The Impact of COVID-19 on Tourism Sector in India

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Abstract

The novel coronavirus (COVID-19), which is one of its kind of humanitarian disasters, has affected people and businesses worldwide, triggering a global economic crisis. In this aspect, the tourism sector is not being left behind. The pandemic has not only affected the foreign exchange earnings (FEE) but also affected various regional developments, job opportunities, thereby disrupting the local communities as a whole. As there has been a substantial decline in the arrivals of overseas tourists in India in 2020, the paper aims to predict foreign tourists' arrival in India and FEE using artificial neural networks (ANN). Furthermore, we analyze the impact of COVID-19 based on four scenarios considering with and without lockdown in terms of loss and gain in FEE. Lastly, the results obtained will help policymakers make necessary strategic and operational decisions, along with maximizing the FEE.

Keywords: ANN model; COVID-19; Forecasting; Foreign exchange earnings; Tourism demand

1. Introduction

The recent coronavirus (COVID-19) has triggered a concern worldwide in early January 2020, and by the end of March 2020, the outbreak has infected several people globally (WHO, 2020). The severity of the pandemic may be assessed based on the figures of the past epidemics such as SARS, Spanish Flu, etc. Tourism and hospitality businesses are profoundly affected by COVID-19 that has been declared as pandemic on 12th March 2020 (WHO, 2020). Due to the COVID-19 pandemic, the travel and tourism industry's employment loss is predicted to be 100.08 Million worldwide (Statista, 2020). The pandemic has not only affected economically but as well as politically and socially (Cohen, 2012). As the number of infected cases rising throughout the nation, and with the implementation of certain measures and campaigns like social distancing, community lockdowns, work from home, stay at home, self- or mandatory-quarantine, curbs on crowding, etc., pressure is created for halting the tourism industry/business (Sigala, 2020; Gretzel et al. 2020). This change in the current system has led to the beginning of the recession and depression, seeking a transformational change in society. According to Liu et al. (2019), the most dynamic sector is the tourism industry that benefits many other sectors like lodging, catering, transportation, retail, entertainment, etc. contributing to economic growth and recovery globally. It has been reported that tourism growth has outperformed the world GDP growth record from the past consecutively from the year 2011 to 2017 (WTTC, 2018). Furthermore, it has been estimated that there is a drop of international tourists of about 78%, causing a loss in export revenue of US$ 1.2 trillion and representing the largest decline in the tourism job cuts, which is about seven times the impact of the 9/11 incident (UNWTO, 2020). Additionally, the drop in the tourists' demand has led to severe financial problems (Tsionas, 2020).

India is one of the developing nations known for its uniqueness in its tradition, culture and unparalleled hospitality. It is a major destination for many international tourists, creating several employment opportunities and generating enormous taxes (Ahmed & Krohn, 1992). The Indian tourism industry can be divided into three major segments, such as (i) international inbound tourism; (ii) domestic tourism; and (iii) outbound tourism. The Indian tourism industry has created about 87.5 million jobs, with 12.75% of total employment, thereby contributing INR 194 billion to India’s GDP (WTTC, 2018). Moreover, the sector recorded a 3.2% growth from 2018, with 10.8 million foreign tourists arriving in India with a foreign exchange earning of USD 29.9 billion in 2019. In this regard, India ranked 8^{th} with respect to total direct travel and contribution towards tourism of about USD 108 billion (FICCI, 2020). Also, there is a 66.4% decline in overseas tourists' arrivals in India in March 2020 compared to last year (TAN, 2020). It has been estimated that there will be about 40 million direct and indirect job losses in India, with an annual loss in revenue of around USD 17 billion in India (FICCI, 2020; Scroll, 2020).

Tourism is a major source of revenue and employment in many countries. It is a generator for employment, income, tax collections and foreign exchange earnings. The tourism industry became highly competitive; hence, accurate tourism demand forecasting is important to make an appropriate strategic and operational decision. Strategic decisions are planning for opening attractions, modes of transport, accommodation, and tourism promotion for which colossal investment is required. In contrast, operational decisions are the number of parking areas, attendants, number of shuttle buses, hours of service per day, and employees' hiring. Accurate tourism demand forecasting is a challenging task. Forecasting tourism demand help to identify the future pattern which guides planning and policy formation. Forecasting plays a crucial role in tourism planning (Cho, 2001). Moreover, accurate forecasting helps managers and practitioners make appropriate decisions in policy-making, staff and capacity utilization and management, resource management, pricing strategies, etc. during disruption to reduce the risk and uncertainty. Hence, tourism forecasting is one of the significant areas of research.

Many authors proposed different models and methods, such as traditional time series models (Witt & Martin, 1987; Witt et al., 2004; Wong et al., 2006; Wong et al., 2006; Athanasopoulos & Hyndman, 2008; Goh & Law, 2002, Song et al., 2003), artificial intelligence models (Claveria & Torra, 2014; Tsaur & Kuo, 2011) and hybrid models (Silva et al., 2019; Shahrabi et al., 2013; Hadavandi et al., 2011). The time-series ARIMA model is univariate model and applicable to stationary and homoscedastic data series. Hence, before applying the model, it is essential to identify the pattern through various statistical tests. In contrast, artificial neural network (ANN) predicts by mapping the input and output. It has the capability to learn, self-organize and adapt the data pattern. ANN model does not require past statistical information related to the data series. The major benefit of using ANN models is non-parametric data-driven models that capture the functional relationships with the empirical data. Unlike traditional forecasting models like ARIMA, the model can map the linear and non-linear properties, homoscedastic or heteroscedasticity of the data without any prior assumption. Therefore, many researchers applied the ANN model for prediction and proved that it is a suitable model for prediction irrespective of the data pattern (Law 2000; Cho, 2003; Palmer et al., 2006; Claveria & Torra, 2014; Höpken et al., 2020).

Due to COVID-19, tourism is such a highly affected sector and may remain affected in the long term, i.e., approximately more than 1.5 years. Hence, in this scenario, it is necessary to measure the losses due to pandemic so that policies can be redesigned to manage tourism activities. There is a fall in foreign tourists' arrival rate by 68% from February to March 2020 and hence fall in foreign exchange earnings (FEE) by 66.32%, which has a significant impact on the economy (Statista, 2020). Therefore, accurate forecasting of the number of foreign tourists and FEE is crucial in managing tourism activity. Researchers studied different forecasting models to predict the tourism demand, i.e., both inbound and outbound tourists; however, predicting foreign tourists' arrival in India and its impact on the revenue in terms of FEE are scarce. Further, no analysis has been done to measure the impact of a pandemic like COVID-19 on tourism and its leading effect of FEE. Therefore, this paper addresses the following key research questions:

(i) What are the impacts of the black swan event like COVID-19 on Indian tourism sector?

(ii) What are the impact of COVID-19 on foreign tourists' arrival and foreign exchange earnings?

Specifically, the main objectives of the paper are three-fold which is as follow: (i) predicting the number of foreign tourist arrivals, particularly in India using ANN model, (ii) analyzing the impact of COVID-19 on tourism in terms of loss and gain in FEE, and (iii) suggesting the appropriate theoretical and managerial implications.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature, including the impact of the epidemic outbreak on tourism, and forecasting models for predicting the tourists demand. Sections 3 presents the methodology and data for the analysis. Section 4 gives the prediction of the arrival of number of foreign tourists. Section 5 demonstrates the impact of COVID-19 on the tourism economy, and section 6 shows the implications of this study followed by limitations and future research in section 7. The last section concludes the paper as presented in section 8.

2. Literature Review

This paper considers two streams of literature: (1) impact of epidemic outbreak on tourism and (2) forecasting models used for predicting tourism demand.

2.1 Impact of epidemic outbreak on tourism

Global tourism is affected by many types of disruptive events, such as terrorist attacks like 9/11, epidemic outbreaks like SARS-CoV-2, MERS-CoV, Ebola, Swine flu etc. in the past (Wen et al., 2020). However, the recent epidemic outbreak (COVID-19) originated from Wuhan, China has severely impacted almost every industry, including Tourism worldwide (Yeh, 2020). The virus spread to all continents through air transport and still propagates infection exponentially (Nicolaides et al., 2020). To contain the spread, many countries completely/partially close their boarder and cancelled all flights, and events including sports, entertainment, pilgrimages, conferences etc. UNWTO (2020) estimated that international tourists would decline by 1-3% compared to 2019 rather than the forecasted 3-4% growth. As a result, global tourism has slowed down significantly. The number of international flights dropping by more than half following the tourism industry temporarily laid off half of their workforce (Gössling et al., 2020). The World Travel & Tourism Council predicts a tourism-related loss of up to US$ 2.1 trillion in 2020 and up to 75 million jobs (WTTC, 2020).

The travel industry, which includes airlines, hotels and restaurants, will shrink by 50% in 2020, which would mean a significant loss of jobs and revenue. According to the International Air Transport Association (IATA), Airlines worldwide are expected to lose a record of $84 billion in 2020, more than three times the loss made during the Global Financial Crisis (The World Economic Forum, 2020). Most of the airlines are undergrounded. Hotels are being closed due to fewer tourists and many five-star hotels turning into quarantine facilities. Most restaurateurs see operating costs rising further because of social distancing, hygiene, and sanitation-related costs. Therefore, sustaining during this crisis is a challenging task for the tourism industry.

2.2 Forecasting models used for predicting tourism demand

Tourism forecasting has been an important topic of discussion and has evolved over the decades (Liu et al., 2019; Song et al., 2019). Researchers used different forecasting models to predict international tourism demand (Table 1). For example, Witt & Martin (1987) used econometric models, such as Ordinary Least Square (OLS) and Cochrane-Orcutt (CO), to predict international tourist demand. Song et al. (2003) applied six different econometric models to forecast inbound international tourism demand for Denmark. The models are static co-integration regression; two error correction model (ECM); reduced autoregressive distributed lag model (ADLM); time-varying parameter (TVP) approach; vector autoregressive (VAR); autoregressive integrated moving average (ARIMA) model for six different origin countries such as Germany, Netherlands, Norway, Sweden, UK and USA. Further, they tested the forecasting accuracy of the models and ranked over the time horizon. The traditional time series models such as VAR (Witt et al., 2004), BVAR (Wong et al., 2006), ARIMA (Kulendran & Wong, 2005), MARIMA, SARIMA (Goh & Law, 2002), Statistical models like regression model, exponential smoothing (Athanasopoulos & Hyndman, 2008), Basic structural time series model (BSM) and causal structural time series model (STSM) (Turner & Witt, 2001; Kulendran & Witt, 2003), Autoregressive Moving Average with External Variables (ARMAX) (Yang et al., 2015). Witt et al. (2004) used vector autoregressive model to forecast inbound international tourists to Denmark to predict the foreign tourist expenditure. They also discussed the impact of foreign tourist expenditure on employment in Denmark. Wong et al. (2006) applied the Bayesian vector autoregressive (BVAR) model to forecast the tourism demand for Hong Kong, compared with the VAR model, and showed that the BVAR model outperforms the VAR model. Wong et al. (2007) forecasted tourism demand for Hong Kong from ten different countries using four different forecasting models: ARIMA, ADLM, ECM and VAR. They observed that the performance of single and combined forecasting models varies according to the origin-destination tourist flow. Goh & Law (2002) used SARIMA and MARIMA considering intervention like the bird flu epidemic (Dec 1997- Jan 1998) in Hong Kong, Asian economic crisis and the reversion of Hong Kong to China sovereignty and SAR administration to predict the inbound tourism demand for Hong Kong. They proved that the SARIMA and MARIMA model's performance outperforms the other time series models through comparative study.

Machine and deep learning methods are more adaptable and can generate high accurate result (Law et al., 2019; Polyzos et al., 2020). Due to their flexibility and versatile nature, neural networks are considered powerful methods that help classify patterns and estimate continuous variables and forecasting. Hence, it can be applied to a data series of linear/non-linear or stationary/non-stationary type. All these properties make the ANN model advantageous over various traditional methods, such as AR, MA and ARIMA time-series models etc. Several researchers have used ANN model for forecasting the tourist demand, consumer behavior and demand forecasting, segmentation and positioning analysis etc. (Uysal & Roubi, 1999; Burger et al., 2001; Bloom, 2002, 2004, 2005; Sirakaya et al., 2005). The major benefit of using such a methodology is that ANN models are non-parametric data-driven models that capture functional relationships with the empirical data. Cho (2003) investigates the application of three forecasting techniques: exponential smoothing, ARIMA and ANN to predict the inbound demand of Hong Kong and found that ANN is the best method, specifically for unclear data patterns. Palmer et al. (2006) described the step-by-step approach to design neural network (NN) for tourism forecasting. They considered data on tourism expenditure in the Balearic Islands, Spain, from each quarter of 1986 through the year 2000 and verified that ANN is a suitable model for long-term forecasting, as data accuracy does not affect with expanding the forecasting horizon. Claveria & Torra (2014) predicted inbound tourism demand for Catalonia, Spain from different countries using neural network. They verified the forecasting performance ARIMA and self-exciting threshold auto regressions (SETAR). Law (2000) predicted the outbound tourism demand for Taiwan to Hong Kong using a backpropagation neural network. The author found that the backpropagation neural network's forecasting accuracy is high compared to the regression model, time series (Holt's, moving average and naive) models, and feed-forward neural network models. Höpken et al. (2020) predicted tourist arrival using a web-search index with autoregressive approach and compare two methods: ARIMA and ANN.

They found that Google trend data increase tourist prediction performance, and ANN outperforms the ARIMA model. Yao & Cao (2020) empirically investigated neural network enhanced hidden Markovian structural time series model (NehM-STSM). The proposed model achieves a better performance than the chosen benchmark models for two error measures and most forecasting horizons.

Some authors used a hybrid approach to forecast tourism demand (Hadavandi et al., 2011; Chen et al., 2012; Shahrabi et al., 2013; Silva et al., 2019). Shahrabi et al. (2013) applied an integrated approach of genetic algorithm and fuzzy rule called Modular Genetic-Fuzzy Forecasting System (MGFFS) to forecast Japan's tourism demand. Further, they compared the forecasting accuracy with ARIMA, ANN, ANFIS, genetic fuzzy system GFS and proof that the performance of MGFFS is better. Chen et al. (2012) applied empirical mode decomposition (EMD) and backpropagation neural network (EDM-BPN) to predict the volume of international tourist arrival to Taiwan from Japan, Hong Kong and Macao. Further, they showed that the proposed model EDM-BPN outperforms neural network without EDM and ARIMA model. For a detailed review of forecasting methods, the readers can refer to Song et al. (2019) and Li & Jiao (2020).

Table 1. Forecasting models used for predicting tourism demand

Sl. No	Author (Year)	Forecasting Model																			
		OLS	CO	VAR	NN,ANN	BVAR	ARIMA	SARIMA	MARIMA	ECM	ADLM	ARMAX	STSM	BSM	EDM-BPN	SETAR	ES	RM	GFS	MGFFS	AFTS
1	Witt & Martin (1987)	✓	✓																		
2	Turner & Witt (2001)												✓	✓							
3	Goh & Law (2002)							✓	✓												
4	Kulendran & Witt (2003)						✓			✓			✓	✓							
5	Song et al. (2003)			✓			✓			✓	✓										
6	Song & Witt (2003)									✓	✓										
7	Witt et al. (2004)			✓																	
8	Kulendran & Wong (2005)						✓														
9	Palmer et al. (2006)				✓																
10	Wong et al. (2006)			✓		✓															
11	Wong et al. (2007)			✓			✓			✓	✓										
12	Athanasopoulos & Hyndman (2008)																✓	✓			
13	Chang & Liao (2010)							✓													
14	Tsaur & Kuo (2011)																				✓
15	Hadavandi et al. (2011)																		✓		
16	Chen et al. (2012)														✓						
17	Shahrabi et al. (2013)																			✓	
18	Claveria & Torra (2014)				✓		✓									✓					
19	Yang et al. (2015)											✓									
20	Polyzos et al. (2020)				✓																
21	Yao & Cao (2020)				✓																

3. Methodology and Data

This paper uses Artificial Neural Network (ANN) model to predict the impact of the epidemic outbreak COVID-19 on India's foreign tourists' arrival. Further, we predict the loss of Foreign Exchange Earnings (FEE) considering the exchange rate and tourists' number. We use monthly data of foreign tourists' arrival from different countries to India from 30th April 1989 to 31st March 2020 (369 months). The data are obtained from the Centre for Monitoring Indian Economy (economicoutlook, 2020). Moreover, to analyze the impact of inbound tourism on the economy, the monthly foreign exchange earnings from tourism are collected from January 1993 to March 2020.

3.1 Identification of data pattern

It is important to examine the pattern of the data series before implementing any prediction model. Hence, we perform different unit root test for stationary check such as Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) and Phillips-Perron (PP), at 5% significance level, to analyze the pattern of foreign tourist arrival in India. In ADF test and PP test, H=1 indicates rejection of the unit-root null in favor of the alternative model i.e., there is sufficient evidence that data is trend stationary, and H = 0 indicates fail to reject the unit-root null i.e. no sufficient evidence data is trend stationary. KPSS test can check for stationary in the presence of a deterministic trend. KPSS test is an inverse of the ADF and PP test, and it reverses the null and alternate hypotheses. If H=1, it indicates that rejection of the trend-stationary null in favor of the unit root alternative, whereas H= 0 indicates failure to reject the trend-stationary null. Practically, the interpretation of p-value in ADF/PP test and KPSS test is just the opposite of each other. If the p-value is less than the significance level, then the series is non-stationary, whereas, in ADF and PP test/ADF test, it is the opposite of KPSS test. Table 1 shows a summary of the unit root test. From the table, it is observed that, for ADF and PP test, H=0 and p-value >0.05 indicate that the pattern of foreign tourists' arrival to India is non-stationary. Similarly, from KPSS test, we reject the null hypothesis and conclude that data series is non-stationary.

Table 2. Summary unit root test for foreign tourists' arrival

Unit root test	H	P-value	Hypothesis test
ADF test	0	0.1197	Fail to reject the null hypothesis
PP test	0	0.1197	Fail to reject the null hypothesis
KPSS	1	0.0100	Reject the null hypothesis

The statistical test described above shows that the foreign tourists' arrival data series is non-stationary. The time series plot of the arrival of foreign tourists is shown in Figure 1. From the figure, the existence of growth trends and seasonality can be observed. In the autocorrelation function (ACF) plot (Figure 2), the autocorrelation coefficient (r_k) value displayed for 48-lag period is positive, signifies that number of foreign tourist arrival data series is non-stationary. The seasonality pattern in ACF plot, i.e., April to September, is declined in arrival rate. Whereas October to March, "high season" can be observed.

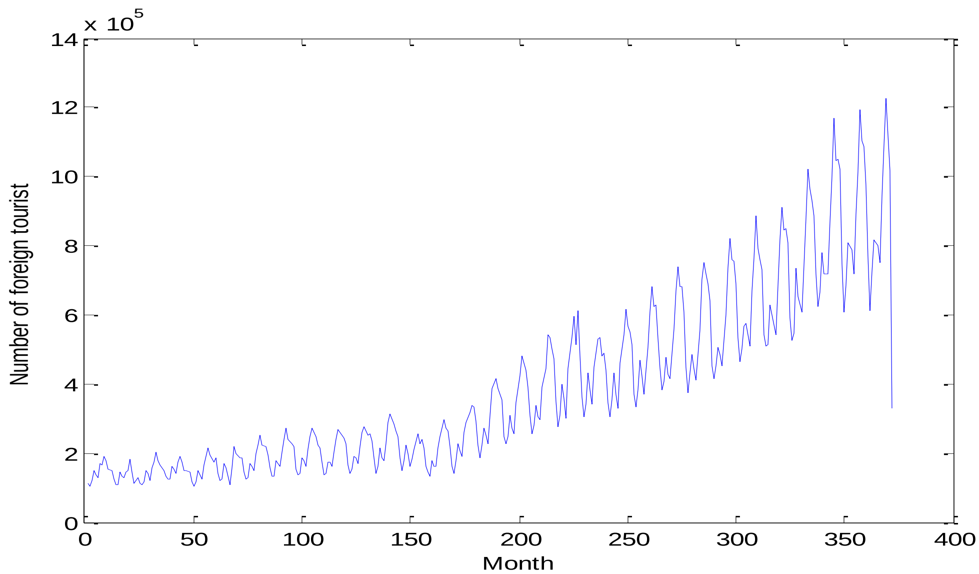


Figure 1. Time series plot for the arrival of number of foreign tourists

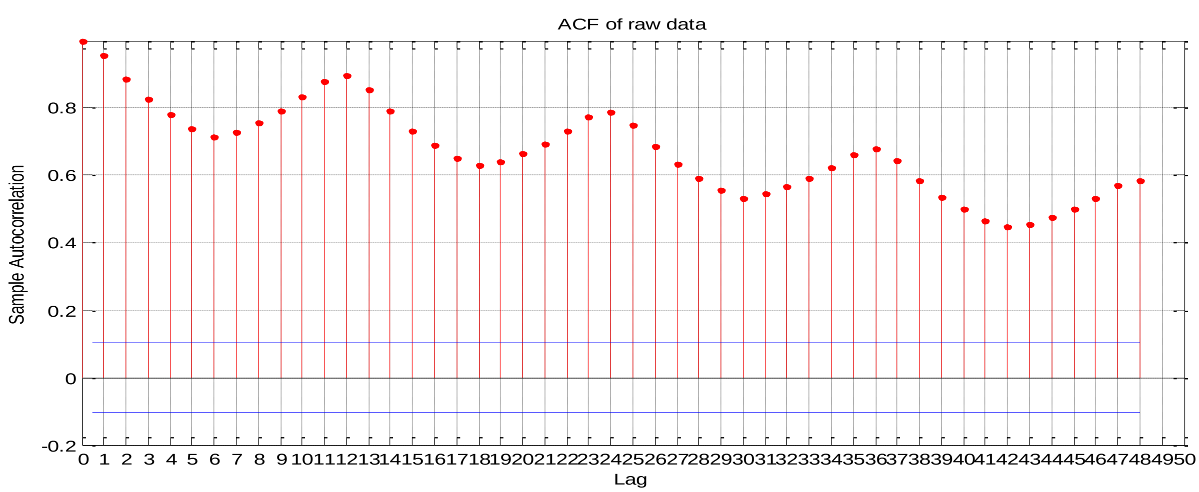


Figure 2.Autocorrelation function plot for the number of tourists arrived

From the above statistical analysis, it has been proved that the data series, the arrival of foreign tourists in India is non-linear and non-stationary. The artificial neural network (ANN) has the capability of self-learning and adopting the data pattern. Hence, it is used to make predictions regardless of the data series of linear/non-linear, stationary, or non-stationary patterns. Therefore, in this study, we have applied ANN model for prediction.

3.2 The Artificial Neural Network

The ANN comprises of three-layer architecture such as input, hidden and output layer. The feed-forward multilayer perceptron (FFML) network is the most commonly used type of ANN. Each layer consists of a certain number of neurons and subsequent layers connected from the previous layer through connection weights. Numbers of neurons in the input layer are equal to external input supplied to the ANN model and represent with "l". The number of neurons in the hidden layer is optimized through experimentation represented with "m" and "n" presents the number of neurons in the output layer that equals the desired output number. Hence, the ANN model is represented as l-m-n. The neurons of one layer connected with next layer using the connection weights. The prediction function in ANN model goes through two processes known as training and testing process.

The training process performs mapping between inputs and outputs by taking the training data set as input and regulating the connection weights. The gradient descent with momentum parameter backpropagation training function is used to train the ANN model. The connection weights between i^{th} neuron in the input layer to j^{th} neuron in the hidden layer are represented as w_{ji}. Similarly, w_{kj} is the connection weights value between j^{th} neuron in ^{the} hidden layer and k^{th} output layer neuron. The p^{th} pattern among n input pattern is represented as $I_p = (I_{p1}, I_{p2} \ldots I_{pl})$, where, p=1, 2,3,…n. Equation 1 gives the output from neurons present in the input layer. The output from the neurons present in the hidden layer, and the output layer is represented using Equation 2 and Equation 3, respectively (Kumar, 2011).

$$O_{pi} = I_{pi}, i = 1,2,3, \ldots, l \tag{1}$$

$$O_{pj} = f\left(\sum_{i=0}^{l} w_{ji}\, O_{pi}\right), j = 1,2, \ldots, m \tag{2}$$

$$O_{pk} = f\left(\sum_{j=0}^{m} w_{kj} O_{pj}\right), k = 1,2, \ldots, n \tag{3}$$

These connecting weights modify the input data set and generate total activation function i.e., the sum of modified values. Further, these values are modified using a sigmoidal transfer function (Equation 4). In the training process, the predicted output is compared with the desired output, and the mean square error (MSE_p) is calculated using Equation 5. If MSE_p is higher than a described limiting value (0.10), then it is backpropagated from output layer to input layer, and weights are further modified using Equation 6 till the error or number of iteration reaches a prescribed limit. Figure 3 describes the general structure of the ANN model.

$$f(x) = \frac{1}{1+e^{x}} \tag{4}$$

$$MSE_p = \sum_{i=1}^{n} \frac{1}{n}\left(D_{pi} - O_{pi}\right)^2 \tag{5}$$

$$\Delta w(t) = -\eta MSE_p(t) + \alpha \Delta w(t-1) \tag{6}$$

where, η is the learning rate, $0 < \eta < 1$; α represents the momentum coefficient and $0 < \alpha < 1$; t is the iteration number, i.e., epoch.

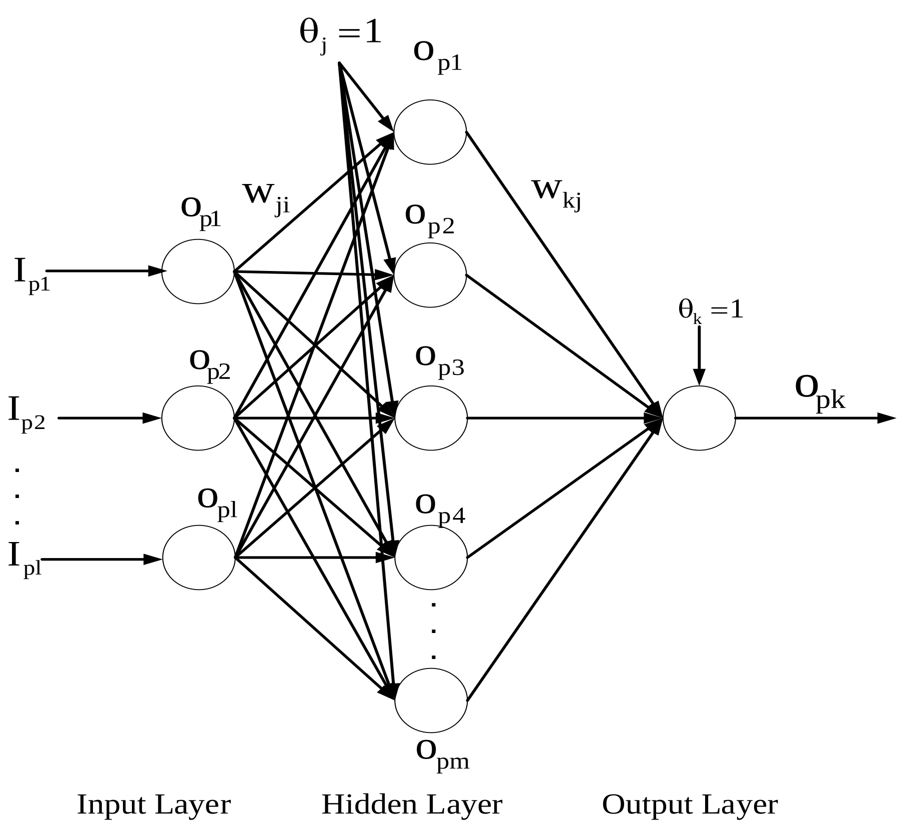


Figure 3. General structure of the ANN model

4. Prediction of the arrival of foreign tourists

From the unit root test (Table 2), Figure 1, and Figure 2, it has been verified that arrival of number of foreign tourist data series is non-linear and non-stationary. Hence, the ANN model is used to forecast the arrival of foreign tourists in India. In this ANN model, the number of neurons in the input layer is equal to number of periods taken to predict the next period. For example, Model 1 (Figure 4) considered recent 2-periods (2 months), i.e. month 1 and month 2 to predict tourists' number in the third month. Similarly, month 2 and month 3 are considered to predict tourists' number in the fourth month. Hence, the number of neurons in the input layer is two. Whereas, Model 2 considered recent 3-periods i.e. month 1, month 2 and month 3 to predict the number of tourists in the fourth month, hence, there are three neurons in the input layer. Likewise, nine different models are formed for the analysis.

	Input	Output
Model 1	t_1 t_2	t_3
	t_2 t_3	t_4
	t_3 t_4	t_5
	.	
	.	
	.	
Model 2	t_1 t_2 t_3	t_4
	t_2 t_3 t_3	t_5
	t_3 t_4 t_5	t_6
	.	
	.	
	.	

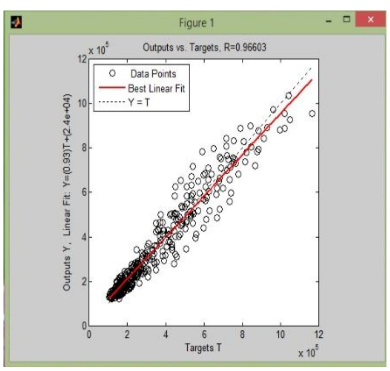
Figure 4. Structure input and output data matrix for ANN model

The number of neurons in the hidden layer has optimized through experimentation during the training process, and the number of neurons in the output layer is one i.e., predicted value. As shown in Figure 4, nine different data matrices are prepared, and hence nine different ANN models are formed as described in Table 3. The data further divided into training and testing data set. Last 24-months of data were kept for testing and rest as training data set. The training data set was taken as input to train the model. After the successful training i.e., either the MSE_p (Equation 5) reached to 0.10 or described epochs, the optimal model parameters are obtained (Table 3). Using optimal model parameters settings, 24 months ahead of foreign tourists' arrival are predicted using testing data set, and the forecast error is calculated in terms of mean absolute percentage error (MAPE) using Equation 7. The fitness of the models is obtained after successful training is pictorially represented in Figure 5. All the model fitness values are above 95%, which represents the best-fitted model. However, when the models are compared in terms of MAPE value, Model 5 has the lowest MAPE i.e., 10.7% (Table 3). Hence, Model 5 is selected as a suitable model for predicting the arrival of foreign tourists in India. In this model, we consider recent 6-periods data to predict the next period. As it has been described in Section 3 that each year April to September (6months duration) “low season”, i.e., decline trend, whereas October to March (6 months duration) “high season” (Figure 2).

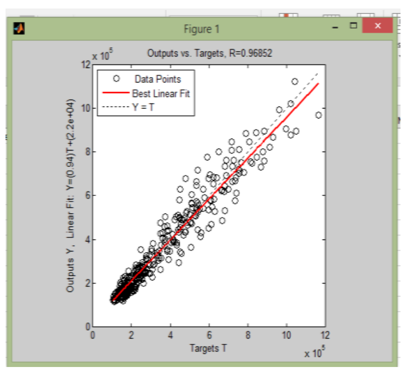
$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|\mathrm{actual}-\mathrm{predicted}|}{\mathrm{actual}}\right) \times 100 \quad (7)$$

Table 3. ANN Model description and optimal model parameters settings

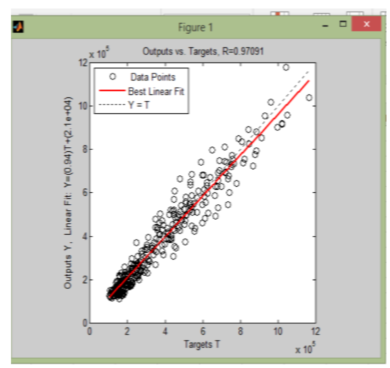
Model	Periods	ANN Model (l-m-n)	ANN model parameters				Training error	Forecast error (MAPE)
			Learning rate (η)	Momentum parameter (α)	epochs	Goal		
Model1	2-period	2-3-1	0.07	0.1	10000	1.00E-03	13.1	19.0
Model2	3-period	3-3-1	0.07	0.1	10000	1.00E-03	12.3	17.5
Model3	4-period	4-7-1	0.07	0.1	10000	1.00E-03	12.0	16.5
Model4	5-period	5-9-1	0.07	0.1	10000	1.00E-03	11.3	13.7
Model5	6-period	6-9-1	0.07	0.1	10000	1.00E-03	9.6	10.7
Model6	7-period	7-10-1	0.07	0.1	10000	1.00E-03	7.2	12.4
Model7	8-period	8-13-1	0.07	0.1	10000	1.00E-03	7.0	12.1
Model8	9-period	9-17-1	0.07	0.1	10000	1.00E-03	7.0	12.2
Model9	10-period	10-18-1	0.07	0.1	10000	1.00E-03	6.8	13.4



Model 1



Model 2



Model 3

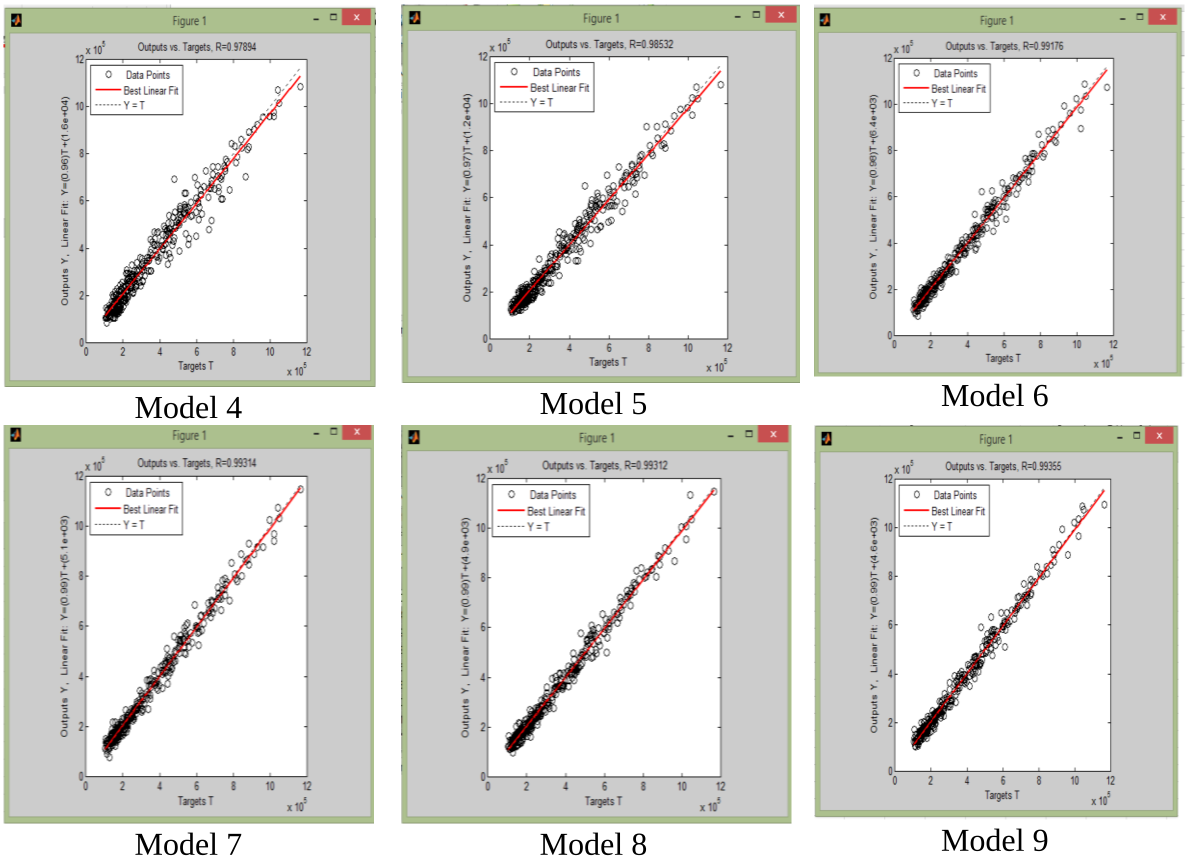


Figure 5. Summary of fitness of ANN model

5. Impact of COVID-19 pandemic on Tourism Economy

The foreign exchange earnings (FEE) from tourism is one of the major revenue source for the Government of India. The FEE is the revenue generated by inbound foreign tourists, and decrease in foreign tourists' number leads to reduce FEE. The entire world is affected by COVID-19, including India. Following the border closure, cancellation of international flights, and a series of lockdowns, the tourist's arrival rate in India has been highly affected. To show the impact of COVID-19 on FEE, a comparative analysis has been done. Here, it has assumed that the effect of COVID-19 will remain until next year. The FEE depends on the arrival of the number of tourists and exchange rate. To analyze the impact, the monthly data related to number of tourists, FEE from tourism and exchange rate are collected from 31st January 1993 to 31st March 2020 from CMIE (economicoutlook, 2020).

The scatter plot (Figure 6) describes the high correlation between foreign tourists' arrival and foreign exchange earnings, and the calculated correlation coefficient is 0.9718. It signifies that both are highly correlated. Similarly, Figure 7 depicts the correlation between exchange rate earnings and foreign exchange earnings, and the calculated correlation coefficient is 0.8570. This signifies that both are highly correlated. Thus, the arrival of the number of foreign tourists and the exchange rate are taken as input to predict the FEE and to measure the impact of COVID-19.

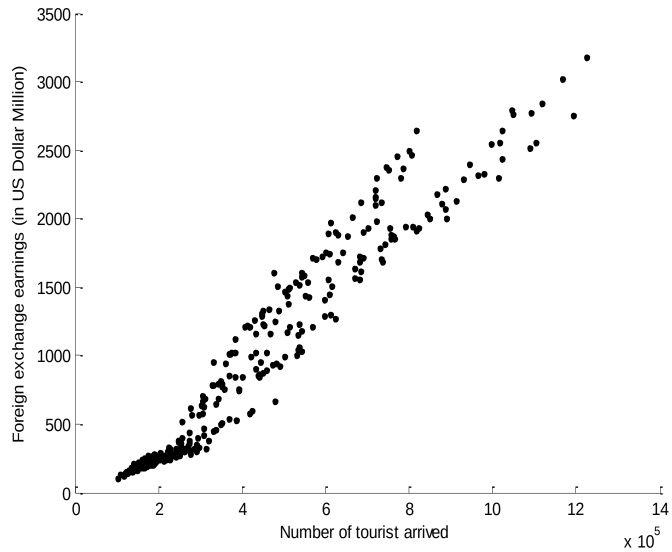


Figure 6. Correlation between the number of tourists arrived and foreign exchange earnings

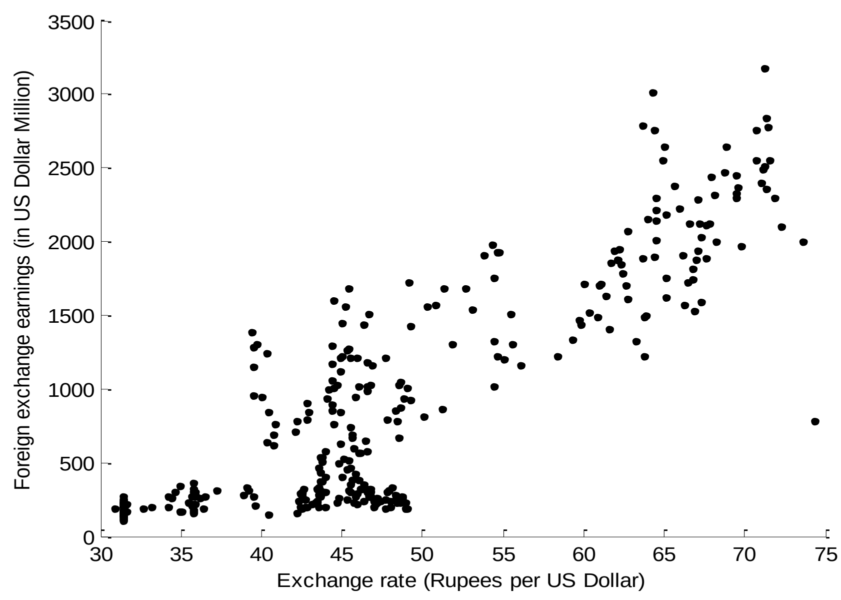


Figure 7. Correlation between the number of tourists arrived and foreign exchange earnings

There is a positive change in the year-to-year arrival rate of foreign tourists in India, as shown in Figure 8. However, it has decreased by 6.63% in February 2020 and further decreased by 66.42% in March.

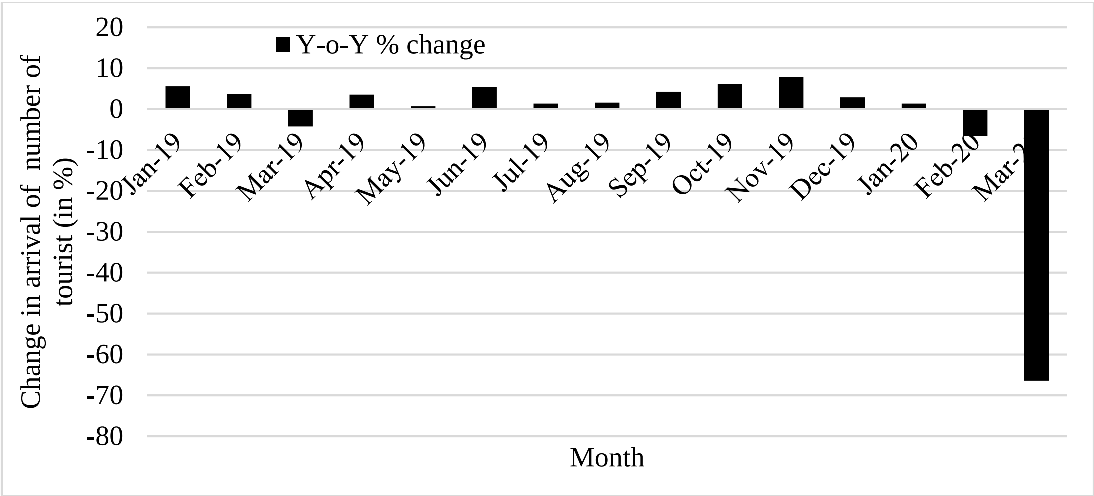


Figure 8. Change in the arrival of number of foreign tourist year-to-year

If the monthly data are compared, a negative change can be observed in Figure 9 from January to March 2020. It means the number of tourists decreases by 67.66%. It is because the COVID-19 virus was first identified on 31st December 2019 in China, and WHO declared a pandemic on 11th March 2020. Hence, there is a need to analyze impact of COVID-19 on arrival of foreign tourists in India in subsequent months and its impact on FEE until next year. Next, to analyze the impact of COVID-19 on FEE, we perform comparative analysis.

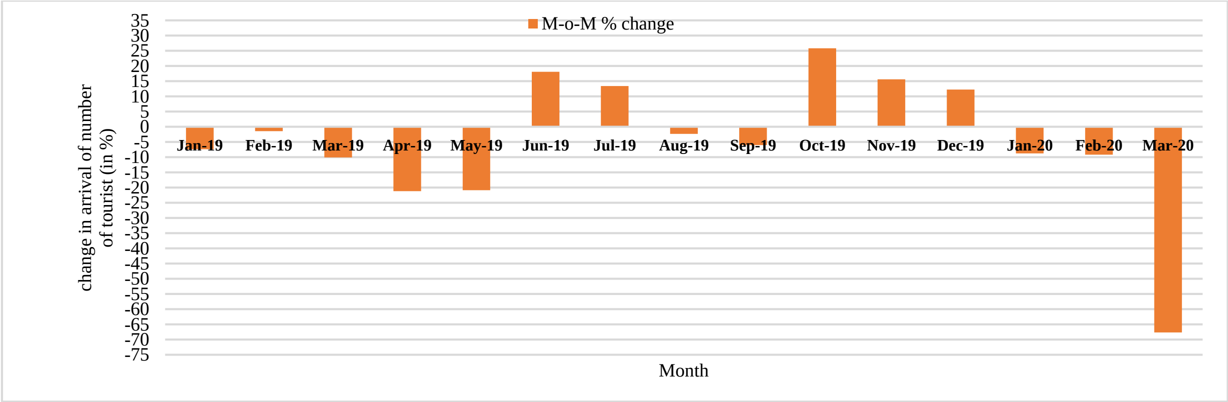


Figure 9. Change in the arrival of number of foreign tourist month- to-month

A comparative study is carried out to measure total FEE from tourism with and without the COVID-19 situation. For this purpose, monthly FEE values for the year 2020-2021 have been predicted considering the number of tourists and exchange rate as the input. Before applying forecasting model for prediction, the past pattern of the exchange rate and FEE has been analyzed. In section 3, we already predicted the number of tourists. Next, we analyze the pattern for the exchange rate and FEE.

The time series plot (Figure 10) and the ACF plot (Figure 11) represent that exchange rate is non-linear and non-stationary. Similarly, from Figure 12 and Figure 13, it can be concluded that the FEE is non-stationary. Further, for stationarity check, the unit root tests such as ADF test, PP test and KPSS are conducted for both the data series at 5% significance level. From the test, we found that exchange rate and foreign exchange earnings follow non-stationary patterns (Table 4).

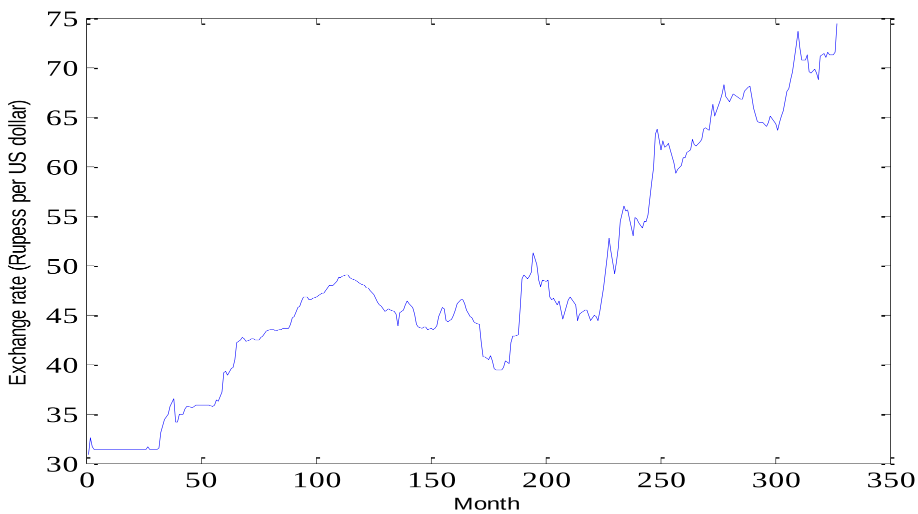


Figure 10. Time series plot for exchange rate (Rupees per US dollar)

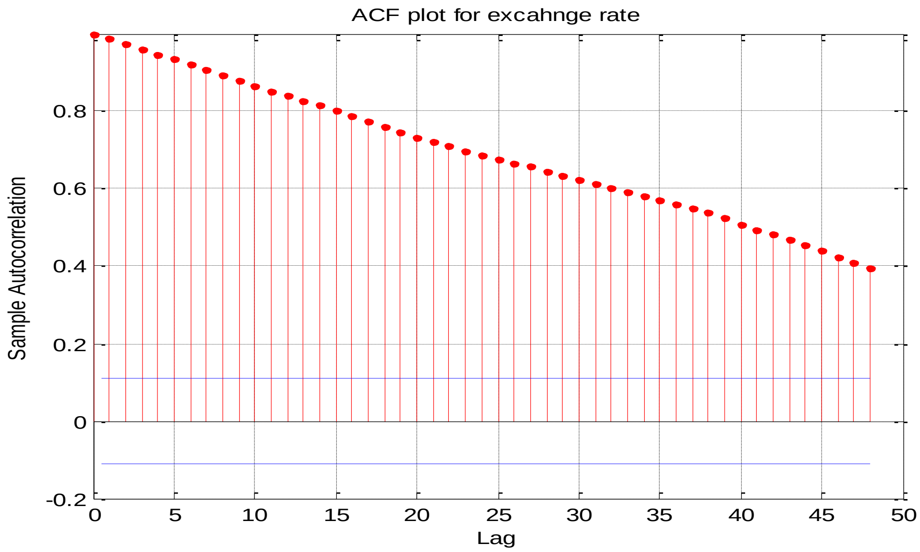


Figure 11. ACF plot for exchange rate (Rupees per US dollar)

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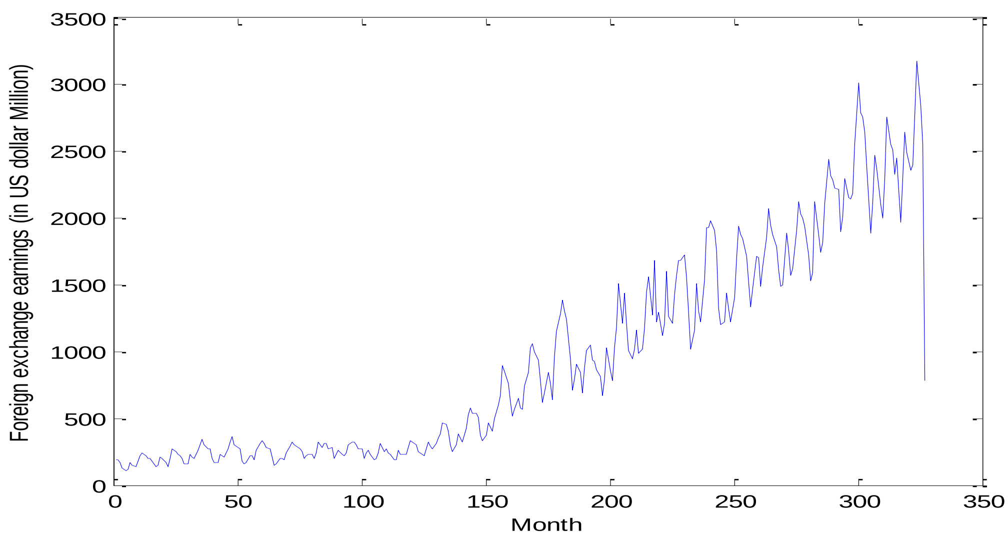

Figure 12. Foreign exchange earnings (in US dollar Million)

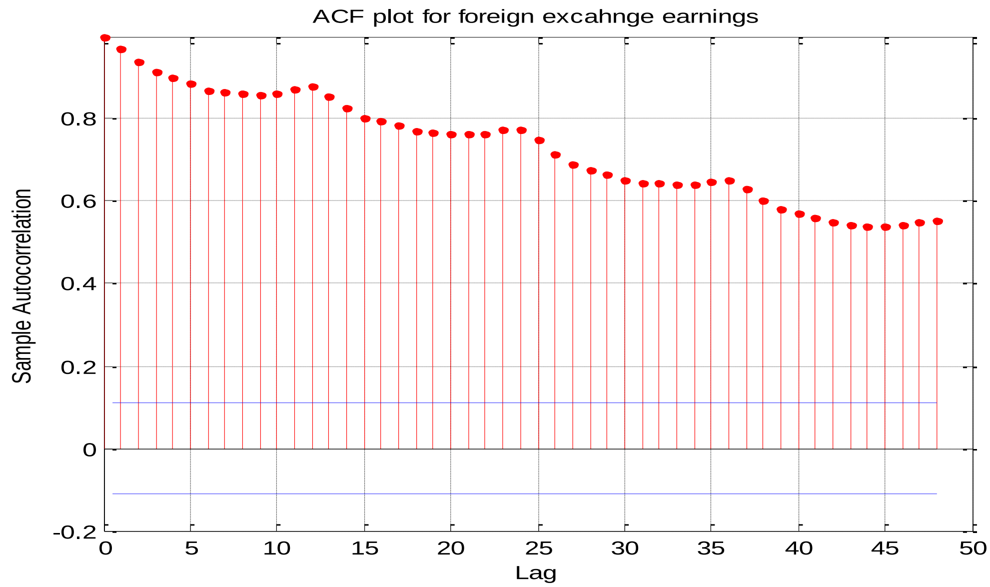

Figure 13. ACF plot for foreign exchange earnings

Table 4. Summary of unit root test for foreign tourists arrival

Unit root test	Exchange rate		Foreign Exchange Earnings		
	h	P-value	h	P-value	Hypothesis test
ADF test	0	0.999	0	0.187	Fail to reject the null hypothesis
PP test	0	0.999	0	0.187	Fail to reject the null hypothesis
KPSS	1	0.01	1	0.01	Reject the null hypothesis

From Table 4, it is verified that the FEE and exchange rate are non-linear and non-stationary. The foreign tourists' arrival pattern is non-linear and non-stationary (Section 3, Table 2). Hence, the ANN model has been used to predict FEE considering the number of tourists and exchange rates as input. Out of 328 months of data, 93% of data points are considered training data set to train the model and rest 7% data, i.e. 24 months, are considered testing data sets. After successful training of the ANN model, the optimal model parameter settings obtained are l=2, m=2 and n=1, the η= 0.07, α= 0.1, goal = 0.001 and epchos=13000. Using these model parameter settings, the testing data is used to predict 24-months FEE, and the forecast error i.e., MAPE is 10.24. The model's fitness is 97.976%, as shown in Figure 14, which signifies the ANN model's fitness.

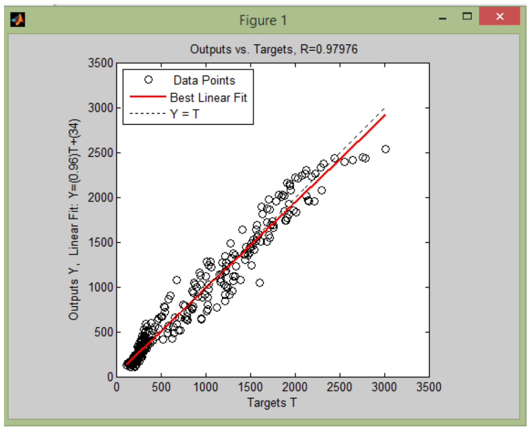

Figure 14. ANN model fitness for prediction of foreign exchange earnings

We generated four scenarios to analyze the impact of COVID-19 on tourism in terms of FEE. These scenarios are:

Scenario1-This is the normal situation where the monthly forecasted FEE value depends on the previous year's actual exchange rate and the number of tourist data from 31st January 1993 to 31st March 2020 collected from CMIE (economicoutlook, 2020).

Scenario2- In this scenario, the monthly FEE is forecasted considering monthly forecasted number of tourist and exchange rate (Longforecast, 2020)

Scenario3- Due to COVID-19, there is a decrease in tourists from February to March 2020, approx. 68% (Figure 9). Hence, there is a continuous decrease in arrival of number of tourists. For example, the predicted number of tourists in April (from section 3) is reduced by 68% to estimate the number of tourists in May 2020. Similarly, it has been done for rest of the months to predict the tourist arrival. Using this estimated number of tourists and forecasted exchange rates, the monthly FEE is predicted.

Scenario4- In this scenario, forecasted arrival of the number of tourist value is reduced by 68%. For example, forecasted number of tourists for August is 1078112.778 (from Section 3); hence it reduced by 68% i.e., 344996.0891. Likewise, it has been done for rest of the months. Using this estimated number of tourist and forecasted exchange rates, the monthly FEE is predicted.

Using the optimal parameter settings in Table 4, the monthly FEE is predicted considering scenario 1, scenario 2 and scenario 3 and described in Table 5. From the table, it can be observed that lockdown has a high impact on the FEE.

Table 5. Foreign exchange earnings based on scenarios

predicted foreign exchange earnings (in US dollar Million)				
	scenario1	scenario2	scenario3	scenario4
August 2020	2139.55	2512.48	99.59	1099.36
September 2020	2043.78	2495.37	94.13	1076.75
October 2020	2324.67	2109.78	95.28	772.31
November 2020	2448.31	1856.62	95.93	651.06
December 2020	2575.02	2061.84	123.83	770.98
January 2021	2518.51	2097.38	132.70	797.38
February 2021	2508.72	2100.68	135.11	801.20
March 2021	2402.38	2163.81	129.62	832.76
April 2021	2112.95	2310.92	140.23	940.41
May 2021	1780.41	2530.58	147.17	1168.91
June 2021	2018.76	2560.08	129.87	1199.24
July 2021	2185.59	2523.37	159.58	1168.92
August 2021	2174.13	2557.02	158.41	1217.33
September 2021	2092.73	2173.08	149.10	854.45
Total FEE	**31325.52**	**32053.01**	**1790.53**	**13351.07**

The actual arrival of tourist and exchange rate data from 31st January 1993 to 31st March 2020 has taken as input for ANN model to predict the next 14 months (August 2020 to September 2021) FEE under the normal situation, as represented in scenario1 (Table 5). Scenario 2 of Table 5 listed the monthly forecasted FEE earnings under normal situation considering the tourist and exchange rate's predicted arrival rate. Table 5 shows that the predicted total FEE for scenario 1 and scenario 2 is USD 31325.52 million, and USD 32053.01 million, i.e., the difference is 2.32%. It signifies the fitness of selected ANN model, i.e., the predicted FEE is very close by considering actual or the expected arrival rate of tourist and exchange rate. Table 5, scenario 1 and scenario 2 confirm that Indian tourism could have earned at least USD 31325.52 million from August 2020 to September 2021 if there was no COVID-19 situation. Scenario 3 describes the monthly forecasted FEE considering COVID-19 situation, i.e., continuously falling in the arrival rate of tourists by 68% from the previous month and hence predicted total FEE is USD 1790.53 million. Scenario 4, the monthly forecasted arrival rate of tourists reduced by 68% and the exchange rate is taken as input to forecast FEE. It has assumed that if Indian tourism industry will somewhat manage the tourist activities and foreign tourists will come to India but with less by 68% from the predicted value. Scenario 4 describes that if tourism activities are managed, and tourists come to India, the FEE would be USD 13351.07 million. Comparing all four scenarios, we conclude that if the tourism activities are not managed well, the FEE falls below USD 1790.53 million and may be lost entirely. If it can be managed at some level, then the FEE value will be at least USD 13351.07 million.

6. Implications of the study

This study has significant theoretical and managerial implications. The total contribution of travel and tourism to India's GDP from 2018 is USD 247.37 billion, and 2019 is USD 268.29 billion (Statista, 2020). Tourism not only generates revenue; it also creates employment. The revenue from tourism to GDP in India is through foreign visitor spending, which is 12.8%. The estimated unorganized workforce in the tourism sector across India from 2017 is 4,01,000. The predicted employment loss in the travel and tourism industry due to COVID-19 in India is 9 million. The FEE is the revenue generated from tourism and profoundly affected by the COVID-19 pandemic. In this study, we predict the number of foreign tourists and its impact on the generated FEE. As observed in scenario 3, there is a reduction in FEE due to a continuous decrease in the tourists' arrival. These predicted values are an alarm to restructure the tourism sector and make policy to manage the activities better to maximize the FEE. From the study, the major theoretical implication exhibited is that if the policies in the tourism sector are not restructured, then the FEE will fall below USD 1790.53 million and maybe entirely lost to the economy. If it is managed at some level, then the FEE value will be at least USD 13351.07 million. On the other side, if the demand is reduced, proper resource utilization will not be possible, which leads to a lower return on investment as the government has already made huge investments under various schemes. Further, it will affect the employment rate in the tourism sector.

Lastly, this study contributes towards managerial implications by laying a foundation towards reacting against the epidemic outbreak. It further helps the decision-makers to make an appropriate and immediate decision based on the forecasted values. The decision-makers may also promote tourism destinations, ease the visa regulations, find better financing options, etc. that may subsidize demand and sustainably boost the international flow of tourists with all the sanitizing protocols followed. It is quite imperative that COVID-19 has also impacted the education sector. In this context, programs and courses related to hospitality and tourism are affected with a smaller number of students registering for those programs. There is also a need to make the curriculum more resilient and agile. Again, there is more scope for social entrepreneurs in this regard, thereby creating social ventures, helping people solve social problems (Sigala, 2020).

7. Limitations and future research

The shortcomings of this study are worth mentioning. Due to lack of updated information related to this pandemic, the study could not consider other economic variables for the analysis. The study is only limited to a specific country that may be extended further by considering cross-country data. Lastly, the study has only considered international inbound tourists, whereas the situation may be analyzed for domestic and outbound tourists.

In light of the further research avenues, the following future perspectives may be stated. First, a further detailed study of the tourism sector may be conducted to analyze the effects of the epidemic outbreak on the tourism industry with respect to triple bottom line approach (social, financial and environmental) to achieve sustainability and make it resilient (Ying et al., 2020). Second, participation from various stakeholders is also required since millions of people are dependent on the sector. Therefore, forecasting tourism demand may be studied from the macro-level to the micro-level through an inter-disciplinary approach. Lastly, this study can be extended by including the other economic parameters, such as consumer price index (CPI). Instead of ANN model, different other machine/deep learning methods, such as support vector machines, can be used for prediction.

8. Conclusion

The tourism sector has dramatically affected by the widespread of COVID-19 and may remain for a longer time. The arrival of foreign tourists to India from different parts of the world has reduced by 68% in March 2020 compared to the previous month. It has a great impact on revenue generated from tourism in the form of FEE. A suitable forecasting model can help in strategic and operational decision-making. Hence, this study has predicted the number of foreign tourists using the ANN model with respect to COVID-19 outbreak. Also, the FEE has been predicted using the number of tourists and exchange rates. Further, to analyze the impact of COVID-19, four different scenarios are generated, and impact has been measured through predicting FEE.

Our findings suggest that if the tourism sector and policies are not restructured, then the FEE will fall below USD 1790.53 million and maybe entirely lost. If it is managed at some level though reforming policies, then the FEE value will be at least USD 13351.07 million.

In this paper, we make three contributions as well as novelties. Firstly, a well understanding of the mutual interplay between the COVID-19 pandemic and the tourism sector is well explained through a novel approach. Secondly, an enriching contribution is made by predicting foreign tourist arrivals and FEE with the number of foreign tourists and exchange rates (monthly data) as an input to the ANN model. Finally, a decision has been proposed for the various stakeholders of the tourism industry to help recover the sector from the current scenario, which is quite novel. Consequently, the findings presented in this paper will help the stakeholders and the policymakers facilitate strategic and operational planning based on the forecasted value. As per the study, FEE is reduced because of foreign tourists' fewer arrivals in this pandemic outbreak. Therefore, instead of investing more in adding new resources, policymakers and stakeholders can think about making the existing resource more efficient and effective.

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