A New Hybrid Frequency Decomposition Algorithm for Short-Term Reactive Power Forecasting

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Abstract. To address the poor ability of the existing algorithms in predicting reactive power, this paper proposes a new hybrid frequency decomposition reactive power forecasting algorithm, Ensemble Empirical Mode Decomposition Long Short-Term Memory Random Forest Regression (ELR), which adopts a strategy of frequency decomposition predicting after Ensemble Empirical Mode Decomposition and then data reconstruction. That decomposition compresses the high frequency of reactive power and benefits the following separate forecasting. For the high-frequency feature of reactive power, Long Short-Term Memory is proposed to deal with the forecasting difficulty caused by strong signal disturbance and randomness. For the low-frequency part, Random Forest Regression speeds up the forecasting. The proposed algorithm is compared with four conventional algorithms and four hybrid algorithms based on signal decomposition; the results show that the proposed algorithm has the highest predictive performance.

1. Introduce

Many important operations in the power system are closely related to industrial reactive power, such as voltage/var optimization [1, 2] power quality improvement [2, 3] frequency control [4], and steady-state power flow analysis [5, 6]. Accurate forecasting on short-term reactive power does help not only the normal operation of the power system but also the optimal management of energy resources [7], and benefits to reduce the power loss of the power grid [8-10]. But existing forecasting algorithms for short-term reactive power are hard to reach the accuracy acquirement of application, which is caused by the strong waveform randomness, noise and local disturbance of the reactive power.

Those forecasting algorithms can be divided into three categories: statistical mathematical algorithm, machine learning-based algorithm, and hybrid forecasting algorithm. In the statistical mathematical field, F. Wang et al. [11] applied multiple linear regression algorithms to medium- and long-term power load forecasting. A. Laouafi et al. [12] proposed an adaptive exponential smoothing algorithm to improve the ultra-short-term power load forecasting. However, those algorithms based on mathematical statistics are poor in robustness with low accuracy for complex nonlinear systems. The classical representative algorithm based on machine learning is Support Vector Machine (SVM) [13], which presents good results in short-term forecasting of power load with strong periodicity [14, 15], but it has poor forecasting effect on power load data with large random fluctuation. The neural network is widely used in the nonlinear system forecasting because of its strong nonlinear mapping
ability. Y. Ma et al. [16] proposed a power load forecasting algorithm combined Isolated Forest (IForest) with LSTM neural network. However, the neural network has slow convergence speed, easily falling into local minimum value, and overfitting. The hybrid forecasting algorithm, which consists of multiple groups of forecasting algorithms and realizes the forecasting by their result-weighted [17], it can obtain higher forecasting accuracy, but the forecasting performance of reactive power with strong disturbance is still not good enough.

All in all, the difficulty of reactive power prediction lies in its strong randomness, sharp noise and violent local disturbance [18]. From the perspective of signal composition, a time series is considered as a sum of deterministic components (trends, periodic components) possibly merged with structureless noise [19]. Therefore, it is significative to apply the signal decomposition method to reactive power to extract multi-scale local features of power information, which could contribute to higher prediction accuracy. Among all signal decomposition algorithm, Ensemble Empirical Mode Decomposition (EEMD) [20] is not only suitable for both stationary and non-stationary signals but also not need to pre-set the basis function [21]. Therefore, this paper applies this method to the decomposition of reactive power.

This paper proposes a short-term reactive power hybrid forecasting model based on Ensemble Empirical Mode Decomposition Long Short-Term Memory Random Forest Regression (ELR). First, EEMD decomposes the reactive power data into several IMFs for deep mining data information, and the local features representation at different time scales can get rid of the interference within different time scales. Subsequently, the LSTM neural network and the Random Forest Regression (RFR) algorithm are used to predict different frequency components respectively, and the prediction results are superimposed to reconstruct reactive power. In this paper, the reactive power data is noisy with strong disturbance. The proposed algorithm realizes a better prediction and restoration of local details.

2. Analysis of reactive power and feature extraction algorithm

Due to the weak periodicity and strong randomness of the reactive power data, it is meaningful to choose a suitable decomposition method to dig out its deep information. This paper analyzes the data features of the reactive power to select the appropriate decomposition method.

2.1. Analysis of reactive power features

A group of prefecture-level city’s reactive power data in East China is selected. The sampling interval is 15 minutes, and the total number of reactive power data is 10340. Part of them is depicted in Figure 1.

![Figure 1. Data display of reactive power.](image)

As can be seen from Figure 1, based on a certain periodicity, the reactive power data present strong local randomness, including a large number of disturbance signals and noises, which reflect feature information under different time scales. Therefore, it is meaningful to use an appropriate decomposition method to dig out these features, which will help to improve the forecasting accuracy.

2.2 Multi-scale feature extraction algorithm

Ensemble Empirical Mode Decomposition is a data processing and mining method with adaptive capabilities [21]. It decomposes the signal according to the time-scale characteristics of the data itself
and does not require any basis function to be pre-set, which has fundamental difference from the Fourier decomposition and wavelet decomposition based on harmonic basis function and the wavelet basis function. EEMD is very suitable for processing nonlinear, non-stationary time series, which is essentially the smoothing processing of data series or signals. Therefore, EEMD is used to extract multi-scale local features of reactive power to obtain stable and effective feature input. The low-frequency part reflects the overall trend of reactive power stability, and the higher frequency reflects the local random features with strong fluctuation of reactive power.

The multi-scale feature extraction uses EEMD to decompose the complex signal into a linear combination of a finite number of Intrinsic Mode Functions (IMFs) with different frequencies. The decomposed IMF components contain the local feature at different time scales. The decomposition steps are proposed as follows:

1. Add white noise to the original signal.
2. Decompose the signals with white noise by EMD to get the IMF components.
3. Repeat steps 1) and 2) N times, adding new white noise with the same intensity each time.
4. Since the white noise has the feature that the mean spectrum is 0, the final IMF component is the average of the IMF set obtained each time.

It can be seen from Figure 2 that there is no obvious mode aliasing phenomenon in each IMF component after EEMD, and each one has its unique feature at a certain stable frequency and gets rid of the interaction among different time scales, which provides convenience for subsequent forecasts.

After hierarchical clustering, IMF1-5 are classified as the high-frequency part, IMF6-13 are classified as the low-frequency part. The high-frequency part present reactive power’s local randomness, disturbance and noises, while low-frequency part reflect its inherent periodicity.

![Figure 2. Empirical mode decomposition of reactive power.](image)

3. Hybrid forecasting algorithm of reactive power

EEMD decomposes one signal as dozens of IMFs, making the data volume and calculation of training data increased. To improve the training speed and forecasting accuracy, it is necessary to select the appropriate forecasting algorithm according to the time-frequency features of each feature component. In this paper, a hybrid forecasting algorithm of short-term reactive power based on multi-scale local feature extraction is proposed. Firstly, EEMD is used to decompose the reactive power data. Then, according to the different time-frequency features of each feature, the appropriate algorithm is selected for forecasting. Except for the forecasting accuracy, high training speed is also the performance index of the algorithm. Finally, the forecasting results are superimposed to reconstruct the reactive power.
3.1. Research on the different time-frequency feature forecasting algorithm

For the strong periodicity and high linearity of the low-frequency components, compared with deep learning algorithms, machine learning algorithm have higher training speed and stronger interpretability while the accuracy can also meet the requirement of application [22]. Moreover, compared with mainstream machine learning algorithms such as Support Vector Regression (SVR) and Linear Regression (LR), RFR is easier to get accurate forecasting value and avoids the tedious parameter tuning [23]. It is a kind of ensemble learning algorithm, which can improve the forecasting accuracy by integrating the Regression Tree (RT), showing a powerful generalization without overfitting phenomenon usually-occurring in neural networks. The RFR is obtained by integrating RTs based on the loss minimization

$$MSE_{\text{min}} = \min \left\{ \frac{1}{2} \sum_{j=1}^{s} \left[ \frac{1}{n} \sum_{i=1}^{n} \text{BRT}_{i}(x_{ij}) - y_{ij} \right]^2 \right\}$$

where \( \text{BRT}_{i}(x_{ij}) \) is the IMF forecasting value of the \( j \)-th RT, \( x_{ij} \) and \( y_{ij} \) are the values of the \( i \)-th feature input vector and the actual IMF value. The forecasting results of low-frequency features of reactive power are finally obtained by [24]

$$y_{\text{predict}} = \frac{1}{n} \sum_{p=1}^{n} C(p) \text{BRT}_{p}(E)$$

where the weight \( C(p) \) is the sum of the feature correlation coefficients of the \( p \)-th RT; \( \text{BRT}_{p}(E) \) is the output value of the \( p \)-th RT. In this paper, the number of decision trees is set to 100.

The high-frequency components present strong randomness and volatility, traditional machine learning algorithms may not be able to accurately capture the intrinsic feature, while neural network is powerful for nonlinear function fitting, like Back Propagation (BP), Convolutional Neural Networks (CNN) and Recurrent Neural Network (RNN). Among them, RNN is the most mainstream algorithm for time series forecasting by constructing connections between adjacent neurons to capture time information [25]. As an improved algorithm of RNN, LSTM addresses the issue of gradient disappearance or gradient explosion by setting a gating unit based on hidden layer cells [26].

To establish the dependencies between time-series data, LSTM adds a channel of cell state input and output and realizes the memory and transmission of data information through three gating units: forget gate, input gate, and output gate.

The high-frequency component sequence of the reactive power is inputted into LSTM neurons for the forwarding calculation. After the output of LSTM is obtained, the error of each neuron can be calculated backward by the Mean Square Error (MSE) equation as [27]:

$$V_{\text{MSE}} = \frac{1}{n} \sum_{i=1}^{n} (V_{\text{actual}} - V_{\text{predict}})^2$$

where \( V_{\text{actual}} \) represents the true value of the high-frequency component, \( V_{\text{predict}} \) is its prediction value outputted by LSTM, and \( n \) denotes the data number. We build a neural network with two hidden layers of LSTM. The number of neurons in these two hidden layers is 128 and 32 respectively, the number of neurons in the input layer is 48, and the number of neurons in the output layer is 1.

After outputting the value of neuron, the neuron weight is continuously optimized by Adam optimization toward the decrease in the error \( V_{\text{MSE}} \). Through repeated iterations, the forecasting value of LSTM gradually approaches the real value of the training set.

3.2. Validation of the forecasting algorithms

To verified the following algorithms’ performance, in this paper, RFR, LSTM, BPNN, and SVR are used to forecast a group of smooth time sequences \( s(n) \) and a group of strongly disturbed time sequences \( p(n) \). The Root Mean Square Error (RMSE) and the determination coefficient \( R^2 \) are used to evaluate the forecasting accuracy.
Table 1. Forecasting index of each algorithm on smooth time sequences.

| Algorithm | RFR | SVR | BPNN | LSTM |
|-----------|-----|-----|------|------|
| RMSE      | 0.024 | 0.264 | 0.042 | 0.036 |
| $R^2$     | 0.998 | 0.780 | 0.994 | 0.996 |

Table 2. Forecasting index of each algorithm on strongly disturbed time sequences.

| Algorithm | RFR | SVR | BPNN | LSTM |
|-----------|-----|-----|------|------|
| RMSE      | 0.778 | 1.026 | 0.786 | 0.762 |
| $R^2$     | 0.396 | -0.051 | 0.384 | 0.419 |

Table 1 shows the forecasting performance indexes of the four algorithms. RFR has the RMSE of only 0.024 and $R^2$ of 0.998, which shows that RFR outperforms SVR, BPNN and LSTM. It has higher forecasting accuracy, and is very suitable for the fast forecasting of low-frequency component data. In Table 2, LSTM has the RMSE of 0.762 and the $R^2$ of 0.419, indicating LSTM is better than SVR, RBF, and BPNN, and the strong nonlinear fitting ability of LSTM can improve the forecasting accuracy of high-frequency components as much as possible.

3.3. Hybrid reactive power forecasting algorithm based on ELR

This paper presents a hybrid forecasting algorithm for short-term reactive power based on ELR, which is illustrated in Figure 3.

For the historical reactive power data, EEMD is used to decompose a group of components with different time scales, and each component data is normalized to a range $[0,1]$. After hierarchical clustering, the IMFs are classified as the high-frequency part and the low-frequency part. For the high-frequency component with strong randomness, LSTM is applied for its forecasting. For the low-frequency component with strong periodicity, RFR is used for rapid forecasting. The forecasting results are denormalized and superimposed to get the forecasting results of reactive power.

![Graph](image)

Figure. 3. ELR hybrid forecasting framework.

4. Case analysis

In this paper, a group of reactive power data in a prefecture-level city of East China is selected as the dataset. The proposed ELR hybrid forecasting algorithm is compared with 4 conventional prediction
algorithms and 4 hybrid prediction algorithms based on signal decomposition. Finally, the effectiveness of the forecasting strategy and superposition reconstruction is verified.

4.1. ELR hybrid forecasting results and analysis

Figure 4a and Figure 4b show the forecasting results of the ELR algorithm on this dataset. It can be seen that most of the forecasting points fit the real value better, and the forecasting effect at the peak decreases compared with that at the flat area, indicating that the forecasting of high-frequency signals with strong randomness is more difficult. The forecasting index $R^2$ reaches 0.943 and the RMSE error is 0.687, which indicates that the ELR algorithm can accurately predict reactive power.

![Figure 4. (a) Forecasting results of ELR (b) Partial enlarged drawing.](image)

4.2. The comparative experiment of the forecasting algorithm

(i). Contrast experiment with a conventional forecasting algorithm

To verify the advantages of ELR in reactive power forecasting, four groups of mainstream conventional forecasting algorithms and four groups of hybrids forecasting algorithms are used, and 12 hours data are predicted, the results are shown in Figure 5a, Figure 5b, Figure 6a, and Figure 6b.

![Figure 5. (a) Forecasting results of EEMD-LSTM-RFR (b) Partial enlarged drawing.](image)

As can be seen from Figure 5a, the forecasting curve of the ELR algorithm proposed in this paper always follows the trend of the real data curve, and the forecasting result is far better than the other four conventional forecasting algorithms. Figure 5b shows that the forecasting RMSE and $R^2$ of this algorithm are less than 0.7 and close to 1, respectively, while that of other algorithms are higher than 2 and less than 0.5, respectively, which shows the highest forecasting accuracy of the ELR method. The proposed algorithm experiences the lowest RMSE and the highest $R^2$, maintaining its best forecasting performance.

(ii). Comparison with hybrid forecasting algorithm based on signal decomposition

The comparative hybrid forecasting algorithms based on signal decomposition are as follows:
1) After using EEMD to decompose the reactive power data, SVR is used for the low-frequency part and BPNN is used for the high-frequency part, which is abbreviated as EBS (EEMD-BPNN-SVR).
2) After using EEMD to decompose the reactive power data, SVR is used for the low-frequency part and LSTM is used for the high-frequency part, which is abbreviated as ELS (EEMD-LSTM-SVR).
3) After using Discrete Wavelet Transform (DWT) to decompose the reactive power data, SVR is used to predict the result, which is abbreviated as DS (DWT-SVR).
4) After using DWT to decompose the data of reactive power, the result of forecasting using the RFR algorithm is abbreviated as DR (DWT-RFR).

Figure 6a and Figure 6b show the forecasting curves, RMSE error, and determination coefficient $R^2$ of the five hybrid forecasting algorithms.

As can be seen from Figure 6a, the RMSE and $R^2$ of the ELR algorithm are still significantly better than those of EBS, ELS, DS and DR. Figure 6b shows that ELR has the lowest RMSE and the highest $R^2$, indicating that compared with other hybrid forecasting algorithms, ELR still has the best forecasting performance, which confirm that the signal decomposition and prediction method selected in this paper has better quality. The average RMSE of the four hybrid forecasting algorithms is 1.589, and the average $R^2$ is 0.662, which is much better than the average RMSE (2.337) and the average $R^2$ (0.335) of the four conventional forecasting algorithms, which indicates that the hybrid forecasting algorithm performs better for reactive power forecasting. The RMSE of the forecasting algorithm based on EEMD is lower than 1.3, $R^2$ of that is higher than 0.8. Comparison with the DWT based forecasting algorithm (RMSE is higher than 1.8 and $R^2$ is lower than 0.7) indicates that EEMD has a better effect on improving forecasting accuracy for the reactive power.

5. Conclusion

To analyse the forecasting of reactive power, a hybrid forecasting algorithm based on ELR is proposed in this paper. Firstly, the reactive power data is decomposed into several IMFs by EEMD, and it benefits the following reactive power forecasting. After hierarchical clustering, the IMFs are classified as the high-frequency part and the low-frequency part. Secondly, different algorithms are used to predict the IMFs of high-frequency and low-frequency respectively. Finally, the forecasting results are superimposed to reconstruct the predicted value of reactive power. The forecasting results of the proposed algorithm show that the hybrid forecasting index $R^2$ is 0.943, RMSE is 0.687, and in total the forecasting curve catches the real value well.

Compared with four conventional forecasting algorithms, the results show that the RMSE of the proposed algorithm is lower than that of the others with its $R^2$ closer to 1, indicating the highest forecasting accuracy. Compared with four hybrid forecasting algorithms based on signal decomposition, the results show that the proposed algorithm has the lowest RMSE and the highest $R^2$, and still has the best forecasting performance.
The accurate forecasting of reactive power can optimize the power flow calculation of smart grid and microgrid, assist the power market to test the technical feasibility of energy path from the power plant to load, finally realize the optimal management of energy resources, and effectively improve the operation performance of power grid.

6. References

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