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Ultra-Short-Term Wind Power Multi-Step Prediction Based On Combined Model

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Original Research Article

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Abstract: According to the non-stationary characteristics of wind power, a novel wind power combined multi-step prediction model based on differential auto regressive moving average model in variational mode decomposition and time series analysis is proposed. Firstly, the wind power sequence is subjected to variational mode decomposition to reduce the non-stationary characteristics of the wind power sequence. Secondly, the ARIMA model is established for each component. Finally, the component prediction results are superimposed to obtain the final wind power prediction value. The experimental results show that the proposed combined prediction model has higher prediction accuracy.

Keywords: wind power prediction; variational modal decomposition; ARIMA model; combination forecast; multi-step forecast.

INTRODUCTION

With the rapid increase of wind power installed capacity in recent years, the proportion of wind power generation in the power grid has also increased rapidly. In order to make full use of wind power resources, wind power forecasting system has become an indispensable link [1]. Due to the characteristics of fluctuation, intermittence and non-linearity of wind speed, the fluctuation and non-stationarity of wind power exist directly. Decomposition of wind power series can effectively improve the prediction accuracy and overcome the fluctuation and non-stationary characteristics of wind power.

The main decomposition methods include empirical mode decomposition [2, 3], wavelet decomposition [4], variational mode decomposition [5, 6] and so on. Although the empirical mode decomposition method has strong adaptive ability, the modal aliasing phenomenon has a great influence on the accuracy of the decomposition, and the prediction effect of the high frequency component imf1 is poor; Wavelet decomposition needs to determine the appropriate wavelet basis function, otherwise it will have a greater impact on the experimental results; The variational mode decomposition method not only avoids the modal aliasing phenomenon, but also eliminates the need to select the wavelet basis function, which reduces the experimental steps and minimizes the prediction error.

At present, wind power prediction models mainly include artificial neural network [7], least squares support vector machine [8], Kalman filtering method [9], time series method [10] and so on. The machine learning model requires a large amount of historical data as a training sample, and the neural network is different for each training, and the results are also different. The ARMA model has the characteristics of simple model, less data required, and short training time. At the same time, it has better prediction effect in the short-term and ultra-short-term prediction process.

Variational Mode Decomposition

Variational mode decomposition (VMD) is a new method of signal decomposition and estimation. The core of VMD is the variational problem, which minimizes the sum of estimated bandwidth of each moe [11]. Assuming that each mode has a finite bandwidth with different central frequencies, an alternating direction multiplier algorithm is used to update the modes and their central frequencies, and demodulate the modes to the corresponding fundamental frequency band step by step. Finally, each mode and the corresponding center frequency are extracted together to show strong robustness.

First, the objective function is constructed to decompose the wind power signal $x(t)$ into K modal functions $u_k(t)$ with a central frequency, and the sum of the estimated bandwidth of each modal is the minimum. Hilbert transform is applied to each modal function $u_k(t)$ to obtain the single-sided spectrum. The spectrum of each modal is transformed to the corresponding fundamental band. The bandwidth of the modal signal is estimated by demodulation signal, and decomposed by the following optimization:

$$\min \sum_k \left\| \partial_t (\delta(t) + \frac{j}{\pi t}) * u_k(t) e^{-iw_k t} \right\|_2^2 \qquad s.t. \sum_k u_k = f(t) \tag{1}$$

The formula: u_k represents the set of patterns; ω_k represents the frequency center of the pattern; $\delta(t)$ represents the impulse function; $f(t)$ represents the decomposed signal. The penalty factor and Lagrange multiplier are introduced to transform the upper form into the non constrained optimization problem:

$$\begin{aligned} L(\{u_k\},\{w_k\},\lambda) = a \sum_k \left\| \partial_t \left[(\delta(t) + \frac{j}{\pi t}) * u(t) \right] e^{-iw_k t} \right\|_2^2 + \\ \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k u_k(t) \right\rangle \end{aligned} \tag{2}$$

The formula: a is the balance parameter to ensure the accuracy of signal reconstruction; λ is the Lagrange multiplier; $\lambda(t)$ is to ensure the strictness of the constraints. The saddle point of Lagrange expression is obtained by alternately updating u_k^{n+1}, w_k^{n+1} and λ^{n+1}, of which u_k^{n+1} can be obtained through Fourier transform.

$$\begin{aligned} \hat{u}_k^{n+1} = \arg\min a \left\| jw\left[1 + \mathrm{sgn}(w + w_k)\right] \hat{u}_k (w + w_k) \right\|_2^2 \square \\ \left\| \hat{f}(w) \sum_{k=1}^{K} \hat{u}_k(w) + \hat{\lambda}(w) \div 2 \right\|_2^2 \end{aligned} \tag{3}$$

The formula: w is random frequency; S is the set of u_k.

$$\hat{u}_k^{n+1}(w) = \frac{\hat{f}(w) - \sum_{i=k} \hat{u}_i^n(w) + \frac{\hat{\lambda}_i^n(w)}{2}}{1 + 2a(w - w_k)^2} \tag{4}$$

$$w_k^{n+1} = \frac{\int_0^\infty w \left| \hat{u}_k^n(w) \right|^2 dw}{\int_0^\infty \left| \hat{u}_k^n(w) \right|^2 dw} \tag{5}$$

The formula: $\hat{u}_k^{n+1}(w)$ is the Wiener filtering of $\hat{f}(w) - \sum_{k=1}^{K} \hat{u}_k(w)$; w_k^{n+1} is the center of gravity of the current power spectrum of modal functions; $f(t)$, $u_i^n(t)$, $\lambda_i^n(t)$ and $u_k^{n+1}(t)$ fourier transforms are $\hat{f}(w)$, $\hat{u}_i^n(w)$, $\hat{\lambda}_i^n(w)$ and $\hat{u}_k^{n+1}(w)$ respectively; n is the number of iterations.

ARIMA model

Differential auto regressive moving average model

Auto regressive moving average model (ARMA) can effectively improve the adaptability of time series model, eliminate the delay problem and improve the prediction accuracy. Auto regressive model AR(p) and moving average model MA(q) can be regarded as the special cases of auto regressive moving average model ARMA(p,q), when $q = 0$, the ARMA(p,q) model becomes AR model; when $p = 0$, the ARMA(p,q) model becomes MA model.

$$Y_t = {}_1Y_{t-1} + \cdots + {}_pY_{t-p} + a_t - \theta_1 a_{t-1} - \cdots - \theta_q a_{t-q} \quad (6)$$

The formula: P-order auto regressive and -q-order moving average model, Y_t is a time series, and a_t is a white noise sequence.

Because the ARMA model can only solve the time series of stationary process, in order to describe the non-stationary time series with ARMA, it is necessary to stabilize the non-stationary time series, and to perform the difference operation on the original non-stationary time series. This model is called differential auto regressive moving average (ARIMA).

$$\nabla^d Y_t = W_t \quad (7)$$

W_t is the stationary time series of random sequence Y_t processed by d order difference. ∇^d is the d order difference operator.

Model order

The Bayesian Information Criterion (BIC) is used to determine the order of the stationary time series model. The penalty term related to the number of model parameters is introduced in the BIC criterion. The criteria are as follows:

$$BIC = k\ln(n) - 2\ln(L) \quad (8)$$

The formula: the k is the number of parameters of the model; the n is the number of selected samples; and the L is the likelihood function.

VMD-ARIMA combination forecasting model

At any point in time (t), the wind power of the next 6 moments can be predicted based on the data of the previous moment (ARMA(p, q)); when the next time point ($Y_{t+1}, Y_{t+2}, \ldots, Y_{t+6}$) is reached, it can be based on historical data. The wind power ($Y'_{t+2}, Y'_{t+3}, \ldots, Y'_{t+7}$) of the next 6 moments is predicted. This cycle is the dynamic prediction process of the time series method, so as to achieve the purpose of continuously correcting the learning.

The experimental steps are as follows:

Step 1: The J-layer decomposition of the historical wind power time series, the historical wind power time series from low-frequency to high-frequency decomposition, so that each layer has a different center frequency.

Step 2: ARIMA model is established for each component, the order of the model is determined by Bayesian information criterion, and the h-Step prediction is carried out.

Step 3: Superimpose all component prediction results to obtain the final predicted value. Figure-1 shows the flow chart of the prediction model:

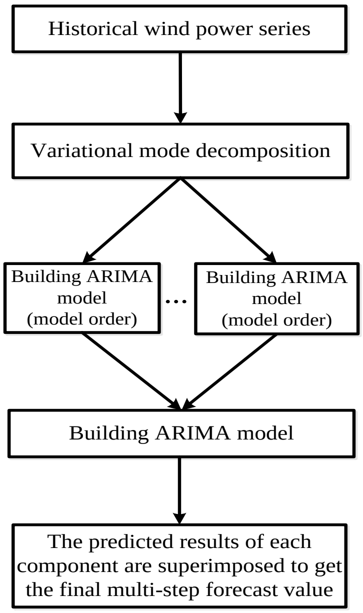


Fig-1: Forecast model flow chart

Example analysis

ARIMA model has the characteristics of simple model, less data needed and short training time, it has better forecasting effect in short-term and ultra-short-term forecasting process. In this paper, 100 historical wind power data of a wind farm in Northwest China on January 2, 2017 are selected as training samples, and the sampling interval is 5 minutes for 6-step prediction. Historical wind power data is shown in Figure-2.

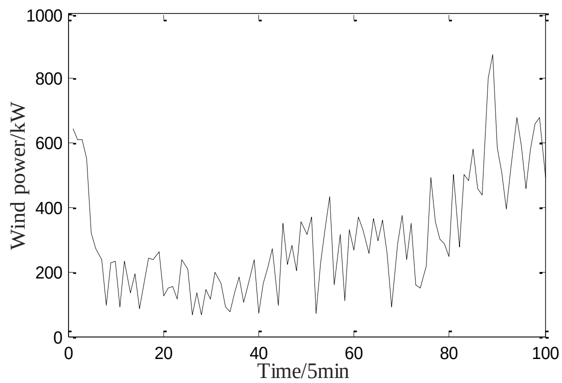


Fig-2: Historical wind power data

Data decomposition

The variational mode decomposition of historical wind power series is carried out to reduce the fluctuation of wind power. The decomposition results are shown in the following figure:

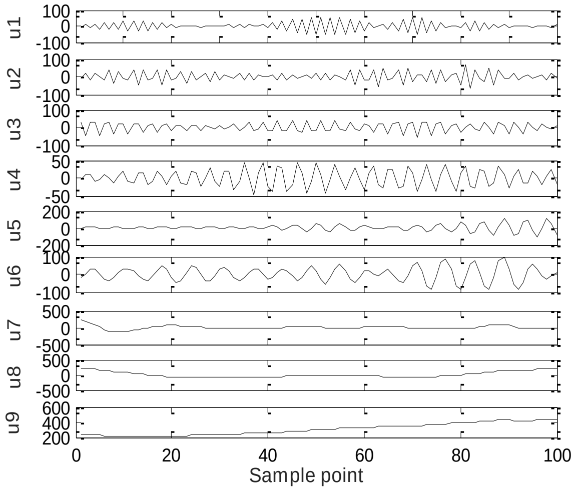


Fig-3: Results of VMD

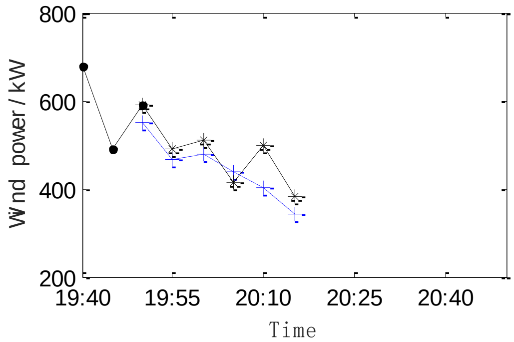
According to the decomposition results, the VMD method achieves the accurate separation of each component through the adaptive decomposition method, thus effectively reducing the non-stationary characteristics of wind power time series.

Forecast results and analysis

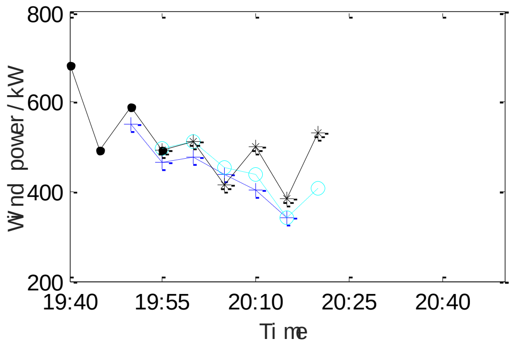
The mean relative error (MRE) error evaluation index was compared and analyzed. $\hat{x}(i)$ and $x(i)$ represent the predicted and actual values respectively, N are the sample size.

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|\hat{x}(i) - x(i)\right|}{x(i)} \times 100\% \tag{9}$$

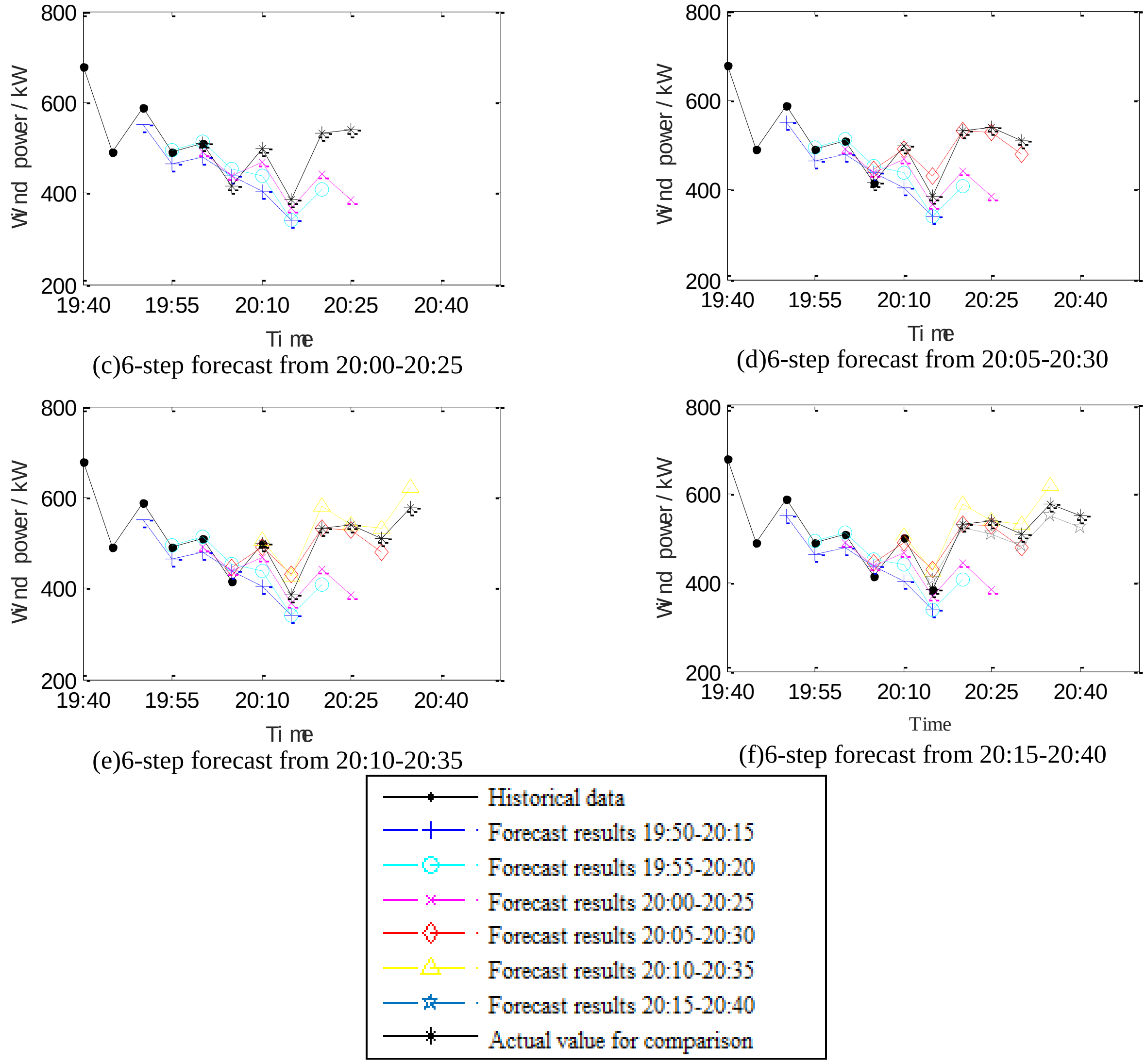
The forecast results are shown below:



(a) 6-step forecast from 19:50-20:15



(b)6-step forecast from 19:55-20:20



(c)6-step forecast from 20:00-20:25

(d)6-step forecast from 20:05-20:30

(e)6-step forecast from 20:10-20:35

(f)6-step forecast from 20:15-20:40

Fig-4: Wind power 6-period dynamic forecasting results in January 2

According to the prediction results, the wind power series predicted by the model and the actual trend of wind power change are generally consistent, but with the increase of prediction steps, the prediction error increases gradually. Table-1 shows the comparison between the neural network prediction model and the model in this paper.

Table-1: Comparison result of prediction error of different models

Forecast model	MRE（%）
BP-neural network model	17.75%
ARIMA model	13.69%
VMD-ARIMA model	8.97%

From table-1, we can see that the prediction model proposed in this paper has higher prediction accuracy. The smaller the root mean square error, the smaller the overall fluctuation of prediction error, the more accurate the prediction. Therefore, the prediction model proposed in this paper can improve the accuracy of ultra-short-term wind power multi-step prediction to a certain extent.

CONCLUSION

In this paper, the historical wind power is decomposed into several components by variationall mode decomposition (VMD) to reduce its non-stationarity; ARIMA model is established for each component; and the final wind power multi-step prediction value is obtained by superimposing the predicted values of each component. Through simulation experiments, we get the following conclusions:

- The VMD-ARIMA combined model proposed in this paper has the advantages of fast prediction speed, high accuracy, good prediction effect of 6-step (30 minutes) ahead of schedule, higher prediction accuracy than BP neural network model, and can be used for real-time scheduling.
- The method needs only a small amount of historical wind power data to establish a multi-step prediction model with high accuracy.

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