obtained by taking weighted mean of the seasonally adjusted value $(y_t - s_{t-m})$ and the non-seasonal forecast $(l_{t-1} + b_{t-1})$ at time t . The equation for trend is same as Holt's linear equation. The equation for seasonality is weighted mean of present seasonal record, $(y_t - l_{t-1} - b_{t-1})$ and the seasonal record of the same season previous year that is m time periods ago.

The components of Holt-Winters model can be determined by finding the values of the parameters α , β and γ to predict starting values. Then these values are used to find the exact values of the parameter that reduces the sum of squares of errors of the next step forecast. The level l_t is calculated by combining the actual and the adjusted at time t , eliminates the effect of seasonality in the dataset. The trend b_t is calculated by taking consecutive difference of two successive levels same as Holt model and the seasonality s_t can be found by merging the actual and the adjusted seasonal record at time t [8].

B. ARIMA Model

Box-Jenkins (1976) developed the ARIMA technique. It consists Autoregressive and Moving Average components also involve differencing in framing the model. In particular there are three parameters in the tool- the autoregressive components (p), required steps of differencing (d), and

moving average component (q). ARIMA (p, d, q) is the notation given by Box-Jenkins for this method.

The first step in developing a ARIMA model is to verify whether the dataset is stationary or not. For this sequence plots of the datasets or Partial Autocorrelation functions and Autocorrelation Function plots are used. In the next step a suitable branch of the general ARIMA model is to be identified.

$$\phi(B)\nabla^d Z_t = \theta(B) a_t \tag{1}$$

A time series can be represented by this expression.

The general procedure is

- (i) To achieve stationarity the time series z_t has to be differenced for required number of times.

$$\phi(B) W_t = \theta(B) a_t \tag{2}$$

Where

$$W_t = (1 - B)^d Z_t = \nabla^d Z_t \tag{3}$$

- (ii) To identify the resulting ARIMA process.

The Autocorrelation and Partial Autocorrelation functions will be used as main tools in attaining (i) and (ii). Stationarity in time series means a uniform mean, Autocorrelation and variance for all time points. Generally a hypothetical dataset will not be stationary. Make it stationary by differencing the dataset for required number of times.

$$W_t = \nabla^d Z_t \tag{4}$$

After differencing the series to identify the sub class of ARIMA model, which is suitable for the series, the components of Autoregressive (p) and Moving Average (q) should be identified. The number of parameters of Autoregressive (p) can be identified by using correlogram of Partial Autocorrelations and the number of parameters of Moving Average (q) can be identified by using correlogram of Autocorrelations. Maximum Likelihood Estimation (MLE) method or Least Squares (LS) technique can be used to estimate the p parameters of Autoregressive $\phi_1, \phi_2, \dots, \phi_p$ and then q parameters of Moving Average $\theta_1, \theta_2, \dots, \theta_q$.

III. ANALYSIS OF DATA

Both ARIMA and Holt-Winters' Additive models were fitted to the data regarding number of passengers travelling monthly by Air India on scheduled Domestic services for the years 2012 to 2018. The data has been taken from the Directorate General of Civil Aviation (DGCA) website. These two models were estimated by using SPSS20 software.

A. ARIMA Modeling

To check the stationarity sequence chart has applied to the data. The graph appeared was non-stationary.



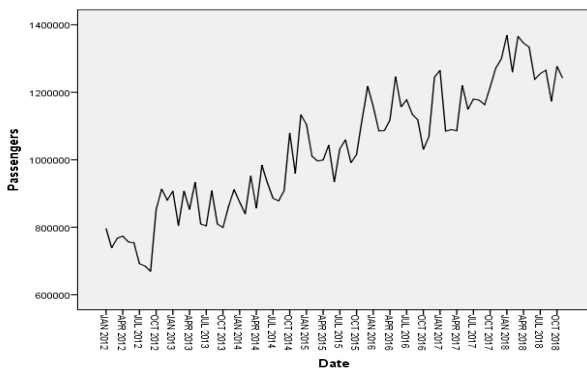


Fig. 1. Sequence Plot of Air Traffic Data

To achieve stationarity in mean the series has been differenced once, Natural log transformation has used to stabilize variance of the air traffic data.

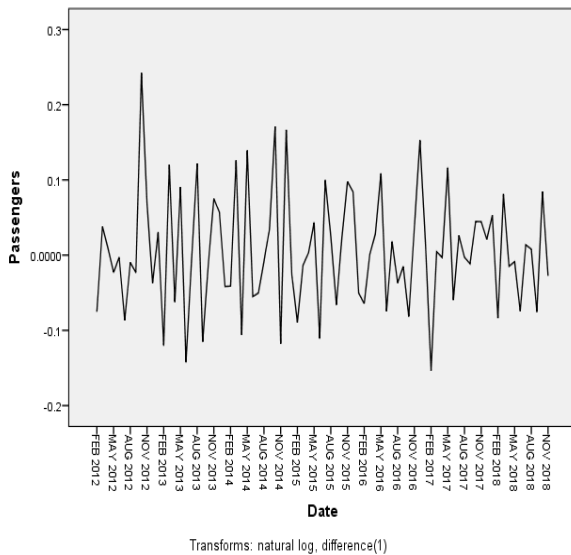


Fig. 2. Stationary Air Traffic Data

To identify p and q values Correlograms of Autocorrelation and partial Autocorrelations were constructed.

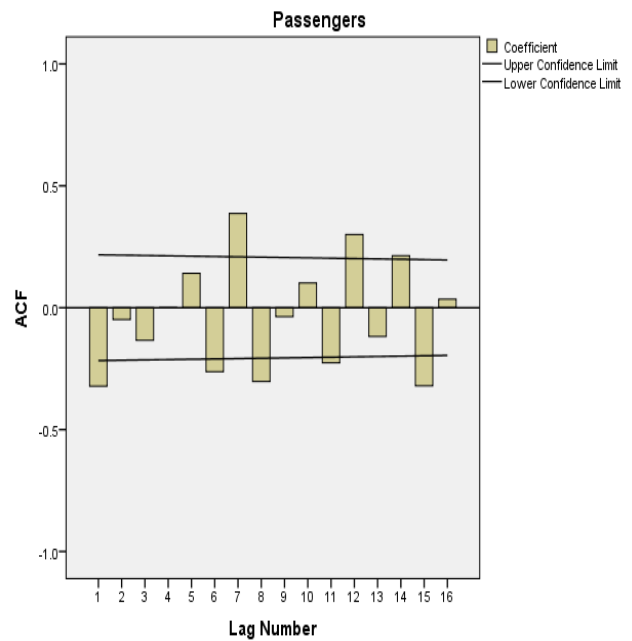


Fig. 3. Graph of ACF

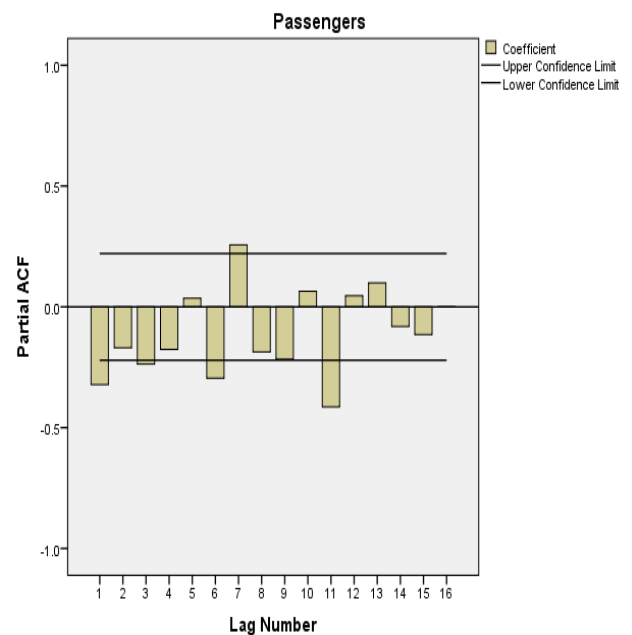


Fig. 4. Graph of PACF

From PACF plot only one Π_1 is beyond the limits $\pm 2/\sqrt{N}$, so order of AR component has taken as 1, similarly MA component has been chosen from the correlogram of the ACF as 1. Then the model is identified as ARIMA (1,1,1). And the coefficients of AR and MA estimated as in the table 1.

Table- I: ARIMA Model Parameters

		Parameter	Estimate
ARIMA(1,1,1)	AR1	ϕ	0.355
	MA1	θ	1.000
	Constant	C	-0.027

The AR coefficient ϕ was estimated to be 0.355 and MA coefficient θ was estimated to be 1.000.

B. HOLT-WINTERS' Additive Model

The SPSS software was used to fit the model to the data and the parameters of the model were estimated as in the table 2.

Table- II: Holt-winters Model Parameters

		Parameter	Estimate
HOLT-WINTERS' Additive model	Level	Alpha(α)	0.401
	Trend	Beta(β)	0.00000218
	Season	Gamma(γ)	0.000001836

The Level component α was estimated as 0.401, Trend component β was estimated as 0.00000218 and Seasonal component γ was estimated as 0.000001836.

C. Model Diagnostic Check

It is verifying the adequacy of the model.

Table- III: ARIMA and Holt-winters Parameters

Model	α	β	γ	p	d	q
ARIMA				1	1	1
Holt-Winter	0.401	0.00000218	0.000001836			

The adequacy of these two models checked by the Mean Absolute Percentage Error (MAPE), Root Mean square Error (RMSE), R^2 and Bayesian Information Criterion (BIC).

Table- IV: Model Fit Statistics

	ARIMA	Holt-Winters' Additive Model
R^2	0.876	0.923
RMSE	65859.068	51662.971
MAPE	5.116	4.158
BIC	22.459	21.865

In practice, the low value of RMSE, MAPE and BIC indicate a best fit for the model and the greater R^2 value indicate an exact prediction. Also less than 10% value of MAPE refers an extremely accurate forecast, lower than 20% potentially good and above 30% potentially in accurate.

For this data, both the models Holt-Winters' Additive and ARIMA have MAPE values less than 10%, which shows both are potentially very good for forecasting but MAPE of Holt-Winters' Additive model is 4.158 and of ARIMA is 5.116. RMSE of Holt-Winters' Additive model is 51662.971 and of ARIMA is 65859.068. BIC of Holt-Winters' Additive model is 21.865 and of ARIMA is 22.459. R-squared value of Holt-Winters' Additive model is 0.923 and of ARIMA is 0.876. Thus RMSE, MAPE and BIC are less for Holt-Winters' Additive model than ARIMA. Also R-squared value is high for Holt-Winters' Additive model than ARIMA, which shows Holt-Winters' Additive model is superior than ARIMA for this data.

D. Forecasting

The analysis proved that Holt-Winters' Additive model is best for this data, forecasts have been computed by using Holt-Winters' Additive model for December 2018 and 12 months of 2019.

Table- V: Holt-winters Mode

Month	Forecast	95% lower limit	95% upper limit
18-Dec	1370850	1473663	1268038
19-Jan	1367227	1477985	1256470
19-Feb	1274013	1392183	1155843
19-Mar	1322956	1448100	1197812
19-Apr	1303974	1435723	1172224
19-May	1373357	1511397	1235318
19-Jun	1295581	1439635	1151526
19-Jul	1303134	1452963	1153306
19-Aug	1314665	1470054	1159277
19-Sep	1275617	1436373	1114861
19-Oct	1338002	1503952	1172052
19-Nov	1361722	1532709	1190736
19-Dec	1456880	1632758	1281001

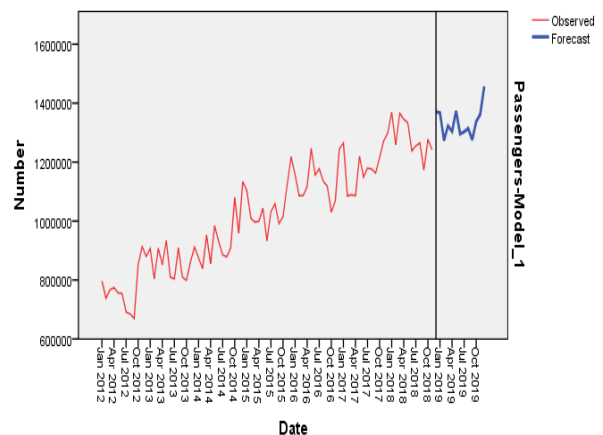


Fig. 5. Forecasted Air Traffic

IV. CONCLUSION



The study focused to make a tool available for Air India domestic flights to analyze the traffic flow month wise during January 2012 to November 2018. Two models ARIMA(1,1,1) and Holt-Winters' Additive model have been fitted to the data. Both models have shown satisfactory results. But by using diagnostic check on these two models proved that Holt-Winters' Additive model is best for this data. Hence forecast have been computed by using Holt-Winters' Additive model. By the time the work has completed, the figure for number of passengers for Dec 2018 has been released it was 1,372,904, our forecasted value for Dec 2018 is 1370850 with 95% UCL and LCL as 1473663 and 1268038 which is a satisfactory result. Even from fore studies it has proven that Holt-Winters' Additive model is best fit for many data concern with traffic, tourist and number of passengers. Therefore, Holt-Winters' Additive model can be used as a tool to forecast number of passengers for a month on Air India domestic flights. This kind of analysis is very useful for forecasting the Air traffic.

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