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FORECASTING ELECTRICAL CONSUMPTION BY CONVENTIONAL AND CONTEMPORARY APPROACHES IN THE STATE OF TELANGANA

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ABSTRACT

Electricity is an essential part of modern life and important to 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 newly developed advanced models to predict the accuracy values. A Conventional model like ARIMA and Long Short Term Memory (LSTM) 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 LSTM showing an optimal fit than ARIMA for the observed data 8 years of data(96 data points)data in the Agriculture sector of power consumption in Telangana State Southern Power Distribution Company Limited.

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

INTRODUCTION

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. In fiscal year 2022, the per capita availability of power across Telangana in India was about 2,004 kilowatt hour. Telangana Power utilities have met the highest peak demand of 14,160 Megawatts on March 22, 2022. The development of the increased production of electrical power which leads to the employment and growth of the nation power generation capacity. Thus, forecasting the power will help in better planning of future and 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. 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 Agriculture.The L.T. tariffs determined in PART 'A' to fit ARIMA and LSTM models are applied to forecast the sales so that to achieve the urging of the power consumption.

In Agriculture applicability of LT-V(A). This tariff shall apply to the Corporate Farmer (includes poly-houses/green-houses). For the year 2014-22, the power consumption data.

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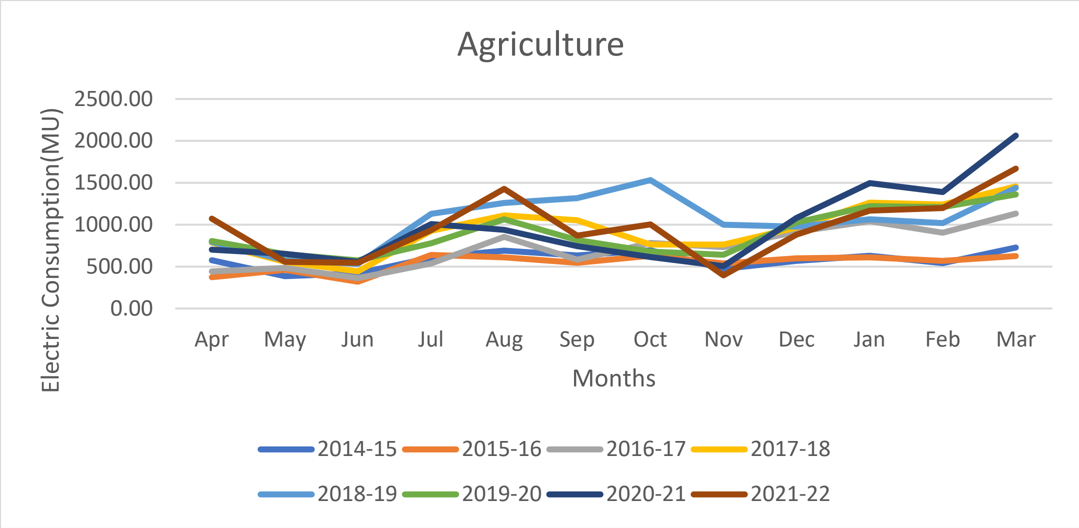

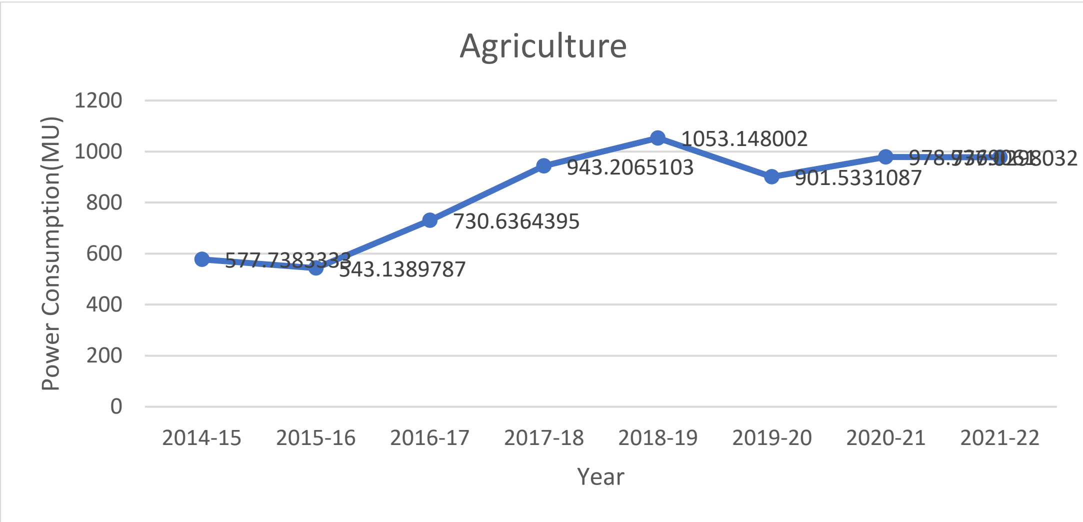

METHODOLOGY

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.

Auto-Regressive Integrated Moving Average (ARIMA)

The ARIMA model is a time series extension of ARMA (Autoregressive Moving Average). In ARIMA, AR stands for Autoregression, MA stands for moving average, I" stands for data values that have been replaced by the difference between their values and the prior values.

Stationary and non-stationary data can both be described using the ARIMA family of linear models. Stationary time series Z_t are usually represented with an ARIMA model. Autoregressive Components (p), Number of Differences (d), and Moving Average Terms are the three components of this model (q). The ARIMA (p, d, q) model is:

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$$\Phi (B)\, ^{d} Z_t = \Theta(B)a_t$$

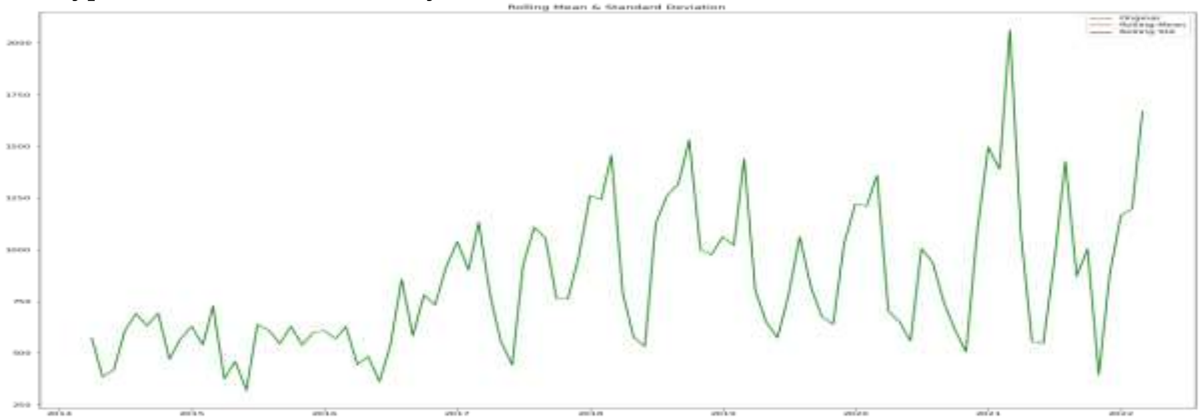
Where $\Phi(B) = 1- \phi_1 B- \phi_2 B^2 - \phi_3 B^3 \ldots\ldots\ldots\ldots \phi_p B^p$ is a polynomial in B of order ‘p’ and is known as AR operator and $\Theta(B) = 1- \Theta_1 B-\Theta_2 B^2- \Theta_3 B^3-\ldots\ldots\ldots\ldots \Theta_q B^q$ is a polynomial in B of order ‘q’ and is known as MA operator. B is the Backward shift operator $B^k Zt = Z_{t-k}$, and d is the number of differences required to obtain stationary.

Long Short Term Memory (LSTM)

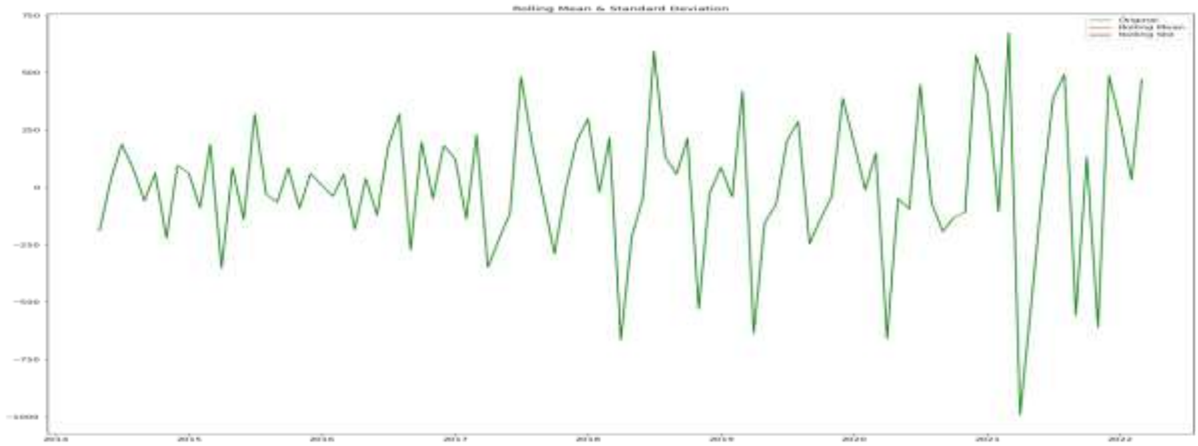
Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) that is specifically designed to handle sequential data, such as time series, speech, and text. LSTM networks are capable of learning long-term dependencies in sequential data, which makes them well suited for tasks such as language translation, speech recognition, and time series forecasting.
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.

Results

Agriculture power consumption versus month wise, Stationarity plot from 2014-22
The hypothesis test for stationarity.



Results of Dickey-Fuller Test:
Test Statistic -1.479680, p-value 0.543538, Lags 12.000000. p-value > 0.05: Fail to reject the null hypothesis (H_0), the data has a unit root and is non-stationary.



Test Statistic -4.088851, p-value - 0.001010, Lags Used 11.000000
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 888.161.

Parameter Estimation

Dep. Variable:	Cat-V(Agriculture)	No. Observations:	69
Model:	SARIMAX(2, 1, 2)	Log Likelihood	-439.080
AIC	888.161	BIC	: 899.033
Sample:	04-01-2014to12.01.2019	HQIC	892.450

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	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.8802	0.344	2.559	0.010	0.206	1.554
ar.L2	-0.4956	0.193	-2.564	0.010	-0.874	-0.117
ma.L1	-1.2241	0.395	-3.097	0.002	-1.999	-0.449
ma.L2	0.3920	0.353	1.109	0.267	-0.301	1.085
sigma2	4.263e+04	9244.704	4.611	0.000	2.45e+04	6.07e+04

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Ljung-Box (L1) (Q):	0.45	Jarque-Bera (JB):	0.33
Prob(Q):	0.50	Prob(JB):	0.85
Heteroskedasticity (H):	4.63	Skew:	-0.11
Prob(H) (two-sided):	0.00	Kurtosis:	2.73

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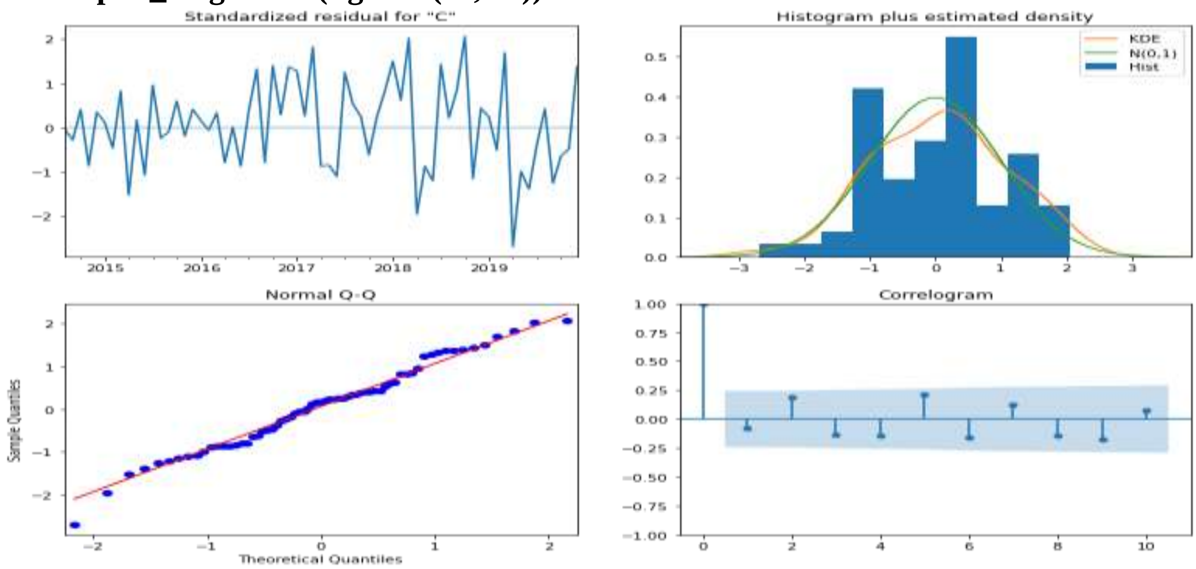
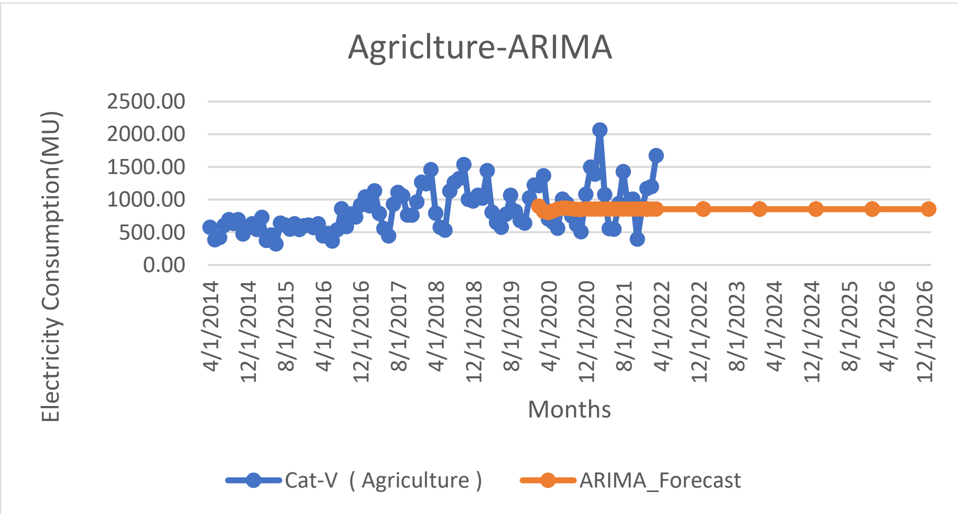
Diagnostic Check

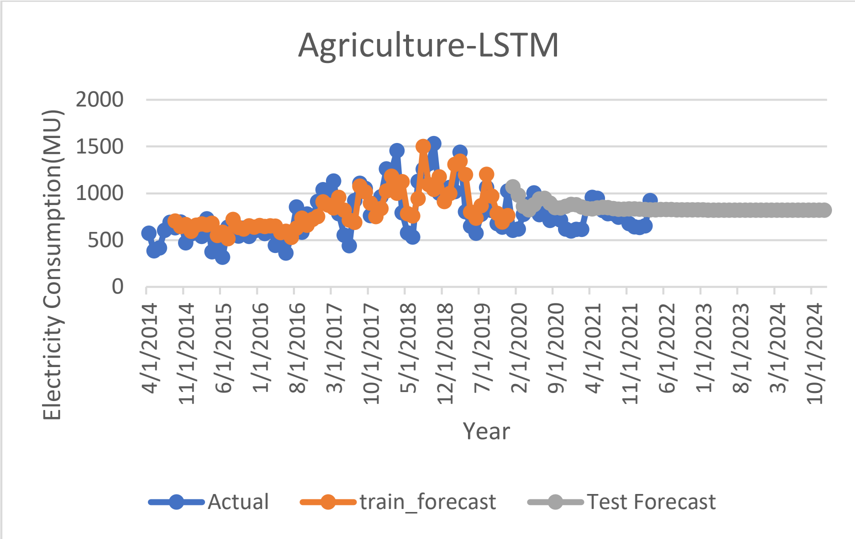
results.plot_diagnostics(figsize=(13, 10))





For ARIMA- MSE-178780.62, RMSE: 422.8245, MAPE- 0.3441

For LSTM dividing the dataset into train and test datasets
train = data[data["Year"]<2020], test = data[data["Year"]>=2020] test.shape (27, 12)
Mean Squared error -55261.00811, Root Mean Squared error-235.076600, MAPE- 0.22099



Conclusion

In this paper the study of two models are taken for analysis to forecast the power consumption in agricultural sector. After the amend of train and test for ARIMA and LSTM model shown these are the best models. And also it is perceived that in findings for ARIMA model the MAPE is 0.3441, for LSTM 0.2209. On the report of the data here the dataset for power consumption LSTM shown optimal fit than ARIMA 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.

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