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Time Series Model for Air Passengers Prediction in Jet Airways

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Abstract
Airlines and civil aviation agencies are interest in forecasting air passengers in domestic and international airlines. Many authors attempted on the same to fit an appropriate time series modelsto forecastexpected number of passengers travelled. In this paper, an attempt is made to fit nonlinear time series models, Auto Regressive Integrated Moving Average and Seasonal Auto Regressive Integrated Moving Average for the number of passengers travelled through Jet Airways, in domestic and international airlines during the 2009 to 2019. The accuracy of the fitted models can be evaluated using Mean Absolute Error, Mean Absolute Percentage Error.
Key words: *ARIMAModel, SARIMA Model, Holt-Winter Model, MASE, MAPE*

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I. INTRODUCTION

The civil aviation sector is one of the consistently growing sector in the economic progress of a nation and is one of the major services industries that considerably add to the wealth of developed and developing nations. It plays an important role in carrying people or goods from one location to another, through domestic and international airways. In general, out of total passengers, approximately, 65% passengers are through domestic and 35% are through international.

To forecast air passenger numbers many studies have used time series models, particularly since the 1990s. Lim and McAleer (2002) and Kulendran and Witt (2003) used time series models to forecast the international business tourism travel demand for Australia. Chen et al. (2009) used Seasonal Autoregressive Integrated Moving Average model for forecasting inbound air travel arrivals to Taiwan.

Time Series Analysis can be viewed as the manifestation of a stochastic process, which is a collection of random variables that are ordered in time. The pattern in a time series data depends on the components like trend, cyclical, seasonal, and irregular. The decomposition is often not straightforward for the data. The time series models used for the data are defined below.

1.1 ARIMA Model: The Autoregressive Integrated Moving Average (ARIMA) model is the modification of Auto-regressive Moving Average (ARMA) by Box and Jenkins (1977). It is a nonlinear time series model used for prediction. The ARIMA Model with parameters (p, d, q) can be expressed as

$$\phi (B)\, (1 - B)^d X_t = \theta(B)\, a_t \qquad (1)$$

Where, p is lagged dependent variables and q lagged error terms and with an order of differencing d and ϕ (B) = $1 - \phi_1 B - \cdots - \phi_p B_p$; and θ (B) = $1 + \theta_1 B + \cdots + \theta_q Bq$

1.2 Holt-Winter Model: The triple exponential smoothing model that considers both trend and seasonality is the Holt-Winters' Method. This approach has two versions, each with a different seasonal component. When the series has constant seasonal variation throughout, the additive method recommended, however when change in seasonal variations is proportional to the series level, the multiplicative is preferable. The additive and multiplicative models are as follows:

$$L_t = \alpha\, (Y_t - S_{t-s}) + (1-\alpha)\, (L_{t-1} + b_{t-1}) \text{ and } L_t = \alpha\, (/S_{t-s}) + (1-\alpha)\, (L_{t-1} + b_{t-1}) \qquad (2)$$

where $L_t$denoteslevel of series; $b_t$represents trend estimate; $S_t$denotes estimate of seasonal component; with 'b' being the number of forecasts ahead and 's' the period of seasonality.

1.3 SARIMA Model: Seasonal Autoregressive Integrated Moving Average (SARIMA)is the most often used model for seasonal time series for forecasting. The SARIMA model with parameters $(p, d, q)\, (P, D, Q)_s$ is:

$$(B)\, \Phi(B_S)\, (1 - B)^d\, (1 - B_S)^D\, Xt = \theta(B)\, \Theta(B_S)\, \varepsilon_t \qquad (3)$$

where: X_t be the observed value of the time series at time 't', t = 1, 2, ..., k ; ε_t be the white noise with mean zero and variance σ^2; 'd' be the number of regular differences;

$\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B_p$ and $\Phi(B) = 1 - \Phi_1 B - \cdots - \Phi_P B_P$

$\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B q$and $\Theta(B) = 1 + \Theta_1 B + \cdots + \Theta_Q B_Q$

This data confined to the number of passengers travelled through Jet Airways from 2009 to 2019. Jet Airways is offering its services at national and international levels. Analysis done for both the services.

II. TIME SERIES MODEL BUILDING

In this section, an attempt is made to fit the ARlMA and SARIMA models to Air Jet ways data. The Holt-Winters approach, a triple exponential smoothing, and are useful in mid-term and long-term projections. The MASE and MAPE are evaluated to the model are presented.

2.1 ARIMA MODEL BUILDING: The model parameters and its efficiency were evaluated and presented in table 2.1.

Table 2.1 : ARIMA MODEL PARAMETERS						
Domestic	MA1	MA2	MA3	**International**	MA1	MA2
ARIMA(0,1,3)	-0.2385	-0.0299	-0.3164	ARIMA(0,1,2)	-0.4399	-0.3123
S.E.:	0.0872	0.0934	0.0939	S.E.	0.0865	0.0899
AIC : 3013.74	MAPE	MASE		AIC: 2858.98	MAPE	MASE
BIC: 3027.64	3.882498	0.298931		BIC: 2870.1	3.195492	0.29327

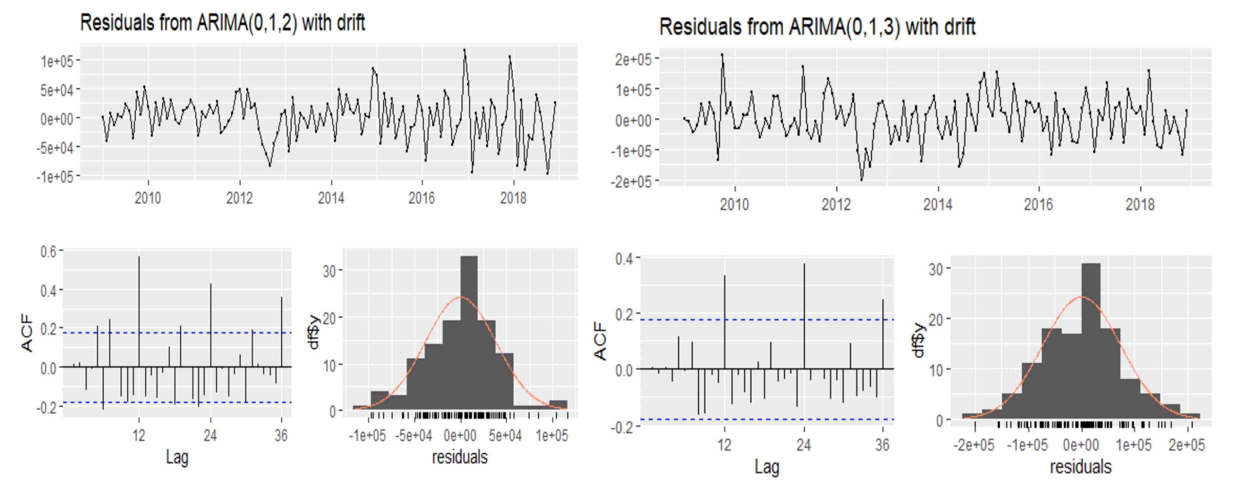

Fig 1(a): Domestic 1(b): International

TABLE 2.2: MODEL PARAMETERS AND EFFICIENCIES

Domestic			International		
	Additive	Multiplicative		Additive	Multiplicative
α	0.9327	0.8521	α	0.6765	0.864
β	0.0038	1.00E-04	β	0.0066	1.00E-04
γ	1.00E-04	1.00E-04	γ	0.3235	2.00E-04
AIC	2895.579	2919.412	AIC	2702.929	2669.919
BIC	2941.175	2967.69	BIC	2748.525	2718.197
MODEL	MAPE	MASE	MODEL	MAPE	MASE
HW(A)	3.513831	0.285394	HW(A)	4.459845	0.291721
HW(M)	3.064873	0.250722	HW(M)	4.522528	0.312667

Note:

1. Both the additive and multiplicative versions of this model display similar data fits.
2. The AIC and BIC values for the additive model are significantly lower for the domestic data,whereas they are lower for the multiplicative model for international data. Thus, the model with the lower error terms will be judged as the best fit for the data sets.
3. The best fitted Holt-Winter model for Domestic data set:

$L_t = (0.8521)\,(Y_t/S_{t-s}) + (1-0.8521)\,(L_{t-1} + b_{t-1})$

Where $b_t = (0.0004)\,(L_t - L_{t-1}) + (1-0.0004)\,bt_{-1}$ and $S_t = (0.0004)\,(Yt/L_t) + (1-0.0004)\,St_{-s}$

$$F_{t+m} = (L_t + b_{tm})S_{t-s+m}$$

4. The best fitted Holt-Winter model for international data set:

$L_t = (0.6765)\,(Y_t - S_{t-s}) + (1-0.6765)\,(L_{t-1} + b_{t-1})$

Where $b_t = (0.0066)\,(L_t - L_{t-1}) + (1-0.0066)\,b_{t-1}$ and $S_t = (0.3235)\,(Y_t - L_t) + (1-0.3235)\,S_{t-s}$

$$F_{t+m} = L_t + b_{tm} + S_{t-s+m},$$

The resulting SARIMA fitted model is presented in table 2.3.

TABLE 2.3: SARIMA MODEL PARAMETERS

Domestic	AR1	SMA1	International	AR1	SMA1
ARIMA (1,0,0)(0,1,1)[12]	0.8736	-0.638	ARIMA (1,0,0)(1,1,0)[12]	0.8589	-0.3427
S.E.	0.0495	0.1095	S.E.	0.0507	0.0959
AIC : 2398.42	MAPE	MASE	AIC: 2200.48	MAPE	MASE
BIC: 2408.68	2.847966	0.241004	BIC: 2210.74	4.106274	0.290209

Fig 2(a) : Domestic

Fig 2(b) International

Note:

1. The White Noise process ‘a_t’ is assumed to be iid normal (0, σ^2) can be verified from the Time sequence plot of residuals.
2. The autocorrelation of lag 1 is insignificant, implies that the ‘a_t’ are independent.
3. The Expected number of air passengers through the SARIMA model is near to the original values when compared with the ARIMA Model (Fig 3).
4. In SARIMA model residuals say that all the assumptions on the White Noise process are satisfied by National and International Models. The models are SARIMA (1,0,0)(0,1,1)[12] for Domestic data and SARIMA

(1,0,0)(1,1,0)[12], respectively. Model adequacy is usually done by generating Forecasts and checking agreement with observed data sets.

5. To test the best-fitted model's adequacy, forecasted values over the test window are generated. The train and forecast data of the Domestic and International data sets are plotted to see the trend of the data. The obtained plots are shown below.

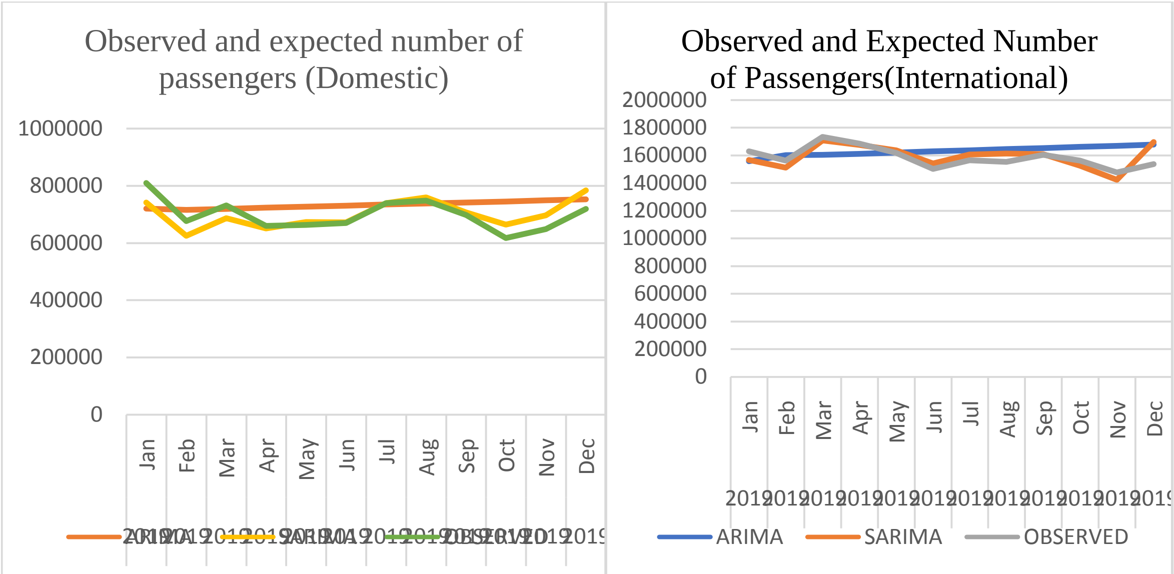

Fig. 3: International Observed and Expected Number of Passengers

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