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Electricity Load Forecasting Based on EMD and GRU

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Abstract: This paper presents a load forecasting method based on empirical mode decomposition algorithm and GRU neural network. In view of the randomness and fluctuation of historical data of electric load, EMD algorithm is used to decompose historical data of electric load, and a series of smooth IMF components are obtained. The components are regarded as GRU neural network. Input is used to forecast the electricity load for the next day. Compared with the prediction model constructed by GRU neural network and SVM, the experimental results prove the validity of the prediction method proposed in this paper .

Keywords: Load forecasting, EMD, GRU, randomicity, volatilit

1. INTRODUCTION

Short-term load forecasting of power system is the basis and premise of safe and economic operation of power system, and it is also an important basis for power department to arrange dispatching plan and power supply plan. With the continuous development of social economy and the constant adjustment of industrial structure, the user's electricity consumption behavior habits show a diversified development trend. For individual industrial users, due to their different division of labor, resource allocation and service objects in social economy, their electricity consumption behavior habits have their own unique periodic characteristics. The accuracy of load forecasting cannot be satisfied by using the overall characteristics of users. At present, short-term load forecasting methods are mainly divided into three categories: classical forecasting methods, traditional forecasting methods and intelligent forecasting methods. Among them, Artificial Neural Network (ANN) in intelligent prediction method can transform the traditional function relationship into high-dimensional non-linear mapping, and has strong adaptive ability. However, because there is no reliable theoretical basis for its generalization ability from experience risk minimization to expectation risk minimization, its generalization ability is often not satisfactory. Support Vector Machine (SVM) converts empirical risk minimization into structural risk minimization, and uses optimization methods to solve the problem of over-fitting and dimension disaster in machine learning. However, its theory is complex, model parameter selection is skillful, and the accuracy of prediction results is difficult to obtain. Further improvement limits the application of SVM model [5]; Random Forest (RF) has fewer parameters to adjust in prediction, less interference from outlier data, and shows good robustness with the increase of data sets, so it is more suitable for short-term load forecasting of power system [6]. This paper presents a load forecasting method based on empirical mode decomposition algorithm and GRU neural network. In view of the randomness and fluctuation of historical data of electric load, EMD algorithm is used to decompose historical data of electric load, and a series of smooth IMF components are obtained. The components are regarded as GRU neural network. Input is used to forecast the electricity load for the next day. Compared with the prediction model constructed by GRU neural network and SVM, the experimental results prove the validity of the prediction method proposed in this paper.

2. EMD PRINCIPLE

EMD is a decomposition algorithm for non-linear and non-stationary complex time series [7]. Essentially, EMD processes a complex signal smoothly, decomposes the trend or fluctuation of different scales of the signal step by step, and obtains a series of sub-sequences with different frequencies and vibration amplitudes, in which each sub-sequence represents the original sequence. The wave modes at the same scale correspond to an IMF. The basic idea of EMD is to determine the "instantaneous equilibrium position" by means of the average value of the upper and lower envelopes of fluctuations, and then extract the eigenmode function. The steps of EMD decomposition are as follows:

(1) The first step is to identify all local maxima and minima in $S(t)$ and interpolate them with cubic splines to fit the upper and lower envelopes of$S(t)$. Among them, $S(t)$ represents the current decomposition sequence, the initial value is the stock logarithmic return sequence,$t = 0, 1, \ldots, T$.

(2) The second step is to calculate the local instantaneous mean of the upper and lower envelopes at each time, so as to obtain the average envelope $m(t)$, and calculate the new sequence $d(t)$ according to formula (1).

$$d(t) = S(t)-m(t) \quad (1)$$

Then, the S_d value shown in equation (2) is used to determine whether $d(t)$ is an eigenmode function.

$$S_d = \frac{\sum_{t=0}^{T} | d_i(t) - d_{i-1}(t) |^2}{\sum_{t=0}^{T} d_i^{\,2}(t)} \tag{2}$$

where $d_i(t)$ is the result of the first screening, and the threshold of S_d is usually set between 0.2 and 0.3. If the S_d value is less than the threshold value, the screening process stops; otherwise, $d(t)$is treated as a new decomposition sequence $S(t)$, and the above iterative process is re-executed

(3) If $d(t)$ satisfies the stopping condition of the above screening process, $d(t)$ is an IMF, and $d(t)$ is separated from $S(t)$ to obtain the remainder $r(t) = S(t)- d(t)$.

(4) If the remainder $r(t)$ has become a monotone function or constant, or the amplitude is lower than the established threshold value and the IMF can not be further extracted, then the whole decomposition process ends; otherwise, $r(t)$ is treated as $S(t)$ to be decomposed and returned to Step1 to re-execute the above iterative process.

When decomposition is completed, the initial sequential data sequence $S(t)$ is iteratively decomposed into n orthogonal eigenmode functions $c_i(t)$ and trend remainder $R_n(t)$, i = 1, 2, ..., n, as shown in Formula (3), where $c_i(t)$ takes the eigenmode function $d(t)$ from Step 3 in turn.

$$S(t) = \sum_{i=1}^{n} c_i(t) + R_n(t) \tag{3}$$

3. GRU NEURAL NETWORK

The structure of GRU is very similar to that of LSTM, which is designed to solve the long-term dependence problem of RNN. LSTM contains three gate functions (input gate, forgetting gate and output gate), as shown in Figure 12. The GRU model only contains two gate functions (reset gate and update gate). If all the reset gates are set to 1, the output gate will be replaced. And when the update gate is set to 0, it degenerates into RNN model. Obviously, because of the lack of calculation of output gate, GRU network parameters are less and training speed is faster. When the experimental data is more, LSTM network is better.

The GRU neural network consists of two gate units (update gate $z$and reset gate r), the structure of which is shown in Figure 3. The greater the value of the update gate, the higher the impact of the previous moment on the current moment. The less the value of the reset gate, the less the impact of the previous moment on the current moment.

Hidden state h uses the update gate to control the degree to which the hidden state at the time before update is combined with the candidate hidden state at the current time. If so, the state between time t1 and t2 is approximately 1. Then, the information between t1 and t2 is hardly input into the hidden state of the current time. This design is helpful to better capture the impact of the long time interval data in the time series on the current time. Candidate hidden state $h^{\sim}$uses reset gate to control whether the hidden state of the previous time series containing historical information is needed for the candidate hidden state of the current time step. If the reset door approximates 0, the hidden state of the previous moment will be discarded. This can capture the influence of short time interval in time series on the current time.

As shown in the structure diagram, x_t is the input of GRU unit structure, h_t is the output of hidden layer, and the related calculation of unit structure is as follows.

$$z_t = \sigma(W^{(z)} x_t + U^{(z)} h_{t-1}) \tag{4}$$

$$r_t = \sigma(W^{(r)} x_t + U^{(r)} h_{t-1}) \tag{5}$$

$$\tilde{h}_t = \tanh(W x_t + U(r_t * h_{t-1})) \tag{6}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{7}$$

where z_t and r_t are update gates and reset gates respectively; $\tilde{h}_t$ is the sum of input x_t and output h_{t-1} of the upper hidden layer; σ is the Sigmoid function; tanh is the hyperbolic tangent function; $W^{(z)}$, $U^{(z)}$, $W^{(r)}$, $U^{(r)}$, W, U is the training parameter matrix; $*$is the product of the matrix.

4. EXPERIMENT

4.1 Prediction Model

The mechanism of the prediction model presented in this paper is shown in the figure. Firstly, the model decomposes the load data with EMD algorithm, and obtains each IMF subsequence. Then the GRU neural network is used to predict each subsequence, and the predicted values of each load component are obtained. Finally, the final load forecasting value is obtained by superimposing the values of each forecasting component. The experimental data obtained in this paper are based on the load data provided by the European Intelligent Technology Network Competition.

4.2 Data Decomposition of Electric Load Based on EMD

The power load data with a time interval of 30 minutes are normalized and decomposed by EMD algorithm. The decomposition results are shown in the Figure 1. From top to bottom, the decomposition results are IMF1 to IMF9, and the last one is the residual component.

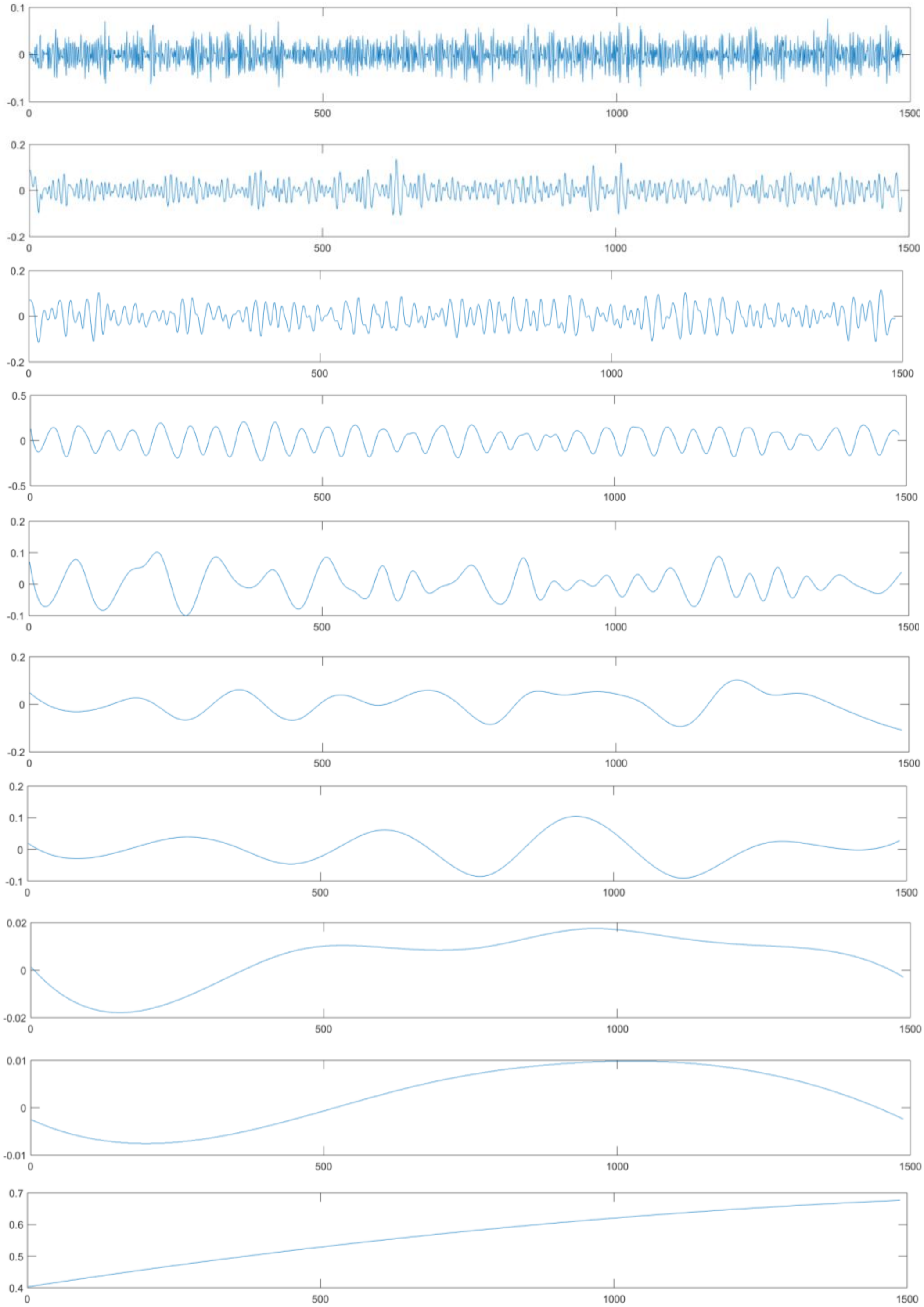

Fig.1 EMD decomposition results of electric load data

4.3 Forecast Results and Analysis

The IMF subsequences decomposed from EMD are used as the input of the forecasting model to predict the power load of each subsequence in the next day, and then the power load of each subsequence is superimposed to get the final power load of the next day. The predicted results are evaluated by using MAPE, and the calculation formula of the indicators is as formula (8).

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|x_t - \hat{x}_t|}{x_t}\times 100\% \tag{8}$$

where x is the actual value, $\hat{x}$ is the predicted value, and N is the number of predicted results.

The results of the forecasting experiment are shown in the following Figure 2. The forecasting results of the three models are shown in Figure 2. Generally, the three models can well track the fluctuation trend of residential power load data and give good forecasting results. However, the load forecasting results based on EMD-GRU are more suitable to the actual load situation than those based on GRU and SVM. From Table 1, it can be concluded that the prediction errors of EMD-GRU model proposed in this paper are 1.03% and 1.93% lower than those of GRU and SVM, respectively. The validity of the forecasting method proposed in this paper is verified.

5. CONCLUSION

In this paper, an ultra-short-term residential load forecasting method based on empirical mode decomposition algorithm and gated cyclic neural network is proposed. In the research of ultra-short-term residential load forecasting, machine learning theory has been widely used because of its strong non-linear mapping fitting ability and flexible forecasting modeling method. According to the randomness and fluctuation of power load data, EMD algorithm is used to decompose the data, and a series of relatively stable IMFs are obtained. The obtained IMF is used as the input of the GRU-based prediction model to predict the electricity load for the next day. Compared with the prediction model based on GRU and SVM, the prediction model based on EMD-GRU proposed in this paper has higher accuracy, which verifies the validity of the model.

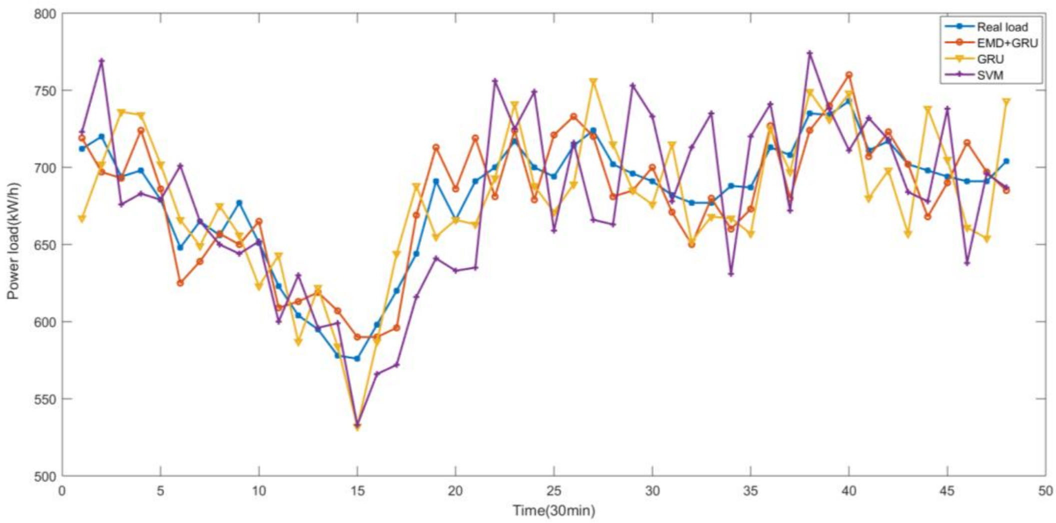

Fig. 2 Prediction result

Table 1 Prediction Errors

	MAPE
EMD-GRU	2.35%
GRU	3.38%
SVM	4.28%

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