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Analysis of Household Power Consumption Using LSTM Technique in Machine Learning

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Abstract

Forecasting household energy consumption is challenging due to the diverse patterns of energy use. However, accurate predictions are essential for optimizing energy production and distribution in a sustainable and efficient manner. Researchers have developed artificial intelligence-based models to forecast energy demand, including Long Short-Term Memory (LSTM) models. With its capacity for accurately and quickly forecast load capacity, the LSTM model is useful for the early detection and handling of power system fault emergencies. The LSTM model is a promising approach that has the potential to improve the performance of power systems. In this paper, three houses consumption data of the January month has been considered and analysed by using LSTM. The results of actual consumption and predicted consumption are drawn by matplot in python which describes the effectiveness of the LSTM.

KEYWORDS: Load Forecasting, Long Short Term Memory, Time Series, Neural Network, Recurrent Neural Network

1.Introduction

As the world's population grows and living conditions improve, residential energy usage continues to increase steadily. In order to keep the supply and demand for electricity in balance, power generation and distribution systems need accurate forecasts of power consumption. The Variations in electric power usage are mostly influenced by the amount of electric appliances in a home and the behaviour of individuals. To correctly forecast household energy usage, machine learning (ML) and deep learning (DL) techniques are used [1]. Precise household energy usage forecasting is crucial for optimizing power generation and distribution. DL models such as CNN and LSTM, combined with The accuracy of energy consumption forecasts can be increased with the help of social IoT-based smart metre readings.

It suggests a hybrid deep learning approach that blends CNN and LSTM models [2] in order to forecast the total generative active power of single homes' weekly energy usage. To enable implementation in practical applications, such as social IoT-based smart grid planning, the study used multi-step forecasting [3]. To avoid future system failures, better forecasting methods that can handle the complexities are required. There are no [4] connections between the brain units of the buried layer in the conventional unidirectional neural network (NN) paradigm. However, a fundamental drawback of conventional NN models is their inability to take into account past and future training data on the current output [5]. Other studies have evaluated load forecasting systems based on artificial neural networks.

The single processing function of Recurrent Neural Network (RNN) neural units can cause gradient disappearance or explosion during repeated training, which has a negative impact on the forecasting results' accuracy. The Long Short-Term Memory (LSTM) neural network is one kind of RNN [6]. Four processing segments make up its neural unit, which aid in resolving the gradient disappearance or explosion issue by handling both initial and cyclical initial data. Several forecasting applications have used LSTM, including market behaviour learning and forecasting LSTM-based trading technology analysis methodology and successful short-term load forecasting methodology [7-10]. However, there are few studies on the use of LSTM to predict load, according to research.

The Household Power Consumption have been analysed using LSTM technique in ML. The document is structured as shown below. In Section II, power consumption analysis is briefly discussed. Section III is about the methodology i.e., Long Short Term Memory. Before the article is ended in Section V, Section IV presents case studies on the household power consumption prediction.

POWER CONSUMPTION ANALYSIS

The Load Forecasting w.r.t power consumption is a crucial component of energy management systems since it aids in system operators schedule spinning reserve allocation and plan for energy interchange with other utilities. Accurate load prediction is essential for minimizing operating costs and ensuring power supply reliability. Underestimating demand can result in under capacity, leading to poor service quality and potential blackouts. Overestimating demand, on the other hand, can result in excess capacity and additional costs for the utility. Therefore, it is crucial to ensure the accuracy of load forecasts to optimize energy management.

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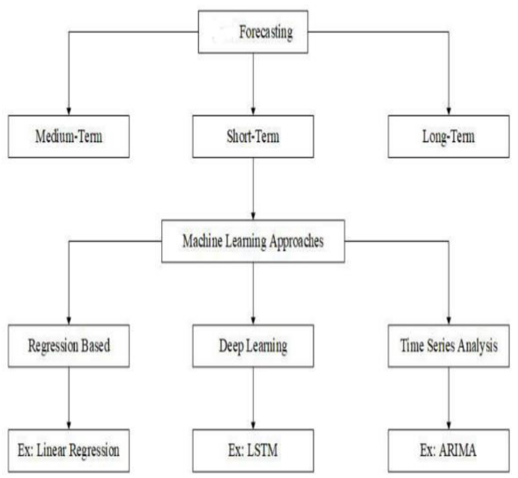

Fig 1: Forecasting Methods

Apart from accurate forecasting, programs for demand-side management and pricing structures should also be highlighted. Supply-side management programs aim to alter the system load shape and are based on hourly load forecasts and end-use components. Four processing segments make up its neural unit, which aid in resolving the gradient disappearance or explosion issue load forecasting w.r.t power consumption.

Different methods as shown in Fig1 are suitable for different situations, and the choice of a forecasting technique is based on the forecasts with the required amount of detail and the facts at hand. To choose the most logical approach, it may be appropriate to evaluate forecasts from different methods. Each utility must therefore select the method that is most suited to the needs of its own application.

LONG SHORT TERM MEMORY

The LSTM network is capable of learning long-term and short-term features of training data, making it a useful tool for load forecasting w.r.t power consumption. However, the performance of LSTM prediction is dependent on the quality of input data. These are the precise steps for K-means clustering: First, K samples are randomly chosen as centroids to establish K groups' K centroids. Second, each sample is assigned to the closest group based on the Euclidean distance between it and each centroid. Thirdly, once all centroids stop changing, signalling the completion of the clustering procedure, the centroids are updated by averaging each group. K groups of training data are supplied to K separate LSTM networks once the training data have been clustered. A new data sample is received, the Euclidean distance between it and each centroid is determined, and it is then assigned to the group that is closest to it. Then, to forecast, the appropriate LSTM neural network is utilised the power load consumption at the next moment. The method of LSTM network-based power load forecasting is illustrated in the Fig2 and Fig3.

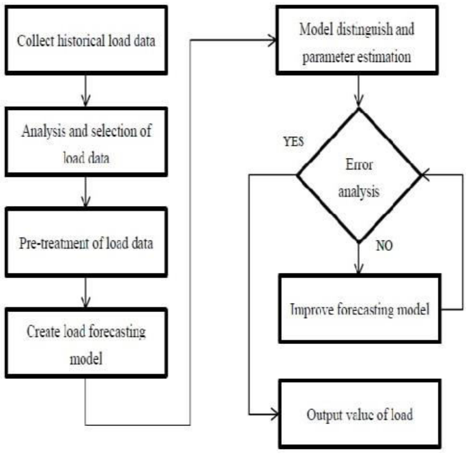

Fig 2: Flowchart of LSTM

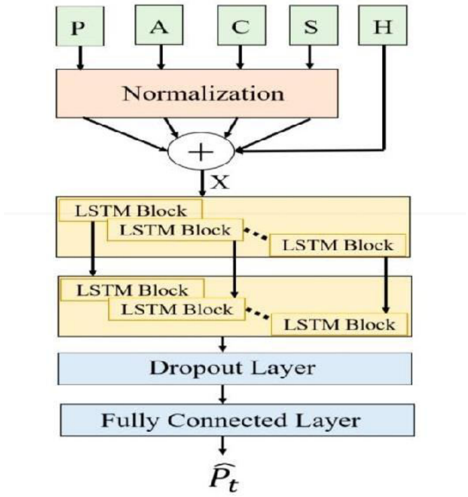

Fig 3: Schematic representation of LSTM

In this study, the LSTM architecture was built using Python, and Back Propagation Through Time (BPTT) were chosen for the network's training. The parameters for the LSTM network, such as the

activation function, loss function, and optimizer, were set accordingly.

The forecasting results of the LSTM network were presented in the paper. In summary, the proposed method of clustering data using the K-means algorithm and using multiple LSTM networks for load forecasting has the capacity to increase forecasting precision. However, the effectiveness of the method is dependent on the quality of input data and appropriate parameter settings for the LSTM network.

RESULTS

Initially, the LSTM model need to be trained by providing the dataset. Then the model is prepared to predict the consumption of the testing data set. For household load forecasting using LSTM, three datasets from three houses have been considered as shown in tables 1,2,3. The three datasets are in the form of excel sheet. The code which takes the input data from excel file gives the output as actual consumption vs predicted consumption plots by using matplot library in python. The excel file which contains two columns date and consumption. The data of the month January 2022 has been considered. The plots are shown in Fig4, Fig5 and Fig6 for houses 1, 2 and 3 respectively. From Fig4, it has been observed that the maximum consumption is 188.57kwh on 17th January and minimum consumption is 79.43kwh on 13th January. From Fig5, it has been observed that the maximum consumption is 206.08kwh on 1st January and minimum consumption is 100.24kwh on 13th January. From Fig6, it has been observed that the maximum consumption is 200.34kwh on 1st January and minimum consumption is 82.57kwh on 13th January. From the three test cases, the maximum power consumption for 2nd and 3rd houses is on same date i.e. 1st January. The minimum power consumption for all the three houses is on same date i.e. 13th January. Further, from figures 4 to 6, it has been observed that the actual consumption is very close to the prediction which indicates the effectiveness of the LSTM.

Table 1: Electricity consumption(kwh) Data of House 1

Date	Consumption
01-01-2022	180
02-01-2022	150.56
03-01-2022	166
04-01-2022	149.71
05-01-2022	175.98
06-01-2022	186.03
07-01-2022	144.86
08-01-2022	115
09-01-2022	143.91
10-01-2022	137.44
11-01-2022	118.35
12-01-2022	105.71
13-01-2022	79.43
14-01-2022	83.12
15-01-2022	148.71
16-01-2022	154.21
17-01-2022	188.57
18-01-2022	182.32
19-01-2022	186.71
20-01-2022	165

Table 2: Electricity consumption(kwh) Data of House 2

Date	Consumption
2022-01-01	206.08
2022-01-02	125.57
2022-01-03	169.23
2022-01-04	154.59
2022-01-05	184.12
2022-01-06	180
2022-01-07	155.3
2022-01-08	130.86
2022-01-09	150
2022-01-10	143.09
2022-01-11	129.53
2022-01-12	110.53
2022-01-13	100.24
2022-01-14	101.29
2022-01-15	160.35
2022-01-16	161.5
2022-01-17	198.57
2022-01-18	180.24
2022-01-19	198.84
2022-01-20	184.43

Table 3: Electricity consumption(kwh) Data of House 3

Date	Consumption
2022-01-01	200.34
2022-01-02	153.56
2022-01-03	159.53
2022-01-04	153.09
2022-01-05	178.21
2022-01-06	186.26
2022-01-07	150.91
2022-01-08	123.14
2022-01-09	142.36
2022-01-10	138.3
2022-01-11	125
2022-01-12	106.81
2022-01-13	82.57
2022-01-14	98.67
2022-01-15	157.12
2022-01-16	157.44
2022-01-17	191.88
2022-01-18	182.67
2022-01-19	190.54
2022-01-20	177.73

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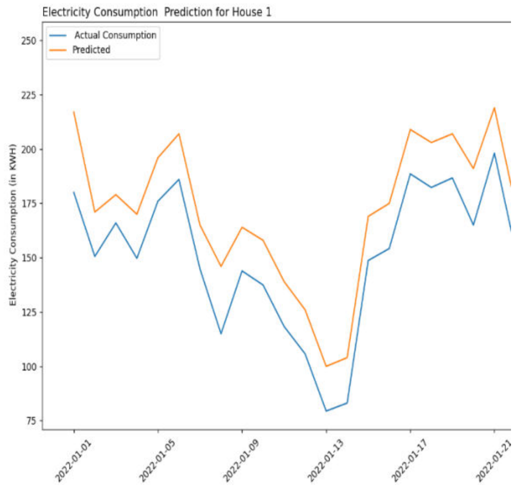

Fig 4 : Actual Consumption vs Prediction plot for House1

Fig 5: Actual Consumption vs Prediction plot for House 2

Fig 6: Actual Consumption vs Prediction plot for House 3

CONCLUSION

In this study, three houses January consumption data has been considered and analysed using LSTM. Python's matplot has been used to analyse the results of actual vs. expected consumption. Results are more accurate when utilising LSTM than with older models. Electricity Load forecasting w.r.t power consumption is the time series forecasting problem. Time series forecasting issues are well suited to LSTM. This study uses deep learning models to predict electrical energy use in singlefamily homes using data from smart metre readings collected through the Social IoT. Short-term load forecasting has become more crucial with the emergence of smart grids. Predictions of power use may be significantly impacted by variables like the weather.

REFERENCES

[1] B.S. Kwon, R.J. Park, and K.B. Song, “Short-term load forecasting based on deep neural networks using LSTM layer, ” J. Electr. Eng. Technol.,vol. 15, no. 4, pp. 1501–1509, Jul. 2020.

[2] H.J.Sadaei , E. Silva, F. G. Guimaraes, and M. H. Lee, “ Short-term load forecasting by using a combined method of convolutional neural networks and fuzzy time series, ” Energy, vol. 175, pp. 365– 377,May 2019.

[3] R. M. Pratapa and A. Laxmi, “ IOT based online load forecasting using machine learning algorithms, ” Procedia Comput. Sci., vol. 171,pp. 551–560, 2020.

[4] S. Acharya, Y. Wi, and J. Lee, “Shortterm load forecasting for a single household based on convolution neural networks using data augmentation,” Energies, vol. 12, no. 18, pp. 3560, Sep. 2019.

[5] X. Fang, S. Misra, G. Xue, and D. Yang, “Smart grid—The new and improved power grid: A survey,” IEEE

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Commun. Surveys Tuts., vol. 14, no. 4, pp. 944–980, 4th Quart., 2012.
[6] L. Ekonomou, C. A. Christodoulo, and V. Mladenov, "A short-term load forecasting method using artificial neural networks and wavelet analysis," Int. J. Power Syst., vol. 1, pp. 64–68, Jul. 2016.
[7] S. Muzaffar and A. Afshari, " Short-term load forecasts using LSTM networks," Energy Procedia, vol. 158, pp. 2922–2927, Feb. 2019.
[8] M. D. Reddy and N. Vishali, " Load forecasting using linear regression analysis in time series model for RGUKT, RK valley campus HT feeder, " Int. J. Eng. Res. Technol., vol. 6, no. 5, pp. 624–625, 2017.
[9] V. Gupta, "An overview of different types of load forecasting methods and the factors affecting the load forecasting," Int. J. Res. Appl. Sci. Eng. Technol., vol. 5, no. 4, pp. 729–733, Apr. 2017.
[10] F. Javed, N. Arshad, F. Wallin, I. Vassileva, and E. Dahlquist, "Forecasting for demand response in smart grids: An analysis on use of anthropologic and structural data and short term multiple loads forecasting," Appl. Energy, vol. 96, pp. 150–160, Aug. 2012.