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FORECASTING POWER CONSUMPTION BY TRADITIONAL AND MODERN APPROACHES IN THE STATE OF TELANGANA

S Jayashree Department of Statistics, R.B.V.R.R Women's College, Telangana, India.
Email: shree.eniganti.jaya@gmail.com
M Raghavender Sharma Department of Statistics, Osmania University, Telangana, India :Email: drmrsstatou@gmail.com

ABSTRACT

Electricity is a vital part of modern life and crucial for the world economy. India is the third-largest producer of electricity in the world. There is a need to conduct continuous research in forecasting power consumption to meet the demand for overall increased consumption in various sectors. This research will enable policymakers to plan. In need of this research, an analysis was done to forecast electricity consumption. We have used the traditional and modern models to predict the accurate values. A traditional model like ARIMA and distinguished advanced learnings such as Long Short Term Memory and Convolutional Neural Network has been used for more effective accounting for the transient in the series, allowing us to forecast the future power consumption demand with a certain degree of accuracy. The analysis fits well with the data for CNN shown an optimal fit than ARIMA and LSTM for the observed 8 years of data(96 data points)data in the Domestic sector of power consumption in Telangana State Southern Power Distribution Company Limited.

Keywords-Electricity Consumption(EC), **ARIMA, LSTM, Forecast(F), CNN, MAPE**

INTRODUCTION

Electricity has now become a part of our normal existence and one cannot think of a world without electricity. Electricity is now a supreme part of every sectors. Thus, forecasting the power will help in better planning of future. India's power consumption grew by 4.5 per cent in December to 110.34 billion units (BU) over the same period a year ago, according to power ministry data. The development of the increased production of electrical power which leads to the employment and growth of the nation power generation capacity.

There is a need to carry out continuous research in forecasting power consumption so as to meet the need of increased population. This will enable policy makers plan ahead. As this need provokes the estimation of power supply. So, proper analysis helps to build and promote their plans to execute and leads to an economic growth. For proper strategy making we elite the problem for the analysis of power consumption and develop a model for forecast. The aim of the present problem is to develop a precise mathematical model that helps in forecasting the power consumption values of the observations primarily based on the characteristics of the records. The time series technique is one of the effective statistical methods for predicting future values.

In this view, the study was taken on the sales of Low Tension(sales) of the sector for Domestic.The L.T. tariffs determined in PART 'A'. Here in the study taken on sector Domestic to fit ARIMA, LSTM and CNN models are applied to forecast the sales so that to achieve the urging of the power consumption.

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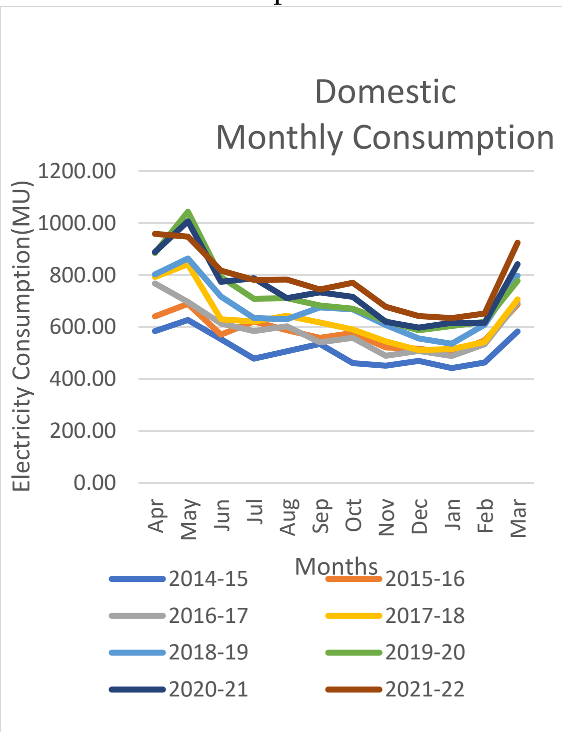
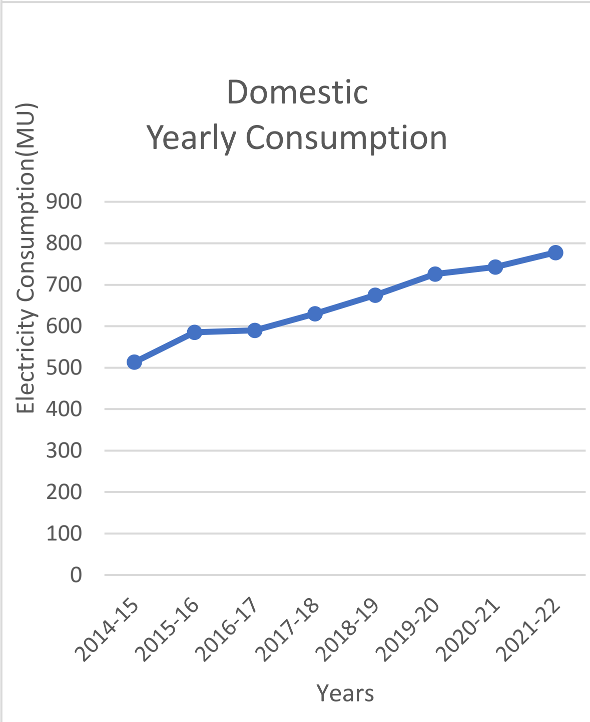
It is applicable for the supply of electricity for lights, fans, and other domestic purposes to domestic premises. Domestic establishment /Premises is one which is used for dwelling/ residential purposes. For the domestic category, the households having a separate kitchen will be treated as separate establishments. For the year 2014-22, the power consumption data





METHODOLOGY

Time Series Analysis

Time series is a arrangement of surveying note at well ordered time intervals. Depending on the frequency of observations, a time series may be hourly, daily, weekly, monthly, quarterly and annual. Time series forecasting occurs when we make scientific predictions based on historical time stamped data. Time series forecasting is using the observations obtained from time-series with the various techniques used to scrutinize data to develop a model for forecasting.

Hence, facsimile should be picked gingerly for a particular task. In order to expand robust time series models for the power sector and circumvent the use of conventional models, ARIMA and Deep learning techniques were chosen in this study. These models selected have been used in forecasting and have demonstrated error metrics to test their accuracy.

AUTOREGRESSIVE INTEGRATED MOVING AVERAGE(ARIMA)

ARIMA is a method for forecasting or predicting future outcomes based on a historical time series. It is the statistical concept of ordered correlation, where past data points influence future data points. An ARIMA model is characterized by 3 terms: p, d, q.

AR: **Autoregression** A model that uses the dependent relationship between observation and some number of lagged observations

‘**p**’ is the order of the ‘Auto Regressive’ (AR) term. It refers to the number of lags of Y to be used as predictors.

An autoregressive model of order p

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_1 y_{t-2} + \ldots + \emptyset_p y_{t-p} + \varepsilon_t$$

where ε_t is white noise. It is like a multiple regression but with lagged values of y_t as predictors. Changing the parameters $\phi_1,..,\phi_p$ results in different time series patterns. The variance of the error term ε_t will only change the scale of the series, not the patterns.

Moving Average

Rather than using past values of the forecast variable in a regression, a moving average model uses past forecast errors in a regression-like model.

$$y_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q}$$

where ε_t is white noise. We refer to this as an MA(q) model, a moving average model of order q. Each value of y_t can be thought of as a weighted moving average of the past few forecast errors.

Differencing

To make the data stationary, transformation is applied to the series. If we combine differencing with autoregression and a moving average model, we obtain a non-seasonal ARIMA model.

The full model can be written

$$y'_t = c + \emptyset_1 y'_{t-1} + \ldots \emptyset_p y'_{t-p} + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} + \varepsilon_t$$

where y'_t is the differenced series. The predictors on the right-hand side include both lagged values of y_t and lagged errors. We call this an ARIMA(p,d,q) model.

Long Short Term Memory (LSTM)

Deep Learning is a subfield of machine learning concerned with algorithms inspired by the structure and function of the brain called Artificial Neural Networks. It is specially framed to handle sequential data, such as time series. There will be four gates for propagation of the data input modulation gate, input gate, forget gate and output gate, representing four sets of parameters.

An LSTM model is implemented on this set of data to examine whether the forecast enhances the precision by this approach. The data is split into training and test data.

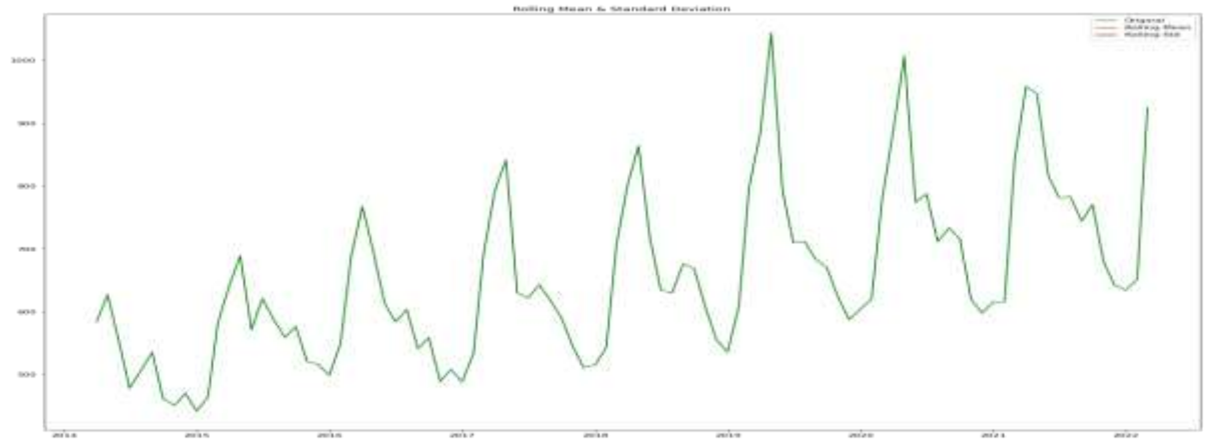
Convolutional Neural Networks (CNNs)

CNN is a deep learning algorithm designed to automatically detect and segment-specific objects and learn spatial hierarchies of features from low to high-level patterns. CNNs, also known as ConvNets, consist of multiple layers and are mainly used for image processing and object detection. CNNs have multiple layers that process and extract features from data. CNN has a convolution layer that has several filters to perform the convolution operation and CNN's have a ReLU layer to perform operations on elements. The output is a rectified feature map. By Pooling Layer the rectified feature map next feeds into a pooling layer. Pooling is a down-sampling operation that reduces the dimensions of the feature map and the layer then converts the resulting two-dimensional arrays from the pooled feature map into a single, long, continuous, linear vector by flattening it.

Results

Domestic power consumption versus month wise, Stationarity plot from 2014-22

The hypothesis test for stationarity.



Results of Dickey-Fuller Test:
Test Statistic -1.005117and p-value 0.751393
p-value > 0.05: Fail to reject the null hypothesis (H0), the data has a unit root and is non-stationary.

Test Statistic-5.574524 and p-value-0.000001
p-value <= 0.05: Reject the null hypothesis (H_0), the data does not have a unit root and is stationary.
train= df[df['Year']<2020] and test = df[df['Year']>=2020] then train.shape, test.shape (69, 2), (27, 2)). At ARIMA(2, 2, 2)the AIC of minimum value is 742.9105422729431

Parameter Estimation:

Dep.Variable:	LT CAT1(DOMESTIC)	No.Observations:	69
Model:	SARIMAX(2, 2, 2)	Log Likelihood	-366.443
AIC	742.886	BIC	753.681
Sample:	04-01-2014 - 12-01-2019	HQIC	747.139

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	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.8516	0.143	5.941	0.000	0.571	1.133
ar.L2	-0.3621	0.166	-2.179	0.029	-0.688	-0.036
ma.L1	-1.9915	1.642	-1.213	0.225	-5.209	1.226
ma.L2	0.9954	1.640	0.607	0.544	-2.220	4.210

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Ljung-Box (L1) (Q):	0.42	Jarque-Bera (JB):	4.95
Prob(Q):	0.52	Prob(JB):	0.08
Heteroskedasticity(H):	2.29	Skew:	0.62
Prob(H) (two-sided):	0.06	Kurtosis:	3.55

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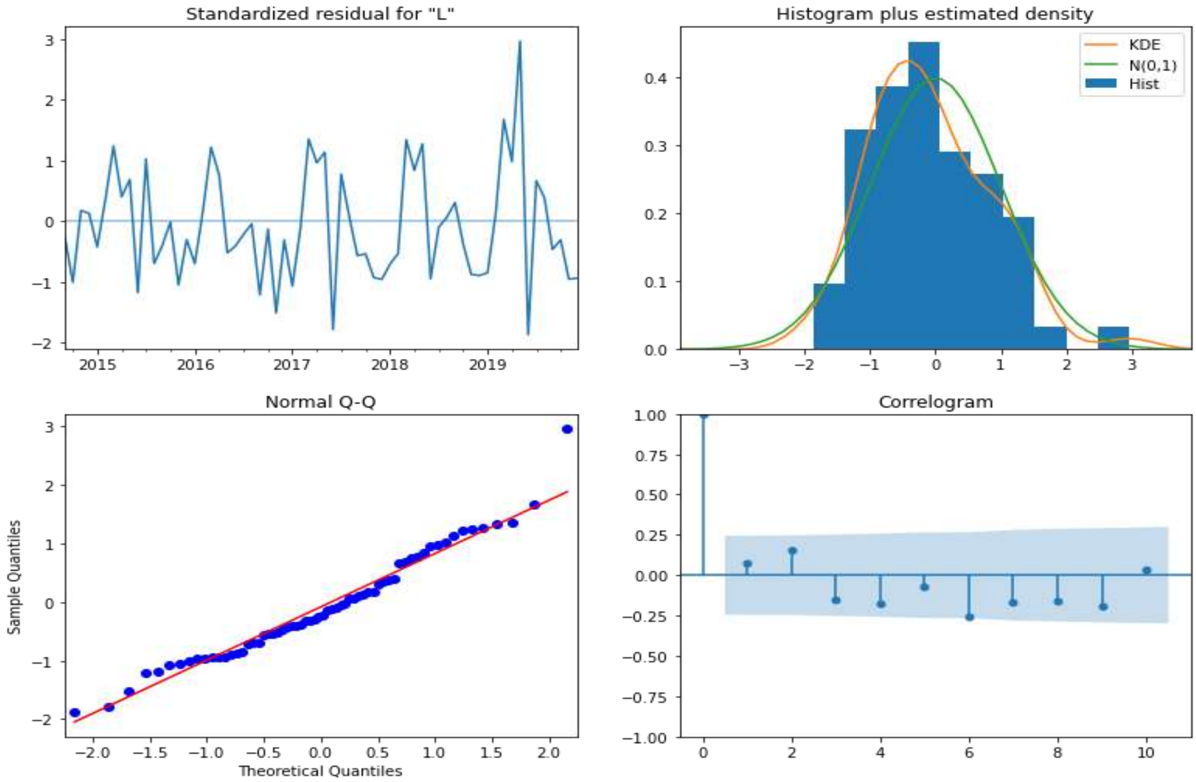
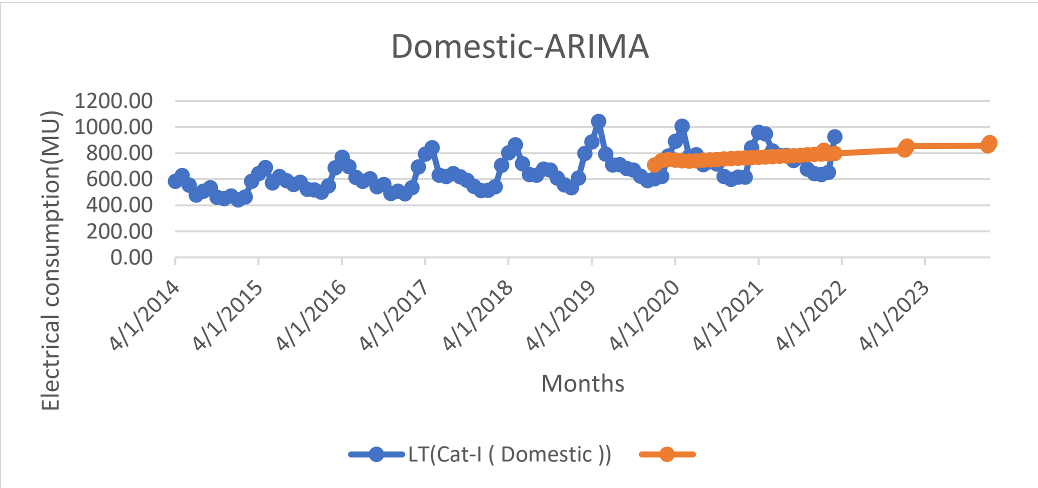
Diagnostic Check:

Results.plot_diagnostics(figsize=(13, 10))



For ARIMA Mean squared error 14136.454976, Root Mean Squared error is 118.896825 and Mean absolute error is 0.13375



For LSTM

train = data[data["Year"]<2020] and test = data[data["Year"]>=2020] test.shape (27, 12)

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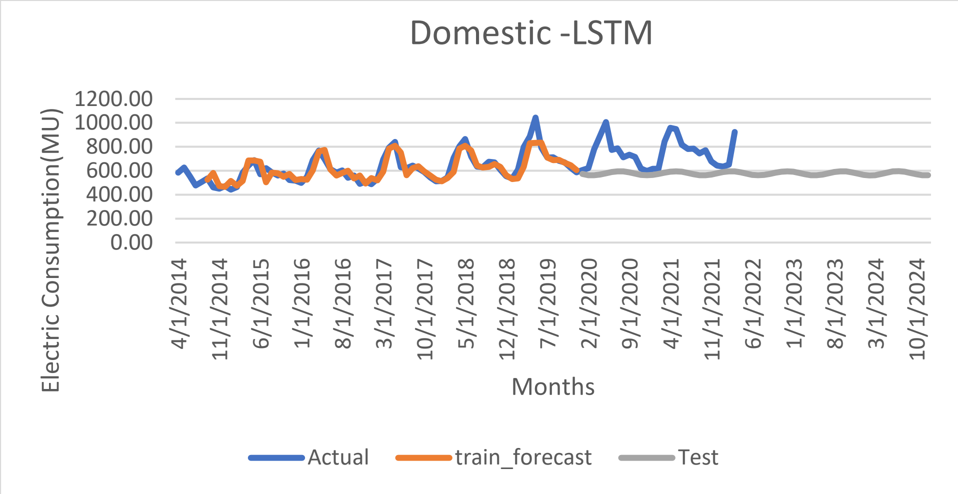
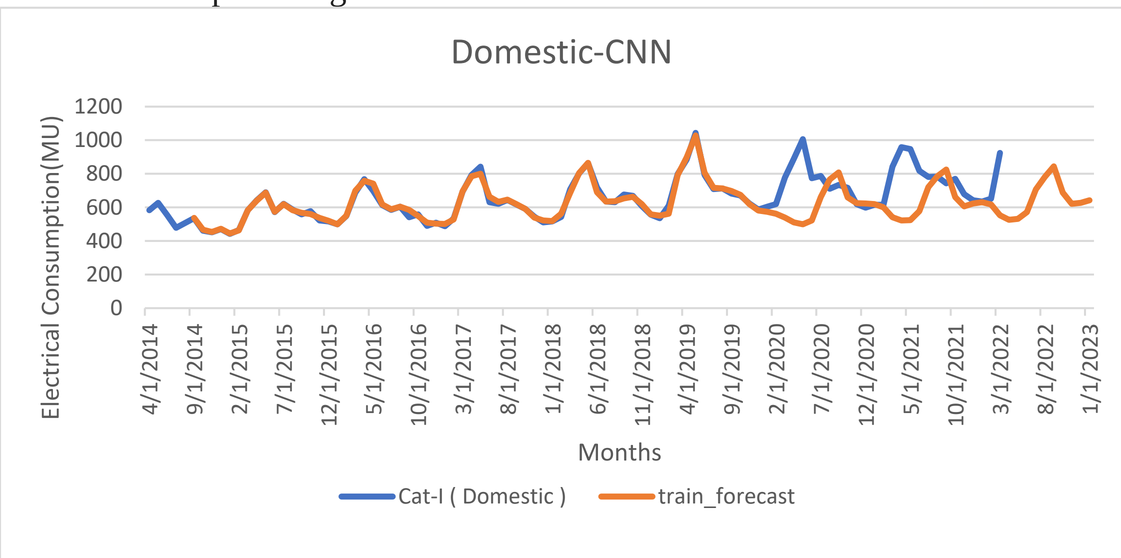


Mean absolute percentage error of LSTM model 0.11666

For CNN dividing the dataset into train and test datasets
train = data[data["Year"]<2020], test = data[data["Year"]>=2020] test.shape (27, 12)
Mean absolute percentage error of CNN model 0.10370604320581929



Conclusion

In this paper the study of three models are ratify for analysis. After the rectification of train and test for ARIMA, LSTM and CNN model shown these are the best models. And also it is perceived that in findings for ARIMA model the MAPE is 0.134964, for LSTM 0.11666 and for CNN MAPE 0.103. On the report of the data here the dataset for power consumption CNN shown optimal fit than ARIMA and LSTM for the observed data. The interpretation will enables the policy makers to use appropriate model to achieve the urging of the power consumption at Southern Power Distribution Company Limited in the state of Telangana.

References

[1] Dimpal Tomar, Pradeep Tomar, Arpit Bhardwaj, and G. R. Sinha Gautam Buddha University, Greater Noida, UP, India BML Munjal University, Gurugram, Haryana, India MIIT Mandalay, Mandalay, Myanmar, Deep Learning Neural Network Prediction System Enhanced with Best Window Size in Sliding Window

Algorithm for Predicting Domestic Power Consumption in a Residential Building, Volume 2022 Article ID 7216959

[2] IEA. World Energy Outlook 2019; IEA: India, 2019. Available online. https://www.iea.org/reports/ world-energy-outlook-2019 (accessed November 2019).

[3] Soliman,S.A.Alkandari, A.M. Electrical Load Forecasting: Modeling and Model Construction; Butterworth-Heinemann: Burlington, MA, USA, (2010), ISBN 978-0-12-381543-9.

[4] Rahman, Aowabin & Srikumar, Vivek & Smith, Amanda D. Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. (2018) Applied energy 212(C) pp. 372-385. DOI: 10.1016/j.apenergy.2017.12.051

[5] Hammad. M.A, Jereb. B, Rosi. B, Dragan. D. Methods and Models for Electric Load Forecasting: A Comprehensive Review. Logistics. Sustain. Transp. **2020**, 11, 51– 76 DOI:10.2478/jlst-2020-0004

[6] T. Hong, Shu Fan, Probabilistic electric load forecasting: A tutorial review. International Journal of Forecast (2016), 32(3), 914–938. DOI:10.1016/j.ijforecast.2015.11.011

[7] Maha Alanbar, Amal Alfarraj, Manal Algieth, Qassim University Energy Consumption Prediction Using Deep Learning Technique, June 2020. International Journal of Interactive Mobile Technologies (iJIM) 14(10):166 DOI:10.3991/ijim.v14i10.14383