

Electricity Demand Forecast of College of Science and Technology, Royal University of Bhutan by 2030

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Abstract

Increase in the number of students and staff in the campus has led to increase in the consumption of electricity from the grid. It is important to have reliable electricity plan to meet the future needs and to become self-sufficient. This paper presents a forecast of the electricity demand of the College of Science and Technology until 2030. The historical electricity consumption data from January 2014 until December 2018 was used for the forecast. The future electricity consumption was forecasted using Autoregressive Integrated Moving Average (ARIMA) model in XLSTAT. ARIMA was specified by three order parameters (p, d, q). To identify the model of ARIMA, the autocorrelation function (ACF), and partial autocorrelation function (PACF) were used. The efficiency of the model was checked using root mean square error (RMSE), mean square error (MSE), and the sum of square error (SSE). The forecast was also validated using the best fit comparison of raw data with the predicted data. The total electricity consumption of the college is forecast to increase from 1.09 MWh in 2018 to 5.75 MWh in 2030 with an average increase of 14.67 % per year. Similarly, electricity consumption in the staff residential zone is projected to increase from 166 MWh in 2018 to 295 MWh in 2030. In the case of student residential zone, the electricity consumption is forecast to increase from 273 MWh in 2018 to 361 MWh by 2030.

Keywords: Time series analysis, ARIMA model, electricity demand, demand forecasting.

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1. Introduction

Energy plays a very important role in the present developing human life (Ozturk & Ozturk, 2018). With the growth in population, their living standards due to the development in the technologies and industrialization eventually leads to an increase in the energy demand (Ozturk & Ozturk, 2018). Over the years, the intake of students at the College of Science and Technology (CST) has gradually increased along with the staff number. The increasing population in the campus has been accompanied by the construction of academic and residential infrastructure thereby increasing the electricity demand too. Between 2014 and 2018, the number of students and staff has increased with an annual average rate of 5.46% and 4.03% respectively. CST currently offers undergraduate degree programmes in Architecture, Civil, Electrical, Electronics & Communication, Information Technology, Engineering Geology, Instrumentation & Control, and Master of Engineering in Renewable Energy. Currently, the college has more than 1000 students and staff. In the next ten years, a few more programmes are likely to be introduced in the college along with an increased number of students and staff simultaneously. With the launching of new programmes, the student number will increase and subsequently electricity demand. Therefore, it is prudent for the college to forecast the electricity demand to ensure reliable and sustainable energy security in the future. Thus, this paper presents the total historical electricity consumption of CST and forecast its expected alterations until 2030.

2. Forecast

According to Fattah, Ezzine, Aman, Moussami, & Lachhab (2018), forecasting is the process of making an assumption about the future value of studied variables. The forecasting model has been classified into different time frames by different authors. Feinberg & Genethliou (2005) has categorized the load forecast into three categories: short-term, medium-term, and long-term forecast. The short-term forecast covers the time duration of one hour to one week. The medium-term forecast covers a time duration of one week to one year and long-term forecasting covers a time duration of more than a year. Forecasting has also been classified as very short term forecasting (1-7 days ahead), short-term forecasting (1-4 weeks ahead), medium-term forecasting (1-12 months), and long-term forecasting (1-20 years)(Elkarmi & Shikhah, 2016).

Debnath & Mourshed (2018) have used different methods for forecasting electricity demand, stand-alone method, and hybrid method. The stand-alone method consists of a single method whereas the hybrid method consists of the combination of more than one stand-alone method. Stand-alone is further classified into statistical, computational intelligence, and mathematical programming. McSharry, Menezes & Taylor (2006) compared four methods, multiplicative seasonal autoregressive integrated moving average, exponential smoothing, artificial neural network, and principal component analysis (PCA) approach for the forecasting electricity demand up to a day ahead. The hourly demand of electricity of Rio de Janeiro and half-hourly electricity demand of England and

Wales for 30 weeks of data were used. Mean absolute percentage error (MAPE) was used to measure the accuracy of the forecasting. The artificial neural network gave relatively poor performance compared to the other three methods. For England and Wales data, the PCA method was found to be more accurate but the overall exponential smoothing method gave better results for both types of time series (J. W. Taylor et al., 2006).

Li et al (2020) worked on a fresh strategy to forecast next-day total electricity usage and peak demand of group of building using cluster analysis, Cubist regression models and Particle Swarm Optimization method. The strategy was validated by using electricity consumption data of 40 buildings inside a university campus. To evaluate the difference in the results of measured and predicted, coefficient of variation of root mean square error CVRMSE and mean absolute percentage error (MAPE) were used. For daily electricity consumption, the difference between the measured and predicted values was 3.3% in MAPE and 4.7% in CVRMSE and for daily peak load the difference between the measured and predicted values was 5.3% in MAPE and 6% in CVRMSE.

Taylor (2013) used one-year electric load and weather data to predict using a knowledge-based expert approach, multiple linear regression, stochastic time series, general exponential smoothing, state-space method, and artificial neural network. Among the above-mentioned methods, the artificial neural network was used to forecast the short-time electric load (24 hours) of Oak Ridge National Laboratory, United States Department of Energy. The mean absolute error of 1% to 3% was considered acceptable since the weather predicted variables were considered 100% accurate which would likely cause an error in the final forecast of the load. Bhardwaj & Bansal (2011) used a single exponential smoothing method for forecasting the demand of electric power until 2023 using population data (1991 to 2001) and temperature (2001 to 2008) of Lucknow city, India. An error of +0.08 was found between the actual and the predicted load (2001 to 2008). It was concluded that there will be a huge power demand which was forecast to be about 2143 MVA by 2023.

Sen, Pal, & Roy (2016) used autoregressive integrated moving average (ARIMA) to forecast energy consumption and greenhouse gas emission in pig iron manufacturing organization in India. Monthly data for energy consumption and greenhouse gas emission from the year 2002 to 2013 was used for the forecast. This forecast was used to propose preventive measures in advance to provide improved environmental performance by the organization. The best ARIMA model was selected based on the lowest values of Akaike Information Criterion, and Schwarz Bayesian Information Criterion generated by different competitive ARIMA model. Based on the above two criteria ARIMA (1,0,0)×(0,1,1) was selected as the best model for the forecasting of energy consumption and ARIMA (0,1,4)×(0,1,1) for the forecasting of greenhouse gas emission. The residue of the autocorrelation function and partial autocorrelation of the competing ARIMA model was also accounted for the selection of the best model for green-house gas emission (Sen, Roy, & Pal, 2016).

Chujai, Kerdprasop, & Kerdprasop (2013) used R and R studio to model the ARIMA and Auto-Regressive Moving Average (ARMA) for analysing the best model for forecasting household electricity consumption and to find the most fitting forecasting period (daily, weekly, monthly, or quarterly). The authors used four years individual household consumption data. For the forecasting periods in monthly and quarterly, the ARIMA model was found to have higher accuracy and for the forecasting periods in daily and weekly ARMA model was found to have higher accuracy (Chujai, Kerdprasop, & Kerdprasop, 2013).

Ho & Xie discusses a comparative study in forecasting failure of the mechanical system using Duane model and ARIMA models. To evaluate the accuracy of models, mean absolute deviation (MAD) was used, the lower value the better accuracy. ARIMA model had a MAD of 4.1 compared to the MAD of 53.4 of Duane model. Due to valuable information being lost in Duane model, ARIMA model was concluded to be more preferable for modeling the failure pattern of any system. Using the ARIMA model the authors could even explore the correlation between the failure data and obtain better estimation (Ho & Xie, 1998).

The performance of three different methods, ARIMA, ANN, and multiple linear regression (MLR) was used to forecast electricity demand in Thailand (Kandananond, 2011) using historical data from the year 1986 to 2010. ANN with a MAPE of 0.996% outperformed ARIMA with a MAPE of 2.81% and MLR with MAPE of 3.26%. They further concluded that due to their simple structure and competitive performance, ARIMA and MLR might be more preferable than ANN (Kandananond, 2011).

Oliveira & Oliveira (2018) did a comparative analysis of forecasting of mid and long-term electricity consumption up to two years ahead for different developed and developing countries. The authors used monthly historical data from 2006 to 2014 as model inputs. By assessing Theil Inequality Coefficient (TIC), symmetrical MAPE, RMSE, and MAPE of the predicted data, the authors concluded that ARIMA gave better performance for Brazilian and Mexican cases whereas the exponential smoothing method gave a better performance in developed countries (de Oliveira & Oliveira, 2018). According to Pai & Chih-Sheng (2004), for forecasting in time series, the ARIMA has been the most popularly used method and was used by several authors in the past to forecast electricity demand (Chujai et al., 2013; de Oliveira & Oliveira, 2018; Ho & Xie, 1998; Sen et al., 2016; Shilpa & Sheshadri, 2017). This paper also adopted the ARIMA model to forecast electricity demand of CST until 2030.

ARIMA model can be performed in different statistical software such as MINITAB (EI Desouky & EI Kateb, 2000) and R and R studio (Chujai et al., 2013). Minitab takes into consideration two things while fitting a time

series model. The first is the past value, which is used in AR models, and secondly, it looks at past prediction error which is the MA model. In time-series data modulating using R package three steps are followed: exploratory analysis, fit the model, and diagnostic measures. The user has to be familiar with R syntax. The load forecast using the ARIMA model in MATLAB, MINITAB, Statistical Analysis System (SAS), and the R package involves several coding. Whereas, XLSTAT extends Excel to an efficient and easily accessible statistics that covers most of the functions needed for the analysis in the modeling of data. The XLSTAT software automatically integrates itself into the Microsoft Excel user interface (STATCON, 2019).

3. Methodology

ARIMA model was used to forecast the electricity demand of CST which is run in the excel using the XLSTAT add-on statistical software. XLSTAT is a statistical add-on software that is integrated as a complement of Microsoft Excel as it has more analysis capabilities. ARIMA is one of the subcategories in the XLSTAT which describes the phenomena that evolve through time and predict the future value. The electricity consumption data for the last five years (2014-2018) was used to predict future demand which was categorized into three zones that is, student and staff residential, and academic. The academic zone includes the administration building, laboratories, and the library. The student residential zone consists of the hostels and the student mess and the consumption from the staff residential buildings categorized as staff zone.

4. Results and Discussion

The historical electricity consumption data of CST was used to forecast its electricity consumption until 2030.

4.1 Student Residential Zone

The number of students on the campus is increasing at a rate of 5.46% annually. With the increase in the number of students, the number and variety of electrical devices also increase thereby increasing the consumption of electricity. However, the actual electricity consumption is also dependent on the efficiency of the appliances being used.

ARIMA model (0, 1, 1) was used to forecast electricity demand in student residential zone as this model provides a stable result. Validation is important to check the reliability of the forecasted model and see how the model has simulated the actual data (Nyatumame & Agodzo, 2018). The predicted data obtained from the ARIMA for the year 2018 was validated with the measured value for the same year in Figure 1. The predicted data series doesn't vary much as compared to the measured data series. The predicted electricity consumption agrees well with the measured value with a correlation coefficient of 0.9994, root mean square error of 0.1244kWh, and mean bias error of 0.0734 kWh. The dip during the July month is due to the students being on vacation.

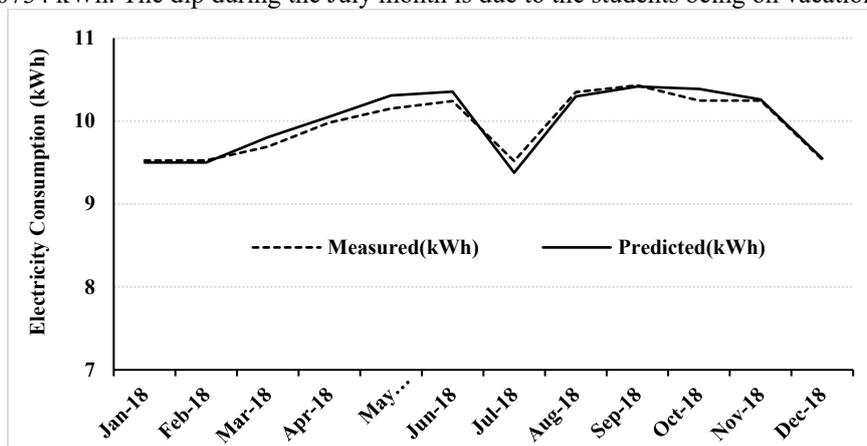


Figure 1. Measured and predicted electricity consumption of student residential zone

Figures 2 and 3 show the ARIMA model forecast of electricity demand for the next ten years. The series fluctuates within the set boundaries and hence shows the stationarity of the data. The normality of the residual's distribution is essential in producing a reasonable confidence interval for the forecast. A constant variance in a residual is said to be homoscedastic. Homoscedasticity refers to a model's ability to predict variables consistently whereas a heteroscedastic residual doesn't provide reliable predictions.

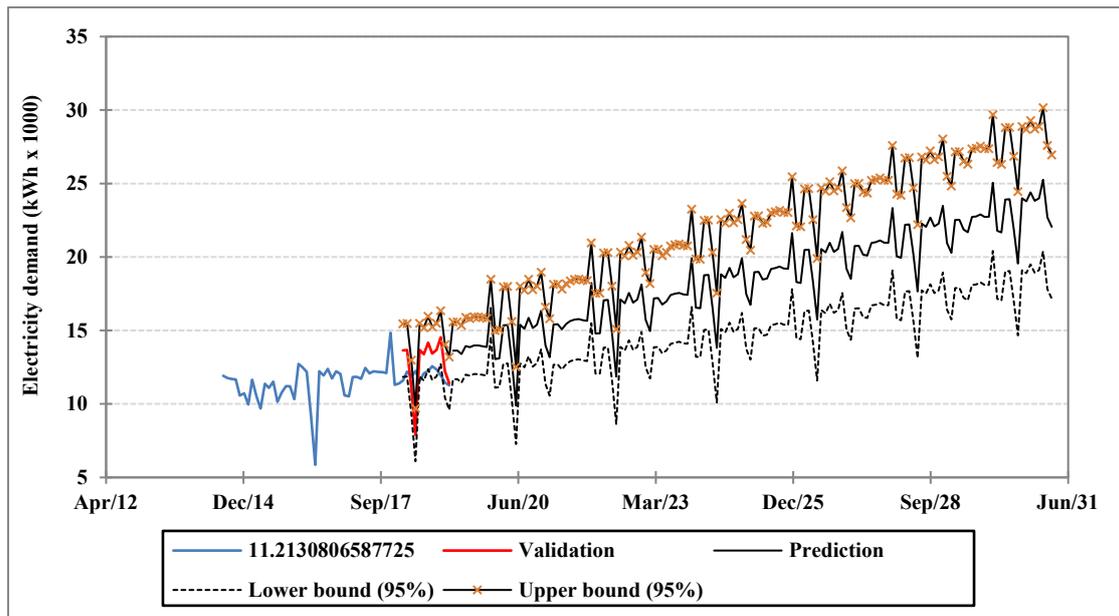


Figure 2. ARIMA forecast of electricity demand for student residential zone

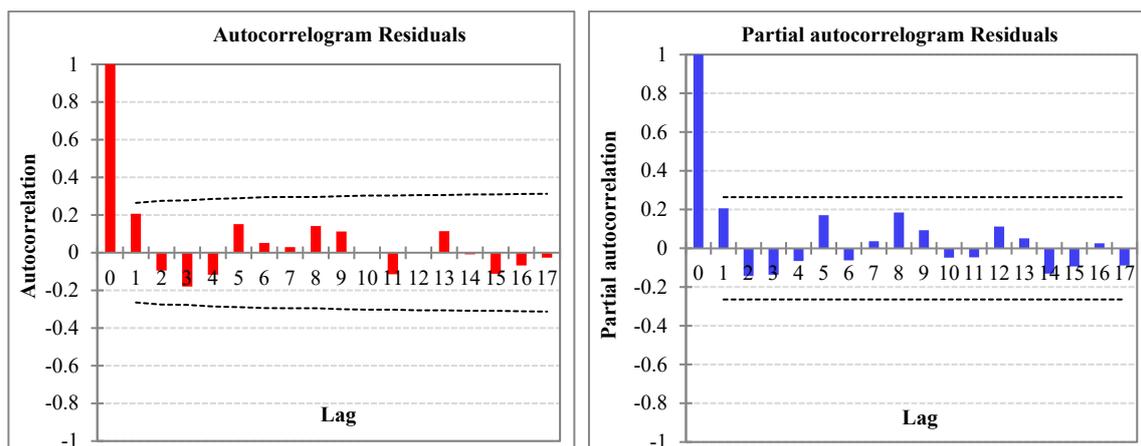


Figure 3. ACF and PACF of electricity demand for student residential zone

4.2 Staff Residential Zone

The population of staff is annually increasing with a rate of 4%. The trend of the measured data shows that there is a linear increase though the rise is very few in numbers. The ARIMA model (0, 1, 1) was used for the forecasting of staff residential zone. The predicted data obtained from the ARIMA for the year 2018 was validated with the measured value for the same year. As shown in Figure 4 the predicted electricity consumption agrees well with the measured value with a correlation coefficient of 0.8636, root mean square error of 0.0934 kWh, and mean bias error of 0.0544 kWh.

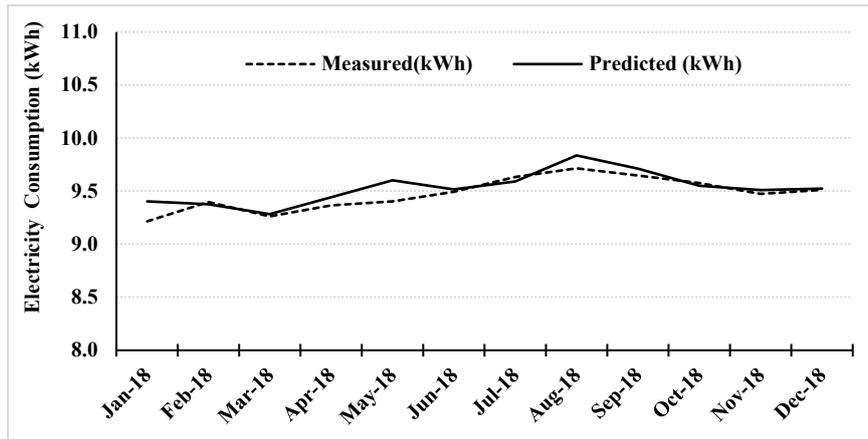


Figure 4. Measured and predicted electricity consumption of staff residential zone

Figure 5 shows the ARIMA forecast of electricity demand and the forecast path indicating a linear slope between both of the limiting bounds adds to further validation. The graphs include the measured, validated, and predicted data series where the predicted data series lies within the 95% confidence interval. Figure 6 shows the ACF and PACF residual of the model for electricity demand. The confidence interval for the forecast is maintained by the normal residual distribution illustrated in Figure 6

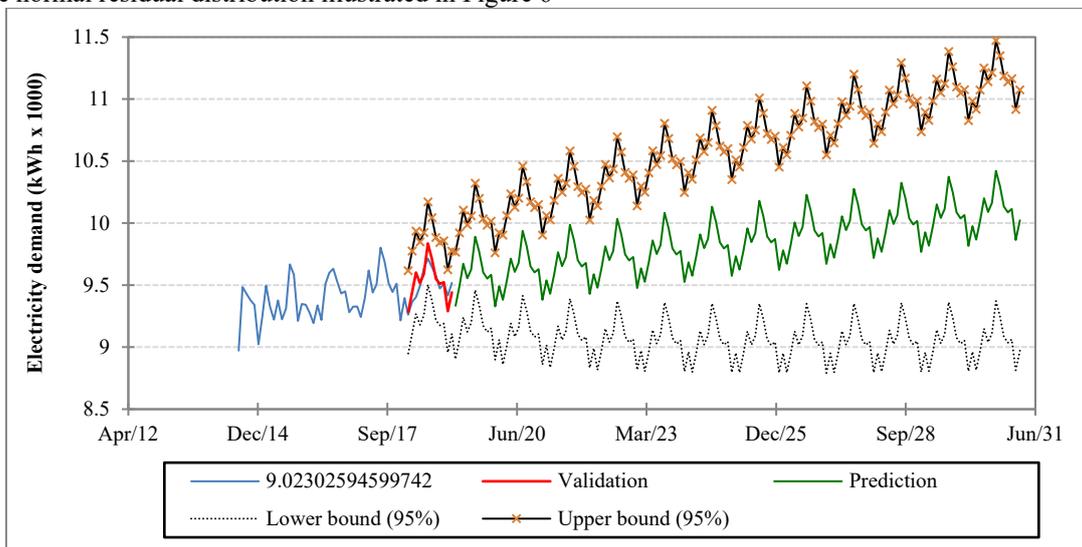


Figure 5. ARIMA forecast of electricity demand for staff residential zone

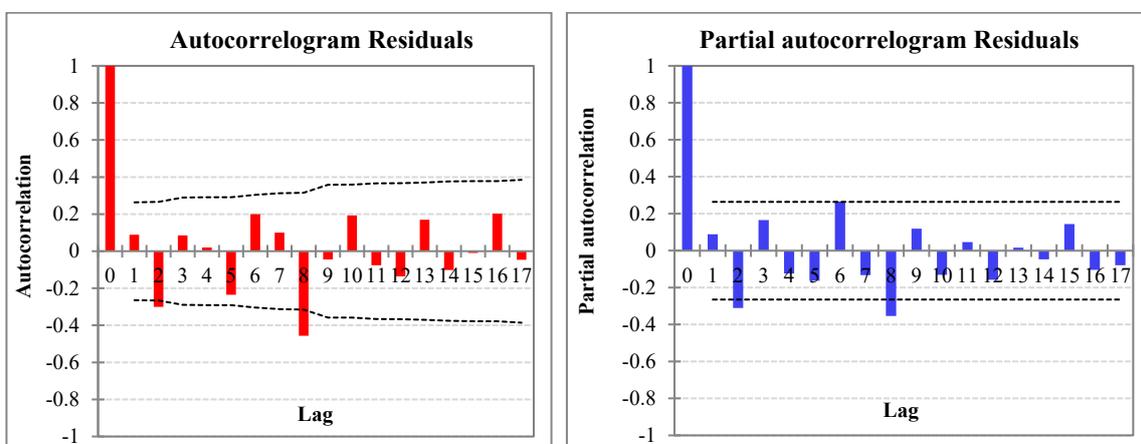


Figure 6. ACF and PACF of electricity demand for staff residential zone

4.3 Academic Zone

In the academic zone, the electricity demand depends upon the number of buildings, laboratory facilities and

equipment used. Over the past five years, the academic infrastructures have not increased except for the new library building. The usage of appliances may vary seasonally due to dynamic climate patterns in the region. The ARIMA model (0, 1, 1) was used for the forecasting electricity demand of academic zone. Figure 7 shows the validation output graph for the year 2018.

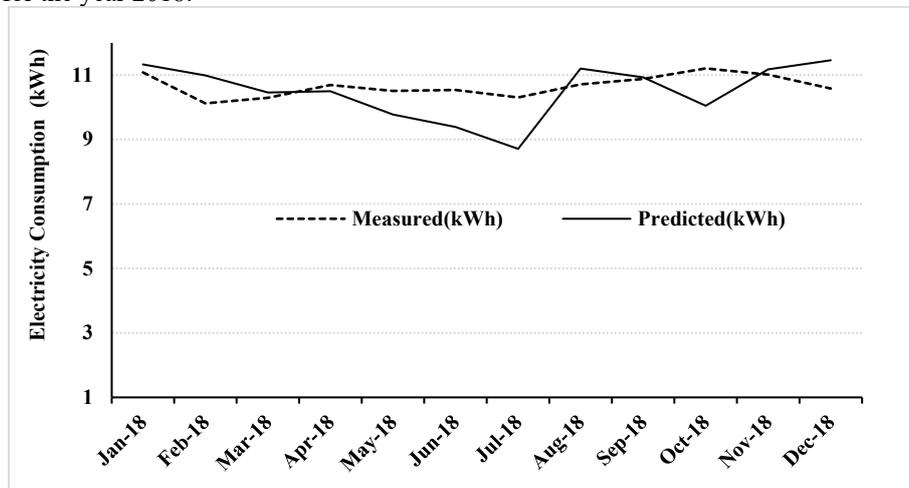


Figure 7. Measured and predicted electricity consumption of academic zone

The forecast of electricity demand is shown below in Figure 8. The forecasted path is restricted within the upper and lower bounds which tells that the forecast model is tethered to the accuracy pole. Figure 9 shows the ACF and PACF of electricity demand in the ARIMA model for the academic zone. ACF describes how well the present value of the series is related to its past values. PACF helps to find any hidden information in the residual which can be modeled by the next lag.

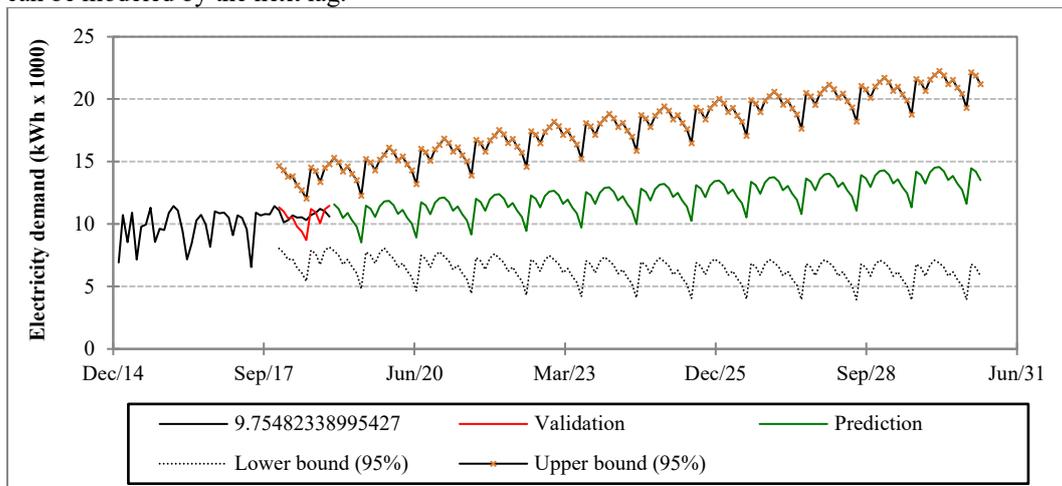


Figure 8. Electricity demand forecast for academic zone

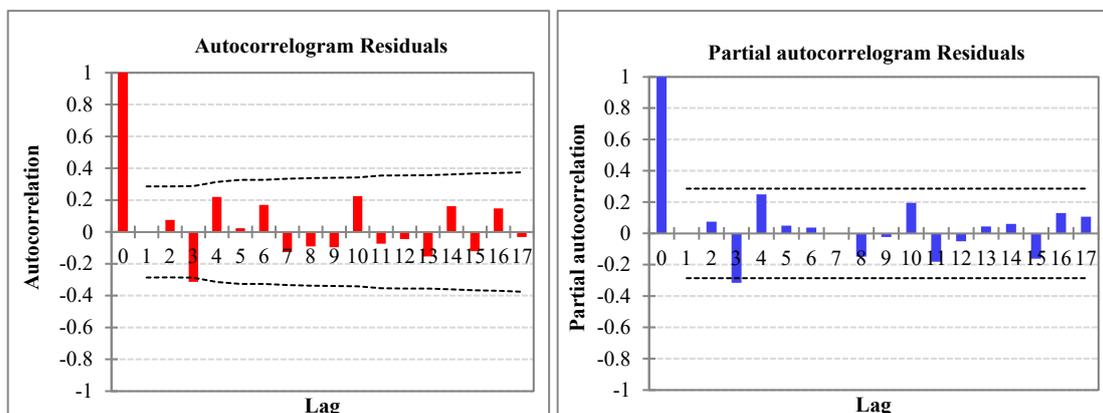


Figure 9. ACF and PACF of electricity demand for academic zone

5 Conclusions

Accurate forecasting models are needed for a secure and reliable energy system operation. This paper presented a long-term load forecasting using ARIMA time series modeling. To implement this ARIMA approach, monthly loads of CST campus for the past five consecutive years was used. ARIMA (0,1,1) was used for forecasting electricity demand of all zones which was validated by actual historical demand information of 2018. ACF and PACF plots were used to check the authenticity of the ARIMA model. For evaluation of the ARIMA models, MSE, SSE, and RMSE were considered for greater accuracy. The total electricity demand of staff residential zone is projected to increase from 166 MWh in 2018 to 295 MWh in 2030. In the case of student residential zone, the electricity consumption is forecast to increase from 273 MWh in 2018 to 361 MWh by 2030. However, there is always a chance of fluctuation in electricity demand that is decreasing due to more energy-efficient appliances coming in place or increase due to the addition of more appliances in the household. The forecast can be used to develop a reliable energy plan for the campus which can be more renewable and less dependent on the grid, helping the campus to become energy self-sufficient. More over similar forecasting can be done for the other areas to understand the future need of electricity in that area and to make a reliable future energy plan.

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