Short-term load forecasting algorithm based on LSTM-DBN considering the flexibility of electric vehicle

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Abstract: Due to the rapid development of electric vehicles, the randomness of charging and discharging modes brings huge challenges to load forecasting. Considering the large-scale gridding of electric vehicles, a load combination forecasting algorithm is proposed in this paper which considers the flexibility of electric vehicles. Firstly, the user behaviors of electric vehicle are modeled based on Monte Carlo method. Secondly, different from traditional single forecasting models, the combination of deep belief network and long short-term memory network is used in order to improve the forecasting accuracy and calculation speed for the complex case. Thirdly, a dynamic weight distribution method is proposed to combine the two forecasting results. Finally, Numerical examples have been performed with the results proving that the proposed method outperforms the state-of-art significantly in load forecasting, and the combined model has a higher forecasting accuracy than traditional methods.

1. Introduction
With the great development of economic society, the form and demand of power load are also increasing. Distribute energy, electric vehicles, heat storage and other flexible loads have an important role in the safety of the power grid [1-3]. The current environmental pollution is getting worse; the replacement of traditional cars by electric vehicles (EV) has become a mega trend. Due to the higher randomness and flexibility of electric vehicles, distribution network’s structure and stable operation would be affected seriously. Precise forecasting of user sides load forecast is essential to power grid’s stable operation.

Currently, the methods of short-term load forecasting mainly include automatic regression moving average model, back propagation model [7], support vector machine [8-10], etc. But these models are too simple to take into account the correlation of different data [11-14]. With the development of big data technology, deep learning algorithm is replacing traditional statistical method and machine learning algorithm[15]. Recurrent neural network (RNN) is a representative method of RNN, and it always is used to solve the forecasting problems which have time-varying characteristic. Long- and short-term memory (LSTM) has solved the disadvantage of RNN effectively. Meanwhile, its interior only could be affected by linear action which reflects the long-term historical information about input times series data fully. So, LSTM provides a possibility of forecasting regional short-term load power.
Although traditional load forecasting method has its advantage to a certain extent, its disadvantage is obvious. Firstly, traditional load forecasting method is more suitable to process less, simple and time-sequential data, but it is not suitable for various complex flexible loads. Secondly, LSTM needs to be set parameter structure before learning process. The selection of parameters determines the topology of the model directly, and has a great influence to the promotion ability of this model. Thirdly, LSTM is more suitable to long-time series, but does not suitable to multi-input case. Deep belief network (DBN) is more appropriate to solve problems of complex working condition. But few studies adopt the combination of these two methods to forecast flexible load. Current forecasting studies are difficult to take flexible load and external environment information into account, which would lead to the insufficient generalization ability.

In all, the EV is taken as the representative of flexible load in this paper. And, the combination of DBN and LSTM is used to build up the model of short-term load forecast for flexible load gridding.

The reliability and accuracy of the model has been verified in the background of a large number of flexible load gridding to the power grid based on power grid experiment data.

2. Electrical vehicle charging statistical model

2.1. Short-term user behavior statistical model
The charging load of EV has strong randomness, especially for district grid which has a relatively small load capacity. We assume that battery status and charge pile has a relatively stable characteristic. So, this paper only considers the impacts of user behaviours. Reference to current development status of EV in the social environment, the following assumption are made to facilitate modelling:

1) The end time of daily trip is taken as the charging start time;
2) The start time of daily trip is taken as the charging end time;
3) The start time of daily trip, trip distance per day and the end time of daily trip (charging start time) are all treated as independent random variables;
4) The battery is fully charged every time the charging is completed.

The impact of user behaviour on EV mainly includes the start time of the daily trip, trip distance per day, and end time of the daily trip.

2.2. Monte Carlo forecasting and processing
The charging behaviour of EV is affected by the random and flexibility of user behaviours greatly. The end time of the daily trip is taken as the charging start time, and daily trip distance could reflect on battery consumption directly, in a result that it reflects on charging needs. So, the Monte Carlo simulation is used to solve the mathematical expectation of random variables and enough samples to compute the result of the simulation. User behaviour of a certain time in the day to forecast is quantified by probability to simplify non-linear relationship between user behaviour and charging load. In this case, the probability that the EV’s user daily trip at a certain time on a certain day to be forecasted is 5.6, which means that the probability of charging need is 0.56, the quantitative value of 0.56 is used as the input of the specific impact factor into the DBN model.

3. Load forecasting model based on deep belief network

3.1. Deep belief network
The main advantage of DBN is that DBN has very tight and high-quality non-linear mapping relations and strong fitting ability. And, DBN could process more data. It has unsupervised pre-training, which could weak the input items continuously with a smaller correlation with the objective function. And its multi-hidden layer model is use to train enough sample data to obtain higher accuracy.

The input of DBN is a column vector X that is n-dimension, $X = [x_1, x_2, ..., x_n]$. If it is used for power system load forecasting, X could be seen as a multi-dimensional column vector which is determined by specific influencing factors (such as historical load information, temperature and weather...
conditions), its dimension is decided by practical problems. Input vectors go through the input layer after being identified transformation. And, then they are imputed into the first hidden layer after identified transformation. \((w, b)\) represent the weight parameter and threshold parameter between the hidden layer of layer 1 and the hidden layer of layer l. In the structure of DBN, the previous layer serves as the input layer to the next layer. The hidden layer 2 is taken as an example; Its input comes from hidden layer 1, and its own activation function \(f\) is read to perform a non-linear transformation. The transformed data result is then passed to the hidden layer 3 neuron as its input, iterative layer by layer, transfer layer by layer to get the total output \(y\).

Activation function could non-linearly transform the input of each layer. Generally, it is used to optimize the performance of the neural network. Here, both activation function \(f\) of hidden layer and activation function \(g\) of output layer use the sigmoid function to make it difficult to diverge in data transmission, linear and non-linear could be better balanced during the process. Sigmoid function could be shown as:

\[
sigmoid(x) = \frac{1}{1+e^{-x}}
\]

Where, \(x\) is the input of the network, \(e=2.718\). Sigmoid function is not like perceptron the value after transformed is not 0 or 1, but a smooth curve limited between 0 and 1.

3.2. Long and short-term memory network forecasting

LSTM acts as a new network under the recurrent neural network (RNN) structurally. LSTN not only solves the "gradient demise" problem of learning of traditional RNN training and learning, but also learn timing series data effectively with long and short-term dependence information. LSTM is currently the most successful time loop network framework, and widely used in the engineering field.

The forget gate, input gate and output gate constitute the basic unit of LSTM. Memory condition is the core of LSTM, whether it is forgotten is determined by three variables, they are input \(x\), last output \(h_{t-1}\) and last memory condition unit \(S_{t-1}\). Calculate formula are as follows (2-7):

\[
f_t = \sigma \left( W_{fx} x_t + W_{fh} h_{t-1} + b_f \right)
\]
\[
i_t = \sigma \left( W_{ix} x_t + W_{ih} h_{t-1} + b_i \right)
\]
\[
g_t = \phi \left( W_{gx} x_t + W_{gh} h_{t-1} + b_g \right)
\]
\[
o_t = \sigma \left( W_{ox} x_t + W_{oh} h_{t-1} + b_o \right)
\]
\[
S_t = g_t \odot i_t + S_{t-1} \odot f_t
\]
\[
h_t = \phi (S_t) \odot o_t
\]

Where, \(f_t\) represent forget gate; \(g_t\) represent input gate; \(o_t\) represent output gate; \(S_t\) as the memory condition of the current unit, \(h_t\) as an intermediate output; \(W\) represents weight matrix of input, the output of last unit and Multiplication of different gate; \(\sigma\) represents function activation of sigmoid; \(b\) represent offset term; \(\odot\) represent an element in the vector is multiplied in order; \(\phi\) represent the change of tanh function.

4. Load forecasting model based on LSTM-DBN combination

4.1. Establishment of LSTM-DBN model

LSTM is an advanced neural network currently, and suitable for analysing and forecasting data with the regularity of time. But in the face of increasing flexible load data, especially for the regional grid, LSTM is difficult to maintain the accuracy of forecast only based on the time series of a historical load. When confronted with the problem that multiple complex factors affect load forecasting, DBN could solve the problem that the internal characteristic of the load is not obvious, and hidden layer is added through RBM stack to hierarchically characterize the relationship between input and output functions.
Based on the above considerations, the overall of the model established in this paper is as follows: LSTM and DBN are combined for the forecasting model to complement the two neural network algorithms. LSTM is used to process historical load data, and to train historical load data. The learned output matrix is combined with artificially screened specific influencing factor matrix (include daily maximum temperature, rainfall and humidity, etc.). These matrices are combined with concat function and form a new function. Its role is to connect two parameter groups, if the object is a parameter—add the element in the array-as the input of DBN network, output of DBN as forecasted value. It not only improves the accuracy of short-term load under the influence of various and complex factors, but also excavates internal characteristics of the load quickly to improve forecast efficiency.

\[ X' = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \]  

\( X' \) is the normalized value, the range is(0, 1). Onehot encoding is used for discrete factors (smog, rainfall, daytime types, holidays, etc.), for example, forecast Monday’s load, its week feature is 1, the remaining bits are 0, that is (1 0 0 0 0 0 0). Other holidays type, a holiday is (1 0), otherwise (0 1), smog type, haze is (1 0), otherwise (0 1). So, if you want to express the forecast day as a Monday that is not a holiday and is hazy, its onehot code is (0 1 1 0 1 0 0 0 0 0). Other specific factors and so on.

For the user behaviours of EV on the day to be forecasted, Monte Carlo simulation could be used to estimate probability which is changed into numerical value also as a specific factor directly.

4.2. Considering flexible load forecast of gridding of electric vehicles

Monte Carlo sampling is used to sample start time of charging, battery charging power, and average charging power generally. Then, charging load curve could be obtained by simple accumulation.
method calculation. Accumulate the charging load of EV to obtain total charging load \( P \), calculation formula is as follows:

\[
P = \sum_{t=0}^{24} \left( \sum_{n=1}^{N} P_{cd}^{n} \right)
\]  

(9)

Where, \( N \) represents the number of private cars collected in one day in this area, \( P_{cd}^{n} \) represents the charging power of 1 day of the \( N \) electric vehicles at time \( t \).

4.3. Considering flexible load forecast of grid connection of electric vehicles

Taking all this factors into account, the solution process used in this paper is as follows:

1) Selecting sample set and pre-process its data, set the day to be tested as the training set; applying the Monte Carlo method to solve the charging behaviour of EV; selecting rainfall, daily maximum temperature, daily minimum temperature, daily tripe distance, end time of the day, day type, etc. As specific factors, performing data encoding and quantization to form a specific factor input matrix.

2) Using the training set to train the LSTM-DBN model and continuously optimizing the weights to obtain the forecasting model.

5. Case analysis

5.1. Case conditions

In this paper, the electric load data of a total of 96 sampling points for 24 hours a day from January 1 to March 1, 2018, in Liaoning Power Grid are used as experimental samples. And, Matlab programming environment and algorithm are used to forecast. The results are compared with the real data from March 2. The supervised fine-tuning of DBN network part based on LM algorithm could speed up iterations and continuously optimize and adjust the weight. To obtain the probability of electric load of EV user in forecast day, the EV charging probability model is used. Monte Carlo method is used to simulate and quantify this probability as a value, and this value is as specific impact factor. After being encoded, it is sent to the input layer of DBN. The model parameters are as follows: 16 input nodes; 2 LSTM layers; the first layer of LSTM network have 9 nodes, the second layer of LSTM network have 6 nodes, form a four-layer neural network of 16-9-6-4; To optimize the network model, each layer uses the sigmoid activation function; Epochs is 78, Batch size is 8; the optimization algorithm is selected as Adam.

It would affect the training time of DBN network by the problems that how to choose the number of the hidden layers, how to set the number of units of each hidden layer. For this reason, for the selection of the number of hidden units, this paper adopts the enumeration method to select each layer separately and then proves the influence of the number of hidden layers in the deep network structure. It is found through data set verification that when the deep belief network is a 4-layer structure, the number of units in the two hidden layers is 20 and 15, respectively. When the number of hidden units in the second layer is 15, the short-term load forecasting effect is the best.
5.2. Comparison of combined forecasting results at different time scales

![LSTM prediction output](image1)

(a) LSTM forecasting results

![Combined predictive output](image2)

(b) Combined forecasting results

Figure 2. One-week load forecast comparison chart

To verify its reliability when considering flexible loads, a 10-month sample from January 1 to November 1 for November 2 (one day) and November 2 to November 9 (one week) is adopted. A single method of deep belief network, the single method of long and short-term memory network, and the combination of the two are separately used to load forecast

Figure 2 reflects the performance of three methods of forecasting in one week. Because the period of one week is longer and contains more complex specific factors, the accuracy of a single LSTM model is not good as a single DBN model. And, the proposed LSTM-DBN has a better accuracy.

For daily and weekly load forecasting, the absolute errors are significantly smaller than a single LSTM and a single DBN model. Compared with these two methods, the forecasting accuracy of the model in this paper is improved by 5% at least. Therefore, the LSTM-DBN forecasting model proposed in this paper is more suitable for the current electricity environment.

5.3. Comparison of forecasting performance under different combinations

This paper takes EV as a typical example, and tests the generalization ability of the method proposed under flexible load gridding conditions. The normalized mean absolute error MAPE and root mean square error RMSE are used as the error evaluation indicators. The direct simple superposition method is compared with the method proposed in this article. The forecasting results are shown in Table 1.

| Forecasted day | The proposed method | Direct overlay forecasting method |
|----------------|---------------------|----------------------------------|
|                | MAPE/% | RMSE/% | MAPE/% | RMSE/% |
| 11.2           | 0.65   | 4.83   | 2.27   | 16.22  |
| 11.3           | 0.62   | 4.04   | 2.02   | 14.78  |
| 11.4           | 0.48   | 3.78   | 1.83   | 11.96  |
It could be seen that the result of short-term load based on LSTM-DBN forecasting model has a higher accuracy than the superposition methods. And in terms of the degree of dispersion from the actual results, the proposed method performs better. In summary, LSTM model could process more training samples, and obtain more effective information combine with DBN. Therefore, it is effective and feasible to apply the LSTM method to the field of short-term load forecasting considering the characteristics of a flexible load gridding.

6. Conclusion
An LSTM-DBN short-term load forecasting algorithm considering flexible load gridding is proposed in this paper. Through the analysis of the example, the following conclusions are drawn:

1) The proposed method not only combines the unique advantages of deep belief networks in non-linear mapping but also the characteristics of long-short-term memory network models with better global processing. The forecasting error results are smaller compared with the actual load of the power grid. And, the model forecasting accuracy is improved by 5% to 10%.

2) Compared with BP neural network and LSTM, DBN analyses massive data effectively. And it could handle complex nonlinear problems properly. It has the advantages of stronger deep learning ability, higher load forecasting accuracy, and more accurate forecasting trends.

3) It is proved by the example that the proposed model performs best in the load forecast considering the charging of electric vehicles, and has better generalization ability. The promotion of the method would assist the grid to respond to various flexible load gridding effectively.

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