Electricity Demand Using Time Series Analysis

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Abstract- Throughout the years, there has been a constant rise in the need for power. A strong predictive model is necessary to comprehend future consumption. The planning of power production and the determination of resources required to run the plants, such as fuels, depend heavily on the forecasting of energy demand. It also aids in the planning of future electricity requirements, which leads to the establishment of additional networks and plants. There are about 10 million people living in the city of London, which also contains 3.6 million homes, numerous businesses, and an industrial sector. Every year, energy bills in London's homes and offices cost upwards of £7.9 billion; this money does not stay in the city's economy.

Keywords- **ARIMA, SARIMAX, LSTM, MLP, EXOG.**

I. INTRODUCTION

Forecasting electricity demand is an important matter for the public sector, which includes the government and energy generation. Predictions that are accurate can result in major cost savings, better preparedness, better maintenance plans, and better fuel management. Furthermore, by employing improved demand projections, a distribution grid operator can preserve stability amongst power grids with a high distribution of renewable energy. This can lead to smart decision-making, increased power supply and distribution system dependability, and significant operational and maintenance cost reductions. Using a sizable dataset of daily mean energy consumption records gathered from UK power networks, this study focuses on the city of London. As forecasting instruments, the SARIMAX and MLP models are contrasted.

The UK government wants to produce 40% of its electricity with low carbon content and 30% from renewable sources.

In this research, we are interest in time series analysis with the most popular method, that is, the Box and Jenkins method [3]. The result model of this method is quite accurate compared to other methods and can be applied to all types of data movement. There were two forecasting techniques that were used in this study; Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Moving Average (ARMA). We applied these methods for detecting patterns and trends of the electric power consumption in the household with real time series period in daily, weekly, monthly, and quarterly [14]. We used program R and Rstudio [4], [5], for constructing the model [6], [7], [8]. The most suitable forecasting method and the best choice of period were chosen by considering the smallest value of AIC (Akaike Information Criterion) and RMSE (Root Mean Square Error), respectively.

II. LITERATURE SURVEY

Numerous research studies on the forecasting of electricity consumption have been published in recent decades. This could be because energy economy research is seeing an increase in the prediction of electricity consumption. For this study, we have examined and evaluated eight international research articles that have been published in the recent 20 years (2000–2020). Research on FOREX market anticipating exchange rates using deep learning and machine learning algorithms has been conducted by Iwona Ajumi and Abhishek Kaushik [1]. The primary goal was utilizing a deep learning method and a single hidden layer feed forward network to forecast the time series using a multi-layer perceptron (MLP). They employed exponential smoothing, RBF, MLP, SVM, ARMA, ARIMA, and the Box-Jenkins technique in addition to the Naive model.

III. METHODOLOGY

During the Requirements Gathering phase, stakeholders provide information regarding data sources, target variables, and desired accuracy levels for the electricity demand forecasting model.

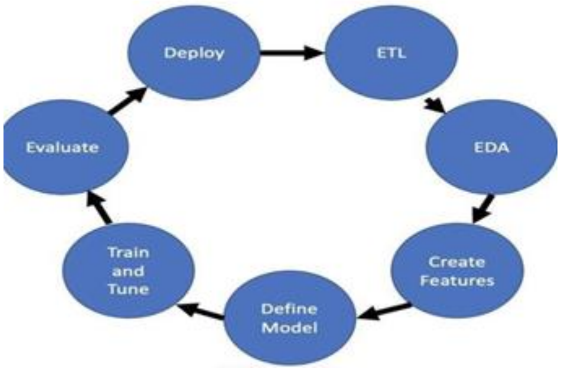

Figure3.1: SDLCMODEL Created by Brandon Walker published on Towards Data Science

Design: During this stage, the structure and layout of the model are developed according to the specifications collected in the prior phase. This involves identifying the right data preprocessing methods, choosing suitable features, and creating SARIMAX and LSTM models.

Execution: During this stage, the model is put into practice utilizing the programming language and machine learning libraries that were chosen. This involves programming the data preprocessing, creating features, training models, and building forecasting algorithms.

Validation: During this stage, the model undergoes testing to confirm that it satisfies the requirements and specifications outlined during the requirements gathering phase. This involves verifying the model's prediction precision and ensuring its ability to handle big datasets and real-time data with scalability and robustness.

Implementation: During this stage, the model is put into operation in the production setting, where it is utilized to create predictions for electricity demand. This involves connecting the model to required infrastructure and giving stakeholders access to the model's outcomes.

Maintenance involves updating and ensuring accuracy of the model to keep it current. This involves incorporating new data into the model, adjusting the model's settings, and resolving any bugs or problems that may occur.

In this study, we examined how weather conditions relate to electricity usage by analyzing data from smart meters in London homes. The aim of the study was to achieve all of its primary goals. We reviewed existing studies on electricity consumption using machine learning methods to improve accuracy and created a user-friendly interface to fill in research gaps. We encountered challenges with incorporating additional weather and holiday information, but we managed to address certain issues. We evaluated the precision of the SARIMAX and LSTM models through the comparison using statistical measures. Both models had similar results, but LSTM slightly outperformed SARIMAX. Temperature, humidity, and windspeed were closely linked to electricity usage, and we used this correlation to identify the factors influencing demand.

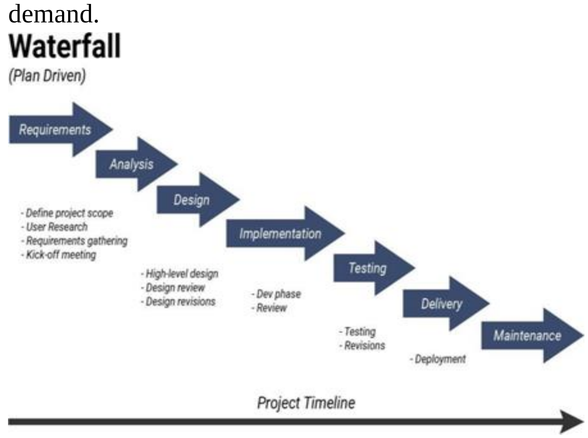

Figure 3.1 WATERFALL MODEL

waterfall model by Dr.Winston W. Royce

Moreover, the study found that there was a rise in electricity consumption in the initial and final months of the year, likely due to cooler temperatures and higher levels of humidity. We analyzed the current energy usage with LSTM and SARIMAX models, choosing the model with the least amount of error to predict electricity needs. After analyzing the statistical measurements, it was found that both models produced comparable results with few errors. The performance of the SARIMAX model was not as good as that of the LSTM model. A user-friendly interface dashboard was created to display visual representations of the results, aiming to enhance user comprehension.

IV. TECHNOLOGY USED

Computer programs :

Google Chrome, Google Colab, Jupyter Notebook, and Tableau are all software applications that are frequently used.

anaconda and navigator remain the same.
- Physical components
- Equipment
- Technology devices

Hardware Utilized: Intel i5 10500K/AMD Ryzen 5 4600h chip, 8GB RAM
1 Terabyte of storage capacity, memory included.
* Book repositories

Utilized libraries include: numpy, pandas, matplotlib, sklearn, statsmodel, keras.seaborn library can be used for data visualization.

V. RESULTS

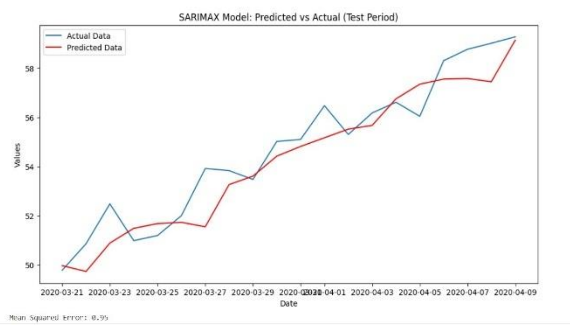

Figure 5.1: SARIMAX Predicted Vs Actual

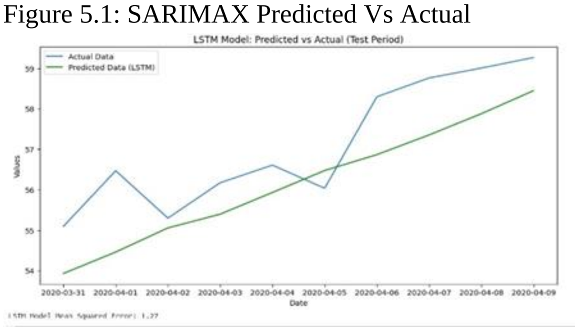

Figure 5.2: LSTM Predicted Vs Actual

VI. CONCLUSION

In this study, we examined how weather conditions relate to electricity usage by analyzing data from smart meters in London homes. The aim of the study was to achieve all of its primary goals. We reviewed existing studies on electricity consumption using machine learning methods to improve accuracy and created a user-friendly interface to fill in research gaps. We encountered challenges with incorporating additional weather and holiday information, but we managed to address certain issues. We evaluated the precision of the SARIMAX and LSTM models through the comparison using statistical measures. Both models had similar results, but LSTM slightly outperformed SARIMAX. Temperature, humidity, and windspeed were closely linked to electricity usage, and we used this correlation to identify the factors influencing demand.

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