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2 November 2019

Online at <https://mpra.ub.uni-muenchen.de/96909/>
MPRA Paper No. 96909, posted 21 Nov 2019 17:28 UTC

“Incredible India” – An Empirical Confirmation From the Box – Jenkins ARIMA Technique

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Abstract

“Incredible India”, is India’s tourism maxim. Using the Box – Jenkins ARIMA approach, this study will attempt to examine the validity and suitability of this maxim. Does tourism data conform to this mind-blowing motto? Is India really incredible? What are the subsequent policy directions? The study uses annual time series data covering the period 1981 to 2017. Using annual time series data, ranging over the period 1981 to 2017, the study applied the general ARIMA technique in order to model and forecast tourist arrivals in India. The ADF tests indicate that the foreign tourists arrivals series in I (2). The study, based on the minimum MAPE value, finally presented the ARIMA (2, 2, 5) model as the appropriate model to forecast foreign tourist arrivals in India. Analysis of the residuals of the ARIMA (2, 2, 5) model indicate that the selected model is stable and appropriate for forecasting foreign tourist arrivals in India. The forecasted foreign tourist arrivals over the period 2018 to 2028 show a sharp upward trend. This proves beyond any reasonable doubt that indeed in India is incredible – tourists all over the world are expected to continue flowing to India because India is just incredible! Surely, tourism data conforms to the motto “Atithidevo Bhava”. The study boasts of three policy directions that are envisioned to add more positive changes in India’s tourism sector.

Key Words: ARIMA, Forecasting, Foreign tourist arrivals, India, Tourism.

JEL Codes: L83, Z31, Z32, Z38

1. Introduction

Tourism significantly contributes to the world economy (Zhang *et al*, 2018) and has become one of the largest and fastest growing industries in the 21st century (Liu *et al*, 2018; Unhapiat & Unhapiat, 2018; English & Ahebwa, 2018; Pathmananda, 2018; Habibi *et al*, 2018; Dogru & Bulut, 2018; Mitra, 2019). In fact, in the last few decades, a myriad of countries across the globe realized the importance and potential of tourism as a strategic economic sector which is not only significant for strengthening the socio-cultural and political economy of a nation, but also pivotal in peace building across the globe (Mishra *et al*, 2018). The growing influence of the tourism sector as an economic powerhouse and its potential as a tool for development is irrefutable (Ministry of Tourism, 2019). Tourism is one of the most essential sectors which have direct impact on the financial and economic development of India (Chandra & Kumari, 2018). Not only

does the tourism sector spearhead growth, it also improves the quality of people's lives with its capacity to create large scale employment of diverse kind. It supports environmental protection, champions diverse cultural heritage and strengthens peace in the world (Ministry of Tourism, 2019). The much celebrated "Incredible India" campaign was hatched in 2002 by the government of India, through the Ministry of Tourism, in order to improve the relations between host and the visiting foreigners. Through this campaign, Indians have drastically improved when it comes to demonstrating generous behaviour towards visiting tourists. Taxi drivers, immigration officers and tourist police officers amongst other tourism personnel have directly benefited from the "Incredible India" campaign. This campaign is the force behind the message: "Atithi Devo Bhava" which means "Guest is God". Owing to good behavior towards tourists, India continues to welcome amazing numbers of foreign tourists each year. This study; based on the generalized Box-Jenkins ARIMA approach, seeks to empirically verify whether India is indeed incredible. The forecasts that will be generated from this study are very important not only to the Ministry of Tourism but also to industry players who always need reliable forecasts of foreign tourist arrivals for decision making purposes, such as hotel chain expansion as well as opening of new retail businesses.

2. Literature Review

A number of scholarly papers have been published on this theme over recent decades and yet in the case of India, as noted by Kumari (2015) and Chandra & Kumari (2018), there still remains a limited number of scholarly works in the area of modeling and forecasting foreign tourist arrivals. This could be attributed to the fact that Tourism Economics is still a growing field of economics and therefore it is not surprising to have a myriad of gaps in terms of empirical works. Given the objectives of this research, the study provides a fair sample of studies undertaken more recently:

Table 1: Empirical Papers Reviewed

Author(s)/Year	Country	Period	Methodology	Key Findings
Chaitip & Chaiboonsri (2009)	India	January 2007 – December 2010	X-12-ARIMA; ARFIMA	<ul style="list-style-type: none"> ➤ The best model is the X-12-ARIMA (0, 1, 2)(0, 1, 1). ➤ International tourist arrivals are on an upwards trajectory.
Kumari (2015)	India	January 2000 – October 2015	SARIMA; HW; GM	<ul style="list-style-type: none"> ➤ SARIMA models perform better than GM models. ➤ Foreign tourist arrivals are expected to increase over the period November 2015 – December 2020.
Chandra & Kumari (2018)	India	January 2003 – December 2016	VECM; Naïve I & II; SARIMA; GM	<ul style="list-style-type: none"> ➤ VECM model performs better than SARIMA. ➤ The combination of the former and the latter gives better results than individual time series models.
Mishra <i>et al</i> (2018)	India	January 2001 – June 2018	HW; SARIMA	<ul style="list-style-type: none"> ➤ HW method is more efficient than SARIMA models. ➤ Foreign tourist are expected to increase

				over the period July 2018 – June 2020.
Makoni & Chikobvu (2018)	Zimbabwe	January 2006 – December 2017	SARIMA, naïve, seasonal naïve, HW	➤ SARIMA (2, 1, 0)(2, 0, 0) ₁₂ model outperforms other models.
Khairudin <i>et al</i> (2018)	Malaysia	January 2010 – December 2015	Trend projection, trend projection with seasonal effect	➤ Trend projection with seasonal effect performs better than the generalized trend projection model.
Zahedjahromi (2018)	USA	1998 – 2011	SAIMA	➤ The SARIMA (0, 1, 2)(0, 1, 1) model is the optimal model. ➤ Number of tourists will increase by 2.6 times in 6 years.
Hamzah <i>et al</i> (2018)	Malaysia	January 1998 – December 2017	SARIMA	➤ The final model selected was the SARIMA (1, 1, 1)(1, 1, 4) ₁₂ model.
Unhapipat & Unhapipat (2018)	Bhutan	January 2012 – December 2016	SARIMA	➤ The SARIMA (0, 0, 0)(1, 1, 0) ₁₂ model is the best.
Nyoni (2019)	Sri Lanka	June 2009 – December 2018	SARIMA	➤ The optimal model is the SARIMA (0, 1, 1)(0, 1, 1) ₁₂ . ➤ International tourist arrivals will increase over the period January 2019 – December 2020.
Jere <i>et al</i> (2019)	Zambia	1995 – 2014	HWES; ARIMA	➤ HWES is better than ARIMA. ➤ A gradual increase in annual international tourist arrivals of about 42% by 2024 is expected.
Purwanto <i>et al</i> (2019)	Indonesia	1991 – 2013	Hybrid Model of ARIMA-Linear Trend	➤ The hybrid model produces better prediction performance compared to ARIMA, Linear trend and HWTES models.

3. Methodology

ARIMA Models

The general form of the ARIMA (p, d, q) can be represented by a backward shift operator as:

$$\phi(B)(1 - B)^d F_t = \theta(B)\mu_t \dots \dots \dots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) \dots \dots \dots [2]$$

$$\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) \dots \dots \dots [3]$$

and

$$(1 - B)^d F_t = \Delta^d F_t \dots \dots \dots [4]$$

Where ϕ is the parameter estimate of the autoregressive component, θ is the parameter estimate of the moving average component, Δ is the difference operator, d is the difference, B is the backshift operator, F_t are foreign tourist arrivals in India and μ_t is the disturbance term.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i).

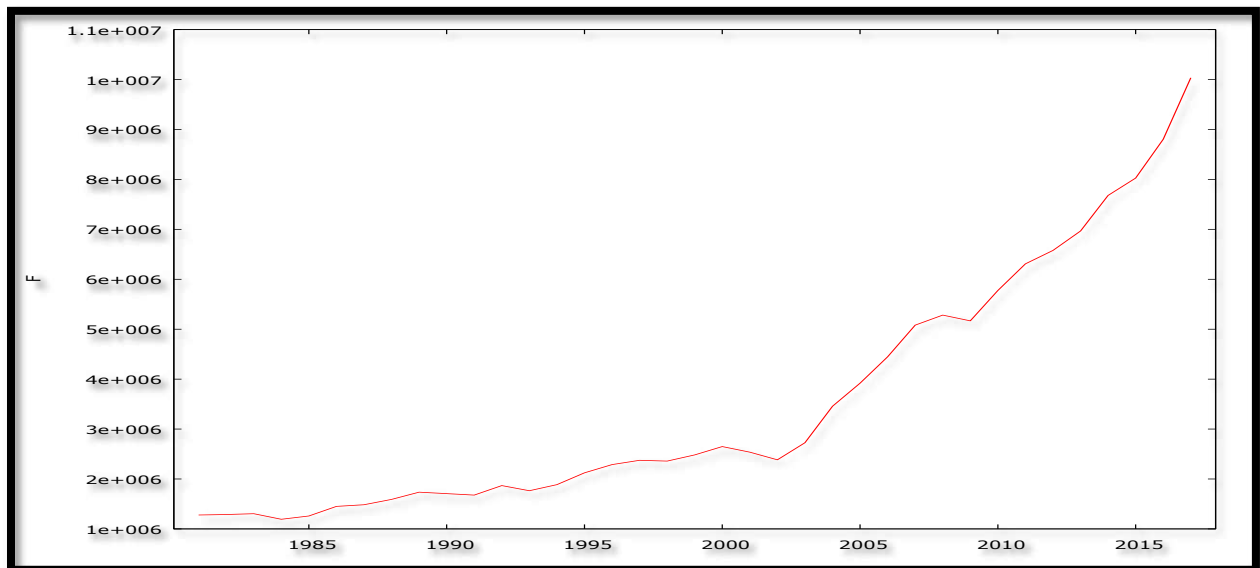
Data Collection

Annual data on foreign tourist arrivals (F) in India has been gathered from the Bureau of Immigration, India. The data ranges over the period 1981 – 2017.

Diagnostic Tests and Model Evaluation (for F)

Stationarity Tests: Graphical Analysis

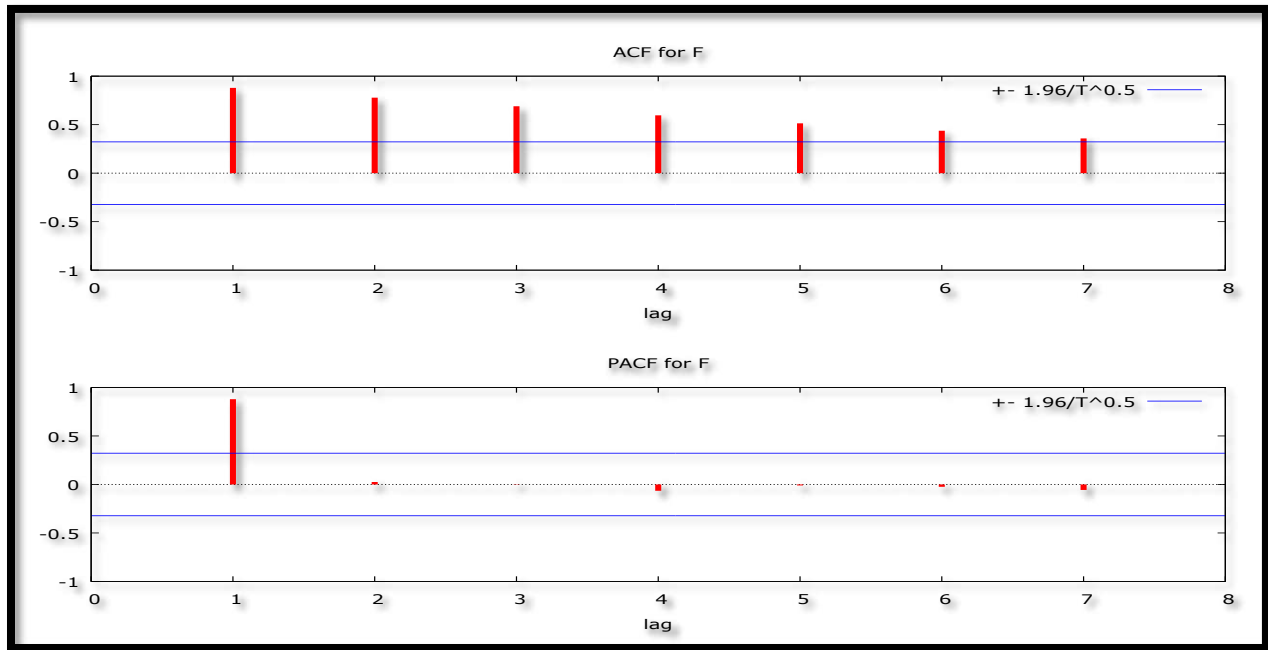
Figure 1: Graphical Analysis



Source: Author's Own Computation

The Correlogram in Levels

Figure 2: Correlogram in Levels



Source: Author's Own Computation

The ADF Test

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion
F	5.884434	1.0000	-3.626784	@1% Not stationary
			-2.945842	@5% Not stationary
			-2.611531	@10% Not stationary

Source: Author's Own Computation

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values	Conclusion
F	1.774535	1.0000	-4.234972	@1% Not stationary
			-3.540328	@5% Not stationary
			-3.202445	@10% Not stationary

Source: Author's Own Computation

Table 4: without intercept and trend & intercept

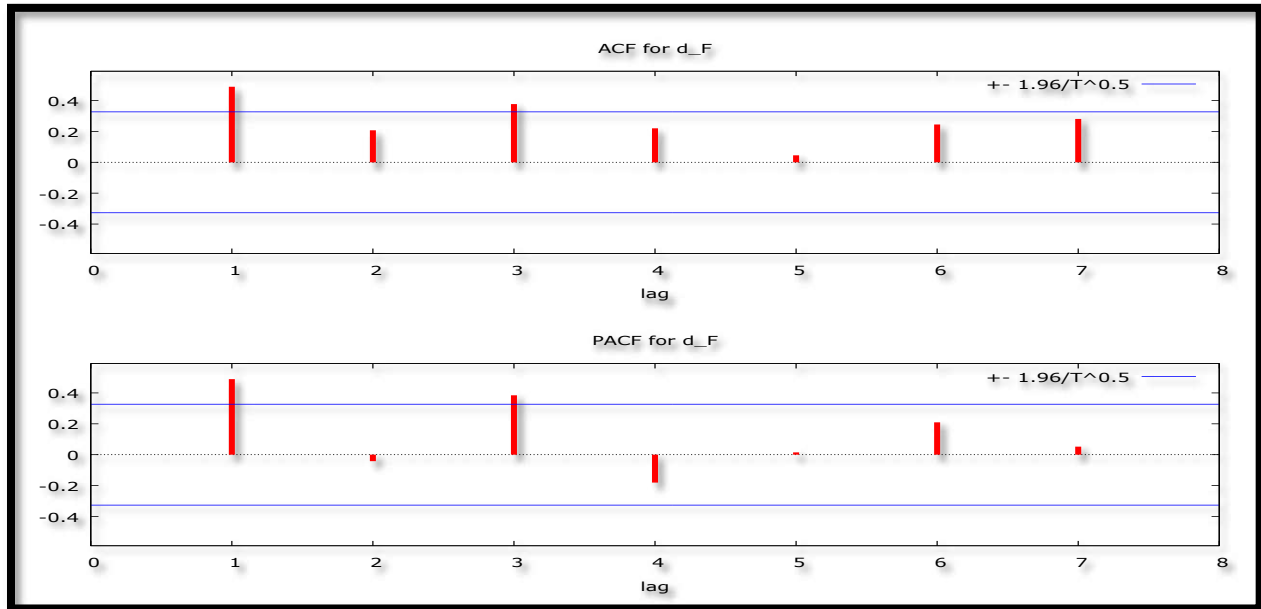
Variable	ADF Statistic	Probability	Critical Values	Conclusion
F	8.601915	1.0000	-2.630762	@1% Not stationary
			-1.950394	@5% Not stationary

		-1.611202	@10%	Not stationary
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Source: Author's Own Computation

The Correlogram at 1st Differences

Figure 3: Correlogram at 1st Differences



Source: Author's Own Computation

Table 5: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	-0.234733	0.9241	-3.646342	@1%	Not stationary
			-2.954021	@5%	Not stationary
			-2.615817	@10%	Not stationary

Source: Author's Own Computation

Table 6: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	-2.578320	0.2918	-4.273277	@1%	Not stationary
			-3.577759	@5%	Not stationary
			-3.212361	@10%	Not stationary

Author's Own Computation

Table 7: 1st Difference-without intercept and trend & intercept

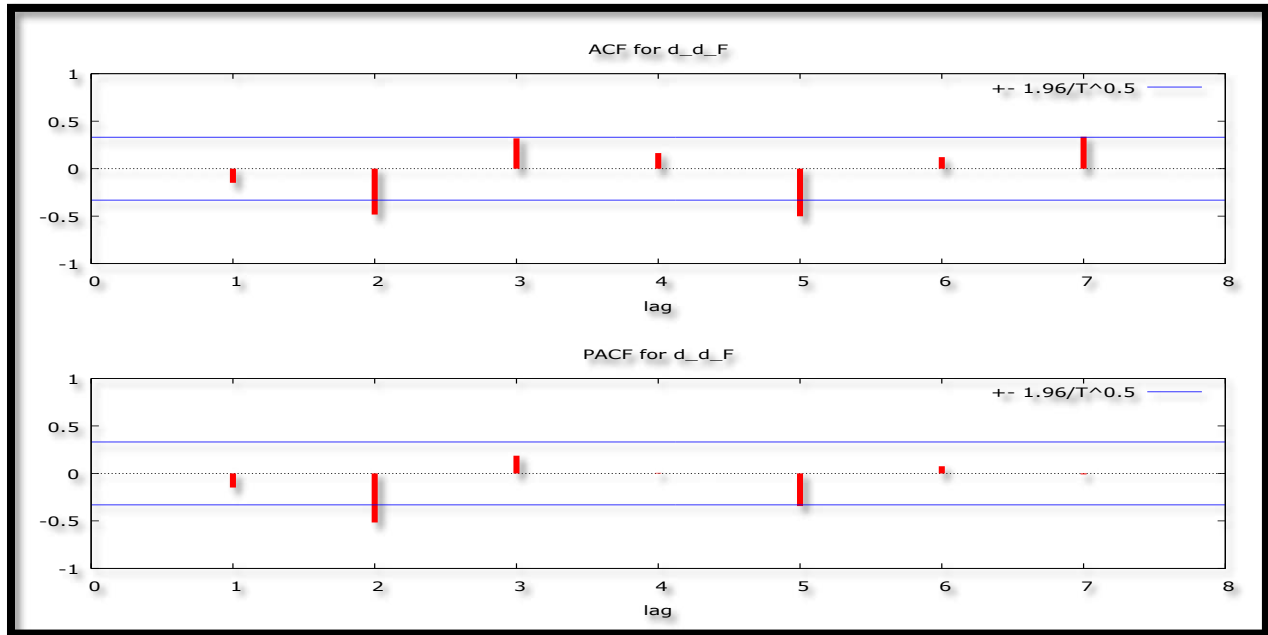
Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	0.816138	0.8835	-2.636901	@1%	Not stationary
			-1.951332	@5%	Not stationary

		-1.610747	@10%	Not stationary
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Author's Own Computation

Correlogram at 2nd Differences

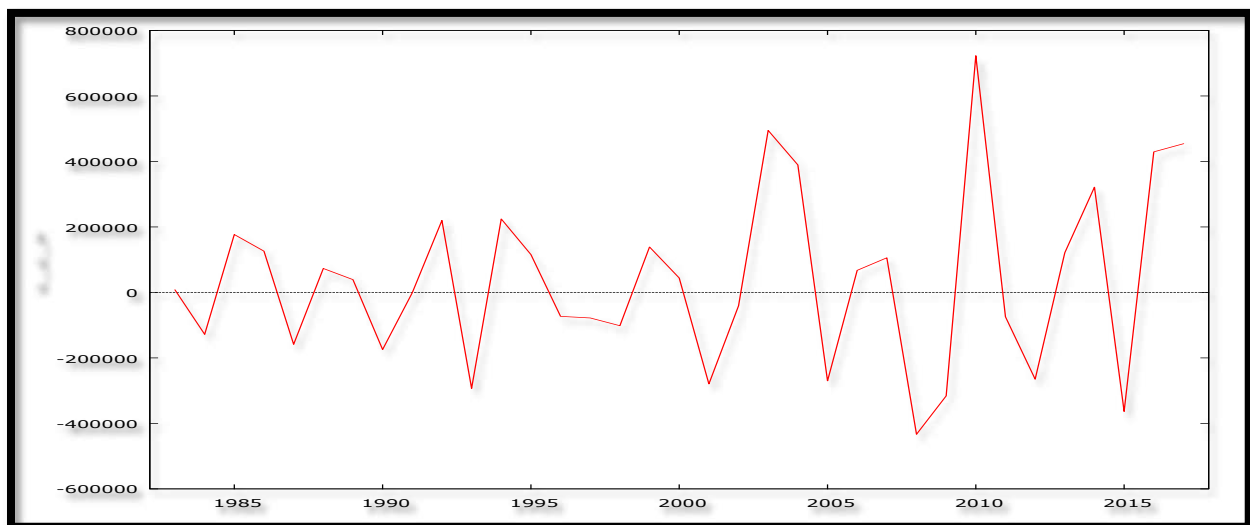
Figure 4: Correlogram at 2nd Differences



Source: Author's Own Computation

Time Series Plot of the Differenced Series (at 2nd Differences)

Figure 5: Time Series Plot of d_d_F



Source: Author's Own Computation

Table 8: 2nd Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	-7.810000	0.0000	-3.646342	@1%	Stationary
			-2.954021	@5%	Stationary
			-2.615817	@10%	Stationary

Author's Own Computation

Table 9: 2nd Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	-7.837684	0.0000	-4.262735	@1%	Stationary
			-3.552973	@5%	Stationary
			-3.209642	@10%	Stationary

Source: Author's Own Computation

Table 10: 2nd Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
F	-7.596681	0.0000	-2.636901	@1%	Stationary
			-1.951332	@5%	Stationary
			-1.610747	@10%	Stationary

Source: Author's Own Computation

Figures 1 – 4 and tables 1 – 9 indicate that F is an I (2) variable. Figure 1 also indicates that foreign tourist arrivals in India are on the rise.

Evaluation of ARIMA Models (without a constant)

Table 11: Evaluation of ARIMA Models (without a constant)

Model	AIC	U	ME	MAPE
ARIMA (1, 2, 1)	974.3155	0.80649	59947	5.9092
ARIMA (1, 2, 0)	976.7789	0.88084	38058	6.4905
ARIMA (0, 2, 1)	973.845	0.82303	55366	5.9586
ARIMA (3, 2, 1)	968.8017	0.74307	39518	5.2997
ARIMA (4, 2, 1)	969.2914	0.72599	53047	5.1353
ARIMA (5, 2, 1)	965.7615	0.74538	45833	5.0313
ARIMA (1, 2, 5)	971.869	0.75372	50346	5.2151
ARIMA (2, 2, 2)	965.8793	0.76115	32420	5.2451
ARIMA (2, 2, 3)	965.7284	0.74612	39157	5.2393
ARIMA (2, 2, 5)	968.3197	0.74102	46871	4.9602
ARIMA (5, 2, 2)	967.7605	0.74491	46028	5.0299
ARIMA (1, 2, 2)	971.5055	0.76108	57360	5.4714
ARIMA (1, 2, 3)	972.0587	0.81376	54304	5.7828
ARIMA (1, 2, 4)	970.7801	0.76391	52266	5.3682
ARIMA (3, 2, 0)	966.8075	0.74328	39408	5.2987
ARIMA (3, 2, 3)	967.1087	0.74715	46016	5.252

ARIMA (4, 2, 0)	968.7746	0.74204	40129	5.302
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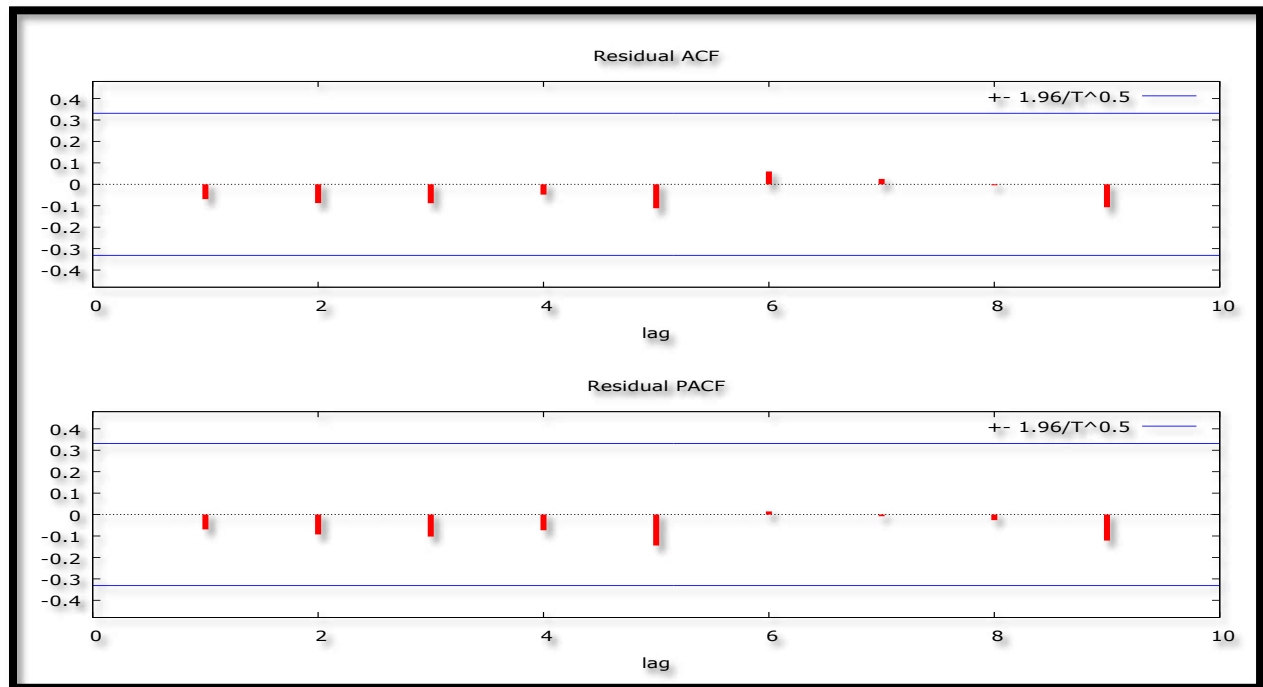
Source: Author's Own Computation

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n) Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018l). The MAPE is usually used to evaluate tourism forecasting models (Yeung & Law, 2005; Saayman & Saayman, 2010; Loganathan & Ibrahim, 2010; Song *et al*, 2011; Saayman & Botha, 2015). Hence, this study will use the MAPE to determine the most appropriate model for forecasting foreign tourist arrivals in India. Thus, the ARIMA (2, 2, 5) model is selected as the optimal model for forecasting foreign tourist arrivals in India, for the out of sample period of 2018 – 2028.

Residual & Stability Tests

Residual Correlogram of the ARIMA (2, 2, 5) Model for F

Figure 6: Residual Correlogram of the ARIMA (2, 2, 5) Model for F



Source: Author's Own Computation

ADF Tests of the Residuals of the ARIMA (2, 2, 5) Model

Table 12: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
RF_t	-5.480720	0.0001	-3.653730	@ 1%	Stationary
			-2.957110	@ 5%	Stationary
			-2.617434	@ 10%	Stationary

Source: Author's Own Computation

Table 13: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
RF _t	-5.575538	0.0004	-4.273277	@1%	Stationary
			-3.557759	@5%	Stationary
			-3.212361	@10%	Stationary

Source: Author's Own Computation

Table 14: without intercept and trend & intercept

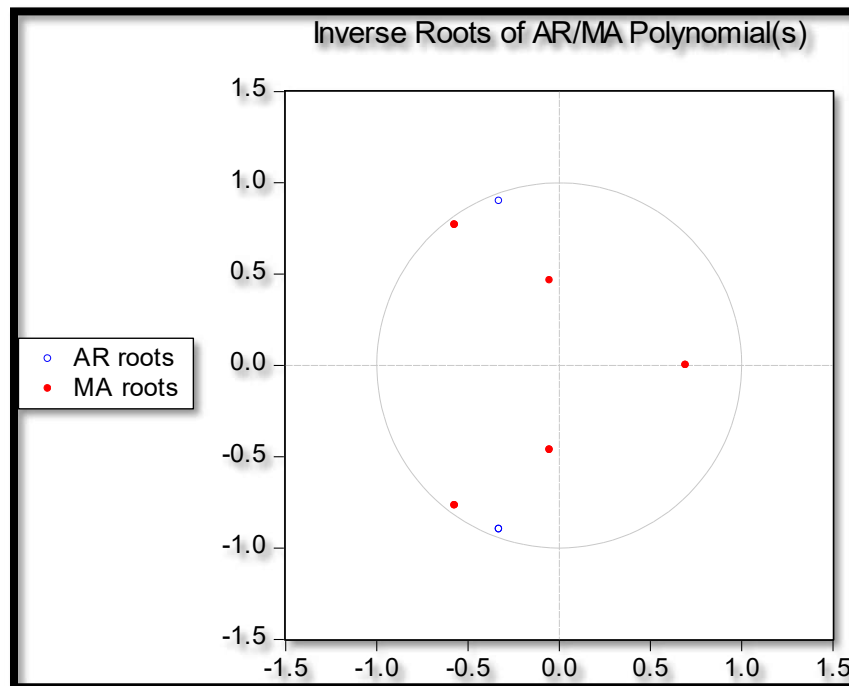
Variable	ADF Statistic	Probability	Critical Values		Conclusion
RF _t	-5.147570	0.0000	-2.639210	@1%	Stationary
			-1.951687	@5%	Stationary
			-1.610579	@10%	Stationary

Source: Author's Own Computation

Figure 6 and tables 11 to 13 show that the residuals of the ARIMA (2, 2, 5) model are stationary.

Stability Test of the ARIMA (2, 2, 5) Model

Figure 7: Inverse Roots of the ARIMA (2, 2, 5) Model



Source: Author's Own Computation

Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, then we can conclude that the chosen ARIMA (2, 2, 5) model is stable and indeed suitable for forecasting annual foreign tourist arrivals in India.

4. Findings of the Study

Table 15: Descriptive Statistics

Description	Statistic (F)
Mean	3539100
Median	2384400
Minimum	1193800
Maximum	10036000
Standard deviation	2461600
Skewness	1.069
Excess kurtosis	-0.014834

Source: Author’s Own Computation

As shown in table 15 above, the mean is positive, that is, 3539100. The median is 2384400. The maximum and minimum are 1193800 and 10036000 respectively. Since skewness statistic is 1.069, it shows that F is positively skewed and non-symmetric. Excess kurtosis is -0.014834 and confirms that F is not normally distributed.

Results Presentation¹

Table 16: Results Presentation (ARIMA (2, 2, 5) model

Variable	Coefficient	Std. Error	z	p-value
ϕ_1	-0.524291	0.210564	-2.490	0.0128**
ϕ_2	-0.842502	0.190426	-4.424	0.000968***
θ_1	0.411585	0.249816	1.648	0.0994*
θ_2	0.339354	0.237666	1.428	0.1533
θ_3	-0.229323	0.262185	-0.8747	0.3818
θ_4	-0.150123	0.254854	-0.5891	0.5558
θ_5	-0.294725	0.236434	-1.247	0.2126

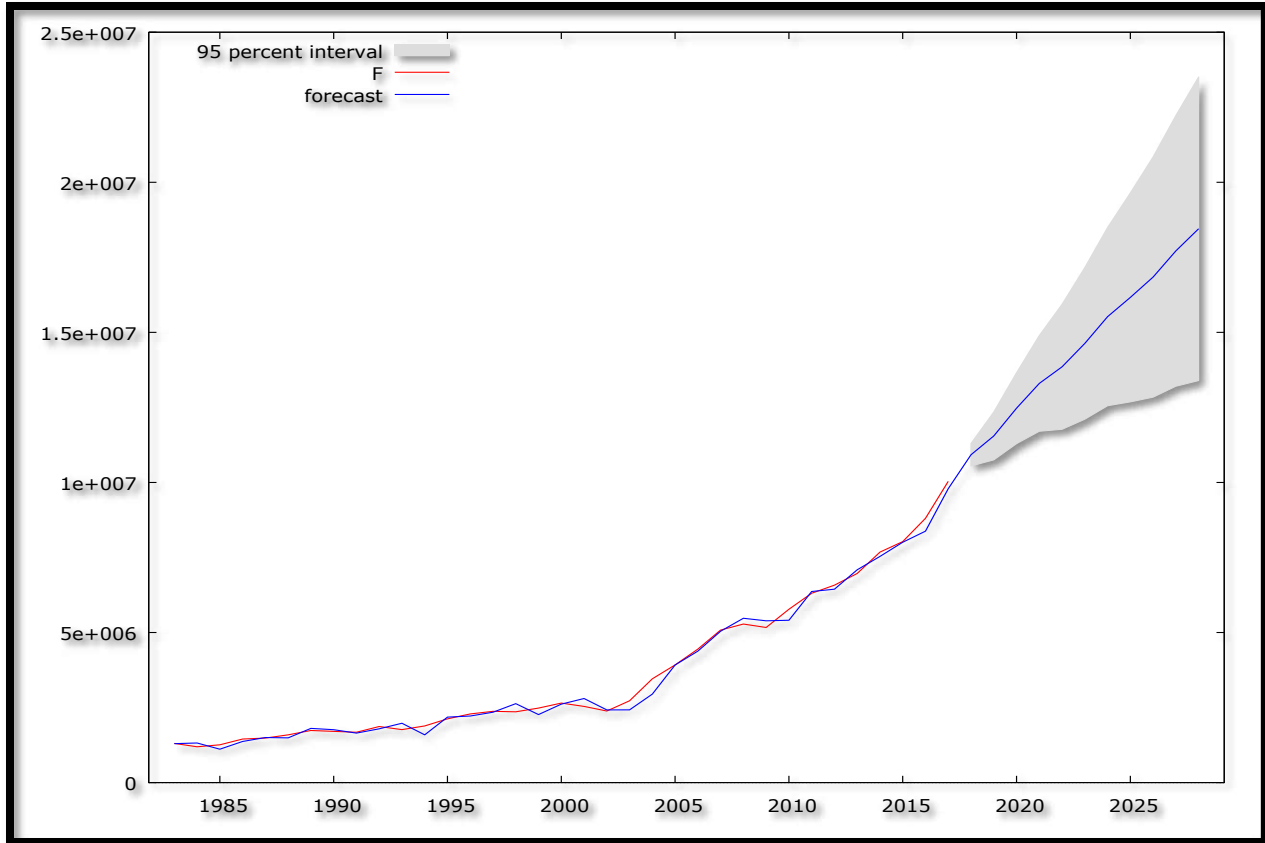
Source: Author’s Own Computation

Mathematical Presentation of the ARIMA (2, 2, 5) Model:

$$\Delta^2 F_{t-1} = -0.524291\Delta^2 F_{t-1} - 0.842502\Delta^2 F_{t-2} + 0.411585\mu_{t-1} + 0.339354\mu_{t-2} - 0.229323\mu_{t-3} - 0.150123\mu_{t-4} - 0.294725\mu_{t-5} \dots \dots \dots [5]$$

Figure 8: Forecast Graph

¹ * means significant at 10% level of significance



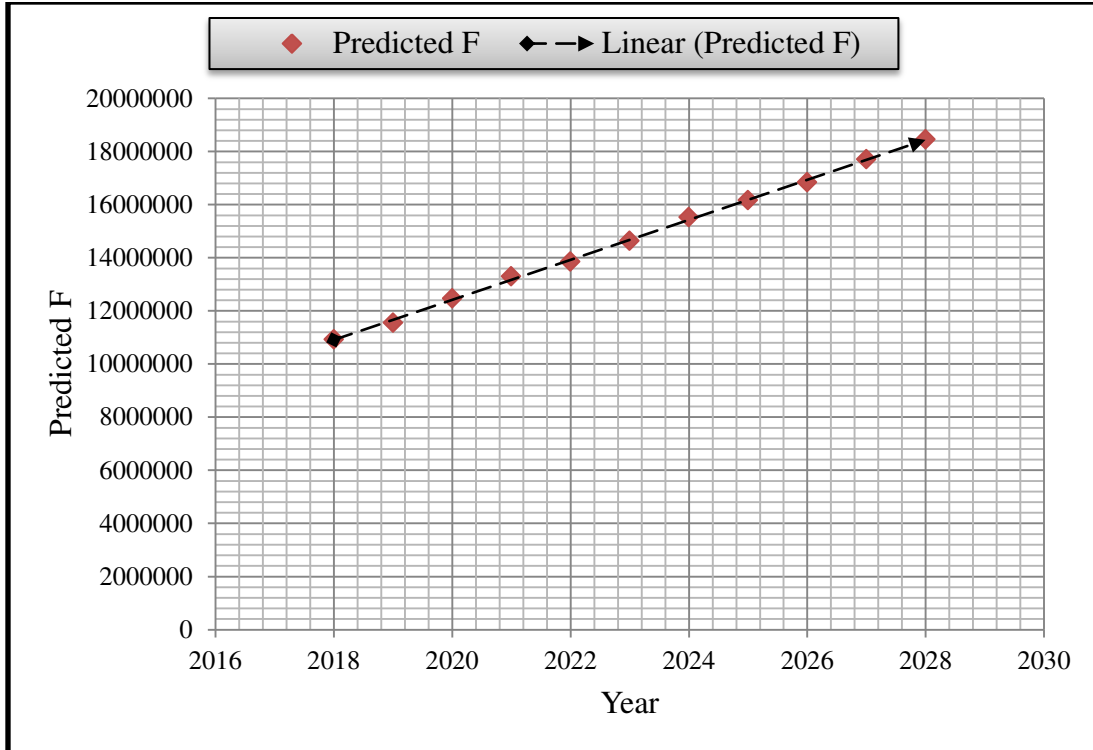
Source: Author's Own Computation

Table 17: Predicted F (2018 – 2028)

Year	Predicted Foreign Tourist Arrivals (F) in India	Standard Error	95% Confidence Interval
2018	10922936.96	190414.555	10549731.29 - 11296142.63
2019	11547293.65	406697.919	10750180.38 - 12344406.93
2020	12473149.51	601940.403	11293368.00 - 13652931.02
2021	13299571.96	813292.348	11705548.25 - 14893595.67
2022	13852170.74	1061964.887	11770757.81 - 15933583.67
2023	14632105.66	1288514.218	12106664.20 - 17157547.12
2024	15523547.29	1514370.285	12555436.07 - 18491658.51
2025	16164995.80	1775385.545	12685304.07 - 19644687.52
2026	16843568.81	2041315.547	12842663.86 - 20844473.76
2027	17713297.50	2300009.250	13205362.21 - 22221232.79
2028	18451527.52	2580167.952	13394491.26 - 23508563.78

Source: Author's Own Computation

Figure 9: Predicted Foreign Tourist Arrivals (in graphical form)



Source: Author's Own Computation

Equation 5 is the mathematical representation of the selected optimal model, the ARIMA (2, 2, 5) model. This is the ARIMA process being exhibited by foreign tourist arrivals in India. Foreign tourist arrivals are likely to increase over the out-of-sample forecast as shown in figures 8 & 9 and table 16 above. Figure 9 clearly shows that it is indeed possible for India to reach her goal of becoming the world's largest aviation market by 2030 and welcoming over 15 million international tourists by 2025. Indeed, India is incredible. Historical data speaks for India, so do our forecasts! The results of this paper are not surprising, they are actually in line with previous studies such as Chaitip & Chaiboonsri (2009), Kumari (2015) and Mishra *et al* (2018).

5. Recommendations

- i. In order to maintain sustainable foreign tourist arrivals in India, there is need to continue spreading the message "Atithi Devo Bhava".
- ii. There is need to improve tourism products in order to enhance the image of India as an incredible tourist destination.
- iii. In order to accommodate the forecasted ballooning numbers of foreign tourist inflows, there is need for the construction of more infrastructure facilities, especially hotels and retail outlets.

6. Conclusion

The tourism industry is an economic powerhouse for any economy and India is not an exception. The government of India, through the Ministry of Tourism must continue to give priority to the tourism industry as it has become one of India's strategic sectors. This study employed the Box-Jenkins ARIMA approach to analyze foreign tourist arrivals in India. After carrying out all the relevant diagnostic checks, the ARIMA (2, 2, 5) model was selected as the best model to forecast foreign tourist arrivals in India. Results generally point to a continuous increase in foreign tourist

inflows in India and overwhelmingly confirm that India is indeed incredible and absolutely justify the need to prioritize the tourism industry as a strategic sector in India.

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