Prediction of Changes in Electrical Power Consumption in future with the help of ARIMA model,with other Machine and Deep Learning Model

MSc Research Project
Data Analytics

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Project Submission Sheet
School of Computing

Student Name:	Syed Mohammad Shahrukh
Student ID:	x20131674
Programme:	MSc in Data Analytics
Year:	2021
Module:	Research Project
Supervisor:	Bharathi Chakravarthi
Submission Due Date:	16/08/2021
Project Title:	Prediction of Changes in Electrical PowerConsumption in future with the help ofARIMA model, Machine and Deep Learning Model
Word Count:	8031
Page Count:	24

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Prediction of Changes in Electrical Power Consumption in future with the help of ARIMA model, with other Machine and Deep Learning Model

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14/08/2021

Abstract

If we see the role of the atmosphere in changing the electricity demand, it plays an immense role. There is an indirect relationship between the demand for electricity load and atmospheric pressure. Also, the change in atmospheric pressure plays a vital role in climate change and global warming, and due to this rise in atmospheric pressure, the earth temperature is exponentially increasing. Nowadays, we can observe that we are getting hotter summers and colder winters every passing year than before. Due to this, the domestic and industrial electricity demand continuously increases, creating enormous challenges for the electricity providing companies and present governments. So, as a result, anticipating future electrical energy requirements based on changes in atmospheric pressure, will be highly beneficial to both the government and the electrical supply firms. Various studies on how to compete with this electrical energy requirement issue have been conducted in the past. In this study, we will look at how atmospheric pressure affects the demand for electrical energy indirectly. Here, we have implemented the (KDD) machine learning method and models like SARIMAX, ANN(LSTM), BiLSTM, linear regression model, Lasso Model, KNN model, Random Forest and ARIMA, which are also used to anticipate future values. We will use these tactics to see if we will get superior accuracy values for our model. The electrical energy industry and government authorities can always use these models to improve their planning and prepare their electrical generating plants for future requirements.

Keywords: Electricity load, Atmospheric Pressure, SARIMAX, ANN(LSTM), BiLSTM, linear regression model, Lasso Model, KNN model ,Random Forest and ARIMA.

1 Introduction

If we see broadly, electricity plays a significant role in our day-to-day life. The electricity demand has been increasing exponentially worldwide continuously for the last two decades, and it has been predicted that it will continuously increase in the upcoming years. The residential sector is responsible for 15 percent consumption of total electricity production. If we see countries like Saudi Arabia, this figure gets higher by up to 50 percent, but this figure is about 11.5 percent of total energy consumption (Payne; 2009). Several policies and technologies have already been implemented to reduce this much energy consumption, like many houses are built to improve thermal efficiency. Some significant steps have already been taken on a large scale to reduce the consumption of energy. Like many counties and societies have built various low energy houses. These new houses have a high level of thermal comfort and integrated renewable energy technologies with solar water heaters and photovoltaic electrical energy. If we see the results, we can find out that we have achieved some reasonable goals to reduce electrical energy requirements. In Australia, the newly built houses have achieved a 6-star rating. The domestic sector is responsible for electricity consumption, but the industrial sector is equally responsible for this rapid increment of electricity consumption. For the production and consumption of goods, electricity plays a vital role. In a study of about 100 years, it has been found that there is a strong relationship between the increment of electricity consumption and economic development (Seungho Lee* and Saman; 2014). If we see the requirement of electricity demand, it has also increased all over the world, making a concerning issue for the local authorities. Similarly, in a study of changing electricity demand in Brazil, it has been analysed that the existing hydroelectricity plant must increase their energy production due to rapid increment in electricity demand. Because of this rapid energy production, slow construction of electric plants and planning has created significant issues. Now, the authorities need to use the reserved water stored in water dams, and due to this, a drought-like condition has been created. Now the destruction that has been made because of this rapid demand do not stop here. It was found that the impact has been seen on the environment due to the extensive use of fossil fuels and in terms of economic burden also. After seeing all these issues, the government has taken some significant steps to counter this problem. They have launched National Electrical Energy Conservation Program (PROCEL). Under the (PROCEL) scheme, authorities have built wind plants. In this program, they have built renewable energy resources to protect the environment and their monetary funds. After some of these significant steps, they have also taken steps like peak load tariff differentials that can directly affect large and residential consumers with new electric meters. If we talk about the usage of electricity in Brazil, so in 2014, the country recorded the peak load which is almost 85.708 GW and if we talked about the installed facilities system that has the capacity of 134 GW, in which 67 percent is the hydro generation, 9.4 percent natural gas, 9.2 percent biomass, 5.9 percent fossil oil, 2.5 percent coal, 1.5percent nuclear, 3.6 percent wind, 1.2 percent industrial gas and 0.1 percent biogas. So plenty of studies have been done related to electricity load or consumption, which has been completed and shows the best results and have been implemented effectively. The studies that have been previously completed also have analysed the generation of power and supply systems. This study have been completed and have shown promising results with the successful forecasting of the electricity load. The studies in recent years have been done on some scientific approaches as well as, they used data records like weather reports and loaded in (MWh) with some machine learning model. The scientific approaches that are used has defined how the scientific reasons are responsible for climate change, and they have used a well-recorded data set with good features. The machine learning approaches can predict or forecast the future value, which can be proven helpful for future preparation or power distribution planning.(Hans H. Zurn a and André Richter c; 2016) There is a study of electric consumption prediction where the analysis has been done after selecting the three model types. The model in the study has been selected based on the square root of average squared error. The study has analysed that the models like decision tree and neural network, in performance, are better as compared to the stepwise regression model. Also, data mining approaches can be used, and different types of other models can be used to compare the selected model performance. Now for our study, we have proposed a research question:

How well does Autoregressive Integrated Moving Average (ARIMA) predict Electrical power consumption due to changes in atmospheric pressure due to carbon emission?

In this study, we have approached the KDD (knowledge-based discovery in the database) and some machine learning as well as deep learning methodology to develop our idea, and it helps define the data collecting processes. Now all around the world, the size of the data is increasing day by day. However, by this method, we can get help to sort our data. Also, we have implemented some data cleaning methods for the better performance of our model. Because our data set has several NA, NAN, and missing values, If we built our model without any pre-processing, it will not forecast or predict the ideal values. So, we have done some data pre-processing methods, and then we have implemented our idea. We have also applied some tests to check the regularity of our data set. The data set used in this study belongs to some electrical companies. However, it has been presented on an open-source website and has enough features that can be used to build a model and help predict our target variables. If we talk about the models we have implemented here, that is, the ARIMA and SARIMAX model. Also, we have chosen the best ARIMA models with the help of running some python code, which helps and shows the direct results, for which type of ARIMA model will be best for our data set, like ARIMA (1,0,1), ARIMA (0,0,1) or any other type and as well as models like ANN(LSTM), BiLSTM, Symbolic regression model, linear regression model, Lasso Model, KNN model, Random Forest and ARIMA model are also used. We have also tried to show some trend or seasonality in our data set and with the help of the graphical representation the data set nature also shown. Finally, at the end of our study, we have tried to compare the values which we have forecasted.

2 Related Work

2.1 Introduction

In this section, we will take a closer look at the methods used for calculating the energy requirements of consumption, which are influenced by various factors. We will also go through distinct machine learning strategies for building different models for different issues. The strategies employed using existing literature includes an optimised algorithm that helped to cut the cost and the time spent for developing the concept.

2.2 Study for calculating the electricity load by using machine learning and deep learning methodology

In the analysis of previous and recent years experiments, we have found a study by (Aowabin Rahmana and Smith; 2017). The analysis has been done on Predicting the electricity consumption for commercial and residential buildings using deep recurrent neural networks. Basically, in this study, the analysis has been done on prediction at a one-hour resolution of electricity consumption in the industrial and commercial sectors by using a recurrent neural network model. For feeding the data in the model, an electricity consumption data record has been used. The models performed here are Neural networks, Recurrent neural networks with LSTM (Long short-term memory). The speciality of the neural network is that it can create a non-linear model relationship between the input vector and target variable. If we see the Recurrent neural network, so it is good to create temporal dependency with the help of present time series and feedback connection, which can help remember the values of steps taken previously. If we talk about the results, the RMS(e2) value for high power is 1.01. So, in the above section, we are talking about load prediction with the machine learning method. Similarly, another study was completed by (Richard E. Edwards a; 012) on Predicting the future hourly residential electricity consumption. Like the previous study, in this, the study has been done on consumption of electricity on a residential building, Where the Analysis has been done on how the difficulty can be in electricity load supply term in traditional buildings because these builds have several output ports and the difference between designed and built-in building. So, in this study, commercial building data set has been used, which also has a record of consumption on an hourly based. There are seven different experiments used, which have been implemented in this study: Linear Regression, Feed Forward Neural Network, Support Vector Regression, Hierarchical Mixture of Experts, and Fuzzy C-Means with Feed Forward Neural Networks ..If we talk about the evaluation part in this study, the performance metrics have been used to evaluate the model performance. It has been noted that Linear Regression, HME with Linear Regression, and LS-SVM has proven to be the best models, which has given the following Coefficient of Variance CV – 10.36 percent, 11.78 percent and 12.79 perncent. So, as we have seen, the above study has focused on how the residential and industrial sectors are increasing the demand for energy. Similarly, by (xiang Zhao and Magoulès; 2012) A review on the prediction of building energy consumption. In this study, analysis has been done on the factors that influence energy demand in any building using some machine learning methodology. The factors found in the study are temperature, the structure of the building, lighting, HVAC system and occupancy. Predicting the future value with all these circumstances is very difficult. The data set implemented here is statistical data, and it has several components available, which help to build a specific model. In this study, several prediction methods have been applied and some unique methods like the Engineering method; this method is used to define or calculate the whole building's thermal dynamic and energy level. Similarly, another method is the statistical method, and it helps to correlate the target variable with the other features present in the data set. Similarly, Neural networks, Support vector machines and grey models are also used. If we discuss the results achieved here, Elaborate engineering and SVMs models results show relatively high accuracy. When we talk about the load prediction, which gets affected by weather, also the record has some seasonality, as seen in the above analysis, the analysis will depend more on future value prediction. In another study, (Karimtabar and Alipour; 2015) analysed and predicted electrical energy consumption using data mining techniques. In this study, analysis has been done on how the policy making technique can help manage power consumption with the help of machine learning methodology. The electricity consumption rate will be predicted with the help of a data mining technique. The analysis revealed some essential and worrying points like consumption between 2006-2013 was more than double compared to 1996 - 2006. The consumption rate from 1996 to 2006 was 28.41 KWh and from 2006 to 2013 was 73.53KWh. If we talk about the data set, it belongs from - Mazandaran province Iran, 1991 to 2013. The target variable here is the consumption rate, and other independent features are Population, Temperatures, Moisture, Electricity price. The machine learning methodology implemented here is the regression model, neural network and SVM (Support Vector Machine). If we talk about the results, the regression model, neural network, and SVM have relative error (percent) 0.9, 1.6 and 11.1. As we have seen, the study shows evidence on how the atmospheric terms provide an indirect effect on energy consumption. In our study, we focus on how these atmospheric terms are indirectly responsible for changes in power consumption. So, another study, by. (Amasyali and El-Gohary; 2017), is a review of data-driven building energy consumption prediction studies. In this study basically, the analysis has been done on how the continuously increasing pollution and co2 gases have put an impact on the temperature and due to this overall demand of energy is also increasing because there will be an increment of comfort for the people. According to the study, it is believed that energy consumption planning, management and conservation is essential. If we talk about data used in this study, so it has a recent four years record of electricity consumption of any building, and other features are also used here, also it gets varied after four weeks. Now, if we see the machine learning models implemented here are ANN (Artificial Neural Network) and SVM (Support Vector Machine) and Decision Tree. If we talk about the parameter which is used here for evaluation are Coefficient of Variation (CV), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), Mean Squared Error (MSE), R Squared (R) and error rate. Now as we have seen that the machine learning models play an essential role in predicting the electricity load. Another by (Nwulu and Agboola; 2012) on Modelling and Predicting Electricity Consumption Using Artificial Neural Networks. In this study, analysis has been done to find out the best machine learning model that can predict the upcoming future electricity demand. The model used here is a backpropagation neural network. It will also have an input key of economic and seasonal indicators which will have a considerable impact. The data set which has been used here is from 1990 to 1998. This data set belongs from the Turkish Republic of Northern Cyprus, State Planning Organization, and can be used. The model used here is ANN (Artificial Neural Network), and if we see the evaluation result. Hence, it scored the Root Mean Square Error 19.74253, Mean Absolute Error 14.92242, Mean Absolute Percent Error 2.838069, Theil Inequality Coefficient 0.015202, Bias Proportion 0.011846, Variance Proportion 0.012861, and Covariance Proportion 0.975293.

There is another study by(Chavan; 2019) on Water, Gas Electricity Consumption and Behaviour Forecasting. Basically, in this study, analysis has been done on conservative energy resources. If we talk about the data set, it has been recorded from the smart meter time series data set in every 3 minutes. This paper has analyzed consumer behaviour regarding the usage of electricity, water, and gas. Suppose we see the machine learning approach used here, so CRISP-DM methodology has been implemented here. On the other side, there is LSTM (Long Short-Term Memory), the results they received with RSME value of electricity data set are Training 0.16 and Testing 0.23.

Now, if we see the evaluation part of this study, so four parameters are used here for the evaluation of our model, which is Mean absolute error (MAE), Mean absolute percentage error (MAPE), Root-mean-square error (RSME) and mean squared error (MSE). For the ARIMAX model, RMSE, MSE, MAE and MAPE received values are 0.76,0.57,0.47 and 6.21. For the SARIMAX model, RMSE, MSE, MAE and MAPE received 0.77,0.60,0.50 and 6.50. For the PROPHET model, RMSE, MSE, MAE and MAPE received 2.89, 8.35 2.42 and 4.27. For Long Short-Term Memory (LSTM) model RMSE, MSE, MAE and MAPE 0.40 0.16, 0.29 and 3.06.

In another study by Chetan et al. (Ramesh; 2019) Electricity Consumption Anomaly

Detection Model Using Deep Learning. The analysis has been done on the electrical loss caused by the technical or non -technical loss. The term analysis of non-technical loss has been done based on illegal usage of electricity, electrical theft, and billing fraud. If we see the data record used here, the technical loss term analysis has been done based on power outage, short circuit, or grid failure. In this study, the data set which has been used here is collected from data.london.gov.uk. The features available in the data set are the electricity data, unique household number, date, and time of consumption. In this study, the approach used here is the KDD (Knowledge Discovery Database). In this research, deep learning models, that is, LSTM and RNN are used. Novel computational effective anomaly detection models are also used like GRU model have MAE value of 0.995 and GRU Model with dropout have MAE value of 0.995.

Now, as we see in our related paper analysis , the model has been implemented after applying the pre-processing of the data, but there is another study where the analysis has been done to optimize the processing work and enhance the model performance in the study by (Ramesh; n.d.) on Optuna Optimization Based CNN-LSTM Model For Predicting Electric Power Energy consumption . The analysis has been done on forecasting the electricity demand by using the CNN-LSTM neural network by integrating the OPTUNA algorithm, which can tune the neural network. The data set used here has been collected from the UCI machine learning public repository; basically, the data is household power consumption. The approach used here is KDD (Knowledge discovery in databases), and the evaluation parameters are Mean Absolute Error (MAE), Root Mean Squared Error (RMSE). The result which is achieved here for CNN$_{L}STMhasRMSEof0.894$.

In a study by K.U. by.(Jaseena and Kovoor; 2020) on Deterministic weather forecasting models based on intelligent predictors. In this study, analysis has been done on forecasting the essential term of weather, which is very important for agriculture, tourism, airport system and mining industry. The data used here is available public data that has the information or feature about the weather. The models implemented here are the ANN-based model,SVM based model, and their evaluation parameters here are MAE, MSE and RMSE.

2.3 Study for calculating the electricity load by Machine learning methodology.

In the study by. (Chaudhary; 2018) on Predictive Modelling of Home Appliances Energy Consumption in Belgium. This paper shows how carbon emission and greenhouse gases are increasing due to the rapid demand for electrical energy. This study has shown the concern on how much the electrical energy prediction is crucial because it is in continuous demand for industrial and residential sectors. The data set which is used here has been collected from a smart meter. The remarkable finding in this paper is that here all three approaches KDD (Knowledge Discovery Data), CRISP-DM and SEMMA, has been implemented, and it has been found that KDD methodology is best for the study. Here, the Lasso Regression model has been applied. Suppose we see the evaluation and result of the study so, In that case, the evaluation parameters are RMSE MAE MAPE, and the result they have got after implementation is RMSE 85.93, MAE 49.55, and MAPE 54.27

A study by. (Panigrahi; 2020) For Forecasting Residential Electricity Load Demand using Machine Learning. In this study, the analysis has been done on how the rapid increment of home appliances and devices in the residential sector is responsible for exponential increment in electricity demand. It has also shown the concern that the electricity demand will increase due to an increment in the number of customers in the future. So, as we see in the above studies, the machine learning models play an essential role in predicting electricity consumption. In this analysis, the approach used here is Knowledge Discovery in Databases (KDD), and the data set for the study has been collected from kaggle.com. Also, it has enough features for predicting the target value and form a specific model. Now, if we see here in this study, ARIMAX (Autoregressive Integrated Moving Average) model, SARIMAX PROPHET, and Long Short-Term Memory (LSTM) models have been implemented. This model can be explained with a different and specific version. This model is multi-dimensional, and it also allows the autocorrelation with the available regression residue for increasing the forecasting accuracy. The speciality of this model is that it can be proved as an appropriate model for forecasting the stationary, non-stationary data set and multivariate data set. The notation used under the ARIMAX model is (p,d,q) along with Greg. Where xreg is defined as an independent external variable, p is defined as many lags available in the observation, d is defined as the degree of difference and q is defined as the order of moving average.

As we have seen in the previous study about the analysis done on how to reserve and save the energy to make that a profitable energy resource. A similar study has been found by by. (Rai; 2019) Predicting the Energy Consumption in Commercial Buildings using its property features and Machine Learning Algorithms. In this study, analysis has been done on how the increase in population creates a huge problem for electrical energy demand. Since most people now want a lavish lifestyle and modern appliances, these appliances need a huge electricity requirement. Also, nowadays these appliances are being used in good numbers in most of the houses. The data set used here belongs to the Commercial Buildings Energy Consumption Survey (CBECS) dataset. The models implemented here are Gaussian Naive Bayes, Random Forest, K-Nearest Neighbour and Logistic Regression using analysis of variance (ANOVA) and principal component analysis (PCA). Apart from this, evaluation parameters used are Accuracy, Precision, recall, and f1. Now, suppose we see the results for ANOVA methodology Gaussian Naive Bayes have Accuracy of 88.95

The results from PCA methodology are : Gaussian Naive Bayes accuracy value is 93.37 percent, precision value is 94 percent, recall value is 93 percent, and F1 score value is 93 percent.Random Forest Classifier accuracy value is 96.50 percent, precision value is 9 percent, recall value is 97 percent and F1 score is 97 percent and K-Nearest Neighbour accuracy value is 98.15 pervent,precision value is 97 percent, recall value is 97 percent, and F1 score value is 97 and Logistic Regression accuracy value is 70.97 percent, precision value is 71 percent, recall value is 72 percent and recall value is 69

Another study by Gabriel et al. (IBUKUN; 2020) on Analysis of Electric Load Forecasts Using Machine Learning Techniques. The analysis has been done based on how to make the supply distribution effective. The data set used here is a 10-year record of electrical energy loads data from PJM transmission, and the weather data set has been taken from daily weather forecasting. The vital part of this study that gives strong support to our analysis are the models being used here like ARIMA and SARIMA, and with these two models, Extra Trees regressor and XGBoost models are also used. The evaluation parameters which are used here are RMSE, MAPE and MAE. The result which has been achieved here is for the SARIMA model. The RSME value for 6- month data length is 0.574, MAPE value is 11.278, MAE value is 0.4. For the SARIMA model, the value for 6-month data length are RSME is 0.146, MAPE value is 14.979 and MAE value is 0.109.

In a study by (Gupta; 2020) on Mid Term Forecasting of Solar Power Generation in

India: A Statistical Approach. The analysis has been done on how a big country like India lacks supply in fulfilling this exponential increment in demand. This study has also shown that most power generating sources are not eco-friendly, and it is not suitable for fulfilling the future demand. If we talk about the data set used here, it is historical data that has a record from June 2017 to June 2020, and it has only two Indian states electricity records: Rajasthan and Andhra Pradesh. If we see the model implemented here, it is the ARIMA model in which the RMSE value for the Rajasthan test data set is 3.447, for the Andhra Pradesh test data set, it is 1.93236, and for the Neural network model, the Rajasthan test data set have RSME value of 19.81523 and Andhra Pradesh test data set have RSME value of 7.291134.

As we see from the given studies, the forecasting has been done on traditional generation and consumption of electrical energy. There is a study by Siddharth et al.(Chaudhary; 2017) on Forecasting the Solar Electricity Generation and Performance Evaluation of Forecasting models using Time Series data. In this study, the analysis has been done to forecast solar power energy generation in two Indian cities. The models which are implemented here are TBATS, ARIMA, simple exponential time series and Holt method. The data set implemented here is solar radiation data, and if we see, the evaluation parameter used here are RSME, MAE, MAPE and MASE (mean absolute scaled error). The study's results for ARIMA are also implemented in our study, so it has received RSME value of 6.17, MAE value is 2.90, MAPE value is 1.44 and MASE value is 0.27.

We have found another study on a very recent analysis by . (Nichanian; 2020a) on Understanding the Impact of COVID-19 on Electrical Demand. The analysis has been done on how the consumption of energy has changed after the COVID-19 lockdown. The data set used here belongs to Ile-De-France, which includes the city of Paris. The time duration in which this study has been done is from March 17th to June 29th, 2020, because at this time, a very strict lockdown has been implemented. The methodology implemented here is General Additive Model (GAM) and ARIMA model, and the MAPE value received for both the models after three months of analysis are 2.31 and 4.08.

In another study by Steven et al.(Nichanian; 2020b), The analysis has been done on Non-Technical Electricity Loss: Predicting and Defining correlation of Electricity Theft Determinants Using Machine Learning Algorithms. In addition, the analysis has been done on how the irregularities can cause electrical energy loss and be rectified. The data set used here is public data, and the size of the data set is 1024 variables, and the methodology implemented here is CRISP-DM. The models implemented here and their Accuracy is as follows: Decision Tree is 95 percent, Random Forest is 86 percent, Naïve Bayes is 71 percent, SVM is 83 percent, kNN is 83percent, and Logistic Regression is 88 percent.

2.4 Summary of Literature Review.

So, as we have conducted a review on previous studies related to our study, we have got the knowledge for so many ideas and approaches used in electrical load and weather forecasting. After the related work analysis, the information about machine learning models like ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal Autoregressive Integrated Moving) has been found more suitable for predicting and forecasting the future value. So, the mentioned machine learning models are also suitable for predicting when various terminology continuously changes the values. However, as observed in our study, the target variables require good pre-processing work and arrangements. Otherwise, it will not be easy to build the desired model.

3 Research Methodology

For our study, the data mining approach we will be using is KDD (Knowledge Discovery in Databases) methodology. The processes by which our data set has been extracted that is ,the data set's information has been extracted using the data mining algorithm, which has five essential steps that will be adequately discussed in further studies below.(fig 1)

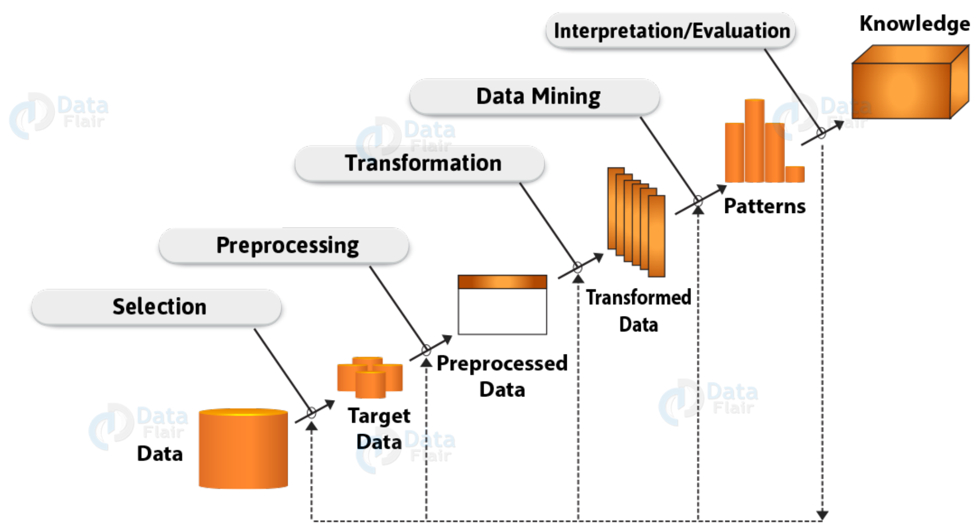

Figure 1: KDD methodology

3.1 Data Selection.

The data set has been selected from Kaggle.com. Data set has been taken from an electrical company, which plans to do some research on the use of electrical load data set and try to optimize electrical production by analysing the past electrical service, the past electrical energy consumption data set. The data set has seven features or columns like ID, Date-time, temperature, anonymise feature 1, Anonymise feature 2, electricity consumption, wind speed and pressure.

3.2 Data Pre-processing and transformation.

The next step after procuring the data set is the data pre -Processing and transformation step. The data pre-processing is a crucial step for the machine learning problem as it ensures getting quality of the result. So now, for our study, we will do the following step.

3.3 Data cleaning.

We will drop the missing values, Repeated N/A values, and NAN values in this step. This will help us in building the model as well, as, in the end, we will get a better accuracy rate. We will do the data cleaning by using python coding. Furthermore, in the end, we will use a heat map also to check and verify that there are no missing values in our data set. With this, we can also fill the blank spaces with zero values.

3.4 Feature Selection.

Feature selection is the step where we will select the valuable feature from the available data set. So, like in our data set, we have seven features; now, we will decide our target variable according to those seven features. So, now in the present table, the variable that will not be used or that will not affect the target variable will drop that feature and select only those that will help predict our target variable.

3.5 Data Split.

Now the data set will be split into two sections that are training and testing. The data set will be divided into a 30:70 ratio, meaning 70 percent of data will be used for training purposes, and 30 percent will be used for testing purposes.(fig 2)

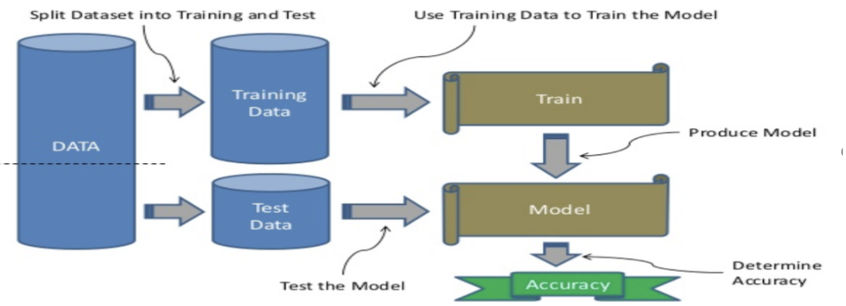

Figure 2: This is a caption

4 Design Specification

With the help of the given figure, we will try to explain the design architecture. The block diagram will help us understand how we have implemented our idea into the machine learning model. After approaching this planned structure, we have an excellent and accurate forecasted result. So, as we can see in the block diagram, the whole project is done in five essential steps. As we can see in the first step, the data extraction is done, and the data set has been extracted from Kaggle.com. The data set has been divided into two parts: data train and data test. Also, the data set has a record of essential features of the electrical term, which can be helpful for the target variable. In the second step, we can see that the EDA processes have been done, and here we have shown how the data look like by some graphical representation. Then data pre-processing step has been implemented, and here we have tried to resolve the issues of missing values in the data set. Then after this, we have applied our machine learning models that are ARIMA,SARIMAX,KNN,Linear Regression,Lasso regression,Random Forest,Lstm and BiLSTM. Then finally, we have evaluated our model with the Root mean square value Mean Absolute Error and Mean Square Error.fig(3)

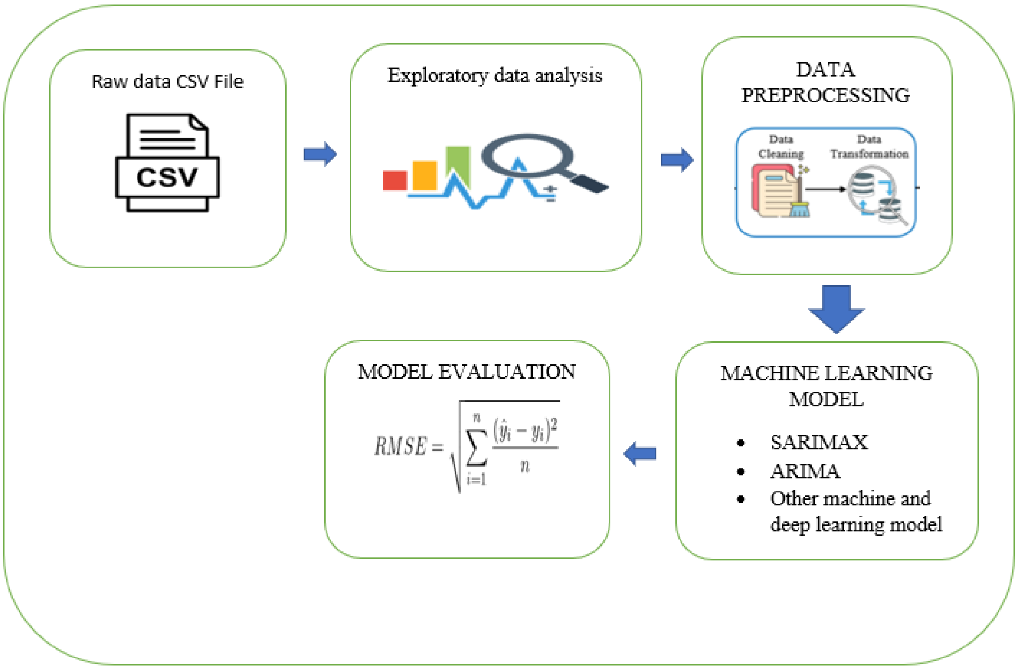

Figure 3: DESIGN APPROACH

4.1 ARIMA.

So, the model which has been used here is ARIMA (Autoregressive integrated moving average). The advantage of this model is that it can forecast future value with the help of using past values. It is a form of regression analysis, and basically, it works on strengthening the target variable in comparison to another target variable. Auto-regression term is explained by the help of its own lagged or initial values. So, the model can show the changing variable. Now integrated means that by the help of raw observation differencing, it will help time series to become stationary. It Means differencing will be found between the previous data values. The data values will replace it. Moving average means the dependency between residual errors and observation values from the lagged observation model to the applied model. If we see the parameters of the ARIMA model, So in the ARIMA model, there are some components, and each component has a notation. The component can be defined as p, d and q, Now the integrated values will be substituted in these parameters, and it will help to find the best ARIMA model.

Our analysis can see these implementations as we have implemented the data set and applied the model; the test has been done to find out the best ARIMA model for our data set. Now, the selection of the model is based on the AIC score of the model. So we can see the ARIMA (2,0,0) having the AIC score is the lowest among the other types of ARIMA model and if we see the computation timing of the model so it was almost 0.70 seconds in the test, as we can see in fig 3. So, therefore, as we can see in our test, we get the best model that is, ARIMA (2,0,0).

4.2 SARIMAX.

The SARIMAX model is somewhat like the ARIMAX model, and a seasonal version exists in this model like other SARIMA and SARMA models. It is one of the most complicated models we have because it must deal with seasonality. As we can see, here in our implementation, it has the value of SARIMAX (2,0,0) for electricity consumption. Like the ARIMA model, the SARIMA model is also selected by the minimum AIC score in the test and minimum computation time. So for our data set, the model SARIMAX (2,0,0,) has the lowest AIC among the other models, and the computation timing is also equal to 0.70. Now, the general equation for SARIMAX model on which this concept is dependent is:

$$Xt = C + \phi 1Xt{-}1 + \theta 1\epsilon t{-}1 + \theta 2\epsilon t{-}2 + \Phi 1\ Xt{-}10 + \phi 1Xt{-}11 + \Phi 2\ Xt{-}20 + \phi 1Xt{-}21 + \Theta 1(\epsilon t{-}10 + \theta 1\epsilon t{-}11 + \theta 2\epsilon t{-}12) + \epsilon.$$

In the context of creating an energy demand forecasting model, meteorological conditions such as temperature might be considered an uncontrolled feature. Therefore, SARIMAX (p, d, q) (P, D, Q)s represents the generic notation of the SARIMAX model.

• p denotes the order of the predicting variable's Autoregressive term.

• d the differencing sequence that must be applied to the data to render the predicting variable stationary.

• q is the order of the predicting variable's Moving Average term.

• P, on the other hand, denotes the order of the seasonal autoregressive term.

• D the seasonal differencing order that must be used to make the data steady.

• Q seasonal movement order.

4.3 LSTM.

In the analysis we have found that the LSTM(Long Short-Term Memory) model will be one of the best model for our implementation of the idea. Because LSTM model is the form of RNN (Recurrent Neural Network) and the speciality of this model is that it uses the previous references for predicting the future values. They way of its working is to collect and feed the data records. It has a cell whose work is to transmit past data to the nodes and to hold the current data. By using the sigmoid function it can operate the gates, the work of gates is to allow and stop the flow of data through them.(fig 4)

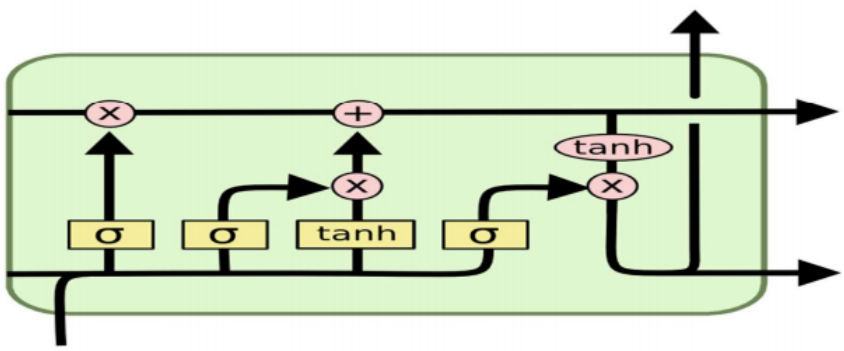

Figure 4: LSTM

Now in Figure we can see that it has 3 input gates and 3 output gates, The work of first input, will contain the present value, second gate is output from hidden layer and then 3rd gate will be output from hidden state. The work of its each gates is to regulate the condition of each cell and there are overall whole model will have three gates. The work of 1st sigma function is to generate 2nd type of values either it will be 0 and 1. 1 means is to store complete value and 0 indicate the forget whole and absolute value. The work of second gate is to provide the fresh data to the cell. And 3rd input determine the what should be the output of the cell which is dependent upon the cell and freshly added data set.

4.4 BiLSTM.

The Speciality of Bi-directional LSTM model is that it has two different states, one for forward and another one for backward inputs which is generated by two different LSTM. The first one starts from the beginning of the sentence and second one generated by the feeding in the opposite order. By the help of this model, we can capture the information which is present in the surrounding.(fig 5)

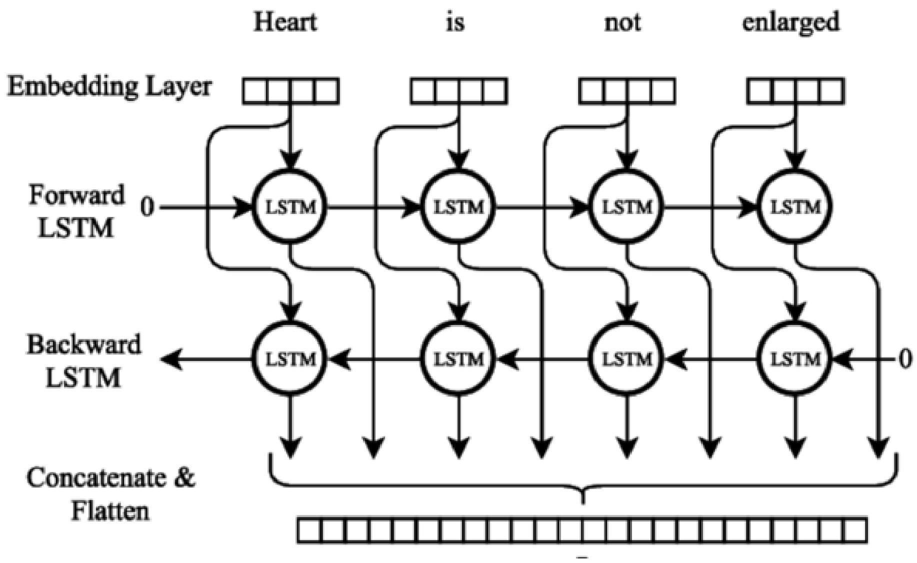

Figure 5: BiLSTM

4.5 LASSO.

This basically a type of regulation technique which is used on the regression model. The main advantage of this model is that it improves the accuracy of the prediction.It works on the concept of shrinkage, means where the data points will spread it will convert into the shrinkage form. Where "LASSO" stands for Least Absolute Shrinkage and Selection Operator.(fig 6)

• Lambda define the amount of shrinkage.

• Lambda= 0 denotes that all features are taken into account, and it is comparable to linear regression, which uses only the residual sum of squares to generate a prediction model.

• Lambda = denotes that no characteristic is taken into account, i.e., as the number approaches infinity, it eliminates more and more features.

• With a Lambda increase in, the bias grows.

Residual Sum of Squares + λ * (Sum of the absolute value of the magnitude of coefficients)

$$\sum_{i=1}^{n}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

Figure 6: LASSO Regression

- With a Lambda decrease in, variance rises.

4.6 KNN model or k-nearest neighbors .

After the implementation of deep learning and some machine learning model we have implemented the K nearest Neighbor model. It is a supervised machine learning model, and the specialty of this machine learning model is that it can calculate the similar thing near to each other.(fig 7)

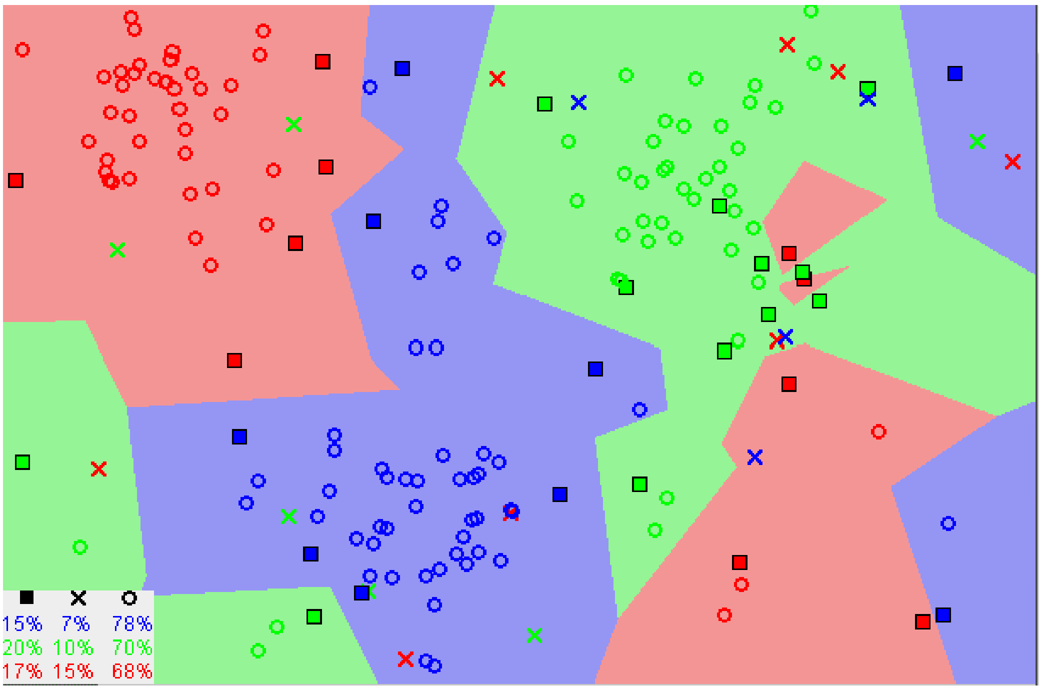

Figure 7: KNN Model

As we can see in the figure similar data points are near to each other, it works on the idea of similarity, or we can say by calculating nearest distance of data points.

4.7 Linear Regression .

The another model which we have used in our study is linear regression model. The linear regression model is one of the well known and good performance models in statistics and machine learning.(fig 8)

$$Y=B0+B1(x)$$

Figure 8: Linear Regression Formula

The work of linear regression model is that it assumes the linear relationship between the input variables (x) and the single output variable (y). We can say that y can be calculated from a linear combination of the input variables (x).

4.8 Random Forest.

It is also supervised machine learning model , basically it builds an assembly of decision tree model. And it will be usually trained by bagging method. The main concept behind the bagging method is that a combination of learning models increases the overall result , which we can see in the figure. fig(9)

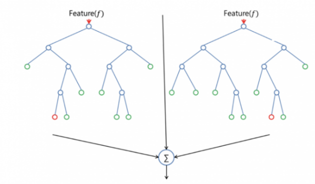

Figure 9: Random Forest

4.9 Technical Configuration.

The technical configuration which is required for implication for our model can be seen in the table.fig(10)

5 Implementation

In this step, we have provided an overview of the different steps involved in building the models, and the model we have built here is ARIMA and SARIMA model. These models can help us to predict the electricity load concerning changes in atmospheric pressure.

5.1 Environmental steps.

This study has been fully implemented in the python programming algorithm, and all the coding work has been completed on the google colab platform. The various initial data

System	**RAM 8G**
Processor	**Intel I5**
Speed	**2.5 GHz**
Software	**Jupyter Notebook**
Programming Language	**Python 3**
Python libraries	**Python libraries**

Figure 10: Technical Configuration

pre-processing steps have been applied, and the ARIMA and SARIMAX models have been implemented with the various essential libraries. With this, there are some different tests also done to check the regularity of the data set and the model's performance. The libraries have been used for the implementation of the model like pmdarima, auto arima and date-time.

5.2 Selection of Data.

The data set has been selected from Kaggle.com, which has the essential record: the station id number, date time, temperature, pressure, wind speed, and electricity consumption. For example, the data set has a record of electricity consumption from 1st July 2013 to 30th July 2017, and similarly, for atmospheric pressure, the data set have a record from 1st July 2013 to 30th July 2017. When we see both the files train and test, the total record of the data is 35064 rows and six columns. The data set is available in CSV format, and the recording is available in two parts: the train and test parts.fig(11)

Now in figure 2, we can see the whole operational processes done during the study. If we follow the hierarchy so first, we have imported the data set, and then we have completed the pre-processing of the data-set, then implementation of the desired model, the evaluation and comparison, and in the last picking up the best model and representation the best model.98

6 Evaluation

After all the implementation, we have applied the evaluation part, which means we evaluated all the models we used in our research and study. So, for better evaluation, we have used the confusion matrix, then we have applied some evaluation parameters like accuracy, sensitivity, and specificity to evaluate the model performance. The working operation of the confusion matrix on the data set will be classified as true positive(tp), which means the result correctly. False-negative(fn) means the data, which was got correct but identified wrong, true negative(tn) means the data which has got wrong but identified correct and false positive (fp)means the data which is incorrect but identified correctly.

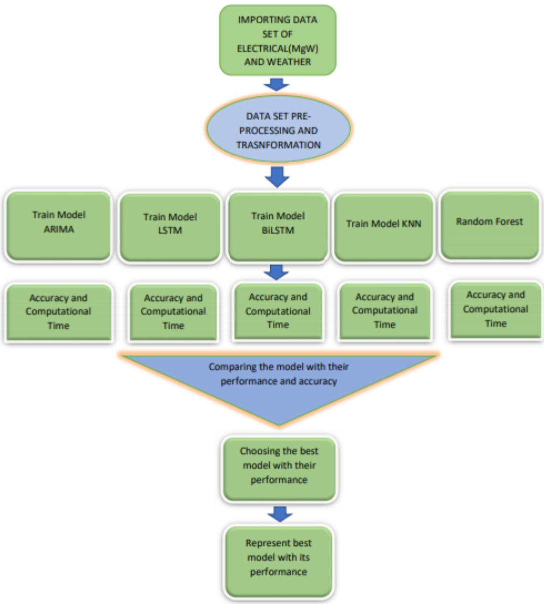

Figure 11: Methodology Processing

Now the formula for accuracy is the ratio of correctly identified results into the number of samples. Accuracy = (tp + tn)/ (tp + tn + fp + fn). If we see the sensitivity, it is determined by the ratio of correctly identified values to the total correct identified samples. Sensitivity = tp / (tp + fn)

RSME (root mean square error) is a type of standard deviation, and we can say that it can identify prediction error. It is a measure of how far data points are present from the regression line, as well as it can measure how to spread out these residuals.

$$\mathrm{RMSD} = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{N}}$$

RMSD = root-mean-square deviation
i = variable i
N = number of non-missing data points
x_i = actual observations time series
$\hat{x}_i$ = estimated time series

Mean Squared Error: It is a type of estimator that can measure the average of square error. It is calculated by the difference between the estimated value and the actual value.

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

MSE = mean squared error
n = number of data points
Y_i = observed values
$\hat{Y}_i$ = predicted values

Mean Absolute Error: It can be measured by the error observation between paired observations.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}$$

6.1 Experiment 1

In our study, the model which have implemented is the ARIMA model, So firstly, we forecasted the electrical consumption.

(I)First, we have performed the Augmented Dickey-Fuller Unit test, which helps us to find either the data set is stationary or not. It always returns an array of values. So, we can see figure (1). Mean Absolute Error: It can be measured by the error observation between paired observations.fig(12) So, the test has been done for both the research

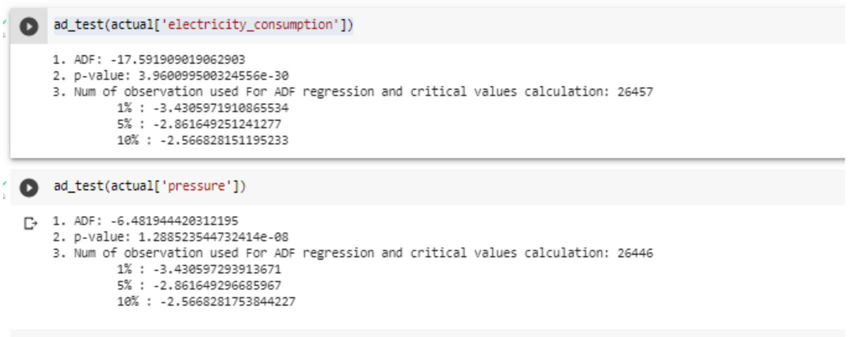

Figure 12: Dickey-Fuller Unit test

parameters that is electricity consumption and pressure. So, the only value which we need to see here is the p-value. The p-value should be smaller as much as possible. Ideally, it should be less than 0.05, so for both the test p-value is smaller than 0.05. This means our data set is stationary, and we can proceed.

(II)So, in the first experiment we tried to find out the best ARIMA model for our data set. As we can see in the table best model is SARIMA (2,0,0) for electrical consumption data set, here SARIMA model is showing because there some seasonality in the data set.fig(13)

(III)Now in the above figure we try to find out the best ARIMA model for our pressure data set, So we have applied python code and we have ARIMA (0,1,1) as the best model for our pressure data set, similarly for electrical consumption ,for pressure data set, ARIMA model (0,1,1) is best for forecasting pressure.fig (14)

(IV)As we can see in the test, the mean value for the electrical consumption data set is 207.9, and the RMSE value is 38.362, which is significantly less than the mean value.

```
Performing stepwise search to minimize aic
 ARIMA(2,0,2)(0,0,0)[0] intercept   : AIC=258842.750, Time=36.29 sec
 ARIMA(0,0,0)(0,0,0)[0] intercept   : AIC=323320.974, Time=0.77 sec
 ARIMA(1,0,0)(0,0,0)[0] intercept   : AIC=258878.212, Time=2.03 sec
 ARIMA(0,0,1)(0,0,0)[0] intercept   : AIC=296740.932, Time=13.02 sec
 ARIMA(0,0,0)(0,0,0)[0]             : AIC=380422.125, Time=0.31 sec
 ARIMA(1,0,2)(0,0,0)[0] intercept   : AIC=258841.295, Time=4.14 sec
 ARIMA(0,0,2)(0,0,0)[0] intercept   : AIC=282337.686, Time=22.59 sec
 ARIMA(1,0,1)(0,0,0)[0] intercept   : AIC=258839.842, Time=10.38 sec
 ARIMA(2,0,1)(0,0,0)[0] intercept   : AIC=258840.982, Time=16.10 sec
 ARIMA(2,0,0)(0,0,0)[0] intercept   : AIC=258839.203, Time=2.80 sec
 ARIMA(3,0,0)(0,0,0)[0] intercept   : AIC=258839.774, Time=3.33 sec
 ARIMA(3,0,1)(0,0,0)[0] intercept   : AIC=258841.915, Time=14.73 sec
 ARIMA(2,0,0)(0,0,0)[0]             : AIC=inf, Time=0.70 sec

Best model:  ARIMA(2,0,0)(0,0,0)[0] intercept
Total fit time: 127.232 seconds
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	26496
Model:	SARIMAX(2, 0, 0)	**Log Likelihood**	-129415.601
Date:	Sun, 11 Jul 2021	**AIC**	258839.203
Time:	10:32:51	**BIC**	258871.942
Sample:	0 - 26496	**HQIC**	258849.770
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	13.9315	0.509	27.372	0.000	12.934	14.929
ar.L1	0.9927	0.002	415.154	0.000	0.988	0.997
ar.L2	-0.0394	0.002	-16.481	0.000	-0.044	-0.035
sigma2	1023.2823	1.793	570.863	0.000	1019.769	1026.796

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	3393154.55
Prob(Q):	0.95	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.83	**Skew:**	0.39
Prob(H) (two-sided):	0.00	**Kurtosis:**	58.43

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Figure 13: ARIMA model selection

```
Best model:  ARIMA(0,1,1)(0,0,0)[0]
Total fit time: 54.137 seconds
```

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	26496
Model:	SARIMAX(0, 1, 1)	**Log Likelihood**	-87392.105
Date:	Sun, 11 Jul 2021	**AIC**	174788.209
Time:	10:35:30	**BIC**	174804.579
Sample:	0 - 26496	**HQIC**	174793.493
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]

Figure 14: ARIMA model selection

```
[ ] test['electricity_consumption'].mean()
```

```
207.9
```

```
[ ] from sklearn.metrics import mean_squared_error
    from math import sqrt
    rmse=sqrt(mean_squared_error(pred,test['electricity_consumption']))
    print(rmse)
```

```
38.3622602443561
```

(V)Now, as we can see, the mean value for the atmospheric data set is 995.775, and the RSME value for the pressure data set is 12.669, which is significantly less than the mean value.

```
[ ] test['pressure'].mean()
```

```
995.775
```

```
[ ] from sklearn.metrics import mean_squared_error
    from math import sqrt
    rmse=sqrt(mean_squared_error(pred,test['pressure']))
    print(rmse)
```

```
12.669236576206902
```

```
[ ] model2=ARIMA(actual['pressure'],order=(2, 0, 0))
    model2=model2.fit()
    actual.tail()
```

6.2 Experiment 2

ANN(LSTM) Now in our second experiment, we have applied an Artificial Neural network (Long Short-Term Memory). When we have implemented ANN(LSTM), the Mean

```
None
290/290 [==============================] - 108s 272ms/step - loss: 1.2483 - val_loss: 1.0229
[INFO] Metrics calculation for LSTM  Starts--------------------------------------------------
Mean Absolute Error- LSTM: 0.7529999258647713
Mean Squared Error:- - LSTM 1.0229281658972678
Root Mean Squared Error: - LSTM 1.0113991130593638
[INFO] Metrics calculation for LSTM  Ends----------------------------------------------------
```

Figure 15: Evaluation Result of ANN(LSTM)

Absolute Error is 0.7529, the mean squared error 1.0229, and the root mean square error 1.011; now, if we talk about the RMSE, so it is near to 1, which is suitable for the model.fig(15)

6.3 Experiment 3

BiLSTM model

We have applied the BiLSTM model where we have selected parameters for evaluation: Mean Absolute Error-0.739, Mean Squared Error is 1.025, and Root Mean Squared Error 1.012, which are comparatively good and show good performance.fig(16)

```
______________________________________________________
None
290/290 [==============================] - 129s 388ms/step - loss: 1.9106 - val_loss: 1.0258
[INFO] Metrics calculation for BiLSTM  Starts--------------------------------------------------
Mean Absolute Error- BiLSTM: 0.7391215996641648
Mean Squared Error:- - BiLSTM 1.0258043706237563
Root Mean Squared Error: - BiLSTM 1.0128200089965425
[INFO] Metrics calculation for BiLSTM  Ends----------------------------------------------------
```

Figure 16: Evaluation Result of BiLSTM

6.4 Experiment 4

Linear Regression

In our second experiment, we have applied the Linear Regression model, so the evaluation parameters are MAE have 0.76, MSE has 1.023 and RMSE have the value of 1.01143, which is same as we have got in ANN(LSTM).fig(17)

```
y_pred [[-0.00105664]
 [-0.00786988]
 [ 0.03133652]
 ...
 [-0.00450107]
 [-0.00682401]
 [ 0.03297506]]
[INFO] Metrics calculation for LR(linear regression)  Starts----------------------
Mean Absolute Error- LR: 0.746646577938117
Mean Squared Error:- - LR 1.023008522978605
Root Mean Squared Error: - LR 1.011438837982112
[INFO] Metrics calculation for LR(linear regression)  Ends------------------------
```

Figure 17: Evaluation Result of Linear regression

6.5 Experiment 5

lasso regression model

After the implementation of the lasso regression model, we have got the value of MAE that is Mean Absolute Error- 0.746, Mean Squared Error Lasso 1.023, Root Mean Squared Error 1.011.fig(18)

```
[INFO] Metrics calculation for Lasso Starts---------
Mean Absolute Error- Lasso: 0.746646577938117
Mean Squared Error:- - Lasso 1.023008522978605
Root Mean Squared Error: - Lasso 1.011438837982112
[INFO] Metrics calculation for Lasso  Ends----------
```

Figure 18: Evaluation Result

6.6 Experiment 6

KNN model

In another experiment machine learning model, we have applied K nearest neighbor model Where we have the evaluation values that is Mean Absolute Error is 0.731, Mean Squared Error is 1.0408, and Root Mean Squared Error is 1.020.35.(Fig 19)

```
[INFO] Metrics calculation for KNN Starts--------------
Mean Absolute Error- KNN: 0.731370530027998
Mean Squared Error:- - KNN 1.0408925779140166
Root Mean Squared Error: - KNN 1.0202414311887245
[INFO] Metrics calculation for KNN  Ends---------------
```

Figure 19: Evaluation Result

6.7 Experiment 7

Random Forest model

In experiment 6, we have applied the random forest. We have applied some parameters to evaluate the random forest model. The values we have got are Mean Absolute Error- Random Forest is 0.705, Mean Squared Error is 0.986, and Root Mean Squared Error is 0.993.47.(Fig 20)

```
[INFO] Metrics calculation for Random Forest  Starts--------
Mean Absolute Error- Random Forest: 0.7050256779963646
Mean Squared Error:- - Random Forest 0.9868080376357748
Root Mean Squared Error: - Random Forest 0.9933821206543708
[INFO] Metrics calculation for Random Forest  Ends----------
```

Figure 20: Evaluation Result

Model	RSME	MAE	MSE
LSTM	1.011	0.752	1.022
BILSTM	1.012	0.739	1.025
Linear Regression	1.011	0.746	1.023
Random Forest	0.993	0.705	0.986
KNN	1.020	0.731	1.040
Lasso Regression	1.011	0.746	1.023

Figure 21: comparison of models result

6.8 Discussion

So, In fig(21) we can see the comparison of the model with 3 parameter on evaluation scale.If we talk about the RSME value so the Random Forest model have the good RSME value comparatively to other models, similarly for MAE and MSE the random forest has scored the good value comparatively to other models.

In this research study, we have shown the different numbers of machine learning models and deep learning model on our selected data set, On the electrical energy consumption (MWh) with atmospheric pressure and other weather affecting features. Now the advantage of forecasting electrical energy will be helpful for the power distribution in the place where the electrical consumption is more because of extreme cold and warm temperatures, As well as electrical energy supply companies and the current ruling government all over the world. So, this study and research have been completed in different steps.

(i) The data set we have selected by the electrical company and is available on an open-source platform kaggle.com, which has the essential information of weather term and electrical consumption term.

(ii) Then, we have applied the pre-processing of the data set for better model performance because the data set has some blank, NA, and NAN values.

(iii) Then, in the final step, we have applied our desired models and try to forecast the electrical consumption as the changes happen in the atmospheric pressure.

7 Conclusion and Future Work

The main aim of our idea is to forecast electrical consumption, which has been done by using the past electrical energy consumption data and weather information data. The models implemented in the study are SARIMAX, ANN(LSTM), BiLSTM, linear regression model, Lasso Model, KNN model, Random Forest and ARIMA. All these models have been applied in a well-structured, well-processed, adequately implemented, and planned way. After the evaluation of all these models, they are showing the best results. The parameter which is set for the evaluation of our model is RSME, MAE and MSE. If we talk about the performance of the model so the ARIMA and SARIMA models are forecasted with two months of usage of electrical energy, which is one of the best results and is valuable, Now the deep learning model, which is ANN(LSTM) model, has shown the RSME value near to 1, which is also suitable for predicting the electrical consumption according to the future. If we talk about the future work, so in the upcoming time, we can also apply some more deep learning models and predict future consumption more accurately. We will also identify the specific region and area where and when the load will be the maximum.

8 Acknowledgement

For the study of my idea and implementation of the desired idea of this project, I want to thank my supervisor Bharathi Chakravarthi for his precious support and feedback. Moreover, I am also very thankful to all the individuals and the resources which has helped me for this study.

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