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Prediction of Load Demand in Home Area Network Using LSTM

Abstract: - Load forecasting is one of the most important tools for the energy management system in the modern world. Forecasting power consumption and load demand calculation became an interesting topic for the stakeholders in the electricity market. Decision-making in purchasing and generating electric power, load switching, and demand side management are dependent on load forecasting. This research work focuses on the prediction of power consumption in a Home Area Network (HAN) using time series forecasting methods like Long short-term memory (LSTM) neural Networks. Our goal was to design a model that could precisely forecast the electrical load required in a Home Area Network. Utility companies and homeowners can utilize this model to better plan and control their power usage. It can assist in lowering the likelihood of power outages and enhancing the effectiveness of the electrical system. The Root Mean Squared Error (RMSE) is used as the performance measure in our work. The dataset considered is from the UCI repository with 350400 rows and 4 parameters such as active power, and 3 submetering values, to achieve realistic data for training the model used the encoder-decoder LSTM model for load prediction and achieved an RMSE value of 23 and an MAE value of 18.6.

Keywords: Time Series Forecasting, Normalization, Encoder-Decoder LSTM, RMSE, Mean Absolute Error (MAE).

I. INTRODUCTION

Electricity demand is rising rapidly as the population grows and the energy infrastructure expands. The power system is becoming more intelligent and flexible with the advancement in science and technology and the way people use electricity in their daily lives results in variation in consumption of power. Regulating the generation and consumption of power helps in preserving the stability of the grid. In a competitive modern electricity market, planning the generation of electricity in advance offers a considerable benefit to the stakeholders, producers, and system operators, for balancing responsible parties, and consumers. Over the year, a given group of the population exhibits several periodic patterns of energy usage. These patterns change based on a wide range of variables. Finding these factors is essential for load forecasting or demand calculation. The ability of the stakeholders to make decisions depends on an accurate short-term projection of energy consumption. Utilizing past data, it is necessary to assess how different input parameters affect consumption in order to forecast it.

Load forecasts are necessary to plan and operate the smart grid to increase efficiency. The effectiveness of load prediction has a significant impact on a variety of choices, including efficient energy transactions, demand-side control, and economic scheduling. However, load prediction is difficult due to the dependency of energy consumption on exogenous variables like temperature, weather, etc. For energy saving, the load demand estimate needs to be as accurate as possible. To achieve this, one must be aware of the elements that affect or control the load demand. The systems in charge of energy management are designed to monitor and regulate the smart grid energy market by performing the necessary optimizations.

1.1 Literature Review

A detailed literature survey on various works by other researchers has been conducted which provides us with the following insights:

[1]. An intelligence system is useful for determining specific power requirements in an area. Prediction is made using a simple linear multivariate regression approach. In this case, the regression was used to predict with the maximum accuracy. Power needs analysis and future use predictions are made using the suggested system. The model's accuracy was not mentioned in this publication.

[2]. Over a year, electricity usage of a given group of the population follows a periodic pattern. These patterns change based on a wide range of factors. This paper focuses mostly on two contributions: SVM and RNN algorithms are used to perform forecasts. The historical real data is used to train these algorithms. A specified set of days spanning edge scenarios in the forecast of power usage is used to evaluate the performance. It has been demonstrated that for almost all feature combinations, RNN produces a greater accuracy. With the given training dataset, RNN is proved to be more suitable than SVM for precise energy forecasting.

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[3]. A rare event can be defined as an occurrence of an event with a very low temporal or spatial frequency in comparison to the parent data population or reference class, such as less than one incidence per a thousand observations. Because rare events can have a significant impact quickly and have cascade effects, the System Operator (SO) has very little time to take appropriate action. This makes anticipating rare event loads crucial. Forecasting frequently involves examining past and present trends in load and climatic data.

[4]. Different home structures consume electricity in different ways depending on how long inhabitants spend at home, electric energy demands differ on weekdays and weekends. A properly clean and correctly pre-processed dataset is used to train and test BP-ANN and SVR models. The tests are set up to forecast how much electricity will be used in five different time periods, such as the morning, the afternoon, the evening, the night, and midnight. Despite a very tiny performance advantage of the BP-ANN model over the SVR model, the SVR model is still capable of producing accurate predictions of electric energy.

[5]. The authors have employed a recursive multi-step technique in this research study to forecast short-term data using Echo State Networks (ESN). In this approach, the first value of the prediction horizon is forecasted from the measured input sequence, and the engine uses the projected values to predict the next horizon steps circularly. The superiority of LSTM NNs over GRNNs and ELMs is finally demonstrated in this research study.

[6]. In this paper, a novel STLF method is used while briefly discussing a traditional time series technique. The predictions made using this method are contrasted with those made using the Elman neural network. RNNs have the advantage of using sequential information. All input and output variables in a conventional neural network are thought to be independent of one another. But that is not acceptable for the STLF work. In this paper, the authors performed a comparison between Elman and LSTM for a common day and a special day.

[7]. In this paper, the authors predict only short-term electricity load consumption (i.e., hourly, daily, weekly, and monthly-based predictions). By using the algorithm called LSTM, they predict month-ahead electricity consumption. Experimentation using a real dataset for performance analysis showed that the suggested strategy was well performed with a prediction accuracy of 82.5. After the model is successfully trained and tested on the existing load profile, predict the future consumption for the next month. According to the final results, the training dataset's prediction accuracy was about 85.5 percent, and the testing data was about 82.5 percent.

[8]. The author incorporated LSTM for load forecasting in smart grids. The results demonstrated that LSTM is the best way compared to all other prediction methods. There are four groups in LSTM based on time scale which are medium-term load forecasting (MTLF), short-term load forecasting (STLF), long-term load forecasting (LTLF), and very short-term load forecasting (VSTLF). The MAE and RMSE for the suggested LSTM model are 92.448 and 127.682 respectively. From the outcome, it is observed that LSTM reduces errors in MAE and RMSE by 52.24 percent and 21.67 percent, respectively. Additionally, the LSTM model was tested using diverse load data for the city of Chattogram in 2019 and exhibits superior performance compared to SVM.

II. Motivation

Due to the shortage of coal stocks available to the thermal plants, India experienced a power supply scarcity of 1,200 million units by the end of 2021. This was the highest in the last 5.5 years. To meet the high demand for electricity, several states across the nation, including Andhra Pradesh, Gujarat, Maharashtra, Jharkhand, Bihar, Haryana, and Uttarakhand, are experiencing protracted power outages. Over 70% of India's electricity production comes from coal. Coal based on imports makes up more than 12% of this. In India, the cost of imported coal is anticipated to increase by 35% in the fiscal year 2022–23 compared to all the prior years. The energy suppliers will be forced to pay premiums of up to 300% in March to obtain coal supply on the domestic spot market. An average of 5% of the electricity used each month is used for standby power. Therefore, by reducing standby power by examining the outcomes predicted by the Machine Learning model, the amount of electricity wasted in home area networks can be controlled. Largescale implementation might reduce the quantity of wasted power.

III. Methodology

The existing LSTM model has given an MAE and RMSE value of 92.448 and 127.682 respectively. The methodology adopted in our research work was the inclusion of the Auto-encoder technique to reduce the RMSE value for a better prediction. We have used the tensor flow to create an ML model and train the model with the dataset. The sample of the dataset is shown in Table 1.

Table 1: Dataset

Date	Time	Averaged_ active_power	Submetering_1	Submetering_2	Submetering_3
01-01-2021	12:00:00 AM	25.228	0	0	275
01-01-2021	12:15:00 AM	20.714	0	0	216
01-01-2021	12:30:00 AM	9.884	0	0	10
01-01-2021	12:45:00 AM	9.326	0	0	10
01-01-2021	1:00:00 AM	9.216	0	9	10
01-01-2021	1:15:00 AM	10.988	0	20	9
01-01-2021	1:30:00 AM	9.604	0	18	10
01-01-2021	1:45:00 AM	9.266	0	1	10
01-01-2021	2:00:00 AM	9.97	0	0	10
01-01-2021	2:15:00 AM	8.722	0	0	10
01-01-2021	2:30:00 AM	8.992	0	0	10
01-01-2021	2:45:00 AM	10.392	0	0	10

3.1 Dataset:

The dataset consists of 350400 rows and 4 columns which contain numerical. We have used dataset from UCI repository for training our model. The 4 parameters of our dataset are: -

3.1.1. Averaged Active Power

Average active power is the amount of power consumed by household devices every 15 minutes (in kilowatts). To achieve realistic data, we need to skew the dataset slightly toward the left. (Refer fig1 & fig 2).

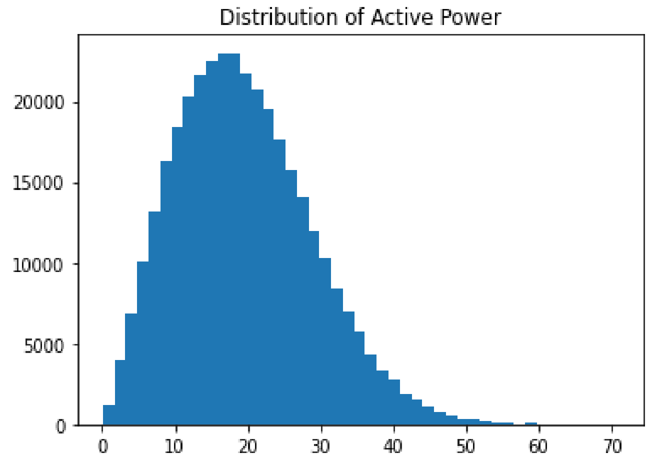


Fig 1: Distribution of Active power

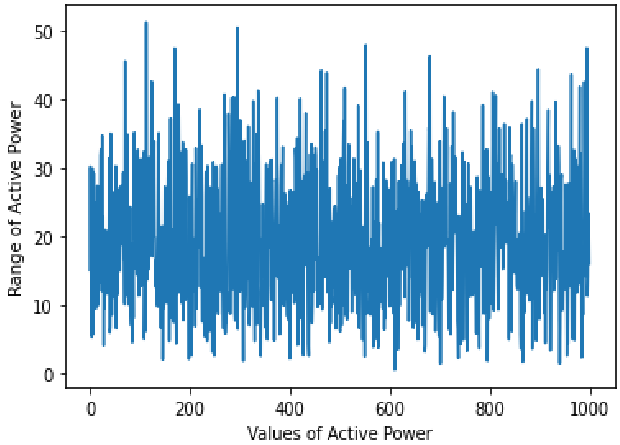


Fig 2: Range of Active power

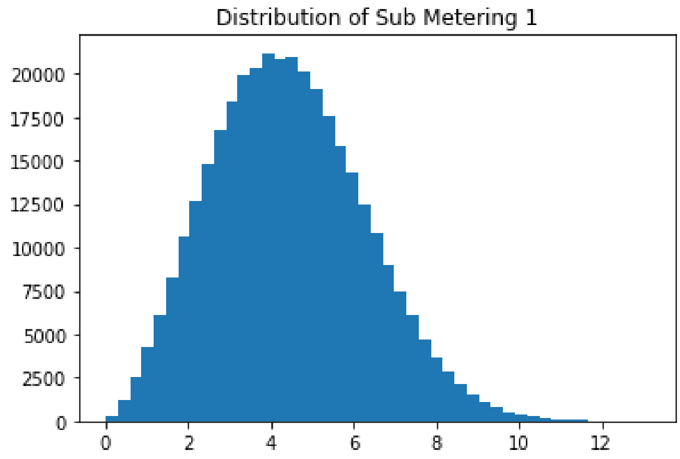


Fig 3: Distribution of Sub Metering 1

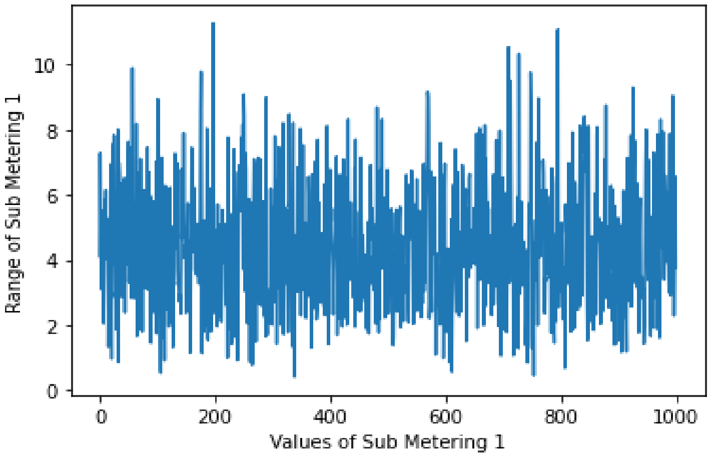


Fig 4: Range of Sub Metering 1

3.1.2 Sub Metering 1

Sub-Metering 1 or Energy-metering-1 corresponds to the energy consumed by household devices like dishwashers, ovens, and a microwave (in watts). (Refer fig 3 & fig 4)

To achieve realistic data, we need to distribute the data equally around the mean.

3.1.3 Sub Metering

Sub-Metering 2 or Energy-metering-2 corresponds to the energy consumed by household devices like a tumble drier, a refrigerator, washing machines, and lights (in watts).

To achieve realistic data, we need to skew the simulated dataset towards the left. (Refer fig 5 & fig 6)

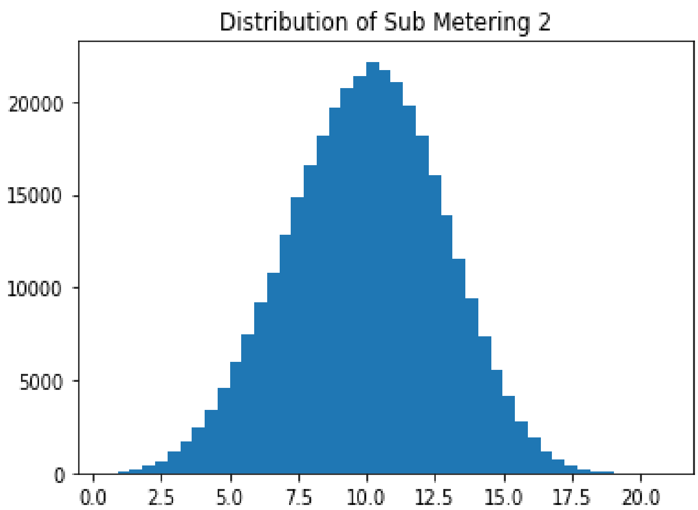


Fig 5: Distribution of Sub Metering 2

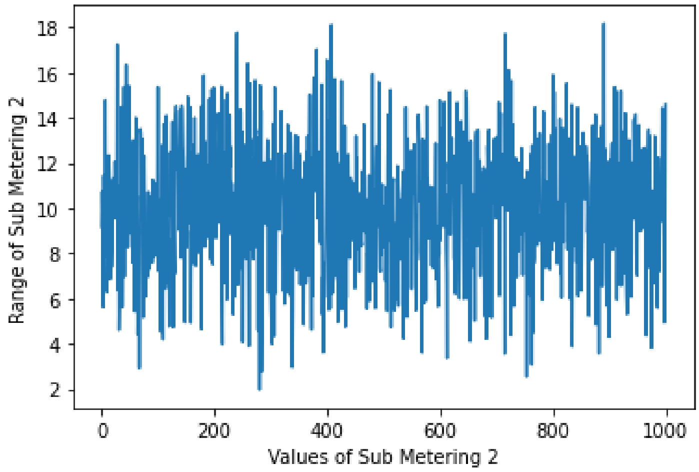


Fig 6: Sub Metering 2 value distribution

3.1.4 Sub Metering 3

Sub-Metering 3 or Energy-metering-3 corresponds to the energy consumed by household devices like a geyser or an air-conditioner (in watts). To achieve realistic data, we need to skew the simulated dataset toward the right.

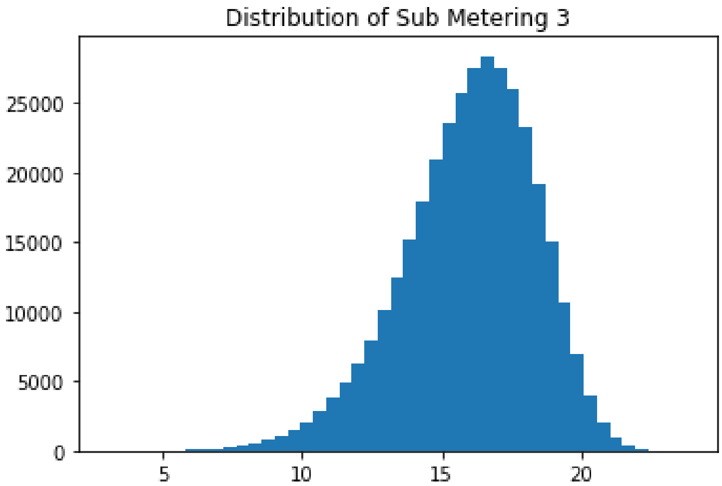


Fig 7: Distribution of Sub Metering 3

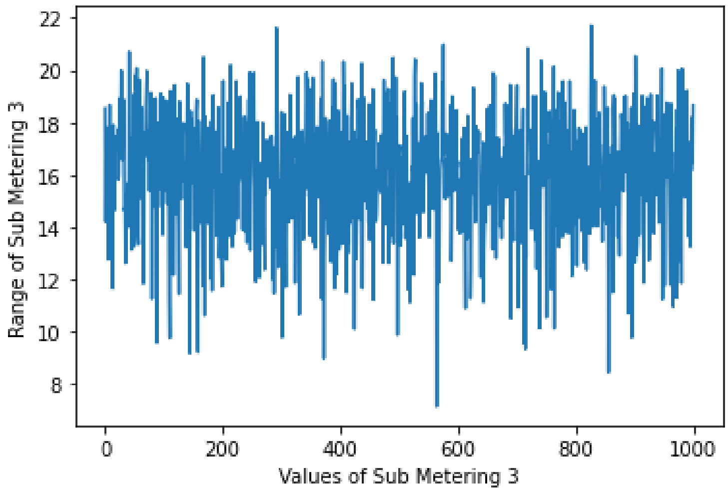


Fig 8: Sub Metering 3 value distribution

IV. MODEL

An encoder-decoder LSTM is a recurrent neural network (RNN) architecture in natural language processing tasks. It is called an encoder-decoder architecture because it consists of two separate components: an encoder and a decoder. The encoder transforms the input sequence and the decoder receives the context vector and utilizes it to produce the output sequence. We built a model which can predict all parameters of a particular period. We used the encoder-decoder LSTM model for sequence-to-sequence prediction. Since there are 4 independent parameters, we used the Min-Max scalar transformation which makes the optimization problem more" numerically stable". The feature scaling prevents the supervised learning models from biasing toward a specific range of values. We used one layer of encoder-decoder, repeat vector, and time distribution layer. Finally, we were able to predict all four parameters.

V. BLOCK DIAGRAMS

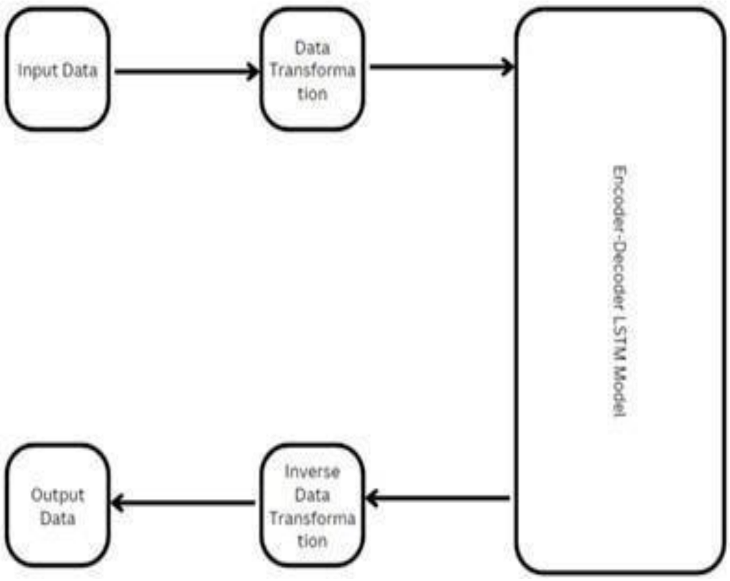


Fig 9: Working of LSTM Model

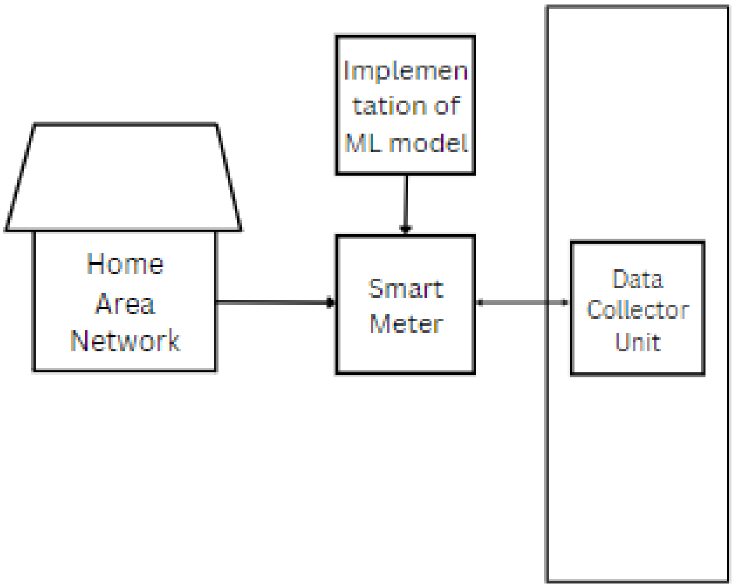


Fig. 10. Implementation of LSTM (ML) model

VI. LSTM WORKING

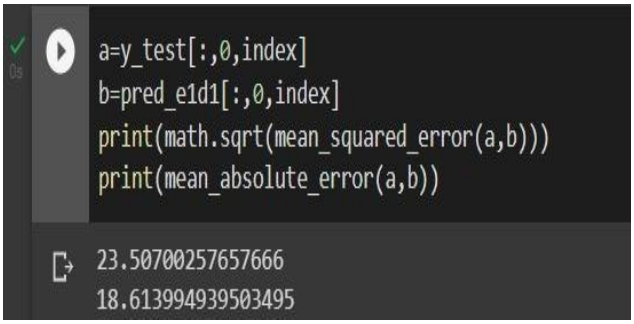
An LSTM, a long short-term memory network, is made up of LSTM cells, which are the building blocks of an LSTM network. For the network to retain long-term knowledge and provide more accurate predictions, each LSTM cell processes a one-time step of the input sequence. The components include the forget, input, and output gates, and the cell state.

VII. ENCODER- DECODER LSTM

In encoder-decoder LSTM, the encoder transforms the input sequence, which consists of a list of words or tokens, into a context vector of fixed length. The decoder then receives this context vector and utilizes it to produce the output sequence. The decoder creates the output sequence one word or token at a time, choosing the subsequent word or token in the sequence based on the context vector and its internal state. By using the context vector, the output sequence is generated by the decoder.

VIII. Result

With the help of the encoder-decoder LSTM model, we have achieved a root mean square value of 23 and a mean absolute error of 18.6. The outcome of a load demand forecast may show the anticipated levels of energy use in a specific location or time frame. This knowledge can help manage and optimize the use of energy resources, provide a dependable and efficient power supply, and cut expenses. To make wise decisions, it is critical to thoroughly evaluate the constraints and uncertainties of the prediction. The accuracy and dependability of the prediction can vary depending on the caliber of the data and the methodologies used.



IX. Conclusion

In this paper, we have considered the dataset from the UCI repository to achieve realistic data and used the encoder-decoder LSTM model for load prediction and achieved a root mean square error value of 23 and a mean absolute error value of 18. However, the level of improvement in root mean square error is not satisfactory for the time series forecasting model, as the dataset does not contain periodic samples and normal distribution. It is also possible to design optimal demand responses using dynamic real-time pricing. To increase the smart grid's dependability, stability, security, and effectiveness, a variety of machine-learning approaches are utilized. The Smart grid will include machine learning in the future to increase efficiency, comfort, convenience, control, and conservation.

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