A New Wind Speed Evaluation Method Based on Pinball Loss and Winkler Score

Guomin LI[1], Jinghui ZHANG[1], Xiaoyu SHEN[1], Chunhui KONG[1], Yagang ZHANG[1,2], Gengyin LI[1]
[1]*Institute of Data Science and Statistical Analysis, North China Electric Power University, Baoding, 071003, China*
[2]*Interdisciplinary Mathematics Institute, University of South Carolina, Columbia, SC 29208, United States*
yagangzhang@ncepu.edu.cn

***Abstract*—To reduce the adverse effects of the inherent stochastic volatility and uncontrollability of new energy on wind energy forecasting, this paper starting from the two aspects of improving the deterministic forecast and enhancing the predictability of volatility risk, the combination of variational modal decomposition (VMD), neural network and statistical model is applied to point forecasting, and the forecast model selection is based on the statistical characteristics of the components to enhance the degree of preciseness of wind speed forecasting. Then Monte Carlo-Markov Chain (MCMC) stimulation based on different quantiles is proposed to make interval prediction, and a new interval evaluation method is introduced, pinball loss function and Winkler score, to select the best interval prediction results for achieving precise control of wind power within a certain period of time. Finally, through experimental case verification, the performance of the advanced hybrid deterministic forecasting model is more advantageous than that of the traditional model. At the same time, the proposed interval prediction method better quantifies the uncertainty risk of wind power, makes up for the lack of a single evaluation method in the current interval prediction research, and can provide information support for the stable operation.**

***Index Terms*—wind speed forecasting, variational modal decomposition, neural network, Monte Carlo-Markov Chain stimulation, Winkler score.**

I. INTRODUCTION

As a renewable, green and clean energy, wind energy has gradually become the most important energy consumption channel for future power generation in the world. However, its inherent random volatility and uncontrollability have brought high levels of undesirable effects to the power generation on the supply and demand side of the new energy power system. Solving this type of uncertainty problem can be based on a high-level wind power forecasting system, and the forecasting system relies on high-precision forecasting of wind power. Therefore, the establishment of an innovative and high-precision wind power portfolio forecasting program is of great importance in accelerating the construction of a new power system with new energy as the main body, and promoting energy industry structure optimization and green energy saving development.

At present, wind power prediction is directly linked to the characteristics of wind speed series, data preprocessing techniques and forecast methods. General preprocessing methods contain Empirical Mode Decomposition (EMD) [1-2] and Wavelet decomposition (WD) [3-4], multi-factor PCA analysis [5], and so on. WD and EMD are mainly used for single variable and time series with strong volatility. However, it is difficult to select wavelet basis and decomposition scale in the wavelet transform. EMD has fixed algorithm without parameter selection difficulty, but the endpoint effect is obvious. And the decomposition amount is too large in some cases, resulting in a problem of information loss. Compared with the above, the more popular VMD not only has superior denoising performance, but also the instantaneous frequency of each decomposed component has practical physical meaning. From the prediction techniques, the current mainstream methods include physical techniques, statistical methods and artificial intelligence means. Physical method [6] is mainly to predict wind speed through meteorological information such as terrain characteristics, atmospheric pressure, ambient temperature, and so on. Numerical weather prediction is a typical physical prediction method, however, which has a large and sophisticated solution. Traditional statistical methods and artificial intelligence methods mainly contain time series model [7-8], machine learning model [9-12], wind speed distribution fitting model [13], and mixed application of various models [14-19].

However, the strong stochastic volatility and intermittent nature of the wind hinder the accuracy improvement of the single forecasting model. Using a single model to predict the relevant wind series cannot accurately mine the feature information of the data. Therefore, mixture models including preprocessing techniques for denoising decomposition are widely emerging. At the same time, from the perspective of the forecast form, although the point forecast gives the theoretical forecast value of the wind speed at some point in the future, the single deterministic forecast cannot capture the uncertainty and fluctuation risk of the wind speed. Therefore, interval prediction gives the upper and lower limits of wind speed under a certain confidence level in this period of time, which has more accurate practical guiding significance [20].

To better mine wind speed characteristics, this article introduces the VMD algorithm [21-22] to decompose the wind speed into multiple components for separate research. By extracting the unstable non-linear part and the stable linear part of the data, the artificial neural network with strong non-linear mapping ability and the autoregressive integrated moving average model (ARIMA) which has the advantage in fitting linear time series are respectively used

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up to the nonlinear and linear characteristics of wind speed to build a deterministic predictive model. Meanwhile, for accurately controlling the risk of wind speed fluctuations, MCMC technique is applied to construct a discrete distribution [23]. Through this method, multiple random prediction curves can be obtained, and then different interval predictions can be obtained. However, the traditional evaluation methods [24-27] cannot comprehensively consider the relationship between interval prediction results and confidence. Therefore, this paper selects Winkler score [28] for evaluation, which can improve the wind speed interval prediction results, decrease the effect of grid-connected wind power on the electric grid, and improve the control level of wind turbines and the economy of the power grid. The innovations of this article are as follows:

(1) Denoising and Decomposition of original wind power data using VMD, in which the nonlinear features are extracted by neural network, and ARIMA is used to obtain linear information, thereby constructing a mixed point prediction model considering component characteristics. At the same time, MCMC is introduced for interval prediction, and a sampling mode based on the quantile method is innovatively proposed, which makes the sampling data more suitable for the sample data, and the final prediction result is more realistic;

(2) The more comprehensive evaluation criterion, Pinball Loss Function and Winkler Score, are introduced to comprehensively evaluate interval prediction so as to find a better prediction interval.

The structure of this article is introduced as followings: The second part expounds the theoretical basis, the model integration process and related evaluation methods are in the third part, the fourth part is case verification, and finally the summary of the paper and the prospect of further research.

II. Theoretical Basis

A. VMD Algorithm

As a self-adaptable completely non-recursive decomposition [29], VMD can extract the corresponding center frequency by decomposing the signal sequence into k natural mode functions which has limited bandwidth. The specific iterative formula is given as follows:

$$\hat{u}_k^{n+1}(\omega)=\frac{\hat{f}(\omega)-\sum_{1\neq k}\hat{u}_i^{n}(\omega)+\hat{\lambda}_i^{n}(\omega)/2}{1+2\alpha\left(\omega-\omega_k^{n}\right)^2}, \tag{1}$$

$$\omega_k^{n+1}=\frac{\int_0^{\infty}\omega\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^{\infty}\left|\hat{u}_k^{n+1}(\omega)\right|^2 d\omega} \tag{2}$$

$$\hat{\lambda}^{n+1}(\omega)=\hat{\lambda}^{n}(\omega)+\tau\left(\hat{u}(\omega)-\sum_{k=1}^{K}\hat{u}_k^{n+1}(\omega)\right) \tag{3}$$

where, k is the decomposition quantity, while u_k means shorthand notations for the set of all modes and ω_k are their center frequencies respectively, λ is Lagrange multiplier in order to render the problem unconstrained.

According to the above iterative formula, the decomposition algorithm of VMD can be obtained as follows:

Step1: Initialization $\left\{\hat{u}_k^{1}\right\},\left\{\hat{\omega}_k^{1}\right\},\left\{\hat{\lambda}_k^{1}\right\}$

Step2: For $k=1, 2, \ldots, K$, update $\hat{u}_k^{n+1}(\omega)$, ω_k^{n+1} according to formula (1), (2).

Step3: Using $\hat{u}_k^{n+1}(\omega)$, ω_k^{n+1} after iterated to update $\hat{\lambda}^{n+1}(\omega)$ according to formula (3).

Step4: Judge whether the current mode converges according to the following convergence conditions (4). If converging, output K IMF components, otherwise return Step2:

$$\sum_k\frac{\left\|\hat{u}_k^{n+1}-\hat{u}_k^{n}\right\|^2}{\left\|\hat{u}_k^{n}\right\|^2}<\varepsilon \tag{4}$$

B. ARIMA

ARIMA (p, d, q) is a model that regresses on different time structures, including serial lag values, current values of random error terms and lag values, and is modeled based on difference stationary. Then, the specific steps are shown below:

Step1: Judging the stationarity of the sequence. If it is non-stationary, perform the difference operation and perform the non-white noise test on the sequence.

Step2: Model evaluation. Traverse the values of p, d, q, and select the optimal model according to the lowest AIC:

$$AIC=2k-2ln(L) \tag{5}$$

where, k is the number of parameters and L is the likelihood function.

Step3: Model validation. Use the built model to make predictions and perform Durbin-Watson (DW) tests on the residuals to assess model value:

$$dw=\frac{\sum_{t=2}^{T}\left(e_t-e_{t-1}\right)^2}{\sum_{t=1}^{T}e_t^2} \tag{6}$$

Among them, e_i represents the residual value at the i-th time, $i=1, 2, \ldots, T$. When the dw value is close to 2, there is no residual autocorrelation, indicating that the model is better.

C. BP Neural Network

BP is a three layers feedforward neural network including input layer, hidden layer and output layer. It is composed of m input elements and n output elements, in which several hidden neurons are set. The neurons nodes of each layer are calculated by the linear operation of the previous layer and the activation function. The commonly used activation function is sigmoid function:

$$\sigma(x)=\frac{1}{1+e^{-x}}, \quad x\in(-\infty,\infty) \tag{7}$$

This function can map an arbitrary real number x to (0, 1), and the mapping near $x = 0$ is relatively gentle, but when x is large, it can be pressed to 0 or 1. By adding the correction value to the linear function of each layer, the basic value of the activation value of the next layer can be controlled:

$$l_i=\sigma\left(\sum_{j=1}^{L}w_{i,j}k_j+\beta_i\right) \tag{8}$$

D. MCMC Discrete Distribution

For random unstable data series, we use Monte Carlo method [30] to create random matrices to obtain corresponding random sampling results. Meanwhile, because of the repeatability of the method, the interval estimation can be obtained by taking quantiles from repeated tests. Fig. 1 displays the specific sampling principle of MCMC, which is explained in detail as follows:

Step1: Construct transfer matrix G based on training set

Given the number of states k, the data X is divided into k states $\{S_1, S_2,\ldots, S_k\}$, it is easy to know that the interval length of each state is $(X_{max}-X_{min})/k$, and the number of transitions from state i to j is represented by n_{ij}, so as to gain the transition matrix n by dividing the elements of the matrix n by the sum of the elements of each row, which is the probability transition matrix G. As the training data increases, the element g_{ij} can be roughly looked upon as $P(x_{n+1}=j|x_n=i)$, and it meets the following requirements:

$$g_{ij} \geq 0, \qquad \sum_{j=1}^{k} g_{ij} = 1 \tag{9}$$

Step2: Use matrix G to generate random samples

For a state i, in the i-th row of G, according to the probability $(g_{i1}, g_{i2}, \ldots, g_{ik})$ randomly selects stat j as the next state, and generates a uniform distribution of random number r from (0,1). Meanwhile, in state S_j, r quantiles are selected as the specific values of this sampling. At the same time, using quantile sampling instead of uniform sampling can more effectively retain the information of distribution differences in different states.

Step3: Cyclic sampling

Let $i=j$ sample iteratively until the requirements are met. And in view of the randomness of Monte Carlo, the above sampling process can be repeated m times. After getting m sequences, we can get their quantile series, and get the interval forecast of series based on quantile series.

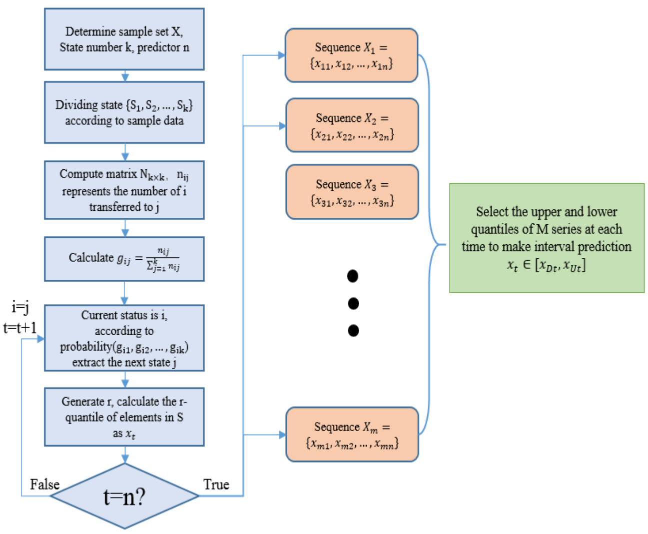

Figure 1. Quantile estimation of MCMC discrete distribution

III. Model Integration and Evaluation Method

A. Model Establishment

To weaken the negative effects of sequence fluctuations and noise on wind power forecasting, this paper proposes a point forecasting hybrid model based on VMD decomposition, and uses the MCMC method to quantify the fluctuation risk to obtain an effective forecast interval. The specific operation is shown in Fig. 2.

1) Point-predictive hybrid model: VMD-BP-ARIMA

Based on the VMD decomposition algorithm, the original sequence y(1~1000) containing 1000 points is firstly divided into the component $y_{IMF1}(1\sim1000)$ with nonlinear trend characteristics and the component $y_{IMF2}(1\sim1000)$ with linear characteristics and random volatility. The former is used as the data set of BPNN [31-33], and the nonlinear information is completely extracted through the mapping activation between hidden layer and output layer and error back propagation, and the prediction result $Pred_1$ is obtained after N=100 predictions. Then, an ARIMA model is established for $y_{IMF2}(1\sim1000)$ based on the stationary principle, and the model is estimated by the AIC criterion to obtain the best predicted value $Pred_2$, so as to accurately mine the linear features of the sequence. Finally, the above results are integrated according to equation (10) to gain the ultimate point-predictive result $Pred$ of the point forecast module.

$$Pred = Pred_1 + Pred_2 \tag{10}$$

2) Interval Model Based on MCMC: VMD-BP-MCMC

According to the MCMC theory, M times of Monte Carlo Markov chain sampling is carried out on the $y_{IMF2}(1\sim1000)$ sequence, and M random sampling results of $y_{IMF2}(1\sim1000)$ are obtained, forming a $E_1,\ldots,E_M$ sampling result matrix. For each column $E_i=[E_{i1}, E_{i2},\ldots,E_{iN}]$ $(i=1, 2,\ldots,M)$ of the matrix, the quantile is calculated, Get the quantile prediction result for that point.

That is, for any time $1 \leq t \leq N$, on the m random sequences, the quantile statistics of M different predicted values at this time can be calculated. For example, for any given confidence level $1\text{-}2q$, it is only necessary to calculate the closed interval composed of the upper and lower q quantiles $D_t(q)$ and $U_t(1\text{-}q)$ of the $(y^1_{IMF2}(t), y^2_{IMF2}(t), \ldots, y^M_{IMF2}(t))$, at time t, and predict it with the $Pred_1$ according to equation (11). After traversing t from 1 to N, the interval predictive result $(P_{1,q}, P_{2,q}, \ldots, P_{t,q}, \ldots, P_{N,q})$ corresponding to the q quantile in the investigated time period can be obtained.

$$P_{i,j} = \left[D_j(q) + pred_1, U_j(q) + pred_1 \right], \qquad j = 1, 2, \ldots, N \tag{11}$$

B. Evaluation Method

1) Evaluation of Point Estimation

The performance of the proposed hybrid forecasting model and other models is evaluated based on the following three important error metrics [34-35], where V_t represents actual value and $Pred_t$ is the predicted value:

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |V_t - \Pr ed_t| \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (V_t - \Pr ed_t)^2} \tag{13}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{V_t - \Pr ed_t}{V_t} \right| \tag{14}$$

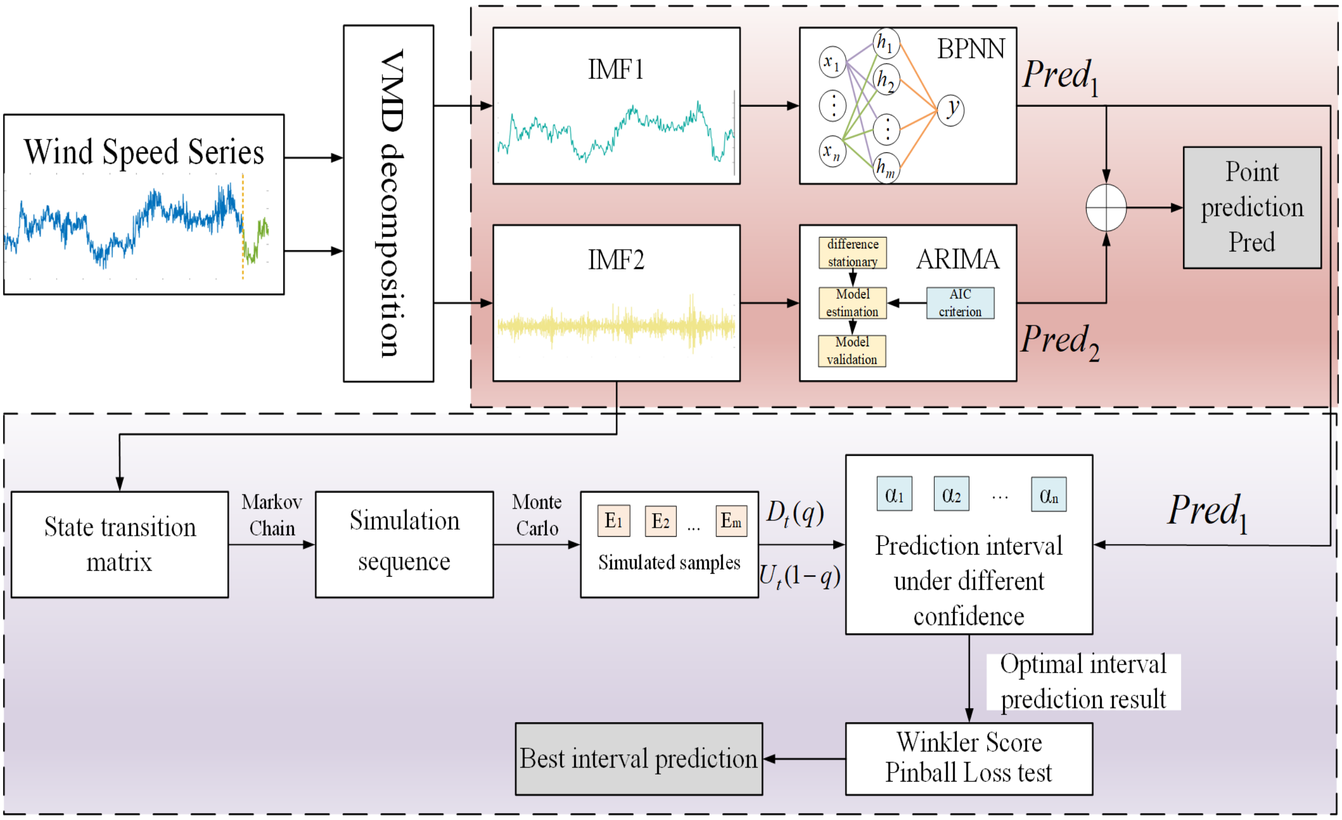

Figure 2. Flow chart of model establishment

2) Evaluation of Interval Estimation

Accuracy is evaluated in terms of the proportion of true values in the prediction interval and the average interval width:

$$I_t = \begin{cases} 1, V_t \in [D_t, U_t] \\ 0, V_t \notin [D_t, U_t] \end{cases} \tag{15}$$

$$Cover \quad Rate = \frac{1}{n}\sum_{t=1}^{n} I_t x100\% \tag{16}$$

$$Avg \quad width = \frac{1}{n}\sum_{t=1}^{n}(U_t - D_t) \tag{17}$$

Coverage and interval width are evaluated in opposite directions, so the advantages and disadvantages of interval estimates cannot be fully drawn. Thus, the pinball loss function and Winkler score are introduced in [36], which can evaluate interval estimation comprehensively in accuracy and effectiveness:

The pinball loss function can measure quantile prediction error, which can be expressed as:

$$Pinball(P_{t,q}, V_t, q) = \begin{cases} (1-q)(P_{t,q} - V_t) V_t < P_{t,q} \\ q(V_t - P_{t,q}) V_t \geq P_{t,q} \end{cases} \tag{18}$$

By calculating the pinball losses across all given quantiles, we can gain the pinball losses matching quantiles. And the lower the score is, the better the prediction interval is.

Another comprehensive measure is the Winkler score, which considers both width and coverage in interval series given by the confidence *(1-α)*. Equation (19) represents the corresponding Winkler score value under the condition of prediction interval of center *(1-α)x100%*, where $\delta_t = U_t - D_t$ represents the interval width. It means that if the actual wind speed is outside the interval, the Winkler score is penalized.

$$Winkler = \begin{cases} \delta_t & D_t \leq V_t \leq U_t \\ \delta_t + 2(D_t - V_t)/\alpha & V_t \leq D_t \\ \delta_t + 2(V_t - U_t)/\alpha & V_t > D_t \end{cases} \tag{19}$$

IV. Example Analysis

A. Data Analysis and Parameter Introduction

This section shows the wind speed prediction results of the proposed prediction model, and gives the optimal wind speed interval prediction results based on the VMD-BPNN-MCMC model and various interval evaluation indicators. The specific parameter information can be seen in Table I. In order to verify the validity of the model, 1000 wind speed data of a wind farm in Yunnan with an interval of 10 minutes in March 2020 were selected. The first 90% are used as the training set, and the last 10% are used to verify the model effect, as shown in Fig. 3.

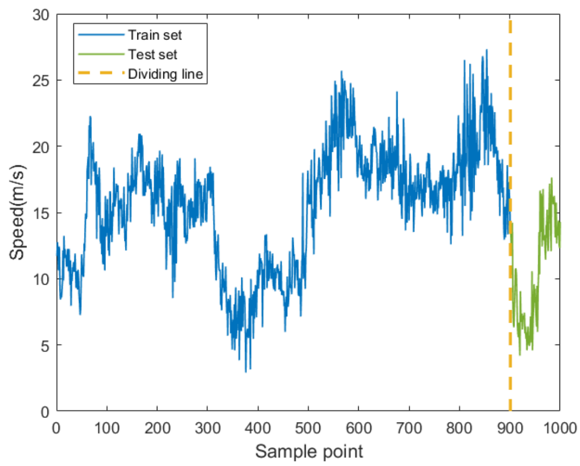

Figure 3. Original wind speed data

TABLE I. INTRODUCTION TO MODEL PARAMETERS

Method	Parameters	Corresponding value
VMD	Decomposition number	2
	The balancing parameter	0.9
	Tolerance of convergence criterion	1e^{-6}
BP	Number of input nodes	5
	Number of output nodes	1
	Number of hidden layer nodes	12
	Training iterations	200
	Learning rate	0.01
RBF	Spread of radial basis functions	1
	Maximum number of neurons	100
MCMC	Matrix order	5
	Sampling times	1000

B. *Point Prediction of Wind Speed*

The results of decomposition of raw data into nonlinear IMF1 and linear IMF2 using VMD are shown in Fig. 4. According to the nonlinear and linear characteristics of the two components and reducing the negative impact of non-stationarity on the prediction accuracy, this paper establishes the mixed point model prediction of VMD-BPNN-ARIMA, so as to make full use of the sequence feature information and conduct comparative experiments with other models, as shown in Fig. 5. It can be seen that the proposed point prediction model is closer to the change trend of original data than other models, eliminates the problem of prediction lag, and shows better prediction effect. To further quantitatively analyze the advantages of the proposed framework, Table II gives the mean, interval and standard deviation between the predicted values of different models and the test set, and Table III calculates the prediction error level of different models under the equations (12) - (14).

Among them, it can be seen from Table II that the prediction statistical characteristics of VMD-BP-ARIMA are closest to the test set, while the statistical characteristics predicted by RBF are most deviated from the test set. And from the error results of Table III, the introduction of VMD decomposition algorithm can improve the performance of the model, and mining the nonlinear or linear characteristics of the component also makes the model performance greatly improved.

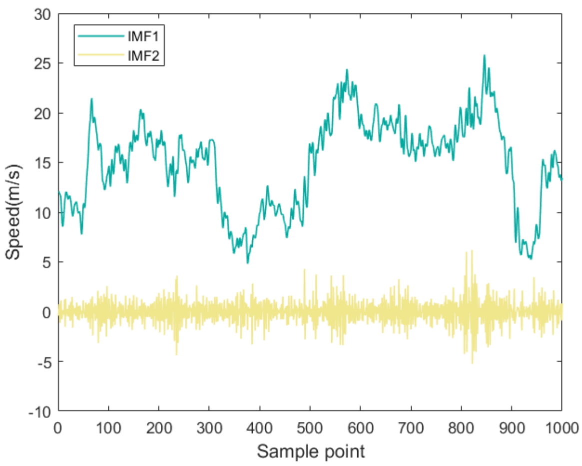

Figure 4. Decomposed sequences by VMD

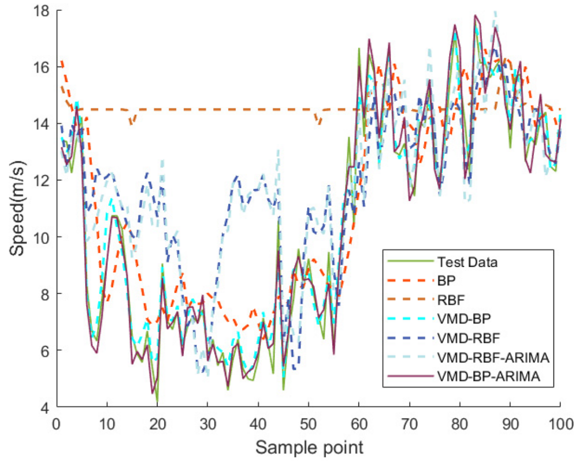

Figure 5. Comparison of different models

Except for the VMD-BP model, the error indexes of the proposed model are optimal. Although the MAE and RMSE values of VMD-BP are slightly lower than the corresponding index values of the proposed model, the index values of the proposed model are significantly lower than those of the MAPE index. Moreover, from Fig. 5, the prediction of VMD-BP-ARIMA model at the peak of the sequence is closer to the fluctuation of the test set. Therefore, it can be further demonstrated that the short-term prediction ability of the VMD-BP-ARIMA model is excellent.

TABLE II. STATISTICAL DATA OF DIFFERENT PREDICTION MODELS

Model comparison	Mean	Std	Max	Min
Test Data	10.506	3.927	17.640	4.187
BP	11.227	3.463	16.613	6.390
RBF	14.547	0.296	16.303	13.869
VMD-BP	10.674	3.764	17.527	5.052
VMD-RBF	11.843	2.704	16.730	5.253
VMD-RBF-ARIMA	11.837	2.807	17.949	5.010
VMD-BP-ARIMA	**10.554**	**4.015**	**17.819**	**4.472**

TABLE III. ERROR ANALYSIS

Model comparison	MAE(m/s)	RMSE(m/s)	MAPE(%)
BP	1.643	2.059	19.289
RBF	4.540	5.569	64.992
VMD-BP	0.534	0.681	6.012
VMD-RBF	2.221	2.931	31.167
VMD-RBF-ARIMA	2.085	2.742	29.298
VMD-BP-ARIMA	**0.544**	**0.696**	**5.575**

C. *Interval Prediction of Wind Speed*

1) *Interval prediction results*

The sequence IMF2 obtained by VMD decomposition has good randomness. Therefore, based on MCMC algorithm, the IMF2 is sampled 1000 times, and the corresponding prediction interval is obtained according to the upper and lower quantiles. As shown in Fig. 6, the confidence interval of 90% can be obtained by selecting the upper and lower 5% quantile at each prediction point, and the coverage rate is 90% and the average prediction width is 3.767 according to the equations (15)-(17). And take $q = 0.1, 0.2, \dots, 0.9$ to calculate the q quantile estimation sequence, see Fig. 7.

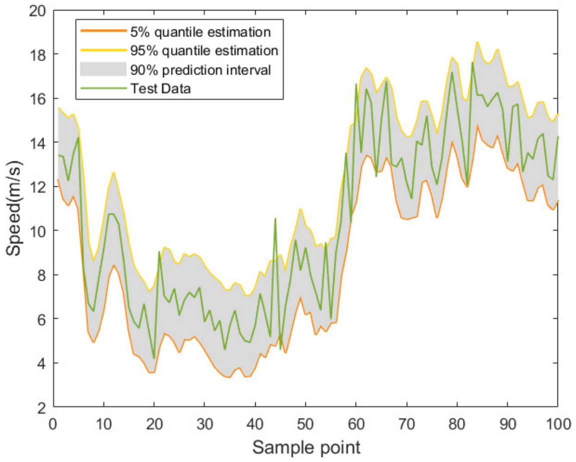

Figure 6. 90% confidence interval with 5%, 95% quantile estimation

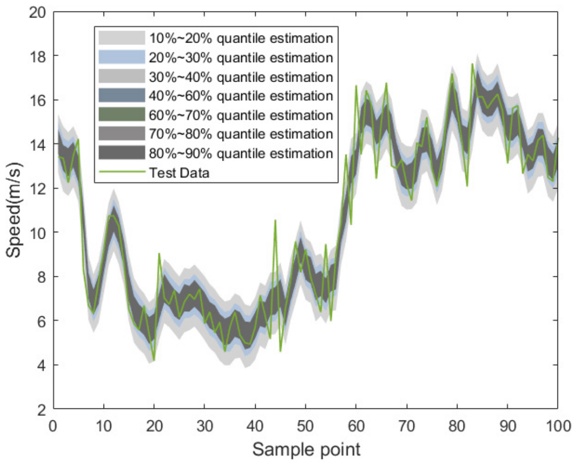

Figure 7. 10%~90% quantile of wind speed prediction

Based on the above quantile estimation, Table IV shows the interval estimated coverage and average prediction band width can be obtained at 90%, 80%, 60%, 40% and 20% confidence levels respectively. It can be seen that with the improvement of confidence, the accuracy of interval prediction, that is, the coverage rate is gradually improved, but it also causes the increase of prediction width. Too high prediction width is not conducive to accurately controlling the actual trend of future wind speed in the actual wind speed prediction.

TABLE IV. EVALUATION OF INTERVAL PREDICTION

Confidence	90%	80%	60%	40%	20%
Cover rate	0.900	0.820	0.680	0.510	0.290
Avg width	3.767	2.992	1.788	1.125	0.603

2) Evaluation of interval prediction

a) Pinball loss

From the analysis of the previous section, as the confidence level is higher, the coverage of the prediction interval is wider and its width increases. Therefore, whether it is worth to gain the accuracy by adding the loss of width has to be discussed quantitively. For example, using the pinball loss function, the Fig. 8 and Fig. 9 below show the pinball loss of quantile estimation at full prediction time when q = 0.1, 0.3, 0.5, 0.7, 0.9. It can be seen that when the prediction is not accurate, the pinball loss predicted by different quantiles is larger, but in the time when the prediction is stable and accurate, with the q approaching 50%, the pinball loss increases gradually. This shows that the prediction of median or approximate median has greater loss.

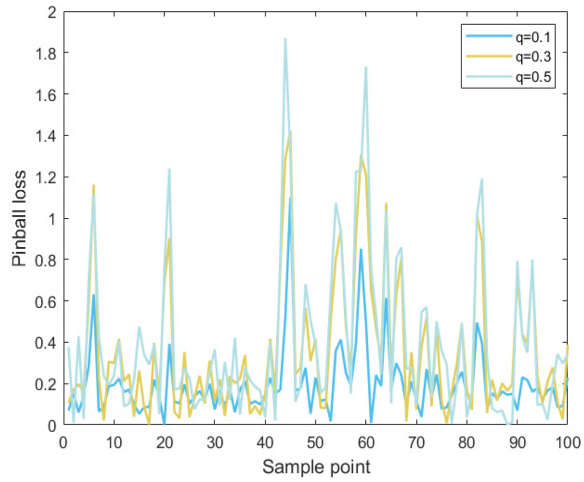

Figure 8. Pinball loss when q = 0.1, 0.3, 0.5

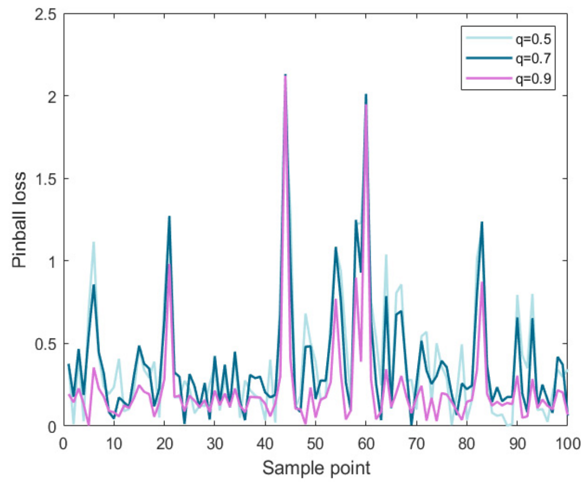

Figure 9. Pinball loss when q= 0.5, 0.7, 0.9

Further, Fig. 10 shows the result of summing the pinball loss for each quantile. It can be found that when the interval prediction technique according to VMD-BPNN-MCMC model expands the confidence interval, the pinball loss brought by it gradually decreases, which is acceptable. Therefore, this method is accurate and effective.

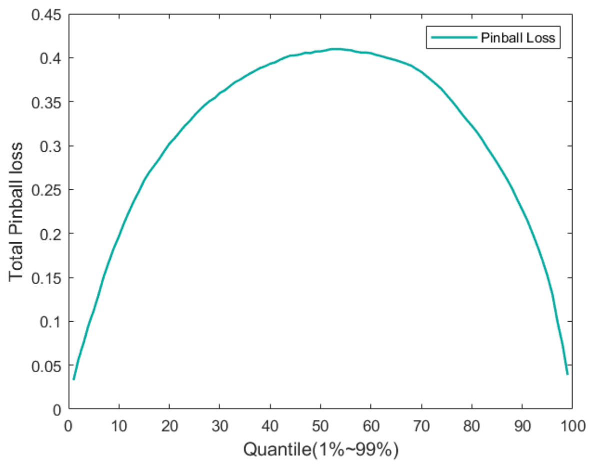

Figure 10. Total pinball loss in the whole time

b) Winkler score

On the other hand, this paper attempts to find better interval estimation according to the Winkler score criterion. For simplicity, only symmetric quantiles are selected as upper and lower bounds for a pair of interval estimates. Fig. 11 shows the approximate loss values of confidence intervals of 80%, 90% and 94% during the prediction accuracy period. In the prediction stage based on VMD-BP-MCMC model, we hope that the prediction is accurate while the Winkler value can be kept relatively small, and the prediction interval can be called optimal. Therefore, based on the interval prediction valid condition of prediction interval nominal confidence (PINC), the Winkler mean in the whole prediction time range corresponding to each quantile is obtained, and the coverage rate, interval width and pinball loss index are measured to obtain the optimal interval.

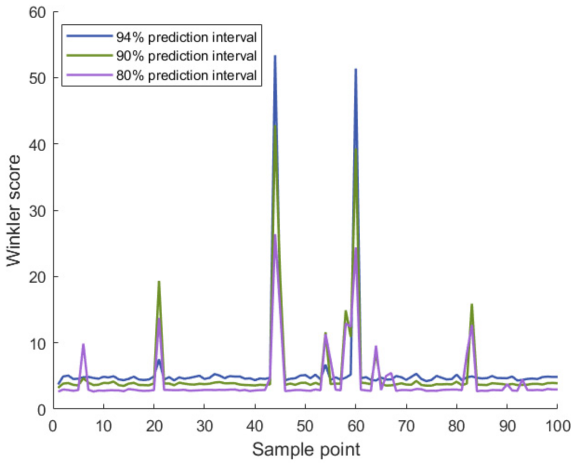

Figure 11. Winkler score of 80%, 90%, 96% confidence interval

Based on the high coverage requirement and the maximum pinball loss corresponding to the quantile of 50% shown in Fig. 10, we obtain the interval prediction effect within the quantile of 1%~49%, and select the optimal selection from the confidence level of more than 90%. At the same time, in order to highlight the advantages of VMD-BP-MCMC, VMD-RBF-MCMC is added to the interval prediction, which can be seen in Table V. However, according to the interval validity principle that *Cover rate* ≥ *PINC*, the interval results under each quantile obtained by VMD-RBF-MCMC are not valid. The proposed interval model is effective at the confidence levels of 90%, 94%, 96% and 98%.

TABLE V. INTERVAL PREDICTION COMPARISON OF DIFFERENT MODELS

Model	PINC	98%	96%	**94%**	92%	90%
VMD-BP-MCMC	Cover rate	0.980	0.970	**0.950**	0.910	0.900
	Avg width	6.606	5.411	**4.682**	4.161	3.767
	Pinball loss	0.033	0.057	**0.096**	0.112	0.131
	Winkler score	7.168	6.519	**5.813**	5.655	5.271
VMD-RBF-MCMC	Cover rate	0.680	0.660	0.590	0.530	0.50
	Avg width	6.635	5.434	4.679	4.139	3.751
	Pinball loss	0.447	0.604	0.731	0.823	0.898
	Winkler score	54.289	37.973	31.214	27.080	24.056

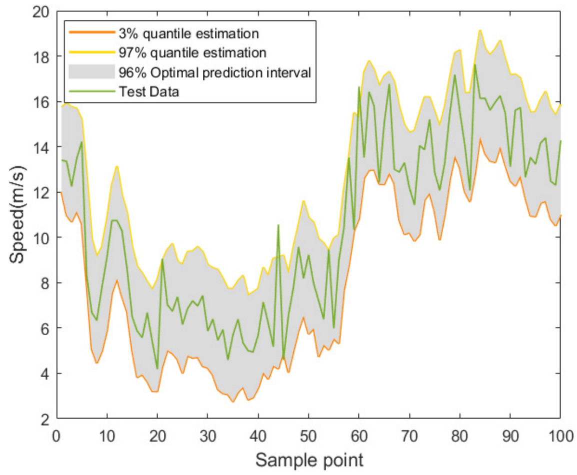

Figure 12. Final interval prediction result

Further, according to the change of Winkler score, with the decrease of confidence level, its value decreases rapidly before the 94% confidence level, and then its value decreases gently. Therefore, 94% can be selected as the optimal interval result, and the corresponding coverage rate and average interval width are 0.950 and 4.682, respectively. Compared with the other three confidence levels, it is in the middle position, and the corresponding pinball loss value is not very high. Therefore, Fig. 12 displays the optimal interval performance based on 94% confidence level.

V. CONCLUSION

Based on the decomposition-integration strategy, this paper establishes a suitable prediction model based on the different feature components received by the VMD algorithm, and obtains the point prediction mixed prediction result after the integrated prediction. Meanwhile, the MCMC method is introduced to process the component with random fluctuations and linear characteristics, which not only effectively restores the characteristic information of the sequence data, but also creates the possibility of interval evaluation according to Monte Carlo properties. The experimental results display that the forecast results of the hybrid model proposed in this article are more accurate, the interval prediction performs well in the whole period, can almost contain all the test data, and has high reliability. To some extent, it can effectively avoid the wind speed randomness in the wind power generation, which has a serious adverse impact on the safety, stable operation and power quality of the power system. Finally, this paper does not fully consider the impact of other atmospheric environment data on wind speed, so there may be a lack of data for wind speed prediction. In future research, more variables should be considered.

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