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Short-Term Load Forecasting Using Long Short-Term Memory Based on EVN NLDC Data

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Abstract

Load forecasting has always been a crucial part of an efficient power system planning an operation. Since the global electricity market has developed rapidly in recent years, a load sequence has gradually become non-stationary and hence makes accurate forecasting difficult. Nowadays, many techniques can be used for load forecasting such as fuzzy logic, similar-day approach, expert systems, etc.. However, these methods normally obtain undesired results due to considerable variation of electricity load. In this paper, a short-term load forecasting model is proposed based on Long Short-Term Memory (LSTM) network combining linear regression algorithm and EVN-NLDC (National Load Dispatch Centre) data. Short-term load forecasting has an enormous impact on unit commitment, strategic power reserve for national power system and enhances the reliability of the power supply. National load data could be considered as a time series sequence consisting of two components which are trend and residual. Linear regression (LR) is adopted for trend forecasting and LSTM is used to residual forecasting. In addition, to evaluate the performance of the proposed model, artificial neural network (ANN) is utilized as a benchmark model. The results show that the proposed model achieves the Mean Absolute Percentage Error (MAPE) ranged from 1% to around 4% for one-day ahead load forecasting, whereas ANN model obtains over 4%.

Keywords: *Short-term load forecasting; Long Short-Term Memory (LSTM); Mean Absolute Percentage Error (MAPE); National Load Dispatching Centre Data; Linear Regression (LR).*

Abbreviations

LSTM	Long short-term memory
MAPE	Mean absolute percentage error
LR	Linear regression
ANN	Artificial Neural Network

Tóm tắt

Dự báo phụ tải luôn là một phần quan trọng của một hệ thống điện làm việc hiệu quả trong việc lên kế hoạch cho bất cứ hoạt động nào. Do thị trường điện toàn cầu phát triển nhanh trong những năm gần đây, phụ tải điện dần dần trở nên không ổn định và từ đó làm cho việc dự báo chính xác trở nên khó khăn. Hiện nay, rất nhiều kỹ thuật có thể được sử dụng cho việc dự báo phụ tải như Logic mờ (Fuzzy Logic), tiếp cận ngày tương đương (Similar-day Approach), hệ thống chuyên gia (Expert Systems),v.v. Tuy nhiên, những phương pháp trên thường đạt những kết quả không mong muốn vì sự thay đổi lớn của phụ tải điện. Trong nghiên cứu này, một mô hình dự báo phụ tải ngắn hạn được đề xuất dựa trên mạng Long Short-Term Memory (LSTM) kết hợp với thuật toán hồi quy tuyến tính (LR) và dữ liệu phụ tải từ Trung tâm Điều độ Hệ thống Điện Quốc Gia (NLDC-EVN). Dự báo phụ tải ngắn hạn có ảnh hưởng lớn đến việc huy động nguồn và chiến lược sử dụng công suất dự trữ cho hệ thống điện quốc gia đồng thời nâng cao độ tin cậy của hệ thống cung cấp điện. Dữ liệu phụ tải điện quốc gia có thể được coi như một chuỗi thời gian bao gồm hai thành phần: xu hướng (trend) và phần dư (residual). Hồi quy tuyến tính (LR) được sử dụng cho việc dự báo trend và LSTM được dùng cho việc dự báo phần dư. Bên cạnh đó, để đánh gia hiệu suất của mô hình đề xuất, mô hình Mạng Nơ-ron nhân tạo (ANN) được coi như mô hình tham chiếu. Kết quả cho thấy mô hình đề xuất đạt sai số Tuyệt đối phần trăm trung bình (MAPE) trong khoảng từ 1% đến 4% cho việc dự báo ngày tới trong khi đó mô hình ANN đạt MAPE lớn hơn 4%.

1. Introduction

Electricity load forecasting has been becoming a crucial research field in electrical engineering over the last decade. The increase of forecast error might occur the considerable economic cost to the electricity power systems. Therefore, accurate load forecasting is significant to address the unbalance between the demand and the power supply. Moreover, effective demand forecasting could enhance the power quality and ensure the safety of the power grid. Based on decision-making activities in operation the power systems, the load forecasting with performed the length of time in the future is divided into three types: short-term load forecasting (STLF) (a few minutes, hours, or days in advance), medium-term load forecasting (MTLF) (a few weeks or months ahead), and long-term load forecasting (LTLF) (a few years in advance). Recent studies concentrating on MTLF and LTLF are [1], [2], [3]. According to [4], the results of STLF is adopted to secure operating planning and the reliability of the power systems. Since many developing countries increasingly focus on improving their power grids, the STLF is prerequisite to address the issues.

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Similarity – based methods for load prediction considered as prevalent conventional methods can deal with non-linear load power, especially the load power in weekend days and special days [5], [6]. However, owing to the development of technology and economy, the electricity demand has been increasing rapidly through recent years. Hence, the accuracy of these methods decreases considerably. In addition, statistical methods [7], [8] view the load power as a time series then utilize regression function to obtain the predictions. Nevertheless, this time series is non-stationary and this can yield the high forecast errors.

Recently, machine learning (ML) – based approaches, such as Linear Regression (LR) [9], Support Vector Machine (SVM) [10], Artificial Neural Networks, etc. are used to solve STLF problems. As the Artificial Neural Networks (ANNs) has the non-linear mapping capabilities and generalization, these approaches are appropriate to address the complicated relationships. Ref. [11] exploited the comparison on the accuracy and the performance of the Feed-forward Deep Neural Network (FFDNN) and the Recurrent Deep Neural Network (RDNN) utilizing time-frequency (TF) feature selection for short-term electricity load forecasting. The results shown that the combination of TF feature selection and DNNs obtain higher accuracy. Song Li. et al [12] proposed a hybrid model blending Extreme Learning Machine (ELM) and the Levenberg-Marquardt method for STLF. The outcomes shown that the proposed model outperforms in comparison with other standard and state-of-the-art methods. Deep learning is considered as an advancement of machine learning with the complex structure. Ref. [13] introduced a Long Short-Term Memory (LSTM) based model with the validation on the publicly available dataset. Zhuofu Deng et al [14] proposed a novel model multi-scale convolutional neural network with time-recognition (TCMS-CNN). In 48-step point load forecasting, the proposed model improved from about 14% to under 35% on MAPE than other benchmark models.

2. Methodology

Long Short-term Memory Neural Network was proposed by Hochreiter and Schmidhuber in 1997 to avoid long-term dependencies through targeted design [15]. An advance of LSTM model in comparison with a single hidden layer RNN is that LSTM stores information in a control unit outside the normal flow of the RNN, hence introducing a new state unit a_t [16]. Fig. 1 depicts the structure of an LSTM cell. In this figure, at each time t, i_t, f_t, o_t and c_t are input gate, forget gate, output gate, and candidate value [17], which can be formulated respectively as these following formulations:

$$i_t = \sigma(W_{i,x}x_t + W_{i,h}h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma(W_{f,x}x_t + W_{f,h}h_{t-1} + b_f) \tag{2}$$

$$o_t = \sigma(W_{o,x}x_t + W_{o,h}h_{t-1} + b_o) \tag{3}$$

$$c_t = \tanh(W_{c,x}x_t + W_{c,h}h_{t-1} + b_c) \tag{4}$$

where $W_{i,x}$, $W_{i,h}$, $W_{f,x}$, $W_{f,h}$, $W_{o,x}$, $W_{o,h}$, $W_{c,x}$ and $W_{c,h}$ are weight matrices, b_i, b_f, b_o and b_c are bias vectors, x_t is the current input, h_{t-1} is the output of the LSTM at the previous time $t-1$, and σ is the Sigmoid activation function. The number of prior memory value from the cell state are considered to be removed by the forget gate [18]. Similarly, the input gate specifies new input to the cell state. Then, the cell state a_t and h_t are calculated as:

$$a_t = f_t \circ a_{t-1} + i_t \circ c_t \tag{5}$$

where $\circ$ denotes the Hadamard product [19]. The output h_t of the LSTM at the time t is computed as below:

$$h_t = o_t \circ \tanh(a_t) \tag{6}$$

Hereafter, the predicted output $\hat{z}_t$ is computed by using the output h_t:

$$\hat{z}_t = M_y h_t \tag{7}$$

where M_y is a projection matrix to reduce the dimension of h_t. The structure of the LSTM networks is presented in Fig. 2. As can be seen from this structure, an input feature vector x_{t-1} is fed into the networks at the time t. The previous LSTM cell provides a feedback h_{t-1} to the current LSTM cell to demonstrate the time dependencies of this network. The network training facilitate to minimize the function f based on targets y_t by utilizing backpropagation with gradient descent:

$$f = \sum_t \|y_t - \hat{z}_t\|^2 \tag{8}$$

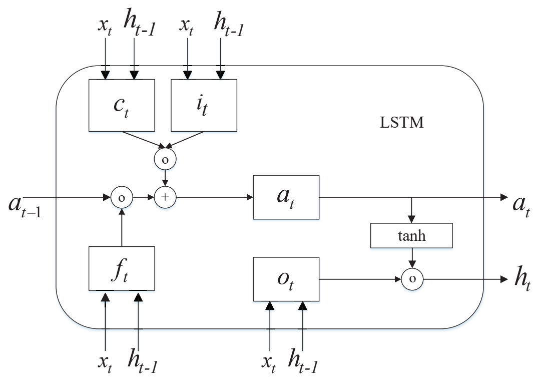

Figure 1: Structure of an LSTM cell

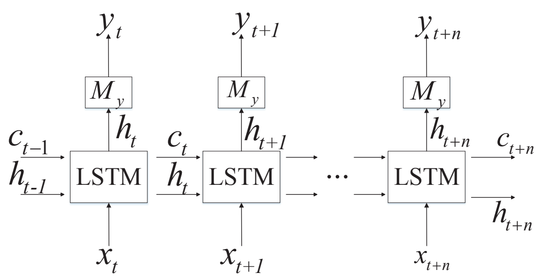

Figure 2: Structure of LSTM networks

3. Data and Performance Metric

3.1. Data

In this study, the raw data from the National Load Dispatching Centre (NLDC) includes the load power in Vietnam and the temperature of several cities that have large electricity consumption. The data are collected from 1/1/2014 to 31/12/2019 with time interval is one hour. Fig. 3 indicates the load power of Vietnam from 2014 to the end of 2019. As can be seen, the load power increased rapidly through the years, for instance, the load power in 2019 obtains over 30000 MW, improving about 200% in comparison with the load power in 2014. Besides, the temperature is the factor that has considerable impact on load power [20]. Therefore, the dataset used as the inputs to the proposed predictive model contains the date-time variable (hour of day, weekday, day of month, weekend, and holiday); the historical load power including the previous day demand power, the average previous day demand power, the previous week demand power, and the previous year demand power; and the previous day temperature, the previous two days temperature, the intra-day temperature. The dataset are divided into two parts: the training set and the testing set. The training set consisting of these above variables from 1/1/2014 to 31/12/2018 is utilized to train the predictive model, thus optimize the parameter of the proposed model. The testing set including these values in 2019 is adopted to predict the load power values in two months (June, 2019 and December, 2019) and validate the performance of the predictive model. Since LSTM is sensitive to data scales [21], the data are normalized using Min-max function and then range in [0, 1]. The Minmax function is defined below:

$$x_{nom} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

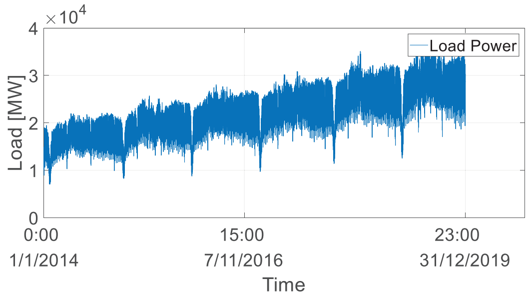

Figure 3: The load power of Vietnam from 1/1/2014 to 31/12/2019

3.2. Performance Metric

In this paper, mean absolute percentage error (MAPE) is dedicated to evaluate the performance of the forecasting model. MAPE is a measure of prediction accuracy of a forecasting method in form of a percentage error, and is defined as:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{GP_i - \widetilde{GP_i}}{GP_i}\right| \times 100\% \tag{10}$$

Where n is the amount of observations; GP is the actual value; $\widetilde{GP}$ is the predicted value. The lower MAPE brings more accuracy in forecasting results.

4. Results and Discussions

4.1. Case Study 1

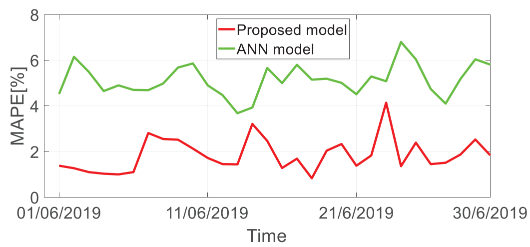

Figure 4: The load forecasting results in June via MAPE

In the first case study, the daily demand forecasting is conducted by using the load power values of everyday in June, 2019 as the testing set to the predictive model. Fig. 4 depicts the load forecasting results in June via MAPE. As can be observed, the proposed model outperforms among two predictive models. In particular, the obtained MAPE from the LSTM is in the range of [1;4]% whereas the ANN model achieves the MAPE ranging from about 4% to 7% in daily prediction. This might be reasonable since the LSTM model is the enhancement of the ANN model. The capability allows the LSTM model capturing the long-term memorization. In other words, the LSTM model could cope with the large number of data points fed into the model in the training process. Besides, dealing with the large data is a weakness of the ANN model because this can result to the overfitting [22]. Fig. 6 indicates the load forecasting results in specific days of June. As can be seen, the predicted values of the proposed model is similar to the actual values than the ANN model. This demonstrates that the proposed predictive model is more accurate than the ANN model. The difference between the predicted values and the actual values leading to the accuracy of the predictive models occur during hour 13:00 to 18:00 of the days. The electricity consumption in this period increases significantly due to the weather characteristic of June as well as the summer.

4.2. Case Study 2

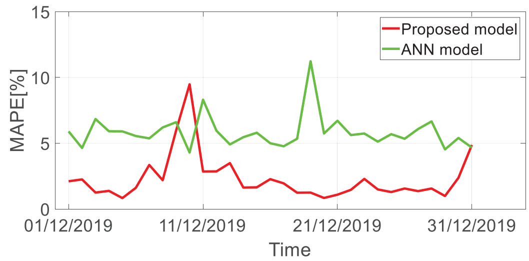

Figure 5: The load forecasting results in December via MAPE

The second case study is implemented by using the demand power values of everyday in December, 2019 as the testing set to the predictive model for daily predicting assessment. Fig. 5 illustrates the demand forecasting results in December via MAPE. The outcomes show that the proposed model has the lower MAPE than the ANN model. For instance, the MAPE achieved from the proposed model ranges from over 1% to over 5% whereas this index of the benchmark model is bigger than 4.5%. Fig. 7 represents the load forecasting results in specific days of December. As can be seen, two predictive models have the slight differences in comparison with the actual values. However, these differences are less considerable than the differences in the first case study. The predicted values obtained from the proposed model remain similar to the actual values. Thus, the impact of weather characteristic on the load power is relatively significant, representing in form of various meteorological factors such as the temperature, the humidity, etc. Obviously, the LSTM model has the higher accuracy than the benchmark model. Nevertheless, the proposed model has a large weakness that the training time is quite large. In particular, the training time of the proposed model is about 2000 seconds while the training time of the ANN model is about 400 seconds.

5. Conclusion

This study proposes the STLF scheme using the combination of Linear Regression (LR) and Long Short-Term Memory (LSTM) based on the real-world data collected from the National Load Dispatching Centre (EVN-NLDC). To assess the performance as well as the accuracy of the proposed model in daily prediction, the Artificial Neural Network (ANN) model is utilized as the referenced model. The outcomes demonstrate that the proposed model outperformed the ANN model. The MAPE obtained from the proposed model ranges from 1% to about 4% in two case studies. In the future, the proposed model could be enhanced by combining with other deep learning models to obtain a complex hybrid model with the high accuracy. To increase the performance of the proposed model, several dataset are collected with various parameters that influence on the target variable. Hence, the data pre-processing need to be more concentrated.

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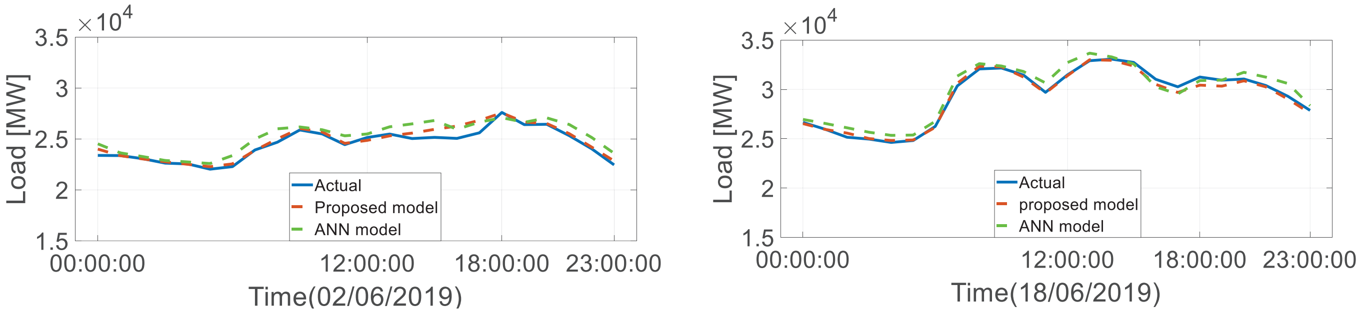

Figure 6: The load forecasting results in specific days of June

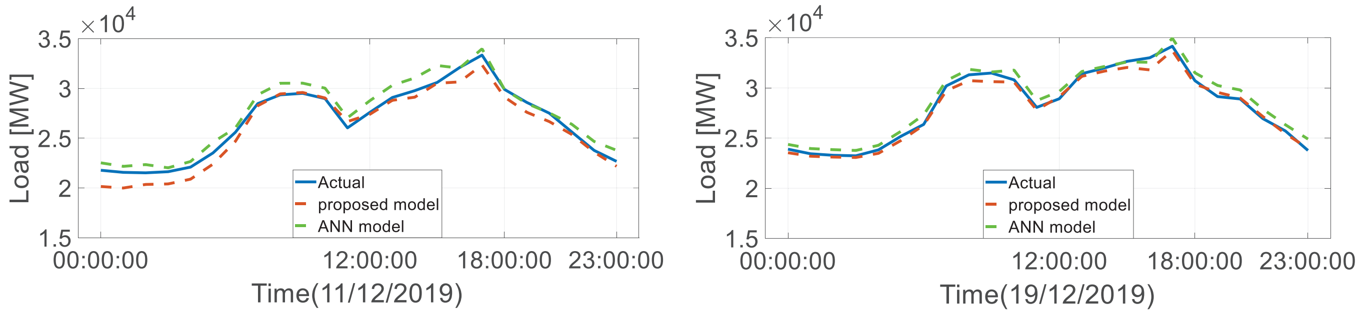

Figure 7: The load forecasting results in specific days of December

on using big data technology, AI in load forecasting for national and regional power systems" according to Decision No. 1166 / QD-EVN.

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