International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-12, October 2019

SARIMA Modelling for Forecasting the Electricity Consumption of a Health Care Building

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***Abstract:** Healthcare buildings have an immense demand for electricity, because of which they exhibit distinctive ability for forecasting of electricity consumption. In this work, ability for forecasting electricity consumption of a large healthcare building was researched. Both the techniques change non-stationary data into stationary data to make an effective and simple data representation and removing of noise subspaces. The comparison of experimental results is done among the SARIMA and ARIMA models. Analysis of the results concludes that performance of SARIMA is better when compared to ARIMA model. The analysis of data from 11 years in the hospital demonstrates that these dynamic models are sufficiently adaptable to forecast the electricity consumption at required accuracy levels.*

***Keywords:** ARIMA model, SARIMA model, Electricity Consumption, Load forecasting, Electricity*

I. INTRODUCTION

Large buildings represent some of the large customers of electric energy. Forecasting the electricity consumption can give imperative data, for energy assessment inside a private utility and for effectiveness purposes, especially when medium and low voltage energy appropriation frameworks are considered [28]. Forecasting the electricity consumption is also called the electric load forecasting. Electric load forecasting is additionally beneficial to the electric utility's financial matters. Load consumption is a key and crucial data for power generation offices and merchants, particularly production planning, everyday operations, unit commitment [8], [26]. Load forecasting of electricity consumption is amongst the critical reason for power trading, water treatment and so on [9], [21], [22]. Electricity is thought to be the reason for the development of the society. It is considered as a significant tool for the technological progress and financial advancement of society. Optimizing its distribution is at present an intriguing issue of research [12].

Revised Manuscript Received on October 30, 2019.
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Lead time ranging between couple of minutes to several days is a fundamental tool in load forecasting to appropriately oversee buildings and facilities. The accurate forecasts will prompt control to unbalance on the system. This might be of awesome significance in small-scale grid configurations, generally expected in future power system [25]. Besides, if the workplace is a healthcare building, where consistent energy and power use is required, all the observations already recorded are enhanced and of a more noteworthy importance, due to a nonstop utilization of technical loads. A healthcare building can be characterized as an exceedingly complex association under a practical, innovative, financial, administrative and procedural point of view. A hospital facility can be contrasted with industry for the assortment and the kind of its capacities, and undertakings. The electric energy is the fundamental component of the activity of a hospital, so it must be estimated and overseen both under the specialized and financial viewpoints. As of the main issues identified with electrical energy utilization have accomplished extensive significance. The acquisition and legitimate utilization of electric energy are the crucial steps for any complex structure needing to come to the ideal level of energy management [14].The energy management system of a building is responsible for monitoring, analysing and maintaining the electrical energy consumption of the respective building. It also helps in wastage of the electrical energy and also creates opportunities for energy conservation. Analysing energy consumption patterns of the buildings is leads to efficient energy management system. This helps in understanding the operational behaviour of buildings under different conditions [22], [27].

Monthly forecast of electricity consumption is significant for the support and arrangement of the grid. In any case, various challenges are related with anticipating the month to month utilization patterns of electric energy frequently change because of macroeconomic conditions and social advancement. In this way, the information utilized for displaying must be gotten from a persistent number of years, amid which macroeconomic conditions may have differed somewhat [10]. In this paper the time series models used for electric load forecasting are SARIMA and ARIMA.

Time series analysis is observing the time sequence and then finding its change in trend, forecasting its future [20].Time series analysis technique becomes a very efficient method when we can't find the important factors that leads to data conversions, from many other factors [1]. Time series methods are the stationary processes, which mean that the mean and variance changes with time [15]. Conversion of the stationary time series data from non-stationary time series is the primary task [17].

We implemented the SARIMA model on the dataset of load consumption of the healthcare institution which allowed us to analyse the patterns of the electricity consumption data. This model is validated using the real dataset. The load consumption dataset is of 11 years of a healthcare building. In [28] ARIMA model was implemented on the dataset of healthcare building, which gave RMSE of 40021.25 and MAPE of 0.22.

II. LITERATURE REVIEW

The review includes the studies of time series forecasting with various forecasting horizons. The articles in electricity consumption forecasting are evaluated with parametric methods and non-parametric methods which also include comparative studies among each other. In [6], a forecasting model is proposed after the combination of the SARIMA model with the neural network. SARIMA models exhibits linearity and the component of randomness of the time series data are not considered. To avoid this, Genetic Programming can also be hybridized with the grey model for forecasting the energy time series[11] [20].

Fig.1 represents the comparative studies of various techniques for electric load forecasting reported worldwide in the respective literature till now. Phatchakorn Areekul et al. [16] in 2010 used ARIMA and neural network for electric load forecasting and build their hybrid model. They concluded that the hybrid model of ARIMA and neural network performed better than the individual models. Similarly, Ming Meng et al. [10] in 2011 compared neural network and grey model and concluded that grey model gave higher accuracy for forecasting electricity. Erasmo cadenas et al. [4] in 2012

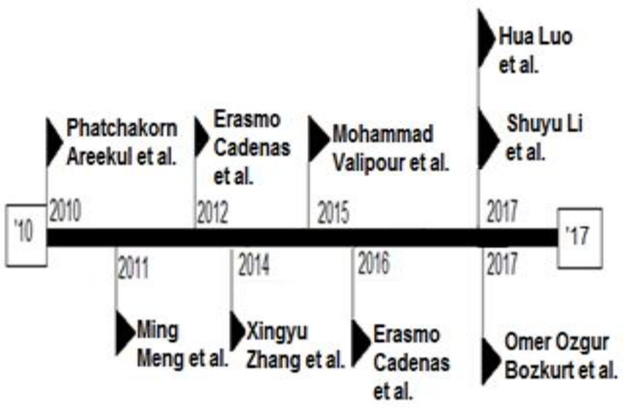

Fig.1 Baseline of the comparative studies of various techniques for electric load forecasting

compared SARIMA and regression-SARIMA from which it was concluded that SARIMA shows better results.

Xingyu Zhang et al. [2] in 2014 compared four time series models i.e., regression, exponential smoothening, ARIMA and SVM, from which it was concluded that SVM performed best. Mohammad Valipour [7] in 2015 compared SARIMA and ARIMA to each other, in which SARIMA showed the higher accuracy. Similarly, Shuyu Li et al. [18] in 2017 compared ARIMA, GM and ARIMA-GM model with each other, in which it was concluded that ARIMA-GM shows high accuracy. Hua Luo et al. [1] in 2017 proposed two hybrid models SARIMA-BP and SSVM. After comparing the two models, SSVM performed better. Erasmo Cadenas et al. [13] in 2016 compared univariate ARIMA model to multivariate NARX model, after which it was concluded that NARX model is performing better. Omer Ozgur Bozkurt et al. [8] in 2017 presented the comparative performances of the SARIMA and ANN. After which he concluded that ANN had better performance.

So, we discussed the comparative studies of techniques in various articles, and it can be observed that SARIMA and ARIMA models are widely used for electric load forecasting either in singular form or in the hybrid forms[6], [11],[19]. Similarly, in our paper we are presenting the analysis of electric load consumption using SARIMA model and comparing it with experimental results of ARIMA model. Analysis and forecasting of electricity consumption using ARIMA model is already done in our previous research article [28].

III. METHODOLOGY

A. Data Collection

In the present study, a healthcare building i.e. Apollo Hospital, Ludhiana, India is used for the contextual analysis. This hospital has large number of patients. The hospital has 350 beds, 80 ICU beds and 7 operating rooms. The hospital operates 7 days a week i.e. 24 hours a day. The electricity consumption data is taken from the database of the I.T department of the hospital. The data used for examination include 132 months, from April 2005 until February 2016.The data analysis has been done in python language.

B. Forecasting Models

In this study two forecasting models are discussed: 1. ARIMA model 2. SARIMA model. SARIMA and ARIMA models are also called the parametric methods, which are used while dealing with non-stationary time series. Here, we introduce stochastic approaches, given by SARIMA and ARIMA. SARIMA proves to be superior to ARIMA, and gives focused outcomes as far as forecasting accuracy is concerned.

- **Fundamentals of ARIMA modeling**

ARIMA model is implemented in this study since it permits a more profound comprehension of the data and can be used to build forecasting model. Initially, the time series is checked for stationarity.

The ARIMA model parameters are differentiation order (d), the autoregressive order (p), and the moving average order (q). The ARIMA equation is as follows:

$$x_t=A+\varphi_1x_{t-1}+\varphi_2x_{t-2}+\ldots+\varphi_px_{t-p}+b_t-\theta_1b_{t-1}-\theta_2b_{t-2}-\ldots-\theta_qb_{t-q} \quad (1)$$

where x_t is the observation's value, t is the time, φ_i is autoregressive parameter order, θ_j is moving average parameter order and b_t is error value.

- **Fundamentals of SARIMA modelling**

Seasonal Autoregressive Integrated Moving Average (SARIMA) is a stochastic linear model used for modeling of seasonal time series.

SARIMA (p, d, q) (P, D, Q):

$$(1-\Phi_1B^{\omega}-\Phi_2B^{2\omega}-\cdot\cdot\cdot-\Phi_PB^{P\omega})\times(1-\varphi_1B-\varphi_2B^2-\cdot\cdot\cdot-\varphi_pB^p)\times(1-B^{\omega})^D(1-B)^dQn(t)=(1-\Theta_1B^{\omega}-\Theta_2B^{2\omega}-\cdot\cdot\cdot-\Theta_QB^{Q\omega})\times(1-\theta_1B-\theta_2B^2-\cdot\cdot\cdot-\theta_qB^q)e(t) \quad (2)$$

Φ is non-seasonal parameter of autoregression and θ is non-seasonal parameter of movingaverage, Φ is seasonal parameter of autoregression and Θ is seasonal parameter of moving average, ω is frequency and B is the differential variable.

Python language is used to identify the SARIMA models. The construction of the models by means of Box-Jenkins procedure [3], [5] has the following steps:

1. Checking for stationarity of the given time series data.
2. Identification of the tentative model.
3. Parameter estimation of the tentative model.
4. Checking the adequacy of the model. If not adequate, then go to step 2.
5. Use the model for forecasting.

- **Evaluation of the model**

For comparing the models, Akaike Information Criterion (AIC) is used. The t-test and the chi-square test are calculated to examine the null hypothesis of the parameters.

IV. FINDINGS

The data used is collected from April 2005 to February 2016. Fig.2. shows the original data through which the patterns in data can be examined. Fig.3. shows that there is a regular seasonal pattern in the data over time, exhibiting the trend.

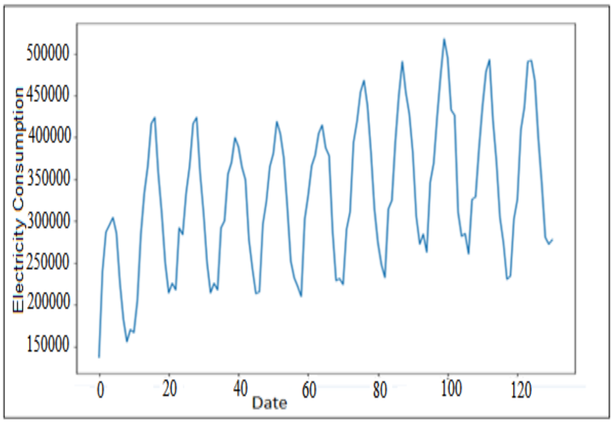

Fig.2 Line plot of the original time series.

Seasonality is represented by the seasonal component at time t. When a time series is influenced by seasonal factors there exists a seasonal pattern. Residual component describes the random or irregular influences at time t.

Non-Stationary time series data has statistical properties, which change with time. So, its required to change the data in stationary time series data by finding the first difference of the time series, before building the predictive model.

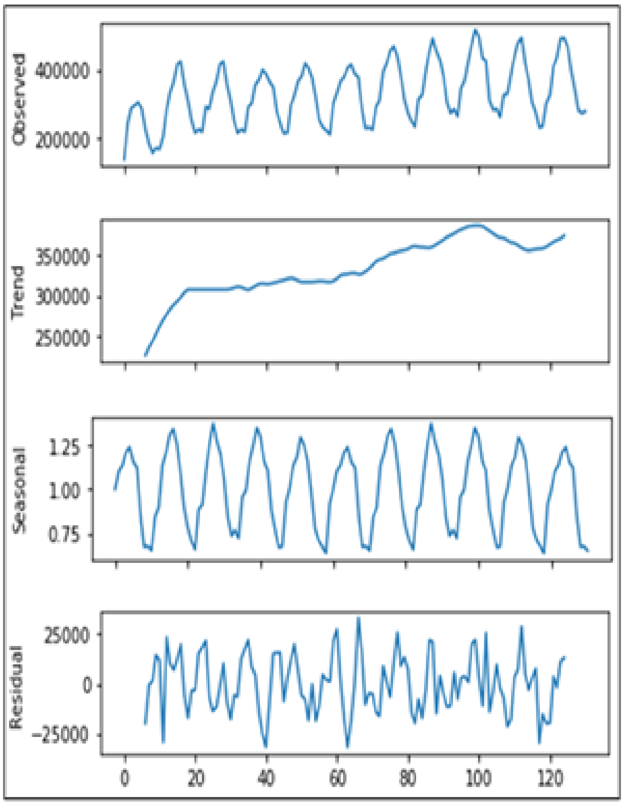

Fig.3 Decomposed time series

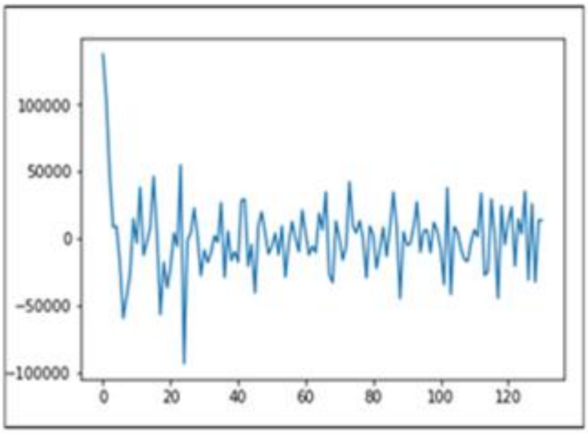

Fig.4 Stationary time series

A. Results of ARIMA model

In [28] ARIMA model is forecasting the future electricity consumption of the health care building. Firstly, The seasonal effects are identified and then removed. Fig.5 shows the graph of seasonal data

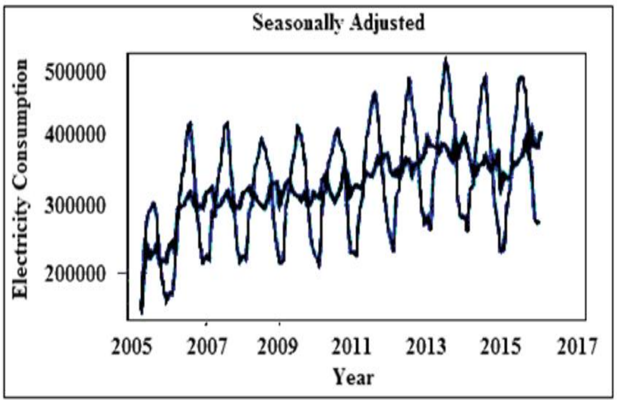

Fig.5 Line plot of seasonal time series [28].

The parameter estimation of the forecasting model is done by conditional least square estimation method. Finally, this forecasting model generates the forecasts. Fig.6 shows the actual data and forecasted data generated by the forecasting ARIMA model.

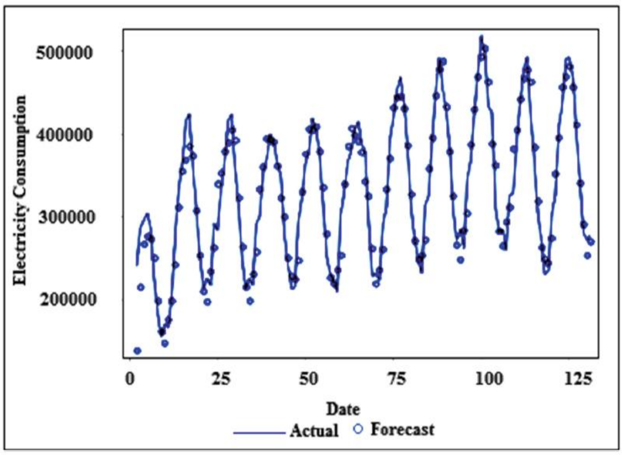

Fig.6 Actual and Forecasted Plot of ARIMA model [28]

B. Results of the SARIMA model

According to the Box – Jenkins Procedure, ACF and PACF plots candidate models can be constructed. In this study, eighteen candidate models are generated.

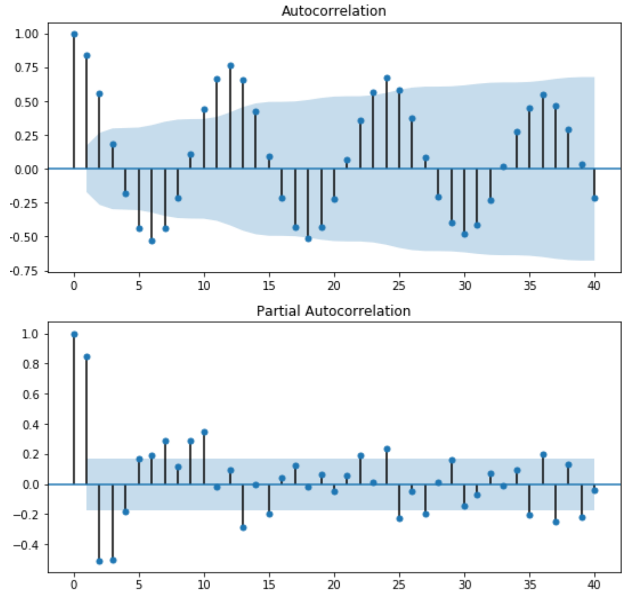

Fig.7Autocorrelation and Partial autocorrelation Plot

Fig.7 shows the autocorrelation and partial autocorrelation plot of stationary time series. After fitting the candidate models to the data, these models are analysed to check which models are adequate and can perform well.

Hence, SARIMA (0, 1, 0) (0, 1, 1)$_{12}$, was selected as the best fitting model because it had the lowest AIC value. Table 1. represents the candidate SARIMA models having significant coefficients.

MODEL TYPE	AR		MA		CHI SQUARE	P	AIC
	LAG	T	LAG	T			
SARIMA(0,0,1)(0,1,0)$_{12}$	1	24.5	0	12.6	13.5	0.046	2208
SARIMA(0,0,1)(0,1,1)$_{12}$	1	36.8	1	16.4	11.7	0.034	2154
SARIMA(1,0,1)(1,1,0)$_{12}$	1	28.3	1	14.9	15.4	0.026	2805
SARIMA(0,1,0)(0,1,1)$_{12}$	1	23.7	1	17.5	18.3	0.046	1637
SARIMA(1,0,0)(0,1,0)$_{12}$	1	24.5	1	12.6	16.8	0.037	1972
SARIMA(1,0,0)(1,1,1)$_{12}$	1	33.5	1	18.7	22.5	0.029	2268

Table.1 Candidate SARIMA models

This study compares SARIMA and ARIMA for forecasting the electricity consumption in a health care building. The data used for analysis include 132 months.

Fig.8 shows the actual data and forecasted data generated by the forecasting SARIMA model.

The forecasting model generated the good empirical results as the forecasted data is very close to the original data. The values of MAPE and RMSE for both forecasting models are shown in Table.2.

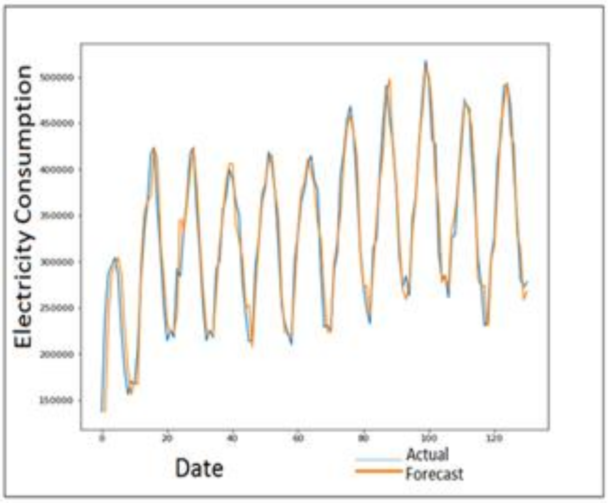

Fig.8 Actual and Forecasted Plot of SARIMA model

	SARIMA(0,1,0)(0,1,1)$_{12}$	ARIMA(2,1,3)
MAPE	0.15	0.24
RMSE	31603.15	40021.25

Table.2 Accuracy of the models

Hence, it can be concluded that SARIMA model is better than ARIMA model for forecasting the electricity consumption in terms of accuracy, since its MAPE and RMSE values are less than ARIMA model.

V. CONCLUSION

The dynamics of ARIMA and SARIMA models were analysed. The models were constructed by using historical dataset of electricity consumption of 11 years of Apollo hospital. By analysing the accuracy of the forecasts using RMSE, MAPE, a comparative analysis of SARIMA and ARIMA model is done. A certain reduction in prediction error has been observed after implementing SARIMA model on the same dataset as compared to previous study using ARIMA. It has been concluded after observing the dynamics of both the models in the building, the performance of SARIMA proved to be better than ARIMA model.

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