Electricity Demand Forecasting for Smart Grid Based on Deep Learning Approach

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***Abstract*—Electric power load demand forecasting plays a very indispensable role in energy management, such as suitable planning and investing in developing more infrastructure, and moderate operating the electricity system. Moreover, the accuracy of the electricity demand forecasting must be paid special attention. Although research on this problem has been conducted in recent years, the authors noticed that elevated accuracy outcomes have not been gained yet and have provoked controversy about forecasting results. In this paper, an electricity demand forecasting method based on a Deep Learning model, namely Long-Short-Term-Memory (LSTM), which is an improvement of Recurrent Neural Networks (RNNs) is proposed. The proposed network architecture includes four layers: sequence input, LSTM, fully connected, and regression output. The proposed method was implemented on the power consumption data in six years, from 2012 to 2017, of Tien Giang province, Vietnam. The forecasting result, evaluated using Root Mean Square Error (RMSE), was 9.63, suggesting that this would be a great contribution to studies in the energy sector.**

Keywords—Electrical Load Forecasting, Smart Grid, Deep Learning, Long-Short-Term-Memory (LSTM), Neural Network.

I. INTRODUCTION

In the energy management industry, forecasting the electric load demand is extremely important because it is closely linked and directly affects the daily lives of people and economic sectors. In addition, load demand forecasting is crucial in ensuring the working safe mode and energy economical for the electricity system. At the same time, it plays a paramount importance role in planning the system development strategy. In this context, electric load forecasting is not only for the detection of system instabilities and protection [1], [2] but also for effective energy management [3]. Because the electrical load is primarily a univariate time series [4], many time series forecasting methods can be put into practice for electrical power load forecasting. Conventional load forecasting methods can often not fully and accurately describe the actual process that occurs, because the number of databases is incomplete, there are many errors or it takes a long time for calculations. In fact, there are no equations with available parameters but only approximate values or mathematical expectations. Therefore, an existing equation must be given with unknown parameters, then an approximate method to find these parameters is used, which will reduce the accuracy remarkably. The traditional methods are used effectively only in cases where the data are linearly related to each other. It is not possible to clearly show the complex, nonlinear relationships between the load and the relevant parameters. To overcome the disadvantages of traditional load forecasting methods, scientists have applied modern forecasting techniques such as neural networks, fuzzy logic, regression…[5], [6], [7], [8], [9], [10]. The forecasting methods aforementioned are increasingly concerned because the forecast results are quite accurate. If the forecast is too much compared to the demand, the mobilization will be too large. As a result, there will be an increase in investment capital, which can possibly cause energy losses. On the contrary, if the load forecast is too low compared to the demand, there will not be enough supply of energy. This will lead to the removal of some loads without prior planning, which may damage the economy. Moreover, many techniques for forecasting the power load have been carried out before such as mathematical methods [11], [12] statistical algorithms [13], and especially, methods related to artificial intelligence. Recently, the artificial neural network has achieved many outstanding results because it is effective, and easy-to-implement. Therefore, electric load demand forecasting using artificial neural network technology is studied in this paper.

The rest of the paper is organized as follows. In Section 2, we present the proposed method of electric load demand forecasting. Experimental results in Section 3 demonstrate the performance of the proposed approach. Section 4 is the conclusion of the paper.

II. PROPOSED METHOD

A. Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) are a type of deep learning of artificial neural network, developed in the 1980s. The main idea of RNNs is to use sequential information independently of each other. RNNs are called “recurrent” because they enforce the same assignment for all elements of a sequence with the output contingent on previous computations. In other words, RNNs have the ability to remember previously computed information. In theory, RNNs can use a piece of very long information, but in practice, it can only remember a few steps before [14].

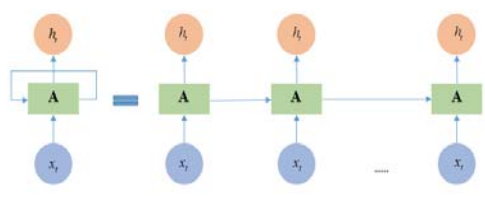

Fig. 1. The description of the RNNs model

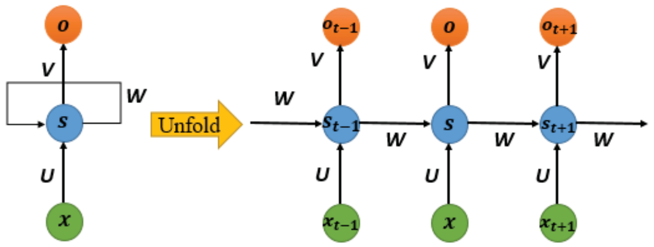

Fig. 2. The math description of the RNNs model

RNNs is a network that includes many identical neural nodes, each is directly connected to every other one. Unlike a traditional deep neural network, which uses different parameters at each layer, an RNNs ability to share the same parameters through whole steps. This significantly decreases the total number of parameters that need to learn. Each connection has an adjustable real weight. Input nodes receive data from outside the network, output nodes are the final result, hidden nodes adjust data on the way from input to output (Figure 1). The details of an RNNs are depicted in Figure 2. In that, x_t, s_t, o_t are input, the hidden state, and output at step t, respectively.

B. Long-Short-Term-Memory (LSTM Networks)

Long-Short-Term-Memory (LSTM Networks) are popular models that have shown the potential in many forecasting tasks [15]. LSTM is designed to avoid long-term dependencies issues [16]. Memorizing information over the long term is an advantage of this network. All RNNs have the outline of a chain of iterative modules of neural networks. In standard RNNs, this iterative module will have a super simple architecture, such as a single hyperbolic tangent layer (Figure 3). LSTM also has this chain-like structure, but the iterative module has various structures. Instead of having a single neural network layer that has a lot of interactions in a very particular modality (Figure 4).

The core of LSTM is the cell state rephrased by the horizontal line running across the top of the schema. The cell state is like a conveyor belt. It runs across the nodes with only some minor linear interactions. So that the information can easily be transmitted smoothly without fear of being changed (Figure 5). The LSTM does have the capability to remove or add information to the cell state, carefully regulated by structures denoted gates (Figure 6). Gates are where the information screening passes through. They are constructed of a sigmoid neural network layer and a point-wise multiplication operation. The output of the sigmoid layer are numbers between zero and one. A value of zero means that no information is transmitted, contrary if it is one, that means all information passes through it.

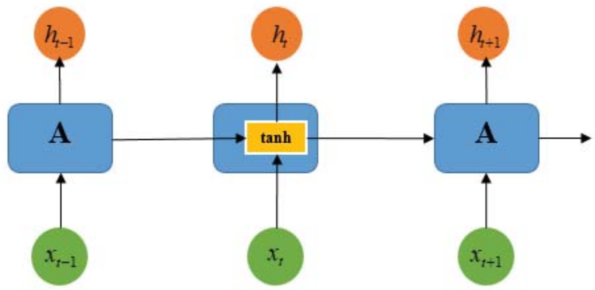

Fig. 3. The iterative module in a standard RNNs includes a single layer.

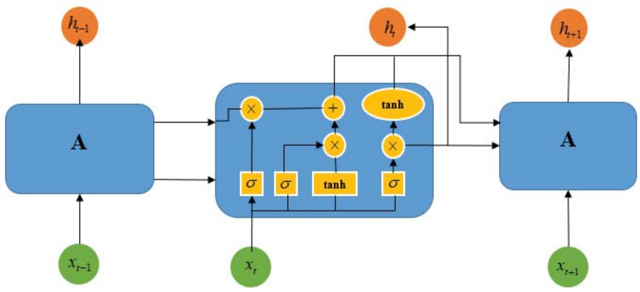

Fig. 4. The iterative module in an LSTM includes four interacting layers.

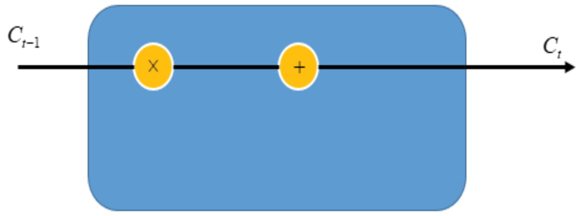

Fig. 5. The cell state of LSTM model.

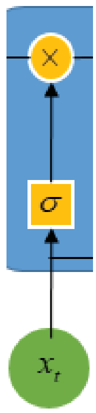

Fig. 6. The cell gate of LSTM model.

C. Math fundamentals

To begin with, LSTM is to decide which information to remove from the cell state. This decision is made by a sigmoid layer also known as the *forget gate cell*:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

The next step is to decide which new information to save to the cell state by input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{3}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{4}$$

Then, the old cell state (C_{t-1}) is updated to the new state C_t:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

In the final step, the output gate decides what the output is by associating the input and memory:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{6}$$

$$h_t = o_t * \tanh(C_t) \tag{7}$$

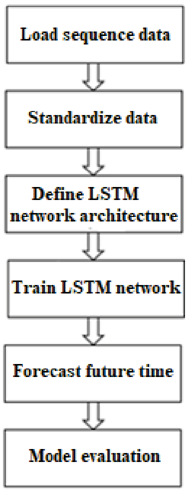

Fig. 7. The proposed flowchart for electrical load forecasting process.

III. EXPERIMENT

A. Dataset

The data set is from the power load consumption in six years of Tien Giang province, Vietnam from 2012 to 2017, from this dataset, it is possible to forecast the electricity demand in the future. The amount of data is about 2200 values. The measurement unit is kWh.

B. Forecasting result

Our proposal model includes three main stages: The first one is loading sequence data. The second stage is to standardize the data. Subsequently, the authors define LSTM network architecture and train the LSTM network. After this phase completes, electricity demand in the future time will be forecasted. In the last stage of this process, we compare the predicted value with the test value to evaluate the model using RMSE. The flowchart of the implementation process of our model is illustrated in Figure 7.

a) Load sequence data: Load sequence data as the load value in a single time series with time steps corresponding to days and values corresponding to the power consumption. The output is a cell array, where each constituent is a single time step (Figure 8). From the database, the authors divide them into two parts separately. One is the training data and another is test data with an 80:20 proportion.

b) Standardize data: To reduce input data's noise as well as to prevent divergence during training, standardization is extremely important. Specifically, we standardize the training data and test data to have zero mean and unit variance (Figure 9). For a random variable vector x made up of N scalar observations, the standard deviation is calculated to follow formulation (8), where μ is the mean of x as (9), a value is standardized as (10).

$$S=\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left|x_i-\mu\right|^2} \tag{8}$$

$$\mu=\frac{1}{N}\sum_{i=1}^{N}x_i \tag{9}$$

$$y=\frac{x_i-\mu}{S} \tag{10}$$

c) Define LSTM network architecture: The four layers of the proposed LSTM regression network structure are Sequence Input, LSTM, Fully Connected, and Regression Output. Specify the LSTM layer have 250 hidden units (Figure 10).

d) Train LSTM network: The training process is set up with 200 epochs and the gradient threshold to 1. The initial learn rate 0.005 and drop the learning rate after 125 epochs by multiplying by a factor of 0.2. The authors took advantage of the NVIDIA GeForce GTX 1080 Ti GPU with 12GB of memory, CUDA Cores 3584 for network training. The total time that the authors conducted the training process in conjunction with 200 epochs for 1760 samples was approximately 100 minutes (Figure 11).

e) Forecast future time: The result of electricity demand forecasting of Tien Giang province, Vietnam is depicted in Figure 12.

f) Model evaluation: The result after forecasting will be compared to the test value in the original dataset. Looking at the Figure 13 more closely, one can see that these two lines fit together, this demonstrates that the forecast results of the electricity demand are relatively accurate. Root Mean Square Error is selected as the error metric. The use of RMSE is a very common error metric for numerical predictions. RMSE is computed as the square of the correlation between the observed y values and the predicted $\hat{y}$ values as (11), namely RMSE=9.6333.

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2}{n}} \tag{11}$$

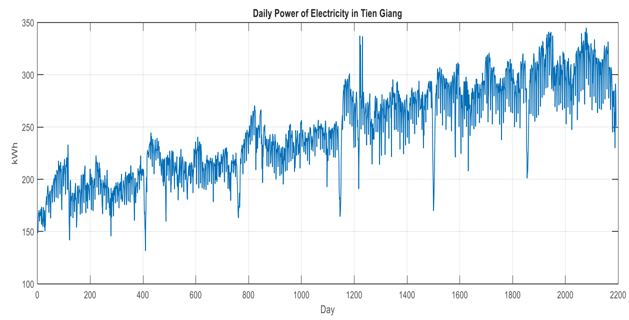

Fig. 8. The daily power data of electricity in Tien Giang province, Vietnam from 2012 to 2017.

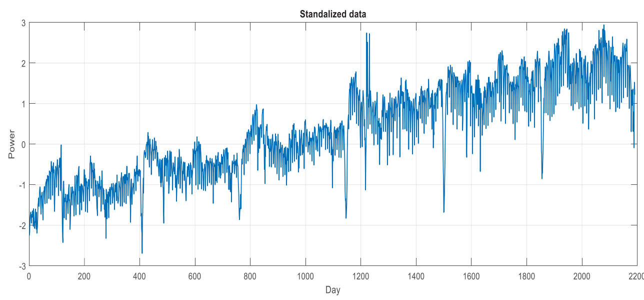

Fig. 9. The daily power data of electricity in Tien Giang province, Vietnam from 2012 to 2017 after standardize process.

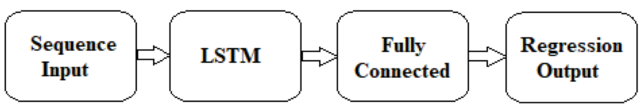

Fig. 10. The block diagram illustrates the architecture of the proposed LSTM network.

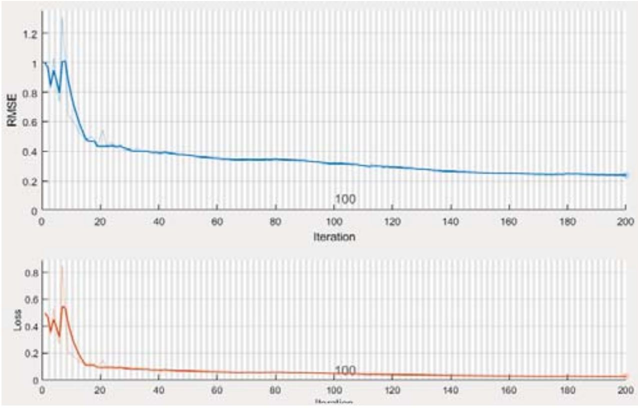

Fig. 11. The training process of the proposed forecasting model.

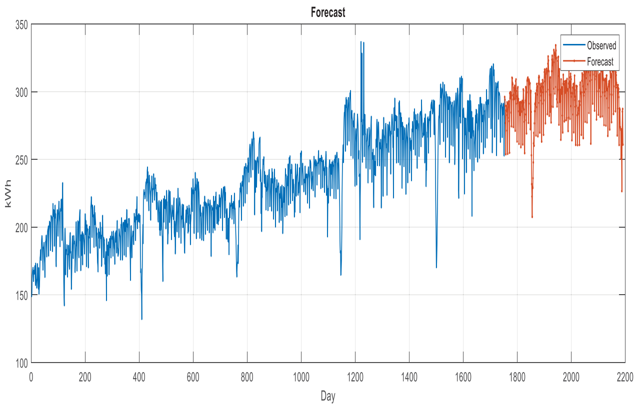

Fig. 12. The electricity demand forecasting results in the future time of Tien Giang province, Vietnam.

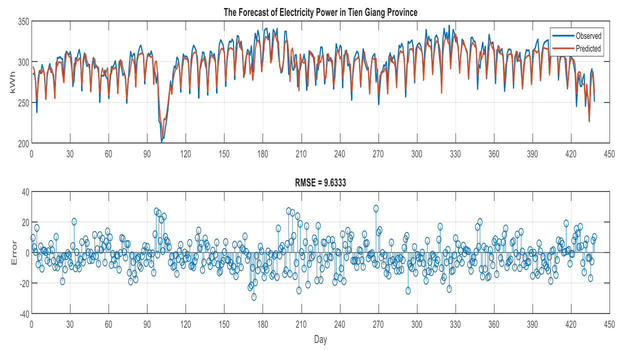

Fig. 13. Model evaluation by comparing the predicted value with the test value.

C. Comparison with other solution

To emphasize the outstanding results of the proposed forecasting method, the authors have experimented with a traditional neural network to forecast load demand based on the same data set. It has been proven that the results of our proposed method are more surpassing than the results of the method using the traditional neural network. Training process diagrams have shown that test results are diverging (Figure 14). This demonstrates that the forecast results are only true at the beginning values, the error of the forecasting results increases gradually from the end values. That is why forecasting results are instability across time. According to figure 15, we can see that when using the traditional neural network, the forecasting results do not fit the test values from the original dataset. This gives rise to the forecast of the load demand which is not highly accurate.

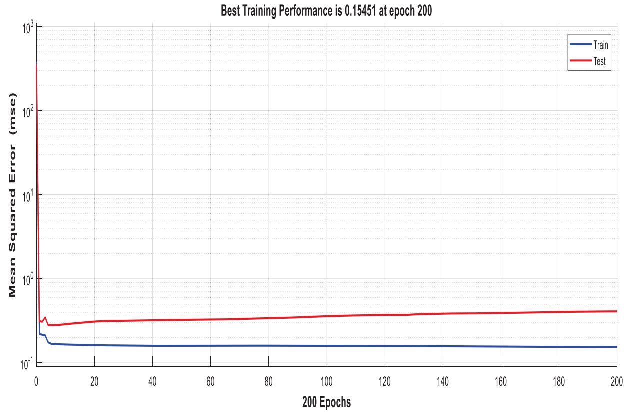

Fig. 14. Training process of traditional neural network.

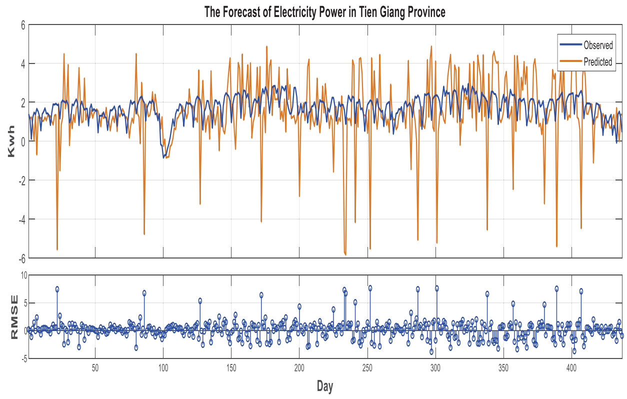

Fig. 15. Model evaluation by comparing the predicted value with the test value when using traditional neural network.

IV. CONCLUSION

Experimental results have shown that Long-Short-Term-Memory networks can solve the disadvantages that traditional networks have not achieved yet. In this paper, the authors forecasted the electric load demand of the real dataset. The authors had analyzed the theory and implemented a forecast on simulation software. The proposed method using the LSTM network to forecast has higher accuracy than the previous traditional methods. To sum up, this research has obtained accurate forecasting results of electricity demand. Therefore, this research result was applicable to reality in electricity agencies nationwide.

Although the results obtained from the study are satisfied, there are still several issues that the authors need to improve. For deep learning applications, data need to be collected on a larger scale to acquire more accurate results. In addition, adjusting the network architecture for more optimal results is also a problem that the authors are interested in.

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AUTHOR CONTRIBUTIONS

These authors contributed equally to this work.

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