Optimal Design Energy Consuption of Fog, Edge Computing Using Green Cloud Computing

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Abstract

The European Union's long-term objectives have made electricity demand forecasting a top priority. Lack of adequate methods for estimating future electricity needs, which leads to either under- or over-investment in energy infrastructure. These problems can be solved by employing predictive analysis and time series forecasting techniques. In this study, we will use the Seasonal ARIMA Integrated Moving Average (SARIMA) to make short-term predictions about power consumption and then compare those predictions to those made using MLP stands for "Multi-Layer Perceptron," which is the name of the algorithm used. The electricity consumption in London is evaluated using a half-hourly dataset gathered from UK power networks between November 2011 and February 2014, which includes information on weather and holidays in the city. Through the use of forecasting plots based on the highest, lowest, and middle points of consumption, the MAE, MAPE, MSE, and RMSE of SARIMA and MLP were calculated (RMSE). The prediction graphs are shown on the user interface, and MLP fared better than SARIMA in the tests.

Keywords: SARIMA, MLP, MAE, RMSE, MSE.

1. Introduction

Government and energy foundations place a high priority on the ability to accurately predict future energy demand. The government's need to plan is crucial, especially when it comes to making long-term investments. Predictive analysis has allowed us to look into the future and make educated guesses about the energy requirements of tomorrow. This strategy allows companies to make significant progress in the energy sector. Correct forecasting is essential for avoiding either under or over generation. The process of generating and distributing power requires extensive preparation, and one aspect of that is modelling electricity consumption. Accurate load forecasting can also improve overall savings, readiness, upkeep planning, and fuel management, as well as reduce costs. A distribution grid operator makes use of upgraded demand forecasts to maintain the stability of power networks in the face of increasing penetration of renewable energy sources. Stable power supply and demand on the grid will reduce the need for costly standby power plants. Generation of solar and wind power would add to already unprecedented price swings in the energy market [2]. Predicting the future with high accuracy reduces the amount of money spent on operations and maintenance, increases confidence in the stability of the electricity grid, and aids in making informed choices about the development of the economy.

In this research, we build electricity demand forecasting models using open-source data collected with the use of machine learning methods. Several common methods of gauging precision in time series analysis and regression are employed. The information comprises numerous electricity-related computations and discoveries [3]. London is the centre of this study, which makes use of a massive dataset consisting of half-hourly electrical measurements obtained from UK power networks. In the past, this information has been put to use in a number of different types of forecasting software. However, the current research is the first to try using them in machine learning models [4]. The Multi-layer perceptron (MLP) model has been compared to other forecasting tools, most notably the seasonal auto-regressive integrated moving average (SARIMA). In order to create the prediction models, the predictors are split into a training set (80%) and a testing set (20%). these models are examined using statistical measures.

1.1. Background

To meet the 20-20 targets, each European Union member state must get 20 percent of its energy from renewables by 2020. At least 30% of the United Kingdom's electricity was supposed to come from renewables by 2020, with another 40% coming from low-carbon fuels. Significant reductions in energy imports led to a 5% drop in European electricity consumption and an 8% drop in Britain's trade imbalance during the European financial crisis. The United Kingdom was ranked sixth on The 2018 version of the Global Environmental Performance Index. Indeed, Germany hopes to reach 80% by the year 2050 [5]. An ever-increasing number of international workers are drawn to London by the city's robust economy. As of right now, they don't have enough money, food, or supplies to ensure their survival. [6] With an ever-increasing population comes a corresponding increase in demand on the world's limited supplies. If we keep wasting our resources, our children and grandchildren will have to beg other countries for aid. I opted to study this topic so that I could provide useful information to the government in preparing for this potential catastrophe by predicting future electricity consumption.

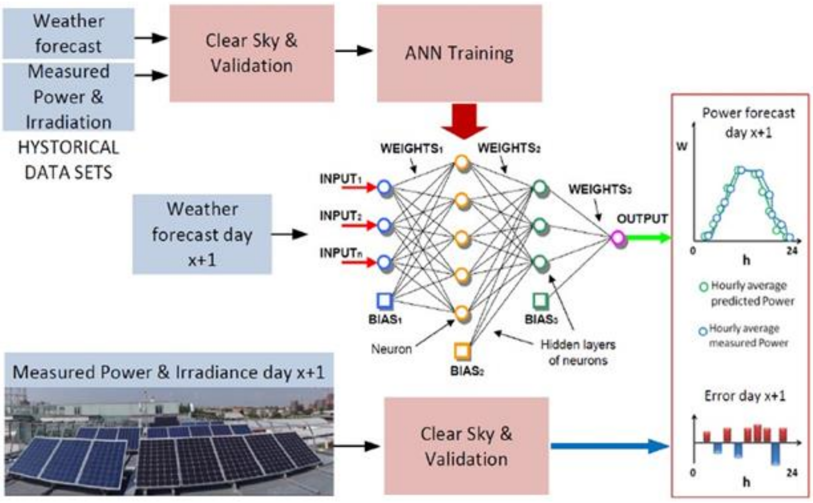


Fig.1: Architecture of ANN to forecast electricity

2. The Literature Review

Several hundred scholarly articles on this topic have appeared during the past few decades. This could be because of the growing interest in forecasting electricity consumption in the study of energy economics. Considering the overarching purpose of this study [7].

Some of the benefits and drawbacks of using neural networks to represent time series for electricity forecasting have been explored in [8]. The ESB dataset was used, which was provided by the Irish power company. When training the neural network algorithm, they used a gradient approach with back propagation. In terms of speed of calculation, the researchers found that neural networks were superior to both the Lervenberg-Marquardt method and the Monte-Carlo technique. The training process involves both analysing the network's multi-step performance and training it for single-step performance. In conclusion, the ANN model was favoured. performed better in deep learning than the competing network models. Oxford University researcher [9] published a work on double seasonal exponential smoothing for forecasting short-term electricity consumption, from half an hour to a day in advance. In order to account for two distinct seasonalities, They used a variant of the Holt-Winters exponential smoothing formulation and the Seasonal Autoregressive Integrated Moving Average (ARIMA) method. This research shows how the Holt-Winters model, which initially can accept only one pattern, can be modified to accommodate time series with two distinct seasonalities. The new double seasonal Holt- Winters method generated forecasts that were superior to those generated by both the original Holt-Winters method and a well-defined multiplicative double seasonal ARIMA model. In another publication ([10]), the same author investigates the use of hourly modelling to forecast electricity costs. These models, which anticipated electricity spot prices, ranged from the autoregressive to the autoregressive moving average to the unobserved component model. Models that account for each hour of the day separately perform better than the full time series in terms of prediction. From the German data market, they gathered a total of 11,688 observations of hourly LPX power spot-prices in Euros per megawatt. The use of more advanced statistical methods is certainly worth investigating further for potential use in future studies. This could be achieved by investigating the potential for electricity spot price forecasting models. In [11], the authors propose a paper that uses multivariate regression analysis to examine energy consumption patterns in Malaysia over an extended time period.

In order to further understand the correctness of the model, the authors of this paper will be developing and testing it using data from previous years.The statistics for the electricity supply industry in Malaysia come from multiple editions of the Malaysia power Centre and the Malaysia energy commission. Unfortunately, they did not put in the time and effort required to make a more accurate prediction using the polynomial regression method and their best fit polynomial curve for the prediction with the smallest standard deviation. Triple seasonal methodology for forecasting short-term shifts in electricity consumption was updated in a 2010 article [12]. They use the most recent empirical research to evaluate the models using double seasonal ARIMA, the Holt-Winters exponential for double seasonality, and other exponential smoothing techniques. Data collected over the course of the past six years in Britain and France is used to make projections about electricity consumption in the future. A comparison between a one-variable neural network and a two-seasonal process and a three-seasonal process reveals that the latter is inferior. They evaluated the results of using

MAPE, MSE, and MAE to evaluate two different approaches. They came to the conclusion that significant more work is required when using ARIMA, the much larger number of parameters compared to the Holt-Winters approach makes for a more stringent specification and a more difficult optimization. Very short-term predictions of power consumption have been made using the seasonal univariate times series method and regression approaches, as detailed in a publication by the same authors [13].

For the purpose of updating prediction intervals, they introduced a non-parametric boot-strap model and contrasted it with several naive approaches. South Australia collects the data every half hour starting on July 6, 1997, and ending on March 31, 2007. For an entire half-hourly forecasts of south Australia's electricity demand were made each week. This research contributes in a novel way by suggesting functional approaches and providing examples of their application to the problem of predicting short-term fluctuations in electricity consumption. Future studies could incorporate other elements, such as weather, seasons, and holidays. Forecasting electricity demand has been studied [14] in the Australian national electricity market. Their main concern is making hourly, daily, monthly, and annual predictions about the system's demand and peak demand. Monash University's Electricity Demand Forecasting Model (MEFM) was created to estimate the likely range of annual and weekly peak electricity demand and annual energy consumption across five areas in Australia. We may be able to learn the forecasts as a set of scenarios, each with its own likelihood, based on their findings. Using NWP models, the researchers in [15] investigated how temperature changes affected electricity demand projections across Italy. Data on electricity use and weather forecasts were incorporated. For the past six years, they have used a naive predictor to keep tabs on the daily load in June and July. Statistical examination of the data on both a national and regional scale is performed. Using the weather data provided by the NWP models, they discovered that heat had a significant impact on power use in the hottest regions of Italy. We have utilised ARIMA/ARIMAX models to train on electrical load data from eight regions and a national aggregate.

The feasibility of smart home sensors for electricity consumption forecasting has been studied [16]. They have employed neural networks and support vector machines to assess the usefulness of individual smart home sensor data in demand forecasting at the household level. Their dataset consists of thirty days of high-resolution information collected from three individual homes. Using ZigBee sensors installed in homes between electrical outlets and appliances, they successfully carried out the trial project to collect electricity load. After analysing the data, they determined that a sample interval of 15 minutes was optimal for forecasting 15-minute average demand, whereas a sample interval of 15 minutes or less was ineffective for forecasting 1-hour demand.

[17] is a study paper on the use of seasonal climate for predicting power consumption in the medium term. Using a combination of linear and non-linear regression, they determined a connection between the climatic patterns prevalent across Europe and Italy's need for electrical power. They used ECMWF's historical seasonal climate forecasts and TERNA's electrical data. SVM outperforms the linear model in short-term forecasting, whereas linear regression produces greater correlation coefficients. They abandoned the long-term future to concentrate on the present-day winter season. Load and supply forecasting for India's

electrical grid has been studied in [18]. The purpose of this article is to utilise the Garch model and the Harvey logistic model to ascertain the degree of volatility present in the electricity market in Nigeria. The National Bureau of Statistics data spanning those 36 years has been compiled. In this study, they employ two distinct models—the Garch model for data training and the Harvey Logistics model for demand and supply forecasting. This study aids India in establishing an overall renewable energy goal, which opens up vast possibilities for the country's power industry.

In [19], a hybrid model for estimating monthly electrical consumption is presented. They merged the neural network algorithm and the genetic algorithm to boost precision (GANN). In order to estimate future electricity demand for energy management, they developed a model to predict monthly power consumption using this novel method. They drew this conclusion with the help of real-world data from commercial enterprises and additional algorithms.

3. Proposed Approach

Research methodology refers to a set of procedures and techniques used in conjunction with a variety of theoretical frameworks. It also discusses the techniques we used throughout development to make the app a fully functional solution with few hurdles.

The data science and data mining processes might employ a number of different approaches. Among these, KDD, SEMMA, and CRISP-DM are the most popular. Similar to KDD and SEMMA, this model exhibits cyclicity. Unique to this setup is the possibility of reversed phase transitions. Comparatively, the CRISP-DM approach integrates the phases of pre-processing collection (KDD) or sample exposure with the phases of data interpretation (BI) and business understanding (Deployment) (SEEMA). The methodology used in this paper is based on data mining, a common practise in many fields (CRISP-DM). This procedure consists of six stages. There is no set order to the phases; rather, they repeat in a continuous loop.

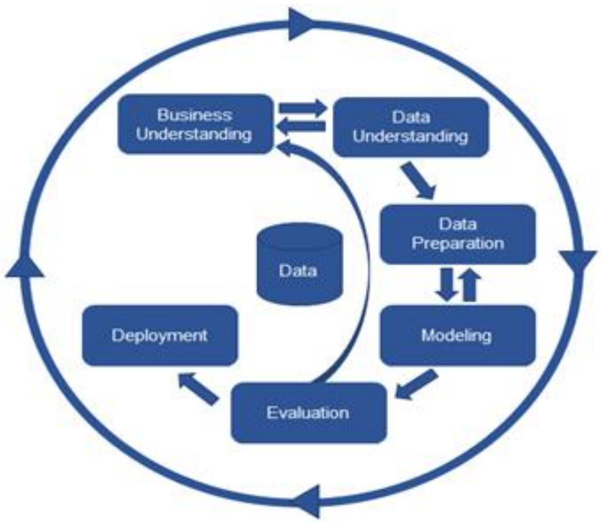


Fig.2. Illustration of the CRISP-DM Process

In the first phase of the process, we analyse the current business climate, project goals, and desired outcomes to determine the best course of action. To design the plan for accomplishingdata mining objectives by first performing a cost-benefit analysis of the tools and techniques that will be required to support the project, and then putting that plan into action.

Our primary goal in writing this work was to develop a method for employing machine learning algorithms to predict the near-term demand for power. Companies can use this information to keep from either under or over producing electricity. The market's supply and demand can be better balanced as a result.

Power grid and lowering demands for supplementary electricity. On weekends, people tend to use more energy than they would during the week. Factors influencing electricity such as weather, season, and holidays are vital for improved accuracy. Most European countries experience extremes of heat and cold throughout the year, making it difficult to predict electricity demand. Greater heat means less need for air conditioning, and vice versa, hence London's electricity consumption is inversely related to its climate.

Selecting the optimal machine learning algorithm from SARIMA and MLP will do this. It's picked because it has the best performance and is the most accurate. Potential applications of this study include the following:

The government can help ensure there isn't too much or too little energy produced, and it can also facilitate the import of the required amount of energy from abroad.

The government is able to plan for the needs of the next decade. Technology firms can build a streamlined app for power utilities that would allow for safe data storage. In order to ensure that there is enough electricity for everyone, the electricity board can keep track of how much is used by each individual household.

- The power board's mobile app allows users to keep tabs on their consumption on a daily, weekly, or monthly basis.
- This information can help businesses and governments make more informed decisions about electricity usage and budget allocation. In order to adapt to the ever-shifting nature of the electrical market.

During this preliminary phase, you will get a fundamental familiarity with the energy market and its current state of affairs from an economic perspective. Various applications and audiences for this research were also considered.

3.1. Comprehending Information

Market tendencies, a synopsis of the company industry, and a list of relevant stakeholders are all derived from this phase. The next step is to implement the machine learning models, and this phase aids in understanding the data collection and source in depth. The section on data interpretation is distinguished by an initial acquisition of information and familiarisation with this data, including data of first class. Improved understanding can be attained through the use of quality management tools. When compared to the six sigma method, which places a premium on minimising the number of variables in an experiment's statistical design, data mining tools have more leeway in the parameters that determine how the algorithm operates.

3.2. Data Gathering

The research uses the Kaggle dataset of London smart metres. Zipped up, this massive Kaggle dataset weighs in at 1 gigabyte and contains 9 individual files covering topics like daily datasets, half-hourly datasets, weather datasets covering both daily and hourly intervals, household information, and a database of UK bank holidays. Three of the nine files we considered for this investigation were block-wise half-hourly consumption data, daily weather data, and data on UK bank holidays. We use half-hourly data from 111 blocks to train the model, with a total of 25287 rows representing 50 individual homes. During the time period of November 2011 - April 2014

	LCLid	date	hh_0	hh_1	hh_2	hh_3	hh_4	hh_5	hh_6	hh_7	...	hh_38	hh_39	hh_40	hh_41	hh_42	hh_43	hh_44	hh_45	hh_46	hh_47
0	MAC000002	13-10-2012	0.263	0.269	0.275	0.256	0.211	0.136	0.161	0.119	...	0.918	0.278	0.267	0.239	0.230	0.233	0.235	0.188	0.259	0.250
1	MAC000002	14-10-2012	0.262	0.166	0.226	0.088	0.126	0.082	0.123	0.083	...	1.075	0.956	0.821	0.745	0.712	0.511	0.231	0.210	0.278	0.159
2	MAC000002	15-10-2012	0.192	0.097	0.141	0.083	0.132	0.070	0.130	0.074	...	1.164	0.249	0.225	0.258	0.260	0.334	0.299	0.236	0.241	0.237
3	MAC000002	16-10-2012	0.237	0.237	0.193	0.118	0.098	0.107	0.094	0.109	...	0.966	0.172	0.192	0.228	0.203	0.211	0.188	0.213	0.157	0.202
4	MAC000002	17-10-2012	0.157	0.211	0.155	0.169	0.101	0.117	0.084	0.118	...	0.223	0.075	0.230	0.208	0.265	0.377	0.327	0.277	0.288	0.256

Fig.3. Characteristics of a typical home

Between November 2011 and April 2014, 5567 London households reported their electricity consumption to UK Power Networks, and that data is shown in the table above. The weather information was retrieved using the darksky api, and the resulting daily weather dataset has 883 rows, 31 different highlighting columns, and the five UK bank holidays displayed in the following format.

	Bank holidays	Type
0	26-12-2012	Boxing Day
1	25-12-2012	Christmas Day
2	27-08-2012	Summer bank holiday
3	06-05-2012	Queen?s Diamond Jubilee (extra bank holiday)
4	06-04-2012	Spring bank holiday (substitute day)

Fig.4. Sample of UK bank holidays

3.2. Collection and Preparation of Data

The dataset's source, size, and characteristics have all been established throughout the comprehension and collection phases. Data normalisation, univariate time series data, and clean data will all be covered as we prepare our data for analysis. Kaggle data, which is publicly available, is used to clean and prepare the data for use in electricity demand forecasting. The dataset is chosen after considering its usefulness, its quality, and a wide range of technical constraints. The cleaning procedure entails the subsequent actions for the chosen data:

- First, purge the data of all zeros.
- Second, Adding new columns to facilitate data analysis
- Third, adjusting the data such that it is normal

Each of the 111 blocks that make up the half-hourly data set comprises around 25000 rows and 50 columns. In addition, between November 2011 and April 2014, there are fifty unique household records for each block. The total number of records for each dwelling in block 0 is considered as part of the data analysis. Predictions can't be made with any degree of accuracy because only one household (MAC000246) has all the values and no nulls. Time series data that is consistent across variables is required for real-time forecasting, and it is assumed that the MAC000246 household from block 0 will be used in the next analysis.

3.3. Insert New Rows

Modifying the dataset by either adding or removing rows from the table can improve both the readability of the data and the accuracy of the resulting conclusions. In this scenario, the only information about individual households is their total KWH of electricity use. Better outcomes can be expected with the addition of a data frame detailing total and average electricity use alongside the relevant dates.

```
LCLid
MAC000002    498
MAC000246    814
MAC000450    410
MAC001074    222
MAC003223    526
MAC003239    526
MAC003252    513
MAC003281    519
MAC003305    519
MAC003348    440
```

Fig.5. Column expansion

Every day from 2011 to 2014, a household's total electricity consumption is tallied. In addition, daily usage is divided by the number of recordings per day to arrive at an average per household.

The calculated fields are written to a new data frame and appended to the existing dataset. Forecasting properties of hourly models for spot electricity prices are consistently better than those of full time series specifications, suggesting that such models may be useful for improving upon existing univariate approaches. This is due to the fact that these models' predictive power is improved by the incorporation of rudimentary probabilistic processes for the arrival of extreme price events.

3.4. Relative Data Normalisation

The purpose of normalisation is to transform the values of the numerical columns in the dataset to a uniform scale, while maintaining the ranges of the original values. Datasets with widely varying feature ranges can be normalised. This method excels in cases where the data scales are inconsistent and the algorithm cannot make any assumptions about the data's distribution. A dataset's normalisation can be done on a single column or on all of them simultaneously. The data on electricity was seen as potentially taking on a variety of values. Data normalisation is an option for making all of the numbers look the same size.

	index	total_consumption	avg_consumption	year	month
0	498	20.763	0.432563	2011	4
1	499	6.020	0.125417	2011	5
2	500	13.322	0.277542	2011	6
3	501	9.062	0.188792	2011	7
4	502	13.664	0.284667	2011	8

Fig.6. Column kinds and data representations

3.5. Collecting and Organising Weather Information

The power dataset is improved by include weather data that accounts for seasonality. We have narrowed the list of columns down to just those that contain numerical data. Date information is given in the dataset so that the results can be calculated daily depending on the current date and the weather data used to determine the amount of electricity used each day.

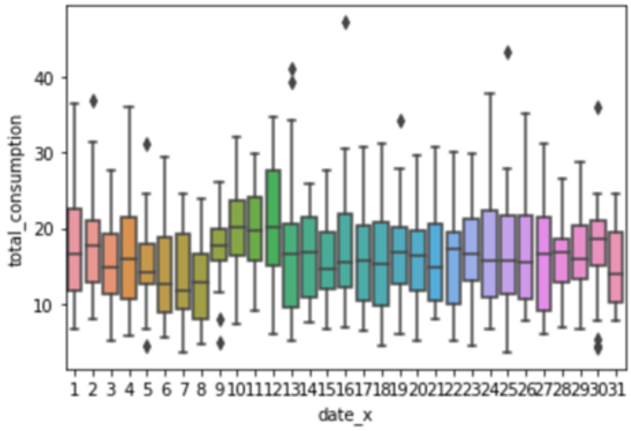


Fig.7. Boxplot of daily electricity use versus climate conditions

We next use time series analysis and machine learning methods to refine the normalised data in the following chapter. In subsequent parts, we dive deep into the specifics of popular machine learning algorithms like ARIMA, SARIMA, and MLP.

4. Analyses and Outcomes

For this task, we use an 80:20 split of the publicly available London power usage information from November 2011 to February 2014 for our training set and our test dataset. Both the autocorrelation function (ACF) and the partial autocorrelation function (PACF) are used to determine which values (p, q) are most suitable.

In contrast to the steady decline seen in the auto correlation plot, the sudden drop seen in the partial auto correlation plot after the first lag is clearly visible. It can be inferred from the graphs that the k=1 lag successfully explains most of the higher-order autocorrelations. Therefore, a 'AR' signature can be seen in the series.

4.1. Temperament Test

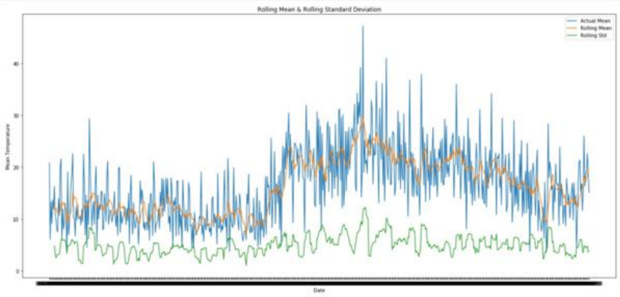
The Dickey Fullers (ADF) test is used to determine if the data are stationary. The unit root hypothesis can be investigated further with the assistance of this test. The alternative stationary will be utilised if the null hypothesis is rejected by the ADF test. The null hypothesis is not rejected, and the data is non-stationary, if the p-value is greater than 0.05. Likewise, data is considered stationary when the p-value is less than or equal to 0.05.

Table 1. Do Not Show Stationarity (P>0.05).

```
Test Statistic                 -1.601199
p-value                         0.482991
#Lags Used                     20.000000
Number of Observations Used   629.000000
dtype: float64
```

Table 2. Non-moving average (P 0.05)

```
Test Statistic                 -5.442368
p-value                         0.000003
#Lags Used                     20.000000
Number of Observations Used   609.000000
dtype: float64
```




```
Test statistic:  -1.6011994675461299
Critical Values: {'1%': -3.4407890899441127, '5%': -2.8661459340578905, '10%': -2.5692228868342766}
```

Fig.8. Standard deviation and mean with the modified Dickey-Fullers test

Next, the trained electricity data is used to fit a SARIMA model along the p, d, q values, taking into account the effect of weather and holidays. The endog and exog are the data observed variables in the forecast. The SARIMA model is used for both the training and testing phases of data analysis, with the MSE and MPP being used for evaluation.

SARIMAX Results

Dep. Variable:	total_consumption	**No. Observations:**	650
Model:	SARIMAX(1, 0, 1)x(1, 1, [], 12)	**Log Likelihood**	-2117.650
Date:	Sun, 23 Aug 2020	**AIC**	4249.300
Time:	16:55:46	**BIC**	4280.508
Sample:	0	**HQIC**	4261.415
	- 650		
Covariance Type:	opg		

	coef	**std err**	**z**	**p** click to expand output; double click to hide output		
const	-1.175e-06	9.12e+04	-1.29e-11	1.000	-1.79e+05	1.79e+05
weather_cluster	-0.1186	0.313	-0.378	0.705	-0.733	0.496
holiday_ind	1.6917	1.180	1.434	0.152	-0.620	4.004
ar.L1	-0.4707	0.526	-0.895	0.371	-1.501	0.560
ma.L1	0.4202	0.544	0.772	0.440	-0.647	1.487
ar.S.L12	-0.4581	0.032	-14.159	0.000	-0.521	-0.395
sigma2	44.5265	2.382	18.692	0.000	39.858	49.195

Ljung-Box (Q):	472.07	**Jarque-Bera (JB):**	2.29
Prob(Q):	0.00	**Prob(JB):**	0.32
Heteroskedasticity (H):	1.57	**Skew:**	0.00
Prob(H) (two-sided):	0.00	**Kurtosis:**	3.29

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

Fig.9. SARIMAX Outcomes

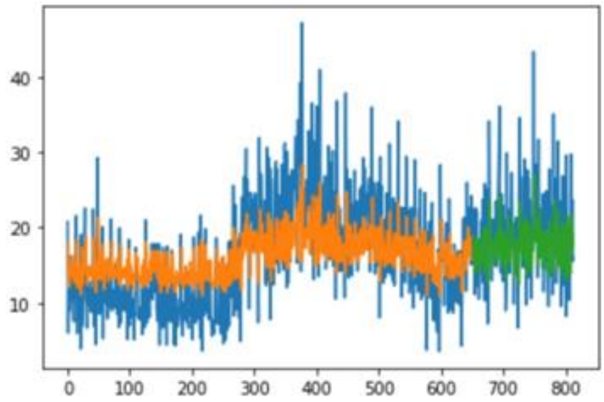


Fig.10. A graphical depiction of the available historical and forecast data

When comparing SARIMA and MLP, it is clear that MLP has a little edge in terms of evaluation findings due to its higher accuracy. The FLASK programme is used to create a graphical user interface that is hosted on a server and displays information on each residence in all 111 blocks. Furthermore, The page also features a data exploration

5. Conclusion

We can characterise the components influencing demand by looking at their strong correlation with overall electricity consumption: temperature, humidity, visibility, and the UV index. Data analysis reveals that colder temperatures and higher humidity make January and December the two months of the year with the highest electricity consumption.With both the MLP and SARIMA models for forecasting short-term electricity demand examined, the one with the lowest error values was selected.

The statistical measures allow us to infer that both models provide very comparable results, with very small differences between them and a range of decimals. MLP model outperforms SARIMA by a small margin. The user-interface dashboard is designed to be intuitive and easy to comprehend by displaying visual representations of all the outcomes.

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