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Power Consumption Analysis using LSTM Neural Networks for Residential Building

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Abstract. Energy consumption prediction is becoming popular research topic as many countries want to know the requirements of power consumption so that they can generate sufficient power to provide uninterrupted electricity. The aim of our work is to develop an effective predictive model for a building located in Clamart, France and then do performance analysis with the existing deep learning models. For this purpose, we develop a long-short-term memory (LSTM) neural network model which uses acute parameters as well as monitored data with different time resolutions to determine the levels of accuracy for prediction. The model used a dataset to train and test for getting the best accuracy. The results showed that the developed LSTM model is more applicable to predict energy consumption using 1-min resolution dataset rather than other time resolutions. The analysis of the results using the dataset of 1-minute resolution showed that the proposed model outperformed other existing predictive deep learning models.

Keywords; Energy consumption, Energy prediction, Time series, Time series predicting strategies, Deep learning, Recurrent neural network, Long short-term memory

1. Introduction

In recent decades, the energy consumption has been accelerated exponentially due to the high demand for electricity because of rapid population and economic growth [1]. This happens because of an accelerated development of production capacity contributed by Japan, China, and India. The significant change is observed in electricity

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generation in 2017 from Asia. Consequently, there is significant growth in Asia, and this growth is to a small extent in EU and Canada. However, the demand of generating electricity in USA is declining, in the EU and Canada to a smaller extent. In the past, there have been numerous studies in electricity demand forecasting, electricity load forecasting, electricity storage, short-term load prediction and occupant behaviour [2-6].

As it is predominant to develop effective ways to predict the load or consumption models accurately, the efficacy of techniques is imperative. Some techniques for energy consumption prediction include linear regression (LR) models [7], ARIMA [8], artificial neural networks [9], SVM and SVR [10], and time series [11]. These models can be divided into four major groups: statistical models, machine learning (ML) models, deep learning and hybrid models.

On the other hand, recurrent neural network (RNN) stores the time series data in a hidden memory in order to process, represent, store, and update the data over time [12]. Recently, much study has been focused on obtaining temporal and spatial features through models developed by the combinations of CNN and LSTM. Wang et al. also used CNN-LSTM model to analyse the emotions with text input in the field of natural language processing [13].

In general, it is not easy to forecast electric energy consumption using traditional prediction approaches as the data for electric power consumption show not only regular seasonal pattern but also irregular trend components [14]. In Section 2, we describe the features as well as statistical information of datasets. Section 3 includes the detailed analysis of our results with discussions. Finally, we conclude with the summary of the proposed work with the comparisons among the existing works.

2. Data and Methods

The University of California at Irvine machine learning repository has the electricity consumption dataset which consists of a total of 2,075,259 time-series instances and 12 variables (https://archive.ics.uci.edu/ml/datasets/). The dataset has four- year power consumption data (from December 16, 2006 to November 26, 2010) of homes in France [15]. Table I provides information about attributes with description of dataset and Table II represents the statistical information of the dataset. Figure 1 shows the graph of how the global active power consumption differs from one year to another year. Figure 2 shows a basic diagram Long Short Term Memory (LSTM) network.

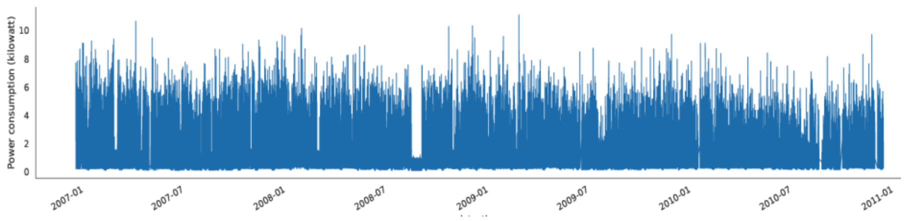

Figure 1. The global active power consumption for the years (2006-2010).

TABLE I
THE ATTRIBUTES AND DESCRIPTION OF HOUSEHOLD POWER CONSUMPTION DATASET.

No.	Attribute	Description
1	date	Date in format dd/mm/yyyy
2	time	Time in format hh:mm:ss
3	global_active_power (kilowatt)	Power consumption by electrical appliances excluded corresponds to Sub Meters.
4	global_reactive_power (kilowatt)	Global reactive power consumption of imaginary power considered wattless power.
5	voltage (volt)	minute averaged voltage
6	global_intensity (ampere)	Global intensity consumption by household considered as strength of current.
7	Sub metering 1(watt-hour)	Electric consumption of appliances such as oven, microwave, and dishwasher.
8	Sub metering 2(watt-hour)	Electric consumption of laundry room such as refrigerator, washing-machine,etc.
9	Sub metering 3(watt-hour)	Electric consumption for an air-conditioner and an electric water-heater.

TABLE II
STATISTICAL INFORMATION OF THE DATASET

Year	Count	Mean	Std	Min	Max	25%	50%	75%	Kurtosis	Skewness
2006-10	2049280	1.09161	1.05729	0.076	11.122	0.3080	0.6020	1.5280	4.21867	1.78623

We applied long-short-term memory (LSTM) neural network model in our model which uses acute parameters as well as monitored data with different time resolutions to determine the levels of accuracy for prediction. The model used a dataset to train and test for getting the best accuracy. The results showed that the developed LSTM model is more applicable to predict energy consumption using different time resolutions:1-min, 15-min, 30-min, 45-min, and 60-min.

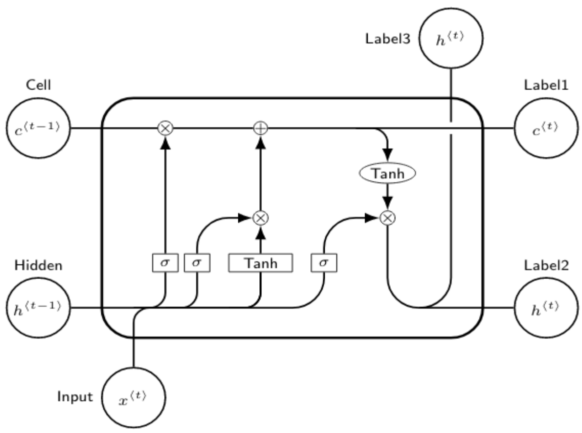

Figure 2. Diagram of basic Long Short Term Memory (LSTM) network

3. Results and Discussion

In this section, we provide quantitative analysis of the proposed technique. The most important thing is that the results from RNNs will be established its robustness for predicting consumption patterns by comparing our approach with machine learning and deep learning methods.

3.1. Evaluation Metrics

In order to evaluate the proposed approach with other approaches, we will use four useful metrics: Mean Square Error (MSE) Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE).

$$MSE = \frac{1}{n}\sum_{1}^{n}(\mathrm{Y_i} - \overline{\mathrm{Y}}_\mathrm{i})^2 \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(\mathrm{Y_i} - \overline{\mathrm{Y}}_\mathrm{i})^2} \qquad (2)$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|\mathrm{Y_i} - \overline{\mathrm{Y}}_\mathrm{i}| \qquad (3)$$

$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{\mathrm{Y_i} - \overline{\mathrm{Y}}_\mathrm{i}}{\mathrm{Y_i}}\right| \qquad (4)$$

3.2. Comparisons

We have focused on the time resolutions of the different step lengths: 1 minute, 15 minutes, 30 minutes, 45 minutes and 60 minutes, and observations of dataset are selected according to each time resolution. We have made 5 different types of observations of dataset to train and test the model. Figure 3 compares the actual and predicted global active power consumption for epoch of different time resolutions: (a) 1 min, (b) 15 min, (c) 30 min, (d) 45 min, (e) 60 min, respectively. Figure 4 shows the error values of these error metrics for the dataset of time resolution in a bar diagram.

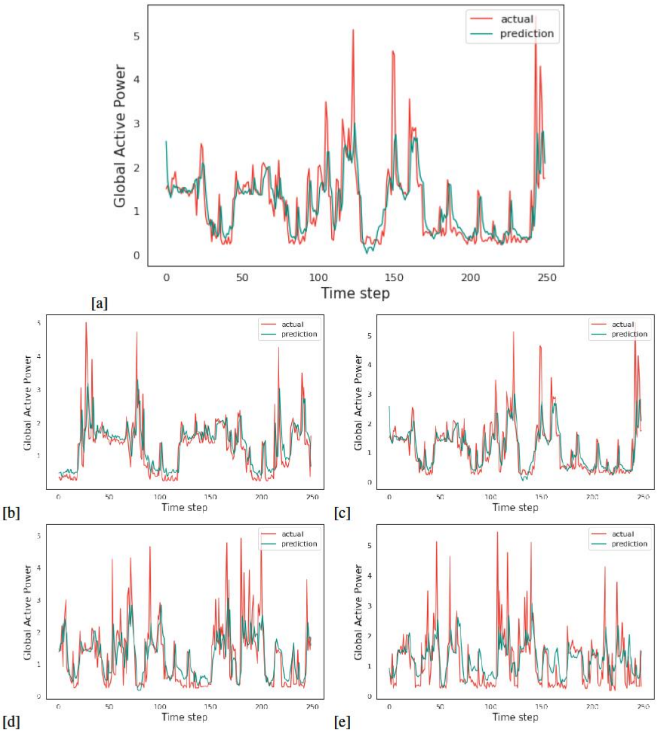

Figure 3. Comparison of actual and predicted global active power consumption for each epoch for different time resolutions: (a) 1 min, (b) 15 min (c) 30 min (d) 45 min (e) 60 min.

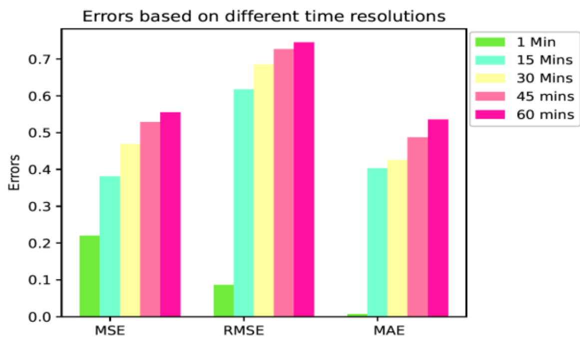

Figure 4. Values of error metrics (MSE, RMSE, and MAE) for (a) different time resolutions.

TABLE III

Comparison between existing models and proposed model

Recent Works	MSE	RMSE	MAE
Rajabi et al., 2019 [16]	0.62	0.79	0.59
Ullah et al., 2020 [17]	0.31	0.56	0.34
Proposed (1 min Res.)	**0.048**	**0.22**	**0.08**

For the evaluation of efficacy, Rajabi et al., 2019 claims that the errors ware lowest for MSE, RMSE, and MAE respectively [16]. The performances of the research work of Ullah et al., 2020 [17] is better than the results of Rajabi as can be seen in Table III. On the other hand, our proposed model achieves 0.048, 0.22, 0.08 for MSE, RMSE, and MAE respectively while using whole dataset (2006-10) with 1 min time resolution in the same table. Thus, the proposed model performs the best among the three methods while using whole daily household dataset.

4. Conclusion

In this work, we developed a deep learning framework in order to predict the electricity consumption in a residential building for UCI household electricity consumption data to evaluate it. After pre-processing the dataset, we apply it to the developed LSTM model for training and testing in order to validate the efficacy of the model. We observed that our proposed model achieves 0.048, 0.22, 0.08 for MSE, RMSE, and MAE respectively while using whole dataset (2006-10) with 1 min time resolution. It shows the best performance while comparing the other works to predict the electricity energy consumption. Therefore, the analysis of the results showed that the proposed model outperformed other existing predictive deep learning models while using 1-minute resolution of the dataset.

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