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Seasonality in Tourism and Forecasting Foreign Tourist Arrivals in India

P. K. Mishra[1*], Himanshu B. Rout[2], B. B. Pradhan[2]
1. Central University of Punjab, Bathinda, Punjab, India
2. Siksha 'O' Anusandhan, Deemed to be University, Bhubaneswar, Odisha, India

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Abstract
In the present age of globalization, technology-revolution and sustainable development, the presence of seasonality in tourist arrivals is considered as a key policy issue that affects the global tourism industry by creating instability in the demand and revenues. The seasonal component in a time-series distorts the prediction attempts for policy-making. In this context, it is quintessential to suggest an accurate method of producing the reliable forecast of foreign tourist arrivals. This paper evaluated the performance of Holt-Winters' and Seasonal ARIMA models for forecasting foreign tourist arrivals in India. The data on India's inbound tourism from Jan-2001 to June-2018 were used for preparing the forecast for the period July-2018 to June-2020. On the basis of Mean Absolute Error, Mean Absolute Percentage Error and Mean Square Error, the findings infer the relative efficiency of Holt-Winters' model over Seasonal ARIMA model in forecasting the foreign tourist arrivals in India. Thus, to reduce the perceived negative impacts of seasonality in Indian inbound tourism and to ensure foreign tourist visits round the year, niche products best suitable for Indian climatic and socio-cultural-institutional conditions need to be introduced and promoted in a large scale both at the national and global levels.

Keywords
Seasonality, Tourism, Forecasting, Foreign Tourist Arrivals.

* **Corresponding Author**, **Email**: pkmishra1974@gmail.com

Introduction

In last few decades, most of the countries across the globe realized the importance and potential of travel and tourism as a vital economic sector which is not only significant for strengthening the socio-cultural and political economy of a nation, but also crucial for building up the peaceful bonds of cross-border relationships (Richardson, 2010; Gill & Singh, 2011; Gill & Singh, 2013; Rout *et al*. 2016a; Mishra *et al*. 2016; Mishra & Verma, 2017). In recent years, tourism across the world has emerged as a key economic sector capable of diffusing the benefits of inclusive growth and sustainable development by providing job opportunities and contributing to enhanced standards of living of masses (Ashley, 2007; Mishra *et al.* 2011; Pleumarom, 2012; Mishra & Rout, 2012-13; Munshi & Mishra, 2016). In 2016, the travel and tourism in India have contributed INR 14,018.50 billion (USD 208.90 billion) to the Gross Domestic Product and created 25,394,500 number of jobs (WTTC, 2017) which in 2017, has increased to INR 15,239.60 billion (USD 234.0 billion) and 41,622,500 number of jobs, respectively (WTTC, 2018). This clearly signifies the importance of travel and tourism for the inclusive and sustainable development of the country.

The travel and tourism is considered as a highly labor-intensive economic sector in the country. As per the estimation by Planning Commission of India, the travel and tourism industry has the potential to create 89 jobs (compared to 45 jobs in primary and 13 jobs in secondary sectors) for one million rupees invested in this sector (Rout *et al*. 2016b, 2016c). Besides, it has the potential to generate employment opportunities in the country such that the ratio of indirect jobs to direct jobs due to travel and tourism is 3:1 (Das, 2013). This is the reason why travel and tourism can be considered as a significant source of employment creation, foreign exchange and revenue earnings, and as a means of developing the socio-economic infrastructure in the economy (Mishra *et al*. 2016). So, the growth of the tourism is crucial for the economic growth of a nation. The growth of tourism industry broadly depends on the growth in the arrivals of both domestic and foreign tourists. Particularly, the importance of Foreign Tourist Arrivals (FTAs), often called inbound tourism, is noteworthy in this context. Inbound tourism boosts the economy by increasing income, creating job opportunities, raising the volume of investments and stimulating the growth of the nation. Its contribution also lies in infrastructure development which has positive effects on other industries, the publicity of individual destinations attracting tourists, and foreign exchange earnings for the public exchequer (RRPLT, 2014).

In India, the top ten countries, viz., Bangladesh (15.68 percent), United States (14.73 percent), United Kingdom (10.7 percent), Canada (3.6 percent), Malaysia (3.43 percent), Sri Lanka (3.38 percent), Australia (3.33 percent), Germany (3.02 percent), China (2.85 percent) and France (2.71 percent) have contributed about 63.43 per cent of total inbound tourism during the year 2016 (MoT, 2017). This inbound tourism has linkage effects on the Indian economy in terms of job creation, revenue generation, foreign exchange earnings, infrastructure development, the growth of local business and poverty alleviation (Rout *et al* 2016a).

Table 1. **Quarterly Percentage Distribution of FTAs in India, 2001-2017**

Year	Total FTAs	1st Quarter Jan-Mar (%)	2nd Quarter Apr-June (%)	3rd Quarter July-Sept (%)	4th Quarter Oct-Dec (%)
2001	2537282	31.3	20.2	23.0	25.5
2002	2384364	28.8	18.4	21.1	31.7
2003	2726214	27.7	17.6	22.8	31.9
2004	3457477	27.8	18.3	21.8	32.1
2005	3918610	28.3	18.4	21.4	31.9
2006	4447167	28.5	19.2	20.9	31.4
2007	5081504	29.7	18.4	20.9	31.0
2008	5282603	30.9	19.5	21.7	27.9
2009	5167699	27.2	19.3	21.8	31.7
2010	5775692	28.3	18.8	21.8	31.1
2011	6309222	28.3	19.6	20.9	31.2
2012	6577745	29.8	19.1	20.5	30.6
2013	6967601	29.4	18.9	20.8	30.9
2014	7679099	28.7	19.6	21.5	30.2
2015	8027133	28.4	19.5	22.1	30.0
2016	8804411	28.4	18.9	22.6	30.0
2017	10154872	28.0	19.9	22.0	30.1

Source: Compiled from Bureau of Immigration, India

However, the issue is that the inbound tourism in India does not present a consistent pattern of flows of foreign tourist arrivals. Precisely, the foreign tourist arrivals in the country depict seasonal fluctuations which happen to adversely affect the growth policies of the tourism industry, thereby distorting its positive impacts on the economy. This seasonal variation is primarily governed by the weather conditions at various tourist destinations in the country, and a quick overview of such variation broadly classifies the 1st and the 4th quarters of a calendar year as peak seasons whereas the 2nd and the 3rd quarters as lean seasons for foreign tourist arrivals in the country (see Table 1 and Fig.1).

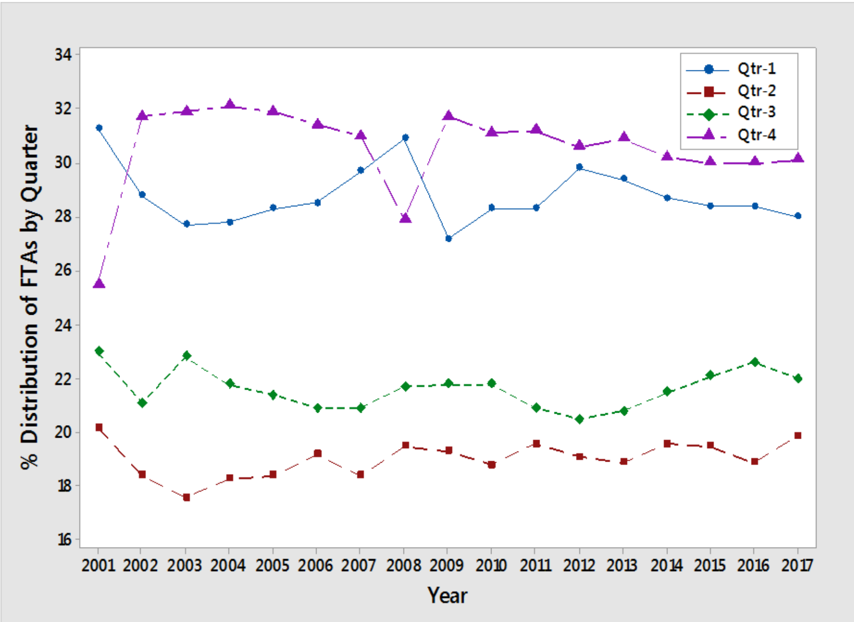

Fig. 1. **Quarterly Percentage Distribution of FTAs in India, 2001-2017**
Source: Own Plot of Data from Table-1

Further, it is observed that the foreign tourist arrivals in the country have been invariably the lowest during the summer (2nd quarter) of every year. But, the arrivals during the rainy season (3rd quarter) are better than that of the summer in the country. Such an observation indicates the presence of seasonality in Indian inbound tourism. In addition to the seasonality in quarterly data, the monthly data on FTAs were also used for better capturing the seasonality in Indian inbound tourism. The Table-2 presents the monthly share of foreign tourist arrivals in the country during the last five years and the Fig.2 depicts the time series plot of the monthly FTAs for the period Jan-2001 and June-2018.

Table 2. Monthly Percentage Share of FTAs in India, 2013-2017

Months	2013	2014	2015	2016	2017
Jan	10.3	9.9	9.9	9.6	9.7
Feb	9.9	9.8	9.5	9.6	9.4
Mar	9.2	9.0	9.1	9.2	8.9
Apr	6.5	7.0	6.7	6.7	7.1
May	6.0	6.1	6.4	6.0	6.2
June	6.5	6.5	6.4	6.2	6.6
July	7.3	7.4	7.8	8.3	7.8
Aug	7.0	7.5	7.5	7.4	7.1
Sept	6.5	6.6	6.8	6.9	7.1
Oct	8.6	8.7	8.5	8.4	8.6
Nov	10.5	10.0	10.2	10.0	9.9
Dec	11.8	11.5	11.4	11.6	11.6
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Source: Own Calculations from Monthly FTAs data

It is observed from Table-2 that the peak month of FTAs in India is December (about 11.58 percent per year) and the lean month is May (about 6.14 percent per year). The following months of the peak month are January (about 9.88 percent per year) and November (about 10.12 percent per year) of each year. In these months, a good number of foreign tourist arrivals takes place which has several direct and indirect benefits that accrue to the Indian economy. Similar to this observation, Fig.2 also infers that December is the peak and May is the lean seasons of foreign tourist arrivals in the country during Jan-2001 to June-2018. Further, it is noticed that the foreign tourist arrivals are relatively low during September month of every year, but it is not as low as during May. This pattern of FTAs is mainly guided by the weather conditions of tourist destinations in the country and it clearly indicates the presence of seasonality in Indian inbound tourism. The Fig.2 also unveils the rising trend of the foreign tourist arrivals in the country over the last seventeen years. This rising trend clearly indicates the preference of foreign tourists for Indian natural serenity, socio-cultural prosperity, colorful fairs & festivals, and fascinating food & beverage. Singh (2013) aptly remarked that this rising trend of foreign tourist arrivals brought with it ample cross-border tourist receipts in past years and contributed substantially to the Gross Domestic Product and foreign exchange earnings of the country. On the basis of this trend pattern in FTAs, it can be said that the country is experiencing a considerable growth in inbound tourism capable of generating spirals for inclusive and sustainable growth in the long-run.

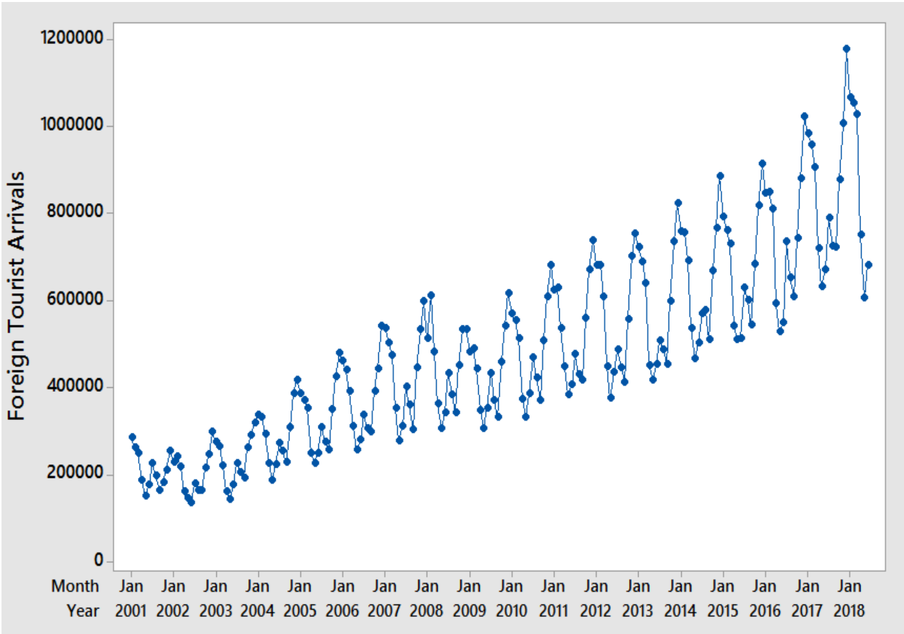

Fig. 2. Monthly Foreign Tourist Arrivals in India, Jan-2001 to June-2018
Source: Authors' Own Plot

Thus, it is desirable that the policy circle should come out with prudent strategies and policies for sustaining such a rising trend in Indian inbound tourism. For this purpose, it is essential to have a precisely predicted trend pattern of FTAs before-hand. Song & Witt (2006) opined that the pro-active decisions for the development of travel & tourism and allied activities in a country depend on the prediction of rising trend of tourist arrivals. Thus, the FTAs in the country need to be forecasted by applying appropriate analytics capable of dealing with seasonal fluctuations.

Therefore, this paper attempts to produce monthly forecasts of the foreign tourist arrivals in the country during July-2018 to June-2020 using FTAs datasets for the period Jan-2001 to June-2018. This study aims to contribute to the literature a reliable method of forecasting the FTAs capable of capturing the inherent seasonal variations in Indian inbound tourism. The forecasts made by this paper can be used by the stakeholders while planning for effective marketing and promotion of tourism in the country. It is argued that the availability of better forecast can help the policy-makers reduce the revenue loss from reduced tourist arrivals during lean seasons and protect the allied activities by devising appropriate strategies. The availability of better forecast can also provide a safeguard against the over-use and/or under-use of resources and other facilities in the country which has far-reaching implications for sustainable development.

Seasonality in Tourism

Seasonality in tourism can be considered as any systematic ups and downs over time in tourism specific activities including tourist arrivals, spending by tourists, visits to particular destinations, etc. (Butler, 1994, 2001). Butler further pointed out two important causes of seasonality in tourism namely, natural and institutional. The former is the outcome of regular variations in climatic conditions such as temperature, rainfall, snowfall and daylight. Institutional seasonality, according to Butler, "is the result of human decisions and is much more widespread and less predictable than natural seasonality. It is the outcome of a combination of religious, cultural, ethnic and social factors".

The inbound tourism in India presents the case of seasonality both due to natural and institutional factors. The inbound tourism in India is subject to natural seasonality in terms of extremes of temperature, monsoon rainfall and consequential humidity. Particularly, the lower arrivals of foreign tourist during May and September (see fig.2) can be attributed to natural causes. Similarly, the important institutional factors causing seasonal fluctuations in Indian inbound tourism include festivals, periods of religious worship, school vacations, and other public holidays among others. Predominantly, the higher arrivals of the foreign tourists in the country during December (see fig.2) are due to the institutional factors.

Besides the causes, the literature also reveals the key impacts of seasonality on tourism. In the supply side, the impacts of seasonality on tourism include packaging, distribution, and pricing activities of marketing; nature and quality of employment, skills availability, and sustainability of employment in the labor market; cash flow, pricing, and investment in business finance; suppliers and intermediaries as stakeholders of tourism management; and all aspects of operations (Baum, 1999; Baum & Lundtorp, 2001). In the demand side, the impacts of seasonality in tourism include high prices with difficulty of getting quality and satisfaction due to crowding (Jang, 2004), reduced availability of accommodation (Krakover, 2000), and excessive pressure on transport system and infrastructure (Commons & Page, 2001) during the peak seasons of FTAs.

Later, Cannas (2012) went a step ahead to group the seasonal effects into three main categories, namely, economic impacts, socio-cultural impacts and ecological impacts. The economic impacts of seasonality in tourism mainly deal with the loss of revenues/profits because of uneconomical use of resources and other facilities at the destination (Sutcliffe & Sinclair, 1980; Manning & Powers, 1984; William & Shaw, 1991). Seasonality has both positive and negative impacts on employment (Ball, 1988, 1989; Ashworth & Thomas, 1999; Baum, 1998; Flognfeldt, 2001). The key issues are the difficulties faced in recruiting and retaining full-time staff in travel and tourism sector (Yacoumis, 1980) and related to this, there is the problem of maintaining product quality standards (Baum, 1999). On the positive side, seasonality offers job opportunities temporarily to some people, such as students, artists, and housewives (Cannas, 2012). Second, regarding the socio-cultural impacts (e.g. crime, congestion, higher prices), Manning & Powers (1984) argued that all these put “a strain on the social carrying capacity of the destination”, which may “result in resentment from the local community towards all tourism activities”. Third, the ecological impacts are more or less identical with the unhealthy effects, such as physical erosion of footpaths and other natural resources, litter problems, disturbance of wildlife and congestion of rural areas (Cannas, 2012) because of the high degree of concentration of tourists during peak season at destinations.

It is, thus, learned that seasonality in tourism can result in critical socio-economic problems such as unstable labor market at destination, and loss in returns to investments in concerned/allied activities. All these are more likely to distort the policies meant for improving social well-being at large. Thus, it is imperative to produce a reliable forecast for foreign tourist arrivals in the presence of seasonality in an emerging market economy like India. Song & Witt (2006) rightly pointed out that the accuracy in tourism forecasts has positive impacts on business successes, marketing decisions, government's investment policies as well as the macroeconomic policies of a country. Archer (1987) further added that an accurate forecast of tourism demand is of great significance to ensure the availability of all such allied services that cannot be accumulated. The seasonality in tourism often leads to a typical cyclical problem in which shortage in capacity follows the excess capacity. The stakeholders can eliminate such problems if they have the forecasted FTAs beforehand for the destination.

India, because of its rich social traditions, cultural heritage, spiritual footprints, colorful fairs & festivals, and natural beauties (Chaiboonsri & Chaitip, 2012), offers a wide range of tourism products including heritage tourism, spiritual tourism, eco-tourism, adventure tourism, science tourism, rural tourism, agri-tourism and medical tourism (Dhariwal, 2005) which attract foreign tourists to the country from different parts of the globe. Nonetheless, the natural and institutional factors prohibit the consistent growth of foreign tourist arrivals round the year in India. Consequently, the Indian inbound tourism is subject to seasonal variations. In view of such seasonality in Indian tourism, the entire potential of the travel and tourism industry in the country is not yet fully explored for the larger interest of the nation. However, the researchers argue that if suitable strategies can be developed to reduce the negative effects of seasonality by forecasting the FTAs, then tourism can be a major engine of economic growth in the country. Accurate forecasting of foreign tourist arrivals in India is essential to determine the quantum of investments in the tourism industry by both the public and private sectors (Chang & Liao, 2010).

In this line of thought, certain studies have been undertaken to address the issue of forecasting foreign tourist arrivals in the presence of seasonality in India. Balogh *et al* (2009) and Chaitip & Chaiboonsri (2009) used the X-12-ARIMA model to forecast international tourist arrivals to India and became optimistic about the rising trend of tourist arrivals in the country. In a similar study, Pradhan (2011) found better forecasting efficiency of Seasonal ARIMA model in the context of Indian inbound tourism. Kumari (2015) carried forward this forecasting exercise and found the reliability of Seasonal ARIMA and Holt-Winters models for producing better forecast accuracy in Indian inbound tourism. Sood & Jain (2017) in a recent study found the ARIMA model to be efficient over Holt-Winters' model for forecasting foreign tourist arrivals in India. In another recent work, Chandra & Kumari (2018) compared various time series models to forecast FTAs in India and found Seasonal ARIMA to be better in producing the desired forecast.

It is deduced from the review of related studies that the seasonality is a key issue in Indian inbound tourism and it has negative consequences for the tourism industry as well as for the economy as a whole. This seasonality has dampening effects on the effectiveness of tourism strategies and policies. So a reliable forecasting of FTAs in the country is warranted. Although few studies have been conducted to date in the time-series framework, a consensus is yet to be made in recommending an efficient forecasting tool. In this direction, the present study is a forecasting exercise in the context of Indian inbound tourism that uses updated data sets and alternative forecasting tools to suggest a better forecast so as to facilitate policy effectiveness.

Data and Methodology

Objective of the Study

In view of the significance of foreign tourist arrivals in India in creating job opportunities and generating revenues/profits for public/private sectors, and in the presence of the evidence of consistently growing India's inbound tourism and its persistent seasonal patterns (see fig.1 & fig.2), this research study attempts to produce monthly forecasts of foreign tourist arrivals from July-2018 to June-2020. The outcome of this research work will guide the planners and policy-makers in the government as well as private sectors to come out with judicious strategies & policies for attracting and accommodating international visitors in the country.

Time Series Data

The study used the monthly data on foreign tourist arrivals from Jan-2001 to June-2018. The required data were compiled from various issues of India Tourism Statistics manual published by Market Research Division, Ministry of Tourism of Government of India. This monthly time series is named as FTAs which stands for Foreign Tourist Arrivals, and is divided into two periods – (1) Jan-2001 to June-2017 consisting of 198 observations which were used to fit the forecasting model; and (2) July-2017 to June-2018 consisting of 12 observations which were used to test the accuracy of in-sample forecast. Then the out-of-sample forecast was generated from July-2018 to June-2020 consisting of 24 months having significant policy implications for the Indian tourism industry.

Forecasting Methods

In the literature, it is argued that no single method is superior and thus, different methods should be used in necessary measurements (Karamustafa & Ulama, 2010; Porhallsdottir & Olafsson, 2017). However, Bigovic (2011) opposed the use of different methods in measurements because in most of the cases the discrepancies among the results of different measures are insignificant, and thus, it is sufficient to use only one measure. The extant literature also argues that univariate time-series models are relatively efficient in forecasting tourist arrivals (Saayman & Saayman, 2010; Singh, 2013; Kumari, 2015; Akuno *et al*. 2015; Peiris, 2016; Sood & Jain, 2017). In this line of argument, we employed the univariate time-series framework in our forecasting exercise. In carrying out forecasting of tourist arrivals, Singh (2013) suggests for using alternative methods to reduce the risk of forecasting failure. Since seasonality is an integral component of inbound tourism in India and as it shows a linear trend pattern, we have employed Holt-Winter (HW) and Seasonal Autoregressive Integrated Moving Average (SARIMA) Models for our purpose. The estimation and forecasting procedures of these models are narrated below:

Holt-Winters' Multiplicative Triple Exponential Smoothing Model

This model is considered appropriate for time series depicting a linear time trend and multiplicative seasonal variation (Holt, 1957; Winters, 1960). This method employs a triple exponential smoothing framework comprising level, trend and seasonality equations. These are specified as under:

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

Trend: $T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$

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

Forecast: $\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p}$

Here, L_t is the new smoothed value or current level estimate; α is smoothing constant for level between 0 and 1; Y_t is the new observation or actual value in period t; β is the smoothing constant for trend estimate; T_t is the trend estimate; γ is the smoothing constant for seasonality estimate; S_t is the seasonal estimate; p is the forecasting period ahead; s is the length of seasonality; and $\hat{Y}_{t+p}$ is the forecast for p periods into future. In this case, the best combination of α, β and γ is one which minimizes Mean Absolute Percentage Error (MAPE). The responsiveness of the forecast to varying numbers of foreign tourist arrivals in India is determined by the smoothing constants. Handanhal (2013) pointed out that the forecast is more sensitive to more recent values when α is larger, and also sensitive to more recent trends when β is larger. Thus, the choice of the values of α and β cannot be statistical. This compelled us to draw certain recommendations from the existing literature. Schroeder *et al.* (2013) recommends that the value of α should lie between 0.1 and 0.3. Similarly, Stevenson (2012) recommends that the value of α should lie between 0.05 and 0.5. It is recommended in the existing literature that the value of smoothing constant be chosen so as to ensure accuracy in the forecast as measured by certain forecasting error such as MAPE.

Seasonal Autoregressive Integrated Moving Average Model
The seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. The non-seasonal autoregressive and moving average terms accounting for the correlation at lower lags are used in SARIMA model. Similarly, the seasonal autoregressive and moving average terms accounting for the correlation at seasonal lags are also contained in SARIMA. Seasonal ARIMA model is popular due to its ability to deal with both stationary and non-stationary series. In case of non-stationary time series, the values of the variable are taken in their first differences to estimate the model. The seasonal ARIMA model is usually represented by a multiplicative model in the form of *SARIMA (p, d, q) (P, D, Q)$_s$* where p is the non-seasonal autoregressive order; d is the non-seasonal differencing; q is the non-seasonal moving average order; P is the seasonal autoregressive order; D is the seasonal differentiation; Q is the seasonal moving average order; and s is the time span of repeating seasonal pattern. The multiplicative seasonal ARIMA model can be stated as: $\Phi\left(B^s\right)\Phi(B)\left(1-B^s\right)^D(1-B)^d Y_t=\Theta\left(B^s\right)\Theta(B)e_t$ where B is the backshift operator; s is the seasonal period; $\Phi(B)$ is the non-seasonal AR operator; $\Phi\left(B^s\right)$ is the seasonal AR operator; $\Theta(B)$ is the non-seasonal MA operator; $\Theta\left(B^s\right)$ is the seasonal MA operator; $\left(1-B^s\right)^D(1-B)^d$ is the non-seasonal differencing of order d and seasonal differencing of order D; and Y_t is the observed value at time point *t*. The best fitted seasonal ARIMA model can be selected using Normalized Bayesian Information Criterion (BIC) and MAPE.

Forecasting Accuracy
In this study, the relative performances of forecasting models have been measured by using most dominating techniques of forecast accuracy. The forecast accuracy of a model is required to be evaluated to suggest the most appropriate univariate time-series forecasting method. It is a common practice to measure the forecast accuracy by subtracting the forecast values from the corresponding actual values at time *t* (Fretchling, 2001). This is known as the *error term* or the

residual term. It can be stated as: $e_t = Y_t - \hat{Y}_t$ where Y_t is the actual value; $\hat{Y}_t$ is the forecasted value; and e_t is the residual. The various measures of forecast accuracy are Mean Absolute Error (MAE), Mean Squared Error (MSE) and MAPE. These measures are defined as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \qquad MSE = \frac{1}{n}\sum_{t=1}^{n}e_t^2$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{Y_t}\times 100$$

MAE is useful in cases where the forecast error and the original series are measured in the same unit. MSE considers the square of the error term so as to remove the negative deviations. In cases where the importance of the forecast variable is more, the MAPE is considered suitable.

For all these measures, smaller values generally indicate a better fitting model. The empirical literature on forecasting suggests using MAPE as it is a good accuracy measure which does not depend on the magnitude of the forecast variable (Mamula, 2015). Lewis (1982) and Baggio & Klobas (2011) suggest a rough scale for the accuracy of a time-series forecasting model based on MAPE – highly accurate (MAPE < 10%), good (10% < MAPE < 20%), reasonable (20% < MAPE < 50%) and inaccurate (MAPE > 50%).

Results and Discussion

The time series plot in Fig.2 clearly indicates the linearly increasing trend and the presence of seasonality in foreign tourist arrivals in India. The foreign tourist arrivals are generally higher during December of every year possibly due to favorable weather conditions and availability of holidays. On the contrary, foreign tourist arrivals are invariably the lowest during May of every year possibly due to unfavorable weather conditions in almost every part of the country. It is also noteworthy that the foreign tourist arrivals are lower during September of every year possibly due to monsoon rains. Despite such seasonality in Indian inbound tourism, the arrival of international visitors to India is on the continuous rise over the years. Thus, it is of paramount interest of planners, policy-makers and other stakeholders to know in advance whether such data patterns are going to be persistent in times ahead to enable easier adoption of pro-tourism strategies for reducing the negative impacts of seasonality. This justifies the need for making an accurate forecast of FTAs. Therefore, this study fits two univariate time-series models, namely, HW and SARIMA as discussed earlier for forecasting FTAs in India.

Holt-Winters' Model

The Holt-Winters' model is used because of the presence of an upward trend and seasonality in FTAs series. Smoothing constants α, β and γ were chosen on the basis of the rule: different values of smoothing constants were tried out on past data and as the best ones were chosen those constants which made minimum MAPE. The FTAs data from Jan-2001 to June-2017 were used to fit the forecasting model. The value of the α for smoothening the level equation was set up at 0.5, the value of β for smoothening the trend equation was set up at 0.1 and the value of γ for smoothening the seasonal equation was set up at 0.1. This model fit is shown in Fig.3.

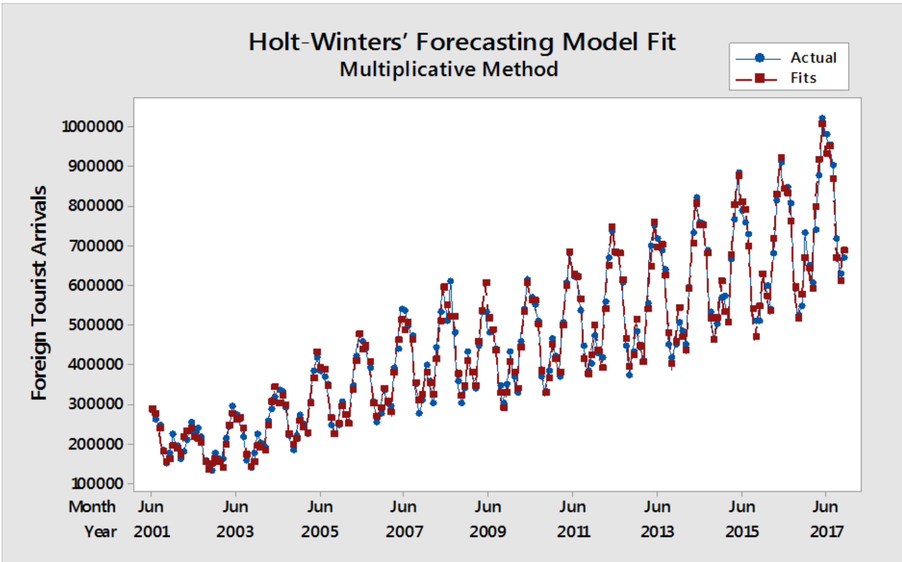

Fig. 3. Holt-Winters' Model Fits, Jan-2001 to June-2017
Source: Authors' Own Calculation

This model is considered the best fit with MAPE of 4 percent being less than 10 percent as suggested by Lewis (1982) and Baggio & Klobas (2011). Then, the in-sample forecast of FTAs from July-2017 to June-2018 was produced to judge the model accuracy, and it is found to be accurate with a high degree of precision (see fig.4). The MAPE of this evaluative model is 1 percent which makes the fit most suitable for making the desirable forecast.

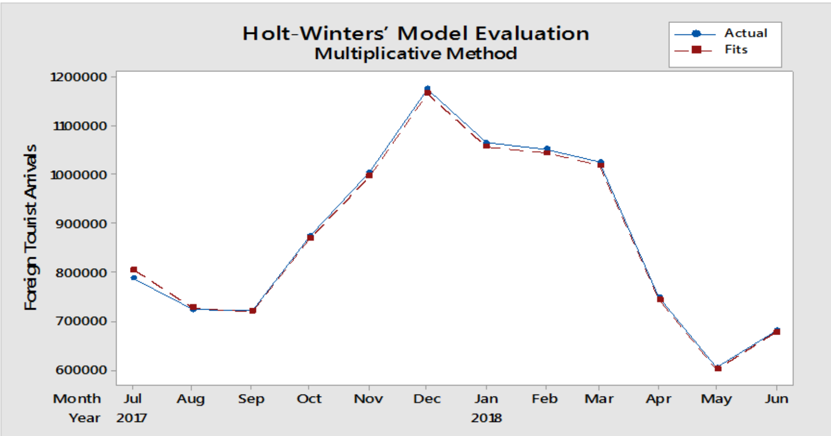

Fig. 4. Holt-Winters' Model Evaluation, July-2017 to June-2018
Source: Authors' Own Calculation

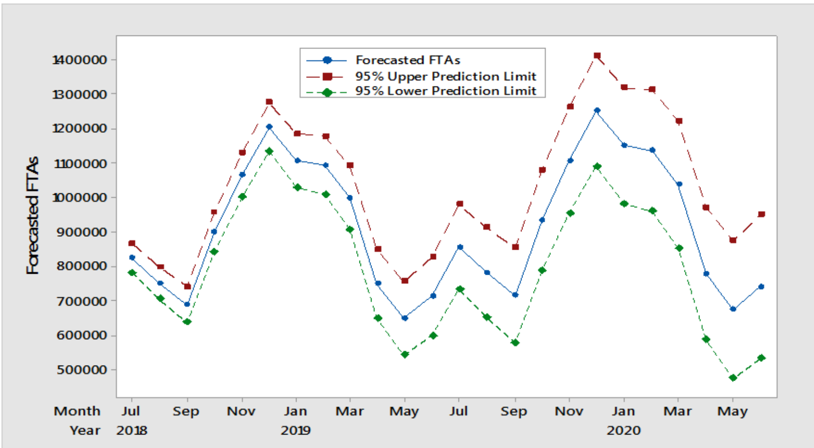

Fig. 5. Out-of-Sample Forecast by Holt-Winters' Method
Source: Authors' Own Calculation

At last, we have employed the above model fit to produce out-of-sample forecasts of FTAs in India from July-2018 to June-2020 (see Appendix-1). The Fig.5 plots the out-of-sample forecast with its 95% Upper Prediction Limit (UPL) and Lower Prediction Limit (LPL). The MAPE of this forecasting exercise is 4 percent. The MAE and MSE of this forecast are 17,348 and 525,585,863, respectively. This forecast clearly follows the past data patterns – increasing trend in FTAs, higher FTAs during December, lower FTAs during May and September, respectively. Since this model captures the seasonality in FTAs well and makes the forecasting with high precision, the results can be used for formulating pro-tourism plans and policies.

SARIMA Model: The seasonal ARIMA model presumes the non-stationarity of underlying time-series. Thus, the non-stationarity of FTAs series was examined by estimating autocorrelation and partial autocorrelation coefficients, and by plotting the corresponding correlograms (see Fig.6A & Fig.6B).

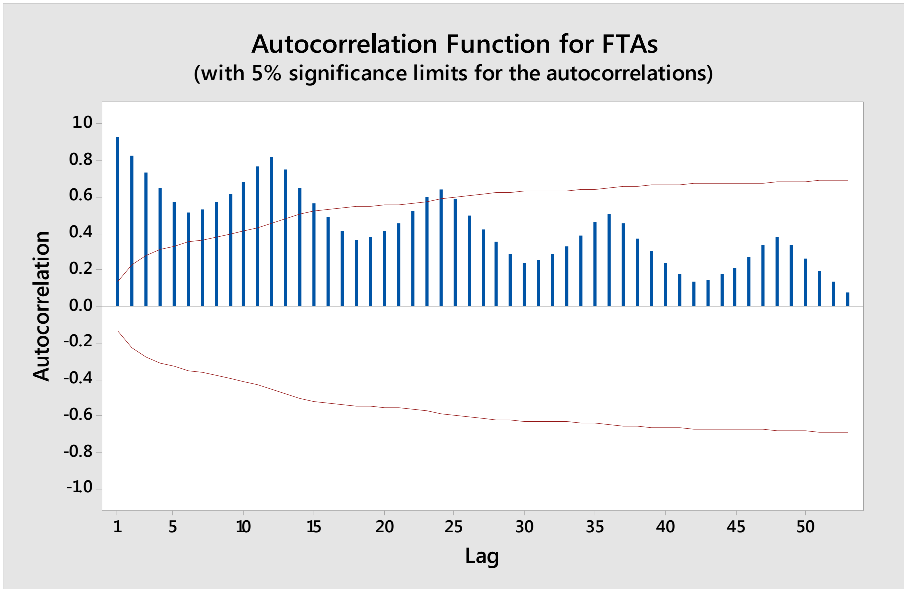

Fig. 6. A. Autocorrelation Function for FTAs
Source: Authors' Own Calculation

It is inferred that the Autocorrelation Function (ACF) as well as Partial ACF dies out slowly upto lag 6 and thereafter increases. Also, there are waverings in ACFs and PACFs. The Ljung-Box Q statistics with corresponding p-values indicate that the ACFs, as well as partial ACFs, are statistically significant up to 50th lag (see Appendix-3), and the coefficient of ACF becomes extinct very slowly after several lags. The coefficient of ACF is also higher at a particular seasonal interval. All these observations clearly justify the non-stationarity of the underlying time series with trend and seasonality.

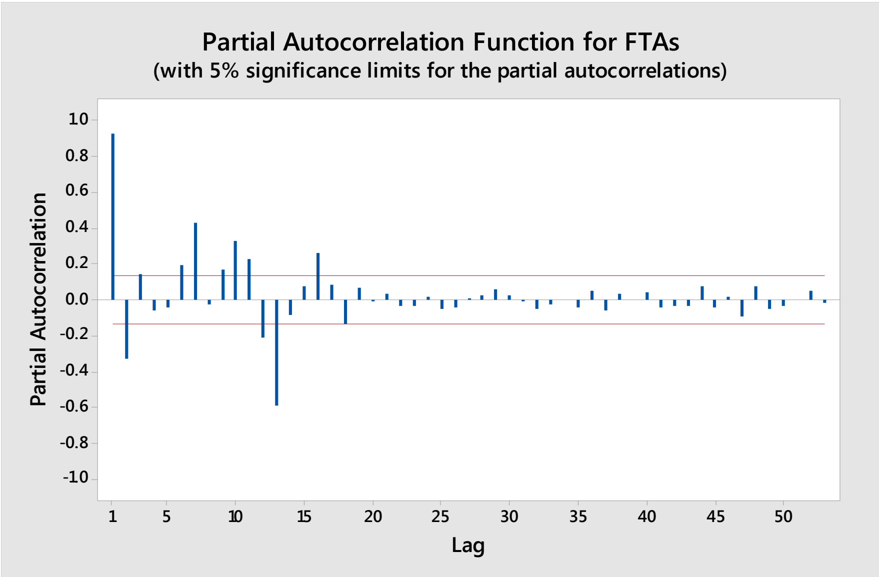

Fig. 6B. Partial Autocorrelation Function for FTAs
Source: Authors' Own Calculation

Table 3. Results of Augmented Dicky-Fuller Unit Root Test

Null Hypothesis	**At Level**		**At First Difference**	
Non-Stationarity	Intercept	Trend and Intercept	Intercept	Trend and Intercept
ADF Statistics	1.3238	-0.8624	-4.5122	-4.7295
p-values	0.9987	0.9569	0.0003	0.0008

Source: Authors' Own Estimation

However, as a conformity measure of non-stationarity, the Augmented Dickey-Fuller (ADF) unit root test (Dickey & Fuller, 1981) was used and results are presented in Table-3. In this test, the null hypothesis of non-stationarity could not be rejected at the level, but could be rejected at the first difference at 1% level when the model has both intercept, and intercept & trend terms. Thus, the non-stationarity of the FTAs series is confirmed.

Given the upward trend, seasonality and non-stationarity of FTAs series, the SARIMA model was used to produce the out-of-sample forecasts values. In order to select the best fit model, we took the help of Expert Modeler in SPSS 22.0. The Expert Modeler automatically determines the best model for the time-series, thereby eliminating the need to identify an appropriate model through trial and error (Rai *et al*., 2014).

Table 4. SARIMA Model Selection

Seasonal ARIMA Model	**Model Fit Statistics**		**Ljung-Box Q Test**		
Selection Criteria	MAPE	Normalized BIC	Statistic	d.f	Sig.
ARIMA (0,1,1) $(0,1,1)_{12}$	4.834	20.375	26.851	18	0.043

Source: Authors' Own Estimation

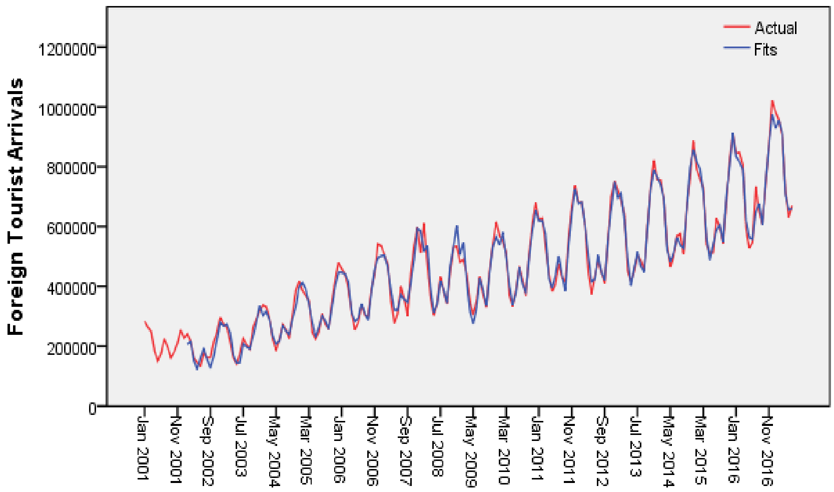

Fig. 7. Model Fits of SARIMA, Jan-2001 to June-2017
Source: Authors' Own Calculation

The FTAs data from Jan-2001 to June-2017 have been used to find the best-fit SARIMA model. And, the SARIMA (0,1,1) $(0,1,1)_{12}$ model was found to be the best fit on the basis of the smaller values of Normalized BIC and MAPE. The Normalized BIC and MAPE are 20.375 and 4.834, respectively. The significance of Ljung-Box Q statistic also supports this choice (see Table-4). Furthermore, Fig.7 depicts how well the model predicts seasonal peaks and troughs. And, it does a good job of capturing the upward trend of the data.

Table 5. Seasonal ARIMA (1,0,0)(0,1,1)12 Model Estimation

Parameters	Estimates	Standard Error	t-statistic	Level of Sig.
Constant	554	662.0	0.840	0.404
Non-seasonal AR(1)	0.435	0.068	6.413	0.000
Seasonal Difference	1			
Seasonal MA(1)	0.362	0.077	4.694	0.000

Source: Authors' Own Estimation

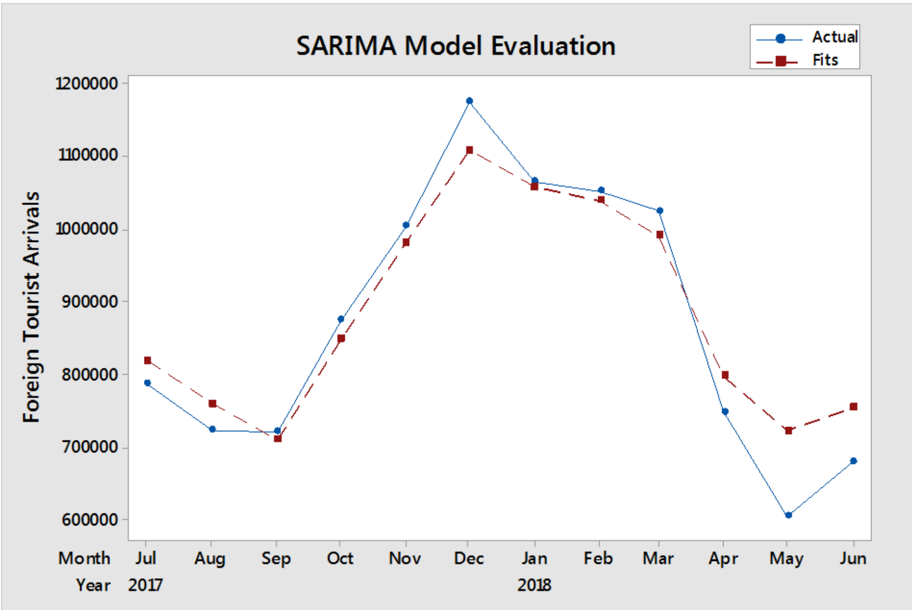

Fig. 8. In-Sample Forecast by SARIMA, July-2017 to June-2018
Source: Authors' Own Calculation

Then we estimated this seasonal ARIMA model and found all parameters to be significant at 1% level except for the constant term, thereby assuring the forecastability of the model. This model estimation has been used to produce the in-sample forecasts of FTAs from July-2017 to June-2018 to judge the forecast accuracy. From Fig.8, it is observed that the Seasonal ARIMA $(0,1,1)(0,1,1)_{12}$ model is capable of making an accurate out-sample forecast of foreign tourist arrivals in India.

Finally, we have used this Seasonal ARIMA model to produce the out-of-sample forecast of FTAs in India from July-2018 to June-2020 (see Appendix-2). The Fig.9 plots the out-of-sample forecast of FTAs with its 95% Upper Prediction and Lower Prediction Limits. This forecast clearly follows the past data patterns – increasing trend in FTAs, higher FTAs during December, lower FTAs during May and September, respectively.

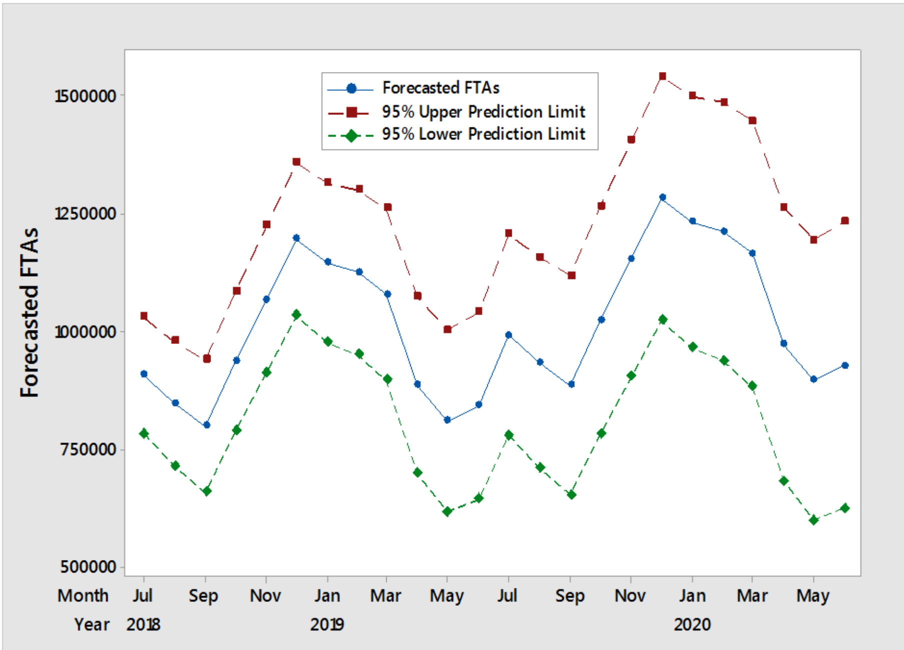

Fig. 9. Out-of-Sample Forecast by SARIMA Model
Source: Authors Own Plot

At last, we compared the forecast accuracy of both the HW and SARIMA models. It is found that the MAPE of Holt-Winters' model is 4.0 percent, whereas that of Seasonal ARIMA model is 4.834 percent. It means in the use of the Holt-Winters' model, the chance of actual values being different from forecasted values of FTAs is only 4 percent which is less than that of the SARIMA model. Therefore, the forecasting performance of HW model is better than that of Seasonal ARIMA. Similarly, the MAE of Holt-Winters' model is 17,348 and that of Seasonal ARIMA model is 19,705.80. Furthermore, the MSE of Holt-Winters' model is 525,585,863 and that of Seasonal ARIMA model is 667,211,992.22. All these justify the forecasting accuracy of the Holt-Winters' model (see Table-6). Therefore, Holt-Winters' model is found to be the best fit model for forecasting foreign tourist arrivals in India. In the Indian context, this finding corroborates to the findings of Kumari (2015) and Sood & Jain (2017), but contradicts to the finding of Pradhan (2011) and Chandra & Kumari (2018). This inconsistency in the findings of the current study and the past studies may be due to different time periods considered for the forecasting exercise.

Table 6. Comparison of Forecast Accuracy

Criteria	Holt-Winters' Model	SARIMA Model
MAPE	4.0	4.834
MAE	17,348.0	19,705.8
MSE	525,585,863.0	667,211,992.22

Source: Authors' Own Estimation

The implication of this result is that, Holt-Winters' model is appropriate to capture the patterns of foreign tourist arrivals and to forecast the same in India with a high accuracy level. The performance of Holt-Winters' model may be better due to the consistency and persistence in seasonality in tourism, i.e., the foreign tourist arrivals in India is maximum in every December and minimum in every May. Thus, the findings of this research work can be used to formulate better growth strategies, especially by the Government for the tourism industry in the country.

Conclusion

In the presence of seasonality in tourism, a key policy issue is making accurate forecasting of tourist arrivals to ensure stakeholders' preparedness for facing sudden ebb and flow in demand and revenue. Thus, this paper first explored the pattern of seasonality in foreign tourist arrivals in India, and then examined the forecasting performance of two multiplicative univariate time-series models, Holt-Winters' model and Seasonal ARIMA model, for producing a better forecast of foreign tourist arrivals in India. The time series plot of the monthly data on foreign tourist arrivals in the country not only reveals the rising trend in such arrivals, but also unveils peak and lean seasons in Indian inbound tourism. Furthermore, the comparison of MAPE, MAE and MSE, concludes about the better forecasting ability of Holt-Winters' multiplicative model in the context of foreign tourist arrivals in India. These findings are significant for the policy circle working on the sustainable development of tourism in India. The finding of a rising trend in foreign tourist arrivals signals the government as well as private stakeholders to remain prepared to welcome an increasing number of international tourists in years ahead. The finding of seasonality in Indian inbound tourism indicates December as the peak month and May as the lean month of every year. This signals the public as well as the private sector to remain prepared for facing a shortage in capacity during peak and excess capacity during lean. In order to get rid of the problems of seasonality in foreign tourist arrivals, it is essential to identify, diversify, develop and promote niche tourism products such as eco-tourism, MICE tourism, adventure tourism, medical tourism, rural tourism, sports tourism, and cruise tourism in the country. These products can ensure round the year tourist visits as well as repeat visits.

Therefore, this paper makes important contributions to the literature on forecasting tourist arrivals. First, the selection of an appropriate forecasting model assists in planning for efficient use of various operational activities by the Indian tourism industry. Second, the preparation of 24-months ahead forecast reveals the relative growth in foreign tourist arrivals in India which is a fairly long-period. However, the study is not free from limitations. First, no specific seasonality identification tool is used. Second, the stationarity of the underlying time-series has not been examined by the seasonal unit root test. Third, the forecasting performances of only two univariate tools have been compared. Hence, there lies a scope for further research. First, the research can be augmented by using appropriate statistical tools for the identification of seasonality in Indian inbound tourism. Second, seasonal unit root test such as HEGY can be used to identify the deterministic seasonality in the underlying time-series. Third, multivariate forecasting techniques can be employed focusing on other factors affecting cross-border tourist demand such as socio-economic and political conditions of host countries, infrastructural facilities at the destination, etc. Fourth, the assessment of model adequacy can be made by considering forecasting horizon, data frequency, etc.

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