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Forecasting of Electricity Consumption by Seasonal Autoregressive Integrated Moving Average Model in Assam, India

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ABSTRACT

Sustainable electricity consumption, which is about balancing economic growth, social development and environmental protection are the core principles of the Sustainable Development Goal (SDG). Accurate forecasting of electricity consumption is very important for attaining SDG - 7 which aims to ensure access to affordable, reliable, sustainable and modern energy for all. Through this paper, attempt is made to forecast monthly electricity consumption in Assam. For this purpose, one of the most widely used time series techniques, viz., Seasonal Autoregressive Integrated Moving Average (SARIMA) is applied by considering the time period April, 2013-February, 2023 to study the seasonal influence on the electricity consumption in Assam. By applying Augmented Dickey Fuller test, it is observed that the data series becomes stationary at first order difference and the result of Canova Hansen test reveals that no seasonal differencing is required for our considering time period. SARIMA (1,1,1) $(1,0,1)_{12}$ has been selected for forecasting purpose by following the results of Akaike Information Criterion. By analyzing the model statistics, residual ACF and PACF plots of the selected model, it is found that SARIMA (1,1,1) $(1,0,1)_{12}$ can be effectively recommended for forecasting of monthly electricity consumption in Assam with Mean Absolute Percentage Error as 3.12%.

Keywords: Assam, Electricity Consumption, Forecasting, SARIMA

JEL Classifications: C02, C22, Q47

1. INTRODUCTION

When we talk about the economic development of a country, then the role of electricity sector for attaining it, is undeniable. That's why electricity consumption experiences a tremendous growth rate all over the world. Globally the electricity consumption increased from 7300 TWh to 22,100 TWh during the period 1980-2013 and since the twenty first century, the average annual electricity consumption experienced 3.4% increasing rate, which is 1.2% higher than the average annual growth of global energy consumption (Zhenya, 2015). As per International Energy Agency 2022 reports, the share of electricity in the total global energy consumption would increase from current 20% to 22% by 2030 and to 28% by 2050 [Stated Policies Scenario (STEPS)], 24% in 2030-39% by 2050 [Announced Pledges Scenario (APS)] and in case of Net Zero Emissions (NZE) scenario, this share would further increase to 28% in 2030 and to 52% by 2050 (World Energy Outlook, 2022). The world-wide demand for electricity increased to 24,700 TWh in the year 2021 showing an increasing rate of 6% from 2020 and it was the biggest annual increase since 2010 (World Energy Outlook, 2022).

Accurate forecasting of electricity consumption is one of the important components of electricity sector as it is contributing to several key areas of nation building like supporting infrastructural development, ensuring energy security, resource optimization, proper policy formulation, promoting socio-economic development, enhancing environmental sustainability etc. Since forecasting is primarily used to guide the decision makers, therefore its accuracy is the most important and should be considered very seriously because both over and under estimations may equally create problems; where over-estimation may lead to the over-investment in network assets while under-estimation may result in unreliable, inconsistent and insecure electricity supply due to under-investment (Diebold and Mariano, 1995 and Hamedmoghadam et al., 2018).

2. LITERATURE REVIEW

From the very beginning to recent times, various forecasting techniques of electricity consumption have been used by the researchers like Time Series Analysis, Regression Analysis, Growth Models, Artificial Neural Networks, Machine learning Algorithms, Time Series Decomposition along with some hybrid approaches which combine two or more methods to get better forecasting adequacy. Among the traditional methods viz., Multiple Lenear Regression was extensively used by the researchers, like Mohamed and Bodger (2005), Bianco et al. (2009), Dudic et al. (2020), Garcia-Guiliany et al. (2020), Cui and Wu (2016) etc. for forecasting of electricity consumption by identifying the effects of economic, demographic, climatic factors for various countries. Again, Ediger and Akar (2007), Yasmeen and Sharif (2014), Miao (2015), Jain et al. (2018), Parreño (2022) found quite high adequacy of one of the widely used time series models – Autoregressive Integrated Moving Average Model (ARIMA) for forecasting of energy (electricity) consumption for Turkey, Pakistan, China, India and Philippines. Ozoh et al. (2014) employed modified Newton's model for modeling of electricity consumption while Hussain et al. (2016) applied Holt-Winter and ARIMA for forecasting electricity consumption in Pakistan and found the Holt-Winter more appropriate than ARIMA for the considering period.

Along with various types of traditional models of forecasting energy (electricity) consumption, Machine learning models are successfully applied by the researchers for various countries, both for short-term and long-term forecasting purposes. Artificial Neural Network (ANN) was used by the researchers, Nizami and Al-Garni (1995), Hsu and Chen (2003), Escriva-Escriva et al. (2011), Widodo and Fitriatien (2016), Adhiswara et al. (2019), Moon et al. (2019), Shahriar et al. (2019) etc. for forecasting of electricity consumption. Liu and Li (2022), while employed Back Propagation Neural Network (BP-NN), Multiple Linear Regression (MLR) and Least Square Support Vector Machine (LS-SVM) for forecasting of annual electricity consumption for UK found the efficiency of LS-SVM better than the other two and similarly, for forecasting of annual electricity consumption of high energy consuming industrial sectors in Iran, Azadeh et al. (2008) found the predictive performance of Artificial Neural Network technique (ANN) better than conventional regression model. Another important machine learning technique, gradient boosting machine-based technique was applied by Xie et al. (2022) for the electricity energy forecasting of New York while Singh et al. (2023) employed Light Gradient Boosting Machine (LGBM) for the prediction of energy saving awareness of households in Kitakyushu, Japan. Yi et al. (2022) made comparison of Multiple Linear Regression (MLR) with the three-machine learning model viz., Random Forest (RF), Deep Neural Network (DNN) and Support Vector Regression (SVR) for prediction of monthly energy consumption in Inter-basin Water Transfer Project, Mokelumne River Aqueduct in California where DNN outperformed RF, SVR and MLR.

To study the seasonal influence on electricity consumption, we have found in various literature about another important method of forecasting of seasonal time series data viz., Seasonal Autoregressive Moving Average (SARIMA). Wang et al. (2012), Joshi et al. (2016), Sim et al. (2019), Kaur and Ahuja (2019), Nguyen et al., (2021), etc. obtained a high accuracy of SARIMA model for forecasting of energy (electricity) consumption for various countries of the world.

3. STUDY AREA

Assam, located in the North-Eastern region of India and sharing international boundaries with Bhutan and Bangladesh has abundant natural resources. The state has been blessed by the mighty Brahmaputra River, Barak River and their tributaries, world heritage sites Kaziranga National Park and Manas National Park along with numerous wildlife sanctuaries, world's largest tea-growing region by production, exclusive producer of geographically tagged Muga silk, four refineries etc. Although it has immense potential of power, ranging from hydel to natural gas including oil and coal resources, yet the progress of power sector in Assam is not satisfactory in comparison to its possibilities. Also, though India has been able to make remarkable progress in the generation of thermal, hydel and in particular, solar, wind and other green energy, but the pace of development of electricity sector in Assam is not commensurate in comparison to the national average. But, with rapid urbanization, increased household income, infrastructural and industrial development, the demand and supply of electricity is also increasing like the worldwide scenario. With thorough review of literature, it is observed that the research works on the electricity consumption in Assam is very limited. Borgohain and Goswami (2015) tried to forecast short-term load for Assam with the help of Regression based time series method with temperature as the explanatory variable. Similarly, in some previous works, Mahanta and Talukdar (2021) compared the predictive performance of Multiple linear regression, considering the effects of population and per capita income and ARIMA, where ARIMA outperformed the Multiple Linear Regression for forecasting of total yearly electricity consumption in Assam. To study the trend and pattern of total electricity consumption in Assam, Mahanta and Talukdar (2021a) when employed various time-dependent growth models, then it was found that total electricity consumption in Assam followed a cubic growth rate and the share of domestic sector in the total consumption is very high in comparison to the sectors like industrial, commercial, agricultural etc. Also, Mahanta and Talukdar (2023) in their study of Domestic

Electricity Consumption in Assam observed that Domestic sector consumption followed an exponential growth rate and here also, ARIMA model was found as the best forecasting model in comparison to various time-dependent growth models and Multiple Linear Regression model.

The factors like availability of data, nature of data, the level of accuracy required etc. lead to the choice of the proper method for forecasting purposes. To our knowledge, SARIMA model has not been yet used for forecasting of electricity consumption in Assam. Therefore, in this study, attempt has been made to forecast electricity consumption with the help of SARIMA model for studying the seasonal influence on monthly electricity consumption in Assam. SARIMA models are well suited for data with seasonal patterns, which is often the case with monthly electricity consumption data as they can capture both the seasonal and non-seasonal components of the time series.

4. DATA AND METHODOLOGY

The present study has been carried out with secondary data**.** Here, total monthly electricity consumption data are collected from the Assam Power Distribution Company Limited (APDCL), O/O: the Chief General Manager (Commercial and Energy Efficiency) for the time period April, 2013-February, 2023.

SARIMA is an extension of the ARIMA model, designed to handle seasonal patterns in time series data which consists of the components Seasonal, Autoregressive (AR), Integrated (I) and Moving Average (MA). To eliminate the influence of periodicity in a forecasting process, SARIMA has been widely applied in various field of forecasting of seasonal time series data. It is denoted by SARIMA (p, d, q) $(P, D, Q)_s$ where p and P represent the order of AR and Seasonal AR respectively, d and D represent degree of differencing and seasonal differencing respectively, q and Q represent order of MA and seasonal MA order and S represents seasonal period length. Being the data under consideration are monthly, S, here will be equal to 12. A time series $\{Zt/t = 1,2,\ldots, k\}$ is generated by a SARIMA (p, d, q) (P, D, Q)s process (where p, d, q, P, D, Q are integers, and s is the periodicity) with mean μ of the Box-Jenkin's model (Tseng and Tzeng, 2002) if

$$\phi(B)\Phi(B^s)\,(1-B)^d\,(1-B^s)^D\,(Z_t-\mu)=\theta(B)\Theta(B^s)a_t. \quad (1.1)$$

Where $\phi(B)=1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p$,

$\Phi(B^s)=1-\Phi_1 B^s-\Phi_2 B^{2s}-\ldots-\Phi_P B^{Ps}$,

$\theta(B)=1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q$ and

$\Theta(B^s)=1-\Theta_1 B^s-\Theta_2 B^{2s}-\ldots-\Theta_Q B^{Qs}$

are polynomials in B of degrees p, q, P and Q; B is the backward shift operator, d is the number of regular differences; D is the number of seasonal differences and Z_t denotes the observed value of the time series data.

Like ARIMA model, this model consists of the steps of identification, estimation and diagnostic checking and forecasting. For finding the appropriate order of integration and integration order in season D, Augmented Dickey Fuller (ADF) and Canova-Hansen test are used respectively. For selecting the number of Autoregressive (AR) and Moving Average (MA) terms in the model, Akaike's Information Criterion (AIC) is used. To find the model accuracy, Mean Absolute Percentage Error (MAPE) is calculated which is given by the formula

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{Y_t-\hat{Y}_t}{Y_t}\right|\times 100 \quad (1.2)$$

5. STATISTICAL ANALYSIS

The monthly total electricity consumption scenario in Assam is depicted in Figure 1 which shows an overall increasing trend with seasonal variation throughout a year.

5.1. The Construction of SARIMA Model

Here, the first step is the model identification of SARIMA (p, d, q) × $(P, D, Q)_S$, the second is to estimate the model parameters and to test the fitness of the model, the last stage is diagnostic checking on the residuals. If the series is non-stationary, then to find the appropriate order of integration to make it stationary, Augmented Dickey Fuller (ADF) test is used. The result of ADF test for the given series is as represented in Table 1.

Using the EViews 12 software we have carried out the Augmented Dickey Fuller test where the null hypothesis to be tested is that the process has a unit root i.e., the series is non-stationary against the alternative that it is stationary. By observing the values of p (given in parenthesis) and critical values at level and first difference found that the series of monthly electricity consumption in Assam become stationary in first order

Table 1: The stationary test of the series of monthly electricity consumption in Assam

Variable	ADF Test	
	Level	First difference
Monthly electricity consumption	−1.712067 (0.7392)	−3.712220 (0.0257)

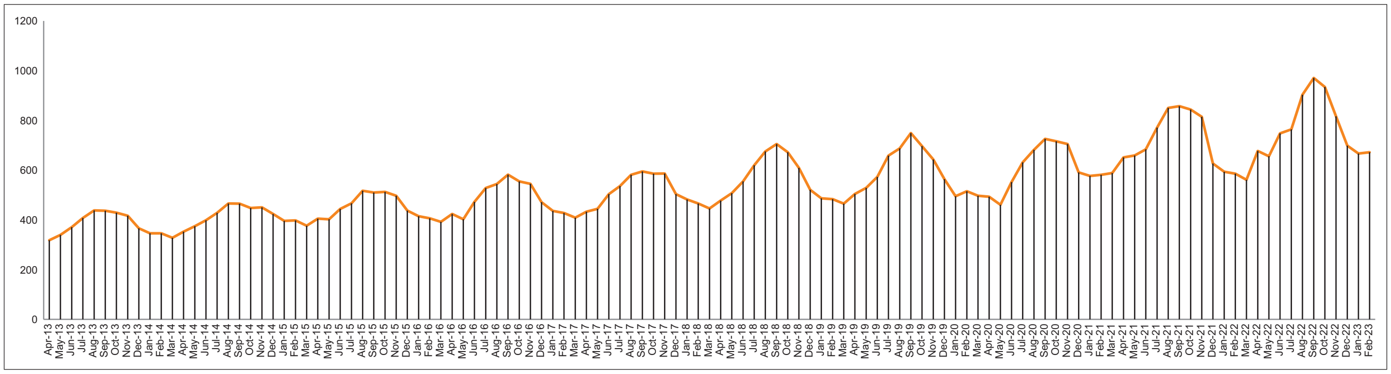
Table 2: The seasonal stationary test monthly electricity consumption in Assam

Frequency	LM statistic	Significance Level (1%)
$\pi/6$	0.187	0.748
$\pi/3$	0.126	0.748
$\pi/2$	0.080	0.748
$2\pi/3$	0.086	0.748
$5\pi/6$	0.333	0.748
π	0.222	0.748

Table 3: Model Statistics

Model	Stationary R Squared	Ljung-BoxQ (18)	d.f.	Sig
Monthly Electricity Consumption	0.726	13.479	14	0.489

Figure 1: Monthly electricity consumption in Assam



Source: The Assam Power Distribution Company Limited, O/O: The chief general manager (Commercial and& Energy Efficiency)

Figure 2: ACF and PACF of the residuals of SARIMA (1,1,1) $(1,0,1)_{12}$ model

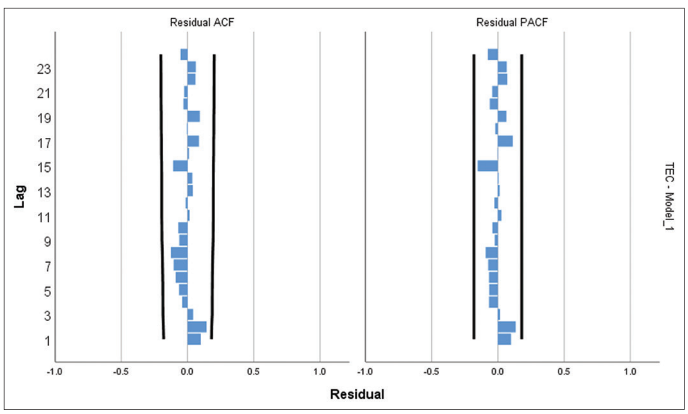
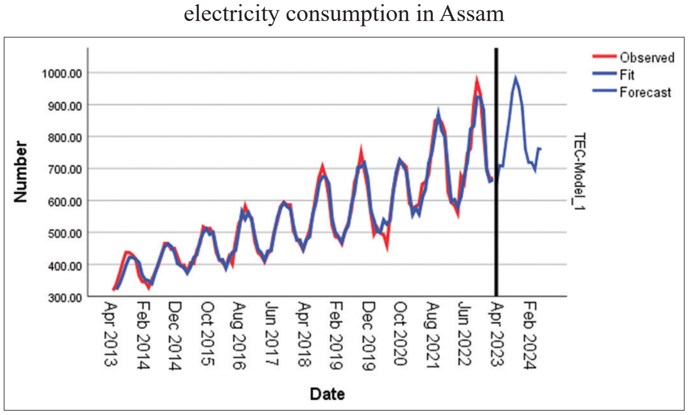


Figure 3: Fitted SARIMA (1,1,1) $(1,0,1)_{12}$ model for the monthly electricity consumption in Assam



differences. Next to find the seasonal difference of the series, Canova Hansen (CH) test is applied. This test was developed by Canova and Hansen in order to test the null hypothesis of no unit roots at seasonal frequencies against the alternative of a unit root at either a single seasonal frequency or a set of seasonal frequencies and the test is based on Lagrange Multiplier (LM) statistic (Canova and Hansen, 1995). The result of CH test is presented in Table 2.

Following the results of Canova Hansen test, it is clear from Table 2 that no seasonal differencing is required for our monthly time series data. The next step is to determine the order p, q and P, Q of AR and MA process. For this purpose, model selection criteria namely Akaike Information Criterion (AIC) is used with the help of EViews 12 software and by considering AIC value (Given in Appendix Table 1), SARIMA $(1,1,1)(1,0,1)_{12}$ model is selected. The further analysis of model statistics, estimation of model parameters which are represented in Table 3 and 4 respectively and fitting are done by using SPSS.

The autocorrelation and partial autocorrelation function plots of the residual of SARIMA (1,1,1) $(1,0,1)_{12}$ model is represented in Figure 2.

From Figure 2, it is clear that the residuals are white noise since almost all the autocorrelation and partial autocorrelation coefficients are small and within the required bounds. For testing for the absence of serial autocorrelation up to a specified lag k i.e., to test whether the residuals are independent and identically distributed or not, the Ljung Box (Ljung and Box, 1978) test is used. By comparing the value of the Ljung-Box statistic from table 3 which is 13.479 for 14 d.f. with the corresponding chi-square (χ^2) value 23.685, we may infer that the correlations are not significant and hence the residuals are white noise. Also, to find the accuracy of the model, when Mean Absolute Percentage Error (MAPE) is calculated from the table 2 given in appendix, it is found to be only 3.12%, which shows the effectiveness of the model. Therefore, we can apply the considered SARIMA model for forecasting of monthly electricity consumption in Assam. The forecasted values for the next 12 months are represented in Table 5 along with the fitted and forecasted values in Figure 3.

Table 4: SARIMA model parameters

Model	Estimate	Sig
Monthly Electricity Consumption		
Constant	0.006	0.000
AR (lag1)	0.726	0.000
Difference	1	0.000
MA (lag1)	1.00	0.000
AR, Seasonal (lag 1)	0.993	0.000
MA, Seasonal (lag1)	0.758	0.000

Table 5: Forecasting of SARIMA (1,1,1) (1,0,1) 12 model

Month	Forecasted figure
Mar 2023	649.43
Apr 2023	709.78
May 2023	707.41
Jun 2023	783.72
Jul 2023	853.68
Aug 2023	938.76
Sep 2023	980.61
Oct 2023	950.87
Nov 2023	895.67
Dec 2023	760.43
Jan 2024	718.60
Feb 2024	718.60

6. CONCLUSION

In this study, forecasting of monthly electricity consumption in Assam has been done with the help of SARIMA model. By analyzing the results of SARIMA, it is found by the application of Augmented Dickey Fuller test that the series is stationary at first order difference and Canova Hansen seasonal unit root test reveals that no seasonal differencing is required. Considering the values of model diagnostic criterion - Akaike Information Criterion (AIC), the chosen SARIMA model for our monthly time series data is found as $(1,1,1)\ (1,0,1)_{12}$. Also, when model statistics and residual ACF and PACF plots of the chosen $(1,1,1)\ (1,0,1)_{12}$ are analyzed it is observed that the model can be effectively used for forecasting purpose. The forecasted figures for monthly electricity consumption in Assam shows an increasing trend from April to September. Due to non-availability of monthly consumption data beyond February, 2023 we have not been able to compare the forecasted figure with the actual one. But the lower MAPE which is only 3.12% and analysis of model parameters and residuals of SARIMA $(1,1,1)\ (1,0,1)_{12}$ show the adequacy of the model. It is observed that in Assam the temperature increases from the month of April and due to heavy rainfall in June and July it goes down a bit and in August and September it reaches its peak.

The peak hours demand is also very high and the problem of load shedding and low voltage also become serious during these months every year in Assam due to demand deficit of electricity. To meet this increasing demand of electricity, the renewable energy can play an important role along with the conventional sources. Though India has been able to play a leadership role globally by witnessing a major transformation in the energy mix from conventional to renewable sources, the position of Nort-Eastern region is not satisfactory in comparison to the Southern, Western and Northern regions of the country. Among the North Eastern states, Assam has the highest potential in solar energy followed by Bio-Energy and Small Hydropower (SHP). But the thermal sector is playing the major role in meeting the electricity needs of the state due to the insufficient growth in the renewable energy sector. Therefore, it is expected that the Government of Assam in collaboration with Central Government, the Ministry of New and Renewable Energy (MNRE) and other state nodal agencies would gain success to achieve their targeted goal in renewable energy generation by 2030 to become a self-sufficient state in power generation for attaining sustainable development goal-7.

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APPENDIX

Appendix Table 1: Values of model diagnostic criteria of SARIMA

Model	AIC	Model	AIC	Model	AIC
(1,1,1) (1,0,1)	−3.391263	(2,1,3) (2,0,2)	−3.335713	(1,1,3) (2,0,0)	−3.229341
(4,1,1) (1,0,1)	−3.382556	(3,1,4) (2,0,1)	−3.335479	(3,1,1) (2,0,0)	−3.229211
(1,1,1) (1,0,2)	−3.376418	(4,1,4) (2,0,1)	−3.334718	(3,1,0) (1,0,2)	−3.227707
(1,1,1) (2,0,1)	−3.375416	(1,1,4) (2,0,2)	−3.333770	(2,1,4) (1,0,0)	−3.226942
(2,1,1) (1,0,1)	−3.374773	(3,1,4) (2,0,2)	−3.332931	(3,1,0) (2,0,1)	−3.226661
(1,1,2) (1,0,1)	−3.374654	(4,1,3) (2,0,1)	−3.330089	(3,1,2) (2,0,0)	−3.224495
(2,1,2) (1,0,1)	−3.372682	(0,1,4) (1,0,2)	−3.326633	(3,1,0) (2,0,2)	−3.221385
(1,1,1) (2,0,2)	−3.370267	(0,1,4) (2,0,1)	−3.325753	(3,1,1) (2,0,2)	−3.220356
(3,1,1) (1,0,1)	−3.369736	(4,1,2) (2,0,2)	−3.324779	(3,1,3) (2,0,0)	−3.217131
(1,1,3) (1,0,1)	−3.367224	(0,1,4) (2,0,2)	−3.322866	(4,1,2) (2,0,0)	−3.216655
(3,1,3) (1,0,1)	−3.362365	(4,1,3) (1,0,2)	−3.302211	(4,1,1) (2,0,1)	−3.216339
(2,1,1) (1,0,2)	−3.359896	(0,1,3) (1,0,1)	−3.294724	(2,1,4) (2,0,0)	−3.216094
(4,1,1) (1,0,1)	−3.359108	(4,1,4) (1,0,0)	−3.279669	(4,1,0) (1,0,2)	−3.214693
(2,1,1) (2,0,1)	−3.358892	(4,1,4) (1,0,2)	−3.278244	(2,1,3) (2,0,1)	−3.213878
(1,1,2) (2,0,1)	−3.358781	(0,1,3) (1,0,2)	−3.277957	(4,1,0) (2,0,1)	−3.213748
(3,1,2) (1,0,1)	−3.357945	(0,1,3) (2,0,1)	−3.277860	(2,1,3) (1,0,0)	−3.211823
(2,1,2) (1,0,2)	−3.357402	(0,1,3) (2,0,2)	−3.274010	(4,1,0) (2,0,2)	−3.208625
(2,1,3) (1,0,1)	−3.357273	(0,1,1) (1,0,1)	−3.273719	(3,1,4) (2,0,0)	−3.200596
(4,1,2) (1,0,1)	−3.356864	(1,1,0) (1,0,1)	−3.271888	(2,1,4) (0,0,1)	−3.195381
(2,1,3) (1,0,2)	−3.356821	(0,1,0) (1,0,1)	−3.263640	(2,1,4) (2,0,2)	−3.193943
(3,1,3) (2,0,1)	−3.354450	(3,1,3) (0,0,1)	−3.262911	(4,1,1) (1,0,0)	−3.193544
(2,1,1) (2,0,2)	−3.353960	(3,1,3) (0,0,2)	−3.261621	(2,1,4) (0,0,2)	−3.189422
(2,1,4) (1,0,1)	−3.353339	(3,1,4) (0,0,1)	−3.260199	(3,1,4) (1,0,0)	−3.189387
(1,1,3) (1,0,2)	−3.353162	(0,1,1) (1,0,2)	−3.259294	(4,1,2) (1,0,0)	−3.186881
(3,1,3) (1,0,2)	−3.352441	(1,1,0) (1,0,2)	−3.258010	(0,1,4) (2,0,0)	−3.178109
(1,1,4) (1,0,1)	−3.352113	(0,1,1) (2,0,1)	−3.258000	(4,1,3) (1,0,0)	−3.175958
(1,1,3) (2,0,1)	−3.351652	(0,1,2) (1,0,1)	−3.257791	(4,1,3) (0,0,2)	−3.163233
(3,1,4) (1,0,1)	−3.351649	(1,1,0) (2,0,1)	−3.256421	(1,1,4) (1,0,0)	−3.158924
(3,1,2) (2,0,2)	−3.51040	(2,1,0) (1,0,1)	−3.255951	(0,1,1) (2,0,0)	−3.156202
(1,1,2) (2,0,2)	−3.349289	(0,1,1) (2,0,2)	−3.252757	(1,1,0) (2,0,0)	−3.153802
(2,1,2) (2,0,2)	−3.348215	(1,1,0) (2,0,2)	−3.251627	(2,1,2) (1,0,0)	−3.139545
(3,1,3) (2,0,2)	−3.345900	(0,1,0) (1,0,2)	−3.250416	(2,1,0) (2,0,0)	−3.139496
(4,1,1) (1,0,2)	−3.344645	(0.1,0) (2,0,1)	−3.248720	(1,1,1) (2,0,0)	−3.139474
(2,1,2) (2,0,1)	−3.344329	(0,1,2) (1,0,2)	−3.242885	(0,1,2) (2,0,0)	−3.139445
(1,1,3) (2,0,2)	−3.343410	(3,1,0) (1,0,1)	−3.242663	(0,1,0) (2,0,0)	−3.138905
(4,1,2) (1,0,2)	−3.343173	(0,1,0) (2,0,2)	−3.242203	(2,1,3) (2,0,0)	−3.136236
(3,1,2) (1,0,2)	−3.342608	(0,1,2) (2,0,1)	−3.241841	(2,1,3) (0,0,2)	−3.126750
(4,1,1) (2,0,2)	−3.342152	(2,1,0) (1,0,2)	−3.241672	(1,1,4) (2,0,1)	−3.125861
(4,1,4) (2,0,2)	−3.341957	(1,1,2) (2,0,0)	−3.240466	(2,1,1) (2,0,0)	−3.122561
(3,1,2) (2,0,1)	−3.341815	(2,1,0) (2,0,1)	−3.240305		
(0,1,4) (1,0,1)	−3.341747	(0,1,2) (2,0,2)	−3.236178		
(4,1,2) (2,0,1)	−3.341407	(2,1,0) (2,0,2)	−3.235116		
(2,1,4) (1,0,2)	−3.339132	(4,1,1) (2,0,0)	−3.233913		
(2,1,4) (2,0,1)	−3.337685	(4,1,4) (2,0,0)	−3.230737		
(3,1,4) (1,0,2)	−3.335735	(4,1,0) (1,0,1)	−3.229863		

Appendix Table 2: Observed and predicted values of through SARIMA (1,1,1) (1,0,1) 12

Month	Observed	Predicted	Month	Observed	Predicted
Apr 2013	317.92		Jul 2016	527.60	503.57
May 2013	339.44	321.19	Aug 2016	544.41	564.60
JUN 2013	370.82	339.97	Sep 2016	581.61	541.46
Jul 2013	407.69	366.67	Oct 2016	554.19	561.76
Aug 2013	437.93	397.26	Nov 2016	544.82	538.94
Sep 2013	436.88	421.88	Dec 2016	470.88	487.90
Oct 2013	428.96	421.80	Jan 2017	436.20	446.21
Nov 2013	416.76	415.75	Feb 2017	427.18	436.33
Dec 2013	365.84	405.67	Mar 2017	408.79	412.87
Jan 2014	346.07	367.08	Apr 2017	432.95	441.56
Feb 2014	345.60	351.34	May 2017	444.59	442.67
Mar 2014	327.96	349.05	Jun 2017	503.15	496.39
Apr 2014	352.39	339.96	Jul 2017	535.56	545.71
May 2014	374.24	372.16	Aug 2017	580.79	576.08
Jun 2014	398.15	402.28	Sep 2017	594.59	591.65
Jul 2014	428.41	431.64	Oct 2017	585.57	580.40
Aug 2014	465.28	456.28	Nov 2017	586.07	574.53
Sep 2014	465.28	463.16	Dec 2017	503.53	520.15
Oct 2014	447.42	456.80	Jan 2018	482.18	475.42
Nov 2014	450.24	438.17	Feb 2018	465.57	476.35
Dec 2014	423.55	401.80	Mar 2018	445.70	447.78
Jan 2015	395.55	396.62	Apr 2018	477.60	477.33
Feb 2015	397.39	389.28	May 2018	506.91	485.97
Mar 2015	376.43	373.26	Jun 2018	554.55	559.18
Apr 2015	404.55	391.60	Jul 2018	619.40	594.59
May 2015	402.34	421.22	Aug 2018	674.79	654.73
Jun 2015	443.96	430.70	Sep 2018	704.99	674.28
Jul 2015	466.16	475.12	Oct 2018	671.59	672.20
Aug 2015	517.21	499.65	Nov 2018	609.06	651.43
Sep 2015	510.09	511.63	Dec 2018	520.61	541.76
Oct 2015	512.67	493.61	Jan 2019	486.46	499.46
Nov 2015	496.73	500.05	Feb 2019	483.14	486.66
Dec 2015	437.43	451.65	Mar 2019	464.85	469.36
Jan 2016	414.55	413.85	Apr 2019	504.16	502.54
Feb 2016	406.25	414.80	May 2019	528.35	521.64
Mar 2016	391.92	388.54	Jun 2019	572.68	586.73
Apr 2016	423.41	417.35	Jul 2019	658.25	627.49
May 2016	402.05	437.40	Aug 2019	687.15	703.52
Jun 2016	472.07	444.00	Sep 2019	748.94	705.12
Oct 2019	696.40	716.82	Jul 2021	770.87	751.41
Nov 2019	642.77	671.20	Aug 2021	849.96	813.39
Dec 2019	563.72	569.82	Sep 2021	857.14	869.36
Jan 2020	494.66	536.93	Oct 2021	843.18	819.63
Feb 2020	514.67	502.16	Nov 2021	814.02	798.98
Mar 2020	496.96	500.78	Dec 2021	626.43	695.91
Apr 2020	493.16	538.95	Jan 2022	593.62	597.99
May 2020	460.32	525.70	Feb 2022	585.32	602.69
Jun 2020	551.78	538.32	Mar 2022	561.04	579.93
Jul 2020	631.22	630.41	Apr 2022	676.70	610.11
Aug 2020	681.33	692.08	May 2022	655.83	673.56
Sep 2020	725.31	725.62	Jun 2022	747.62	720.90
Oct 2020	715.58	709.73	Jul 2022	763.63	823.39
Nov 2020	704.63	691.44	Aug 2022	902.71	832.83
Dec 2020	590.43	620.70	Sep 2022	970.36	923.55
Jan 2021	576.20	555.90	Oct 2022	934.26	921.81
Feb 2021	581.22	576.41	Nov 2022	815.90	882.73
Mar 2021	587.86	557.77	Dec 2022	698.28	694.67
Apr 2021	651.12	608.21	Jan 2023	666.48	659.85
May 2021	658.56	636.12	Feb 2023	671.58	664.82
Jun 2021	683.25	716.81			