Deep Neural Networks for Forecasting Build Energy Load

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Abstract: The consumption of electric power is progressing rapidly with the increase in the human population and technology development. Therefore, for a stable power supply, accurate prediction of power consumption is essential. In recent years, deep neural networks have been one of the main tools in developing methods for predicting energy consumption. This paper aims to propose a method for predicting energy demand in the case of the residential sector. This method uses a deep learning algorithm based on long short-term memory (LSTM). We applied the built model to the electricity consumption data of a house. To evaluate the proposed approach, we compared the performance of the prediction results with Multilayer Perceptron, Recurrent Neural Network, and other methods. The experimental results demonstrate that the proposed method has higher prediction performance and excellent generalization capability.

1 INTRODUCTION

Electric energy consumption accelerating with economic and demographic growth (Zhao et al., 2017). International Energy Agency (IEA) published, according to the World Energy Outlook 2017, that the world energy consumption rises 28% between 2015 and 2040 (T.-Y. Kim & Cho, 2019b). In addition, energy consumption increases over the projection for all fuels (*World Energy Outlook 2017 – Analysis*, s. d.). The residential sector is a large consumer of electrical energy, as it exceeds 27% of global energy consumption. (Nejat et al., 2015). The production and consumption of electrical power must be simultaneously due to its characteristics and its storage (He, 2017). So, to have a steady supply of electricity, an efficient forecast of the demand for electric power is required.

In (Son & Kim, 2020), the authors use a model based on LSTM to forecast monthly consumption energy in the residential sector. The authors of (Wang et al., 2020) are exploited the LSTM method after a well-determined pre-processing process on the industrial sector data.

Several models are designed and validated by using the same database called "Individual household electricity consumption" to forecast energy consumption. In (T.-Y. Kim & Cho, 2019a), the authors associated the CNN (convolutional neural networks) with LSTM to forecast this electricity consumption. In (J.-Y. Kim & Cho, 2019), the proposed model is the combination of RNN (recurrent neural networks) and LSTM. In (Marino et al., 2016), the presented method is based on the LSTM auto-encoder (LSTM-AE). In (Le et al., 2019), the authors have combined two types of neural networks, CNN, and bidirectional LSTM (Bi-LSTM). In (Khan et al., 2020), the authors have formed their models by CNN and LSTM-AE. We can conclude that all five models give acceptable results; however, our goal is to improve this result.

In this paper, we exploit the deep learning technique for robust forecasting of energy consumption in the residential sector. The methodology presented is based on the algorithm of short-term memory. The model built is tested on the same benchmark data for a single residential customer with a one-minute time resolution.

The paper is organized as follows. Section II gives a general presentation on LSTM algorithms. Section III shows the methodology used for forecasting energy demand using LSTM. Section IV explains the data and presents the experimental results. Section VI concludes the document.

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2 LSTM

Recurrent neural networks (RNNs) give the vanishing gradient problem regardless of the learning algorithm used, either the Backpropagation algorithm in time or the real-time recurrent learning algorithm (Taylor et al., s. d.; Werbos, 1990). Long and short-term memories (LSTM) are improved recurrent neural networks (Hochreiter & Schmidhuber, 1997). This type of network makes it possible to remedy the vanishing gradient problem and memorize information for long periods (Marino et al., 2016). An LSTM network is made up of three gates and a cell, as shown in Figure 1. The equations (1) – (6) present the inner workings of a single LSTM cell.

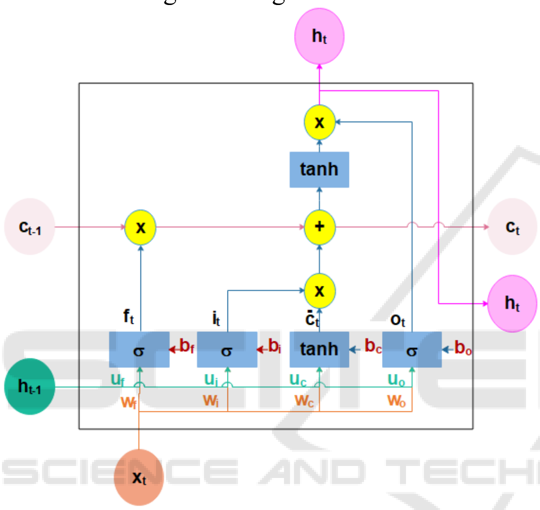

Figure 1: LSTM cell.

$$f_t = \sigma(w_f x_t + u_f h_{t-1} + b_t) \tag{1}$$

$$i_t = \sigma(w_i x_t + u_i h_{t-1} + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(w_c x_t + u_c h_{t-1} + b_C) \tag{3}$$

$$C_t = f_t * C_{t-1} * i_t \tilde{C}_t \tag{4}$$

$$o_t = \sigma(w_o x_t + u_o h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

Where i_t, f_t, and o_t are the input gate, forget gate, and output gate, respectively. C_t is cell state and $\tilde{C}_t$ represents candidate cell state. w_f, w_i, w_c, and w_o are weight matrices of the forgetting gate, the input gate, the memory cell, and the output gate respectively. u_f, u_i, u_c, and u_o the recurrent connections of the forgetting gate, the input gate, the memory cell, and the output gate, respectively. b_f, b_i, b_c, and b_o are bias vectors of the forgetting gate, the input gate, the memory cell, and the output gate, respectively. x_t is the current input. h_t and h_{t-1} are the outputs at the present time t and the previous time t-1, respectively (Zhang et al., 2018).

The role of the input gate is to extract information from the current data. The forge gate makes it possible to decide which data should be kept or not. The output gate its role is to extract the valuable information for the prediction. The operation of the three doors is similar. If we take the forget gate, in the case of the value f_t is close to zero, the information will be forgotten.

3 LOAD FORECASTING USING LSTM

This section presents the load forecasting methodology based on LSTM networks. Figure 2 illustrates the proposed architecture for the electrical load forecast.

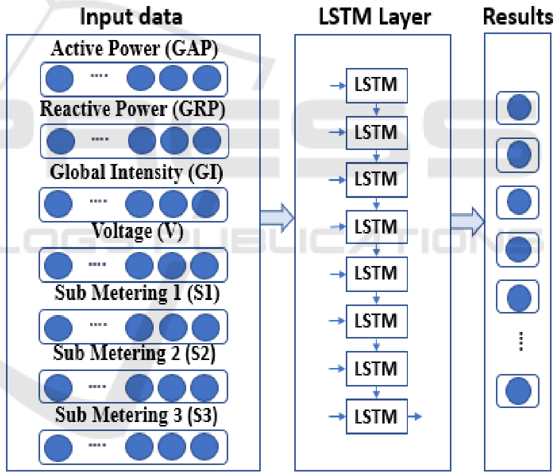

Figure 2: The overview architecture of the LSTM model.

This methodology aims to forecast the global active power for a time step or several time steps in the future, considering the historical data of electrical load. We can be expressed the N available active power measurements as follow:

$$h = \{h_1, h_2, \ldots, h_N\}$$

Where h is the measurement of the actual load for the time step t, the predicted load values for the subsequent time steps T - N can be expressed as follows:

$$\hat{h} = \{\hat{h}_{N+1}, \hat{h}_{N+2}, \ldots, \hat{h}_T\}$$

As shown in figure 2, to forecast active power for 60 minutes, we use the active power, the reactive power, the current, the voltage, S_1, S_2, and S_3 for the previous 60 minutes as inputs for the model. We can be formulated the input matrix as follows:

$$x = \begin{bmatrix} GAP_{t-1} & GRP_{t-1} & \cdots & S2_{t-1} & S3_{t-1} \\ GAP_{t-2} & GRP_{t-2} & \cdots & S2_{t-2} & S3_{t-2} \\ . & . & \cdots & . & . \\ . & . & \cdots & . & . \\ GAP_{t-60} & GRP_{t-60} & \cdots & S2_{t-60} & S3_{t-60} \end{bmatrix} \quad (7)$$

The resulting network is a very deep lattice, so to alleviate the problem of gradient disappearance, we used the ADAM (Adaptive Moment Estimation) optimizer (Kingma & Ba, 2017). We can be presented the minimize loss function as follows:

$$J = \frac{1}{2}\sum_{i=1}^{N} (h_i - \hat{h}_i)^2 \quad (8)$$

4 DATA AND EXPERIMENTAL RESULT

4.1 Data

To test and validate the proposed model, we used the data collected over four years, from 16th of December 2006, until 26th of November, 2010, in a house in France (Household Electric Power Consumptions. d.), named "Individual household electric power consumption". The data contained 2,075,259 measurements with a resolution of one minute. The collected variables encompassing the time variables include day, month, year, hour, and minute. The variables assembled from sensors include global active power (GAP), global reactive power (GRP), global intensity (GI), voltage (V), sub_metering 1 (S_1) for the kitchen, sub_metering 2 (S_2) for the laundry room, and sub_metering 3 (S_3) for the electric water heater and air conditioner (T.-Y. Kim & Cho, 2019a).

4.2 Experimental Results

The proposed model consists of planning the following 60 minutes by introducing 60 minutes of measurements. During the test, a set of data not used during training should be used. Therefore, we must divide the data into two parts, the first part for training the model and the other for testing.

We evaluate the proposed model by comparing the performance of the prediction results with Multi-layer Perceptron (Hamedmoghadam et al., s. d.), the recurrent neural network (Cho et al., 2014) and the models used in (Khan et al., 2020; J.-Y. Kim & Ch o, 2019; T.-Y. Kim & Cho, 2019a; Le et al., 2019; Marino et al., 2016). Figure 3 shows the actual demand and the forecasted energy demand results for the different models. From the figure, we can see that the models based on LSTM and MPL perform well the forecast compared to RNN.

The performance measures to evaluate the models are MSE, RMSE and MAE, which can be expressed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \quad (11)$$

Where y_i is the actual load value, $\hat{y}_i$ is the predicted load value, and N is the number of samples (Huang & Wang, 2018).

Table 1 summarizes the performance of the different models used to test the capacity of the proposed model. We can be concluded that the electric load forecasting using the LSTM model has better accuracy in each of the measures considered in this study. These results demonstrate the ability of the LSTM to predict accurately. Therefore, we can conclude that model's accuracy is related to the number of measurements taken as input.

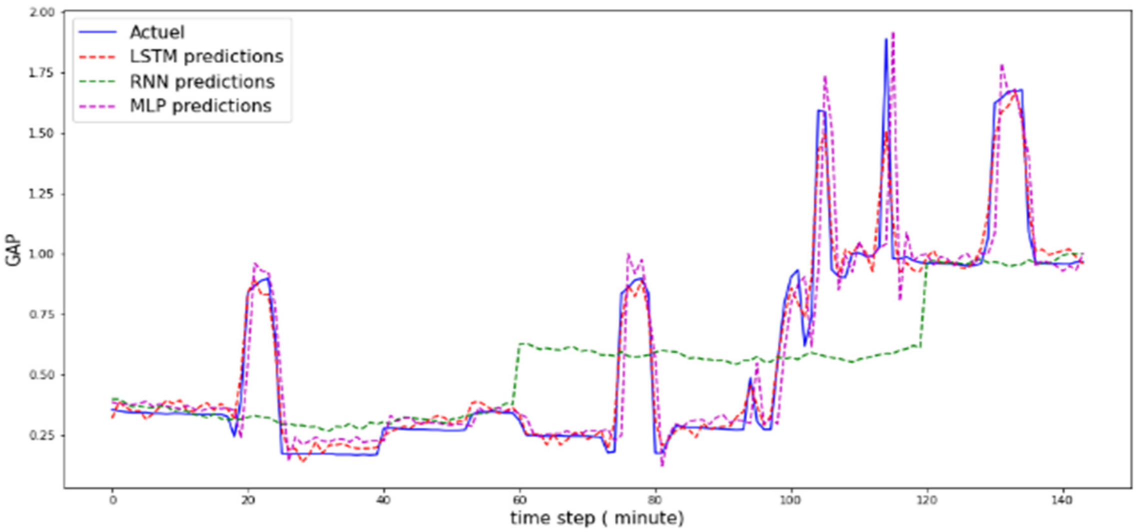

Figure 3: The predicted and actual electric energy consumption demand.

Table 1: The performance of the different models.

Method	RMSE	MSE	MAE
MLP	0.1884	0.0355	0.0846
RNN	0.9396	0.8829	0.7281
Kim and Cho **(J.-Y. Kim & Cho, 2019)**		0.3840	0.3953
Kim and Cho **(T.-Y. Kim & Cho, 2019a)**	0.6114	0.3738	0.3493
Le et al. **(Le et al., 2019)**	0.225	0.051	0.098
Marino et al. **(Marino et al., 2016)**	0.667	-	-
khan and al. **(Khan et al., 2020)**	0.47	0.19	0.31
The proposed method	**0.2941**	**0.0066**	**0.0482**

5 CONCLUSION

The model based on deep neural networks has demonstrated its efficiency in predicting the energy load at the building level. This paper presented the architecture of LSTM-based neural networks to electricity load prediction. The model built was trained and tested on data with a temporal resolution of one minute. The proposed LSTM model has shown its ability to accurately forecast power consumption although its simple architecture. The model produced results comparable to the results presented in (Khan et al., 2020; J.-Y. Kim & Cho, 2019; T.-Y. Kim & Cho, 2019a; Le et al., 2019; Marino et al., 2016) for the same data. In addition, we can be reinforced the proposed solution, either by adding other inputs such as temperature, humidity electricity price, and time variables or by improving deep learning algorithms.

REFERENCES

Cho, K., van Merrienboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. arXiv:1406.1078 [cs, stat]. http://arxiv.org/abs/1406.1078

Hamedmoghadam, H., Joorabloo, N., & Jalili, M. (s. d.). Australia's long-term electricity demand forecasting using deep neural networks. 14.

He, W. (2017). Load Forecasting via Deep Neural Networks. Procedia Computer Science, 122, 308-314. https://doi.org/10.1016/j.procs.2017.11.374

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. Neural Computation, 9(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735

Huang, L., & Wang, J. (2018). Global crude oil price prediction and synchronization based accuracy evaluation using random wavelet neural network. Energy, 151, 875-888. https://doi.org/10.1016/j.energy.2018.03.099

Khan, Z., Hussain, T., Ullah, A., Rho, S., Lee, M., & Baik, S. (2020). Towards Efficient Electricity Forecasting in Residential and Commercial Buildings : A Novel Hybrid CNN with a LSTM-AE based Framework. Sensors, 20(5), 1399. https://doi.org/10.3390/s20051399

Kim, J.-Y., & Cho, S.-B. (2019). Electric Energy Consumption Prediction by Deep Learning with State Explainable Autoencoder. Energies, 12(4), 739. https://doi.org/10.3390/en12040739

Kim, T.-Y., & Cho, S.-B. (2019a). "Load Forecasting via Deep Neural Networks. Energy, 182, 72-81. https://doi.org/10.1016/j.energy.2019.05.230

Kim, T.-Y., & Cho, S.-B. (2019b). Predicting residential energy consumption using CNN-LSTM neural networks. Energy, 182, 72-81. https://doi.org/10.1016/j.energy.2019.05.230

Le, T., Vo, M. T., Vo, B., Hwang, E., Rho, S., & Baik, S. W. (2019). Improving Electric Energy Consumption Prediction Using CNN and Bi-LSTM. Applied Sciences, 9(20), 4237. https://doi.org/10.3390/app9204237

Marino, D. L., Amarasinghe, K., & Manic, M. (2016). Building energy load forecasting using Deep Neural Networks. IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, 7046-7051. https://doi.org/10.1109/IECON.2016.7793413

Nejat, P., Jomehzadeh, F., Taheri, M. M., Gohari, M., & Abd. Majid, M. Z. (2015). A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries). Renewable and Sustainable Energy Reviews, 43, 843-862. https://doi.org/10.1016/j.rser.2014.11.066

Son, H., & Kim, C. (2020). A Deep Learning Approach to Forecasting Monthly Demand for Residential–Sector Electricity. Sustainability, 12(8), 3103. https://doi.org/10.3390/su12083103

Taylor, G. W., Hinton, G. E., & Roweis, S. T. (s. d.). Two Distributed-State Models For Generating High-Dimensional Time Series. 44.

Wang, J. Q., Du, Y., & Wang, J. (2020). LSTM based long-term energy consumption prediction with periodicity. Energy, 197, 117197. https://doi.org/10.1016/j.energy.2020.117197

Werbos, P. J. (1990). Backpropagation through time : What it does and how to do it. Proceedings of the IEEE, 78(10), 1550-1560. https://doi.org/10.1109/5.58337

World Energy Outlook 2017 – Analysis. (s. d.). IEA. Consulté 17 avril 2021, à l'adresse https://www.iea.org/reports/world-energy-outlook-2017

Zhang, Q., Liu, B., Zhou, F., Wang, Q., & Kong, J. (2018). State-of-charge estimation method of lithium-ion batteries based on long-short term memory network. IOP Conference Series: Earth and Environmental Science, 208, 012001. https://doi.org/10.1088/1755-1315/208/1/012001

Zhao, G. Y., Liu, Z. Y., He, Y., Cao, H. J., & Guo, Y. B. (2017). Energy consumption in machining : Classification, prediction, and reduction strategy. Energy, 133, 142-157. https://doi.org/10.1016/j.energy.2017.05.110