Recent Developments in Electronics and Communication Systems
KVS Ramachandra Murthy et al. (Eds.)

doi:10.3233/ATDE221331

Electricity Demand Estimation Using ARIMA Forecasting Model

Shivam Sharma [a,1] and Sudhir Kumar Mishra [b]
[a]shivamsharmawwe3@gmail.com,[b]sudhir.e11413@cumail.in
[a, b] *Department of Electronics & Communication Engineering Chandigarh University Mohali, Punjab*

Abstract. The aim of this study is to estimate the future electricity demand for domestic and commercial purpose. With the rising demand for power at households and industrial levels, it is more critical and important than ever to estimate future electricity needs so that demands in future can be met. In this paper, the ARIMA forecasting model with machine leaning techniques is presented for electricity demands forecasting. Time series decomposition is used to understand and split the data into test and train. ARIMA model is also compared to some similar models and benefits of using ARIMA model are also discussed. The results of this study show that ARIMA model can be used for forecasting electricity demand with lesser train and test error values as 0.10 and 0.04 respectively.

Keywords: Forecasting, Machine Learning, ARIMA model

1. Introduction

The world's electricity demand has risen dramatically in recent years as a result of population growth and other factors. With fluctuating fuel prices and liberalized energy markets, forecasting of electricity demand is emerging as an increasingly important tool for maintenance, planning, management of energy and decision related to the investment in the future. For power system planning, analysis, and operation to deliver a non-interrupted, secure, dependable, and cost-effective electrical supply, knowing the load behavior ahead of time is crucial. Environmental changes can have a significant impact on electricity demand. Electricity demand is nonlinearly related to temperature, increasing in response to both lower and higher temperatures. The sample monthly electric demand graph is shown in Figure 1.

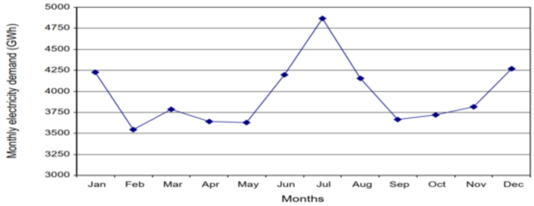


Figure 1: Sample monthly electricity demand graph [1]

Over the last few decades, forecasting using time series has become increasingly popular among academicians. The ARIMA (Autoregressive Integrated Moving Average) model is the prominently prevalent model for random time series models. In time series forecasting, new techniques such as ANN (Artificial Neural Networks) and SVM (Support Vector Machines) have recently acquired prominence [2].

2. Problem Statement, Motivation and Objective

Forecasting is the first step in any planning process. The major goal of Forecasting is to predict the occurrence, timing, and size of future events. Few researches on short-term load demand forecasting have been undertaken due to the growing popularity of demand forecasting [3]. In the electric industry, power demand forecasting is crucial since it is used to make choices concerning power system planning and operation. Electricity demand is projected by electrical companies using a variety of methods. These may be used to make predictions for the short, medium, and long term planning. The quantity of power utilized and the specified peak demand value are used to compute electricity costs. There come situations when the amount of electricity required crosses the value of Electricity Produced which makes the household and industries to use their own Generators or other sources which also results in more Pollution. This motivated us for Forecasting and estimating the Electricity demand so that the Production of electricity is always more than the required. The regulatory procedure frequently uses short-term load demand predictions. A detailed assessment of demand is essential to calculate tariffs.

3. Literature Review

Several models for estimating power consumption in diverse scenarios have been presented in literature. Brookings India published a report that looks at the growth of key end-use sectors through 2030. The study looks at nine distinct scenarios, including low, medium, and high GDP growth forecasts, as well as three scenarios for energy efficiency improvements and conservation initiatives [4]. In 2016 Sungwoo Bae and Mariz B. Arias developed a forecasting model using traffic in the past and meteorological data from South Korea [5]. Pantos, M [6] proposed a probabilistic method for efficient charging of electric vehicles when the renewable energy sources are existing. EVs are grouped into fleets rather than being assessed individually. Hong and Fan [7] conducted an instructional review of probabilistic Energy Demand forecasting. Wang et al. [8] examined the components that affect the Energy Demand forecasting in depth, including the forecasting model, input parameters and assessment metrics. Yadav et.al [9] presents an interesting hybrid model for forecasting direct photovoltaic output that combines an Artificial Neural Network (ANN) with a Wavelet transform. Azam S., Karim A. [10] attempts to give short- and long-term PV power generation projections for Alice Springs, Australia using machine learning. Mohan Tripathi [11] focused on the most important and natural green energy source of electricity which is known as Solar Photovoltaic power. For the combination of PV (Photovoltaic) power and electrical grid, management of grid and stability, accurate prediction of solar PV power is required

4. Data

The data used in this paper for the purpose of Forecasting ARIMA model is taken from an Electricity Providing Company from the State of Pennsylvania. We have used this data only for the data analysis and understanding purposes. The data we have is on monthly from 1st January 1973 to 1st March 2021 in Terawatts (TW) and using this data we have forecasted the electricity requirements for the next 3-5 years.
The first step of understanding data is to plot it in different form. Based on the available data, the graph we obtained shows seasonal and regular variations in Figure 2.

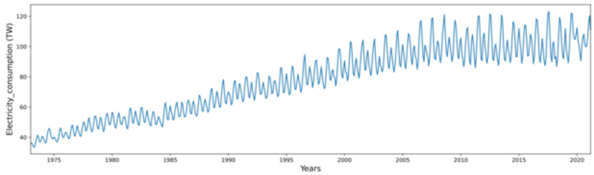


Figure 2: Electricity Consumption graph based on available data

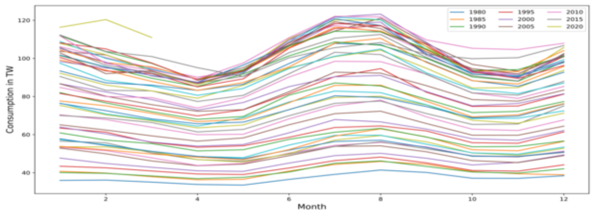


Figure 3: Data behavior based on every month for every year.

The behavior of the available data on monthly basis and yearly basis is shown in Figure 3. Also in Figure 3, we can clearly see a seasonal variation in the electricity consumption. More electricity is required in the months of July, August and December, January because of use of more electrical appliances for cooling and heating purposes. Also the demand of electricity is lower in the months of March, April and October, November.

5. Methodology

5.1 Time Series Decomposition

Taking in to account a time series as an assemblage of components for example level, trend, seasonality, and noise. Decomposition is a conceptual model that may be deployed to explain the general meaning of time series [12], in addition to this it also comprehends the problems that arise while analysis and prediction of time series. Time series analysis benefits from decomposition.

We decomposed the series using available data from the last 25 years; the series may be thought of as a mix of trend, noise component, seasonality, and levels. The level and noise/residual values are the most common components of time series, with trend or seasonality as optional parameters. The anticipated value will be affected if seasonality and trend are present in the time series. This can be because of the difference in the pattern of the forecasted time series and the pattern of the older time series. The components of a time series can be combined in two ways: Additive and Multiplicative. When the components of a time series are multiplicative and combined, the time series is referred to as a multiplicative time series. Visually, a time series can be defined as a multiplicative time series if it demonstrates exponential increase or decrease with time.

$$y(t) = Level * Trend * seasonality$$

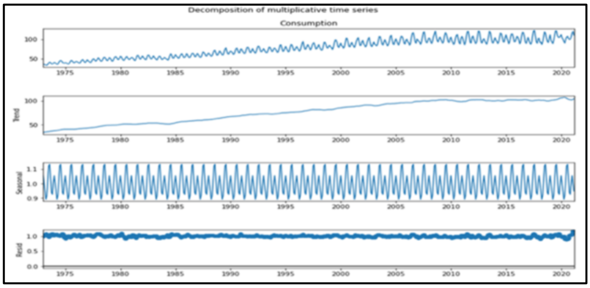


Figure 4: Decomposition of data on basis of seasonality, trend, and irregularity.

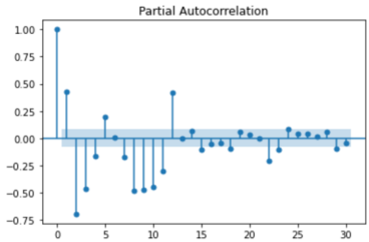
5.2 ARIMA model of Forecasting

The ARIMA models combine Autoregressive (AR), Integrated (I) and Moving Average (MA) models. When it comes to forecasting relatively steady time series data, ARIMA models are very accurate. ARIMA is a forecasting technique that stands for Autoregressive Integrated Moving Average. It predicts future trends by integrating the past data and giving them an autoregressive component. This is done by taking the previous value of a measure and multiplying it with certain parameters to calculate how much it should move from its current value. It is important to remember that seasonal trends are varied and difficult to analyze. The aim of analysis based on ARIMA is to develop a model which properly explains the patterns existing in past and future and are that of a time series, which implies that the methods used to estimate the ARIMA model are designed to deduce the suitable metrics that illustrate the structure below:

$$ARIMA(p,d,q)(P,D,Q)$$

The ARIMA is based on three steps:
The auto-regression (AR) step which is used to predict future values of a time series by using lagged values of itself..
The integrating (I) step which is used to remove the seasonal component in the data.
The moving average (MA) step which gives a smoothed version of a series obtained after differencing and applying an autoregressive step.
By inspecting the Partial Autocorrelation (PACF) plot, we may determine the required number of AR or p terms. We can see in Figure 5(a) that PACF lag 1 is extremely significant because it is much over the significance line, hence p=1.
We can examine the ACF plot for the number of MA or q terms in the same way that we examined the PACF plot for the number of p terms. Technically, an MA term is the lag forecast error. The ACF specifies the number of MA or q terms required to remove any

autocorrelation from the stationarized series. A few of lags are well above the significance line as in figure 5(b) for q values, but lag1 is preferable, therefore q=1. The goal of d value is to make the time series stationary. The series reaches stationarity only after one differencing, hence d=1.



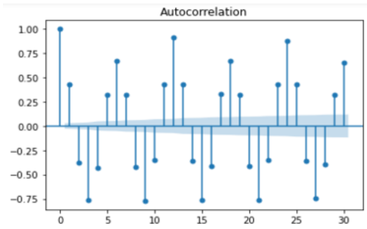


Figure 5(a): Partial Autocorrelation (PACF)

Figure 5(b): Autocorrelation (ACF)

6. Results:

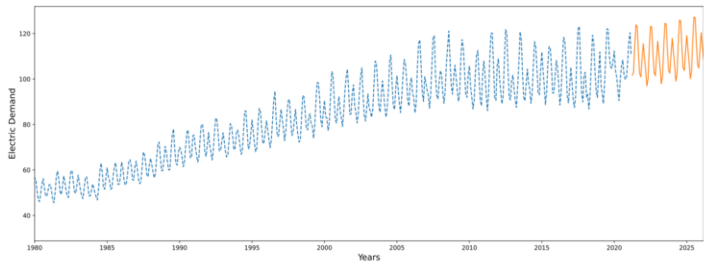


Figure 6: ARIMA model forecasted graph.

After performing the ARIMA analysis on test and train of the available data, we get the test MAPE error calculated based on available data and f_cast data using ARIMA model is given by:

$$test_{MAPE}: 0.10022622800314328$$

While the test error for the last 1 year calculated on the basis of predicted value and actual value using ARIMA model is given by:

$$train_{error_{last1year}}: 0.049553862142736875$$

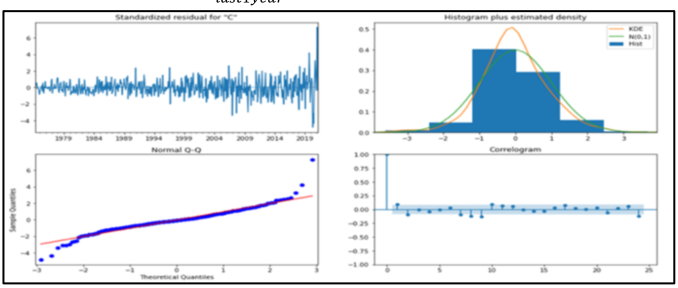


Figure 7: The stationary data, the histogram, Normal Q-Q and Correlogram obtained after ARIMA model.

Figure 6 shows the forecasted results of ARIMA model in the graph. The orange colored lines in figure 6 represents the forecasted values from year 2021-2025. Also test and train gives very less MAPE error values which shows that ARIMA model fits best for this type of forecasting in an easy way. Figure 7 shows the diagnostic outputs of the ARIMA model and from the curve of histogram we can clearly see that our data fits the model very well.

7. Conclusion

The electricity demand forecasting has become a crucial problem which needs efficient and supportive tools. Forecasting the demand of electricity will definitely help us in the prevention of black outs and brown outs. Knowing the demand before helps all of us at domestic and commercial level. The ARIMA model fits the data points comparatively better. The available data is first examined using the Decomposition method and then split into test and train data. The values of test and train errors obtained from ARIMA model are 0.10 and 0.04 respectively. Therefore, on the basis on these results we can say that the ARIMA model with low test and train errors can be considered for forecasting of electricity demand for different purposes like requirement, cost, and production.
In future, the presented method will be combined with other predictive methods along with taking into consideration of other factors to analyze the forecasting performance. More innovative and complicated strategies would be used for this goal, increasing the computational complexity of the hybrid method.

References

[1] Mirasgedis, S., Sarafidis, Y., Georgopoulou, E., Lalas, D.P., Moschovits, M., Karagiannis, F. and Papakonstantinou, D., 2006. Models for mid-term electricity demand forecasting incorporating weather Influences. Energy, 31(2-3), pp.208-227.

[2] Pan X, Lee B. A Comparison of support vector machines and artificial neural networks for mid-term load forecasting. IEEE International Conference on Industrial Technology. 2012;95–101.

[3] D. J. Trudnowski, W. L. McReynolds, J. M. Johnson, “Real-time very short-term load prediction for power-system automatic generation control,” IEEE Transactions on Control Systems Technology, vol. 9, pp. 254-260, Mar. 2001.

[4] Sahil Ali. The future of indian electricity demand, Oct 2018.

[5] Arias, M.B.; Bae, S. Electric vehicle charging demand forecasting model based on big data technologies. Appl. Energy 2016, 183,327–339.

[6] Pantoš, M. Stochastic optimal charging of electric-drive vehicles with renewable energy. Energy 2011, 36, 6567–6576.

[7] Hong T, Fan S (2016) Probabilistic electric load forecasting: a tutorial review. Int J Forecast 32:914–938. https ://doi. org/10.1016/j.ijfor ecast .2015.11.011.

[8] Wang Z, Li J, Zhu S, Zhao J, Deng S, Zhong S, Yin H, Li H, Qi Y, Gan Z. A review of load forecasting of the distributed energy system. InIOP Conference Series: Earth and Environmental Science 2019 Feb 1 (Vol. 237, No. 4, p. 042019). IOP Publishing.

[9] Harendra Kumar Yadav, Yash Pal & Madan Mohan Tripathi (2022) 24-hour ahead PV power forecasting based on the univariate hybrid machine learning model, International Journal of Ambient Energy, DOI: 10.1080/01430750.2022.2050811

[10] Mahmud, K., Azam, S., Karim, A., Zobaed, S., Shanmugam, B. and Mathur, D., 2021. Machine learning based PV power generation forecasting in alice springs. IEEE Access, 9, pp.46117-46128.

[11] Harendra Kumar Yadav, Yash Pal & Madan Mohan Tripathi (2019) A novel GA-ANFIS hybrid model for short-term solar PV power forecasting in Indian electricity market, Journal of Information and Optimization Sciences, 40:2, 377-395, DOI: 10.1080/02522667.2019.1580880