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Research on short-term wind power combined forecasting and its Gaussian cloud uncertainty to support the integration of renewables and EVs

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ABSTRACT

Under the pressure of environmental pollution and energy shortage, wind power generation and EVs with clean and pollution-free characteristics have developed rapidly. However, the randomness of EVs charging and the volatility of wind power output will bring great challenges to the reliability and economy of grid operation. Especially the accuracy and range of wind power forecasting are critical to the operation of the power system with a high proportion of renewable energy and EVs. Aiming at improving the accuracy of short-term wind power forecasting and its uncertainty, this paper puts forward a combined forecasting model, including BP, Wavelet, and RVM by information fusion strategy, Gaussian Cloud model is used to reflect the uncertainty in the forecasting process. According to the measured data of two units, the results of short-term wind power forecasting are analyzed and compared with the single forecasting method. It's found that the combined forecasting model can improve the forecasting accuracy with more reasonable confidence interval. The power grid can guide the EVs to dynamically adjust the EVs charging time according to the forecasting wind power and EVs charging power curves, so as to maximize the absorption of wind power, achieve the economic operation and reduce pollution emissions.

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1. Introduction

Wind power as a green non-polluting renewable energy is inexhaustible and has become a research hot spot in the field of new energy research [1,2]. Increasing sharply during recent years, the global wind power capacity has reached 539.581 GW by the end of 2017 [3,4]; Increasing wind power in grid capacity to improve its use ratio, it can effectively alleviate the problem of resource shortage and environmental pollution. Although wind power generation is clean and economical, the uncertainty and randomness of wind power generation [5,6] often lead to the increase of cost of wind power units due to the need to rotate reserve capacity due to the insufficient forecasting, or wind curtailment often occurs due to the excessive output of wind power.

As a new means of transportation, electric vehicles (EVs) have great advantages in energy saving, emission reduction and climate change control compared with traditional fuel vehicles. Due to the large number and wide distribution of EVs the random charging is not subjected to scheduling planning; as an electricity load, it is likely to cause "peak on peak" and increase the difference between "peak and valley", which will lead to the increase of power generation cost and even affect the safe operation of the power grid. In recent years, the Vehicle to Grid (V2G) [7] theory of EVs has been put forward, which can not only effectively reduce the peak load of the power grid, but also play the role of "cutting peak and filling valley" for power grid operation. V2G theory means that the EVs can feedback electric energy to the distribution network, namely it can not only be charged as the electric load but also feed electric energy to the grid as the distributed power supply when the electric vehicle stops. Wind turbines as the main equipment of power plants and EVs as the energy storage unit of electricity side can be combined, namely EVs should be charged

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Nomenclature

n	n-forecasting algorithm to predict the wind power
P_n	the predicted wind power of n-forecasting algorithm
$R = [p_{tn}]_{n*j}$	Establishment of a Matrix for evaluating indicators; p_{tn} is the forecasting obtained from the forecasting of step j by the n-type forecasting algorithm
ω	the weight of the Evaluation Index
E_x	expectation
E_n	entropy
H_e	superentropy
τ	Preset confidence level or probability level, that is the nominal reliable proportion
$z^{(\tau)}$	The number of data in the predicted range of the actual wind power at confidence level
$g^{(\tau)}$	Indicator variable, binary variable, which indicates whether the measured power falls into the predicted range
$Sc^{(\tau)}$	Technical score at confidence level τ
$\widehat{q}_t^{(\tau)}$	At t time, confidence level τ is the limit value of the predicted interval
S^2	sample variance
$\overline{X}$	the mean value

more or discharged less when wind power output is large, or electric vehicle should be charged less or discharged more when wind power output is less. Hence if we could accurately describe its uncertainty [8,9] and forecast wind power, the penetration of wind power could increase greatly and the wind power output and EVs charging/discharging power would be relatively stable.

Accurate and reliable forecasting of wind power is necessary to alleviate the problem of "wind curtailment". Due to the influence of precision of wind anemometers, numerical weather forecasting accuracy, unit start-up and shutdown, and wake effect, wind power forecasting has errors. As the capacity of single-machine and wind farm increases, there always exists non-neglected discrepancy between the forecasting results and measurements [10]. Wind power forecasting and uncertainty analysis of wind farms is an effective way to improve the wind power forecasting interval and applicability, and have practical significance for improving the utilization of wind resources and solving the problem of "discarding the wind".

The short-term wind power forecasting model can be divided into four types, including physical method, statistical method, learning method, and combined method. The physical method is to use NWP data for forecasting. The NWP mainly predicts the weather based on the geographical location and weather conditions of the wind farm. The learning methods and statistical methods are based on historical statistical data to predict wind power; they are mainly used in the short-term forecasting of wind power. The common learning and statistical methods include Support Vector Machine [11], Chaos Prediction [12], Artificial Neural Network [13], and the multiscale WPF method [14] which establishes a multi-to-multi (m2m) mapping network and uses the stacked demonizing auto encoder (SDAE). The key to the combined method [15,16] is to combine the single methods according to the actual needs and give full play to the advantages of each method. Generally speaking, combined methods are more accurate than single methods [17,18].

In order to improve the accuracy of wind power forecasting, many scholars have done much research on it [19]. References [20,21] have studied the short-term forecasting of wind power based on a single Relevance Vector Machine (RVM) model. The forecasting accuracy of RVM method is more accurate, while the computational cost is expensive. Due to the inevitable disadvantages of various single forecasting models and the limitations of application situations, a combined model could be considered to take advantages of various methods to obtain higher forecasting accuracy [22–26]. For example, a combined of Back-Propagation (BP) neural network [27], Radial Basis Function (RBF) neural network [28], and Support Vector Machine (SVM) [29] model shows better accuracy than single forecasting. It demonstrates the superiority of the combined model, but fails to show its superiority in handling the forecasting of small sample data and uncertainty in the process of forecasting. In the view of the uncertainty of the wind speed law, the accuracy of the conventional analytical models is not high, many scholars have used cloud model to forecast wind power generation, and can further improve the accuracy of forecasting.

EVs mainly influence the distribution network through grid-connected charging, and the result of such influence largely depends on the characteristics of charging load. The cluster load characteristics of a large number of EVs are randomly distributed in time and space, the charge load is difficult to forecast. In recent years, experts and scholars have done a lot of research on this issue. Reference [30] collects the driving behavior, charging location and daily driving distance of the owner, and then uses a large amount of data to predict the spatial and temporal distribution of EVs charging. Reference [31] studies the charging load distribution of EVs under specific scenarios, such as residential communities and office places. Reference [32] proposes a two-stage approach for allocation of EV parking lots and renewable resources (DRRs) in power distribution network. Genetic algorithm (GA) and particle swarm optimization (PSO) are used to minimize the loss of distribution network. Reference [33] proposed a new model to study the influence of power exchange between power grid and EVs on the power system demand curve, the operation stability index and the reliability indices. Reference [34] proposed a simultaneous approach implementing wind-powered electric vehicle charging stations in order to distribute the charging demand of the electric vehicle with wind generating resources. But in fact we should consider the demand response programs to improve the integration of EVs into the power system with the renewable energy.

In this paper, a combined model of BP, Wavelet [35,36], RVM model, and three single-models were used to predict the short-term wind power. The cloud model [37–39] is introduced to solve the uncertainty of single model and combined model wind power forecasting. The error of each model is described not only quantitatively but also qualitatively, thus it further promotes the accuracy of the projections. The result shows that the model is trained by using small sample data and the uncertainty of error in the training process with cloud model, the accuracy of forecasting can be improved remarkably. By studying the wind power forecasting curve of a wind farm and the EVs charging curve of a region, the comprehensive energy scheduling can be coordinated and the charging behavior of EVs can be guided.

2. Forecasting model

2.1. Back-Propagation (BP) neural network

Artificial neural network neurons can be divided into three types: input layer neurons, hidden layer neurons, and output layer neurons. Input layer neurons are used to input training or test signals; the output layer outputs the signal processed by hidden layer neurons; Hidden layer neurons are invisible outside the system and adjust their own weights by learning and memorizing a large amount of data. Its input/output relationship can be expressed as:

$$I = \sum_{j=0}^{n} w_j x_j - \theta \tag{1}$$

$$y = f(I) \tag{2}$$

In the formula: x_j is the input sign; θ is the threshold value; w_j is the weight coefficient, It represents the strength of the connection; $f(x)$ is the excitation function or the transfer function.

As a matter of convenience, $-\theta$ is the weight of the input signal x_0 that equals to 1, the input/output relation becomes:

$$I = \sum_{j=1}^{n} w_j x_j \tag{3}$$

In the formula: $w_0 = -\theta, x_0 = 1$.

The BP network is a multi-layered Feedforward neural network, which is characterized by the propagation of the signal from the input layer to the output layer, while error feedback is propagated from the output layer to the input layer, shown as Fig. 1. BP neural network has strong adaptive ability and can update the weights continuously through error feedback, which makes the output more accurate. However, there are some defects in BP neural network, such as slow learning speed, lacking of corresponding theoretical guidance on the selection of Neuron number, easy to fall into the local minimum.

The forward propagation of neural network signals is shown as follow:

The input net$_i$ of the node i in the hidden layer is

$$net_i = \sum_{j=1}^{M} w_{ij} x_j + \theta_i \tag{4}$$

The output quantity y$_i$ of the node i in the hidden layer is

$$y_i = \phi(net_i) = \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) \tag{5}$$

The output quantity net$_k$ of the node k in the output layer is

$$net_k = \sum_{i=1}^{q} w_{ki} y_i + a_k = \sum_{i=1}^{q} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k \tag{6}$$

The output quantity o$_k$ of the node k in the output layer is

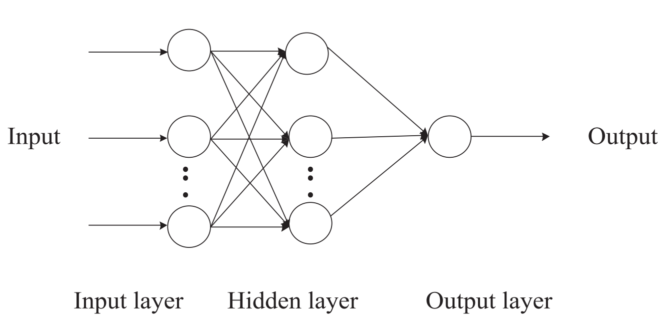

Fig. 1. BP neural network structure.

$$o_k = \psi(net_k) = \psi\left(\sum_{i=1}^{q} w_{ki} y_i + a_k\right) = \psi\left(\sum_{i=1}^{q} w_{ki} \phi\left(\sum_{j=1}^{M} w_{ij} x_j + \theta_i\right) + a_k\right) \tag{7}$$

Remark. x_j means wind speed and o_k means wind power in Formula (4)-(7) of the wind power prediction model.

2.2. Wavelets

Wavelet analysis, also called Wavelet Transform, is a signal based on the Oscillatory waveform of the mother Wavelet, which has better learning ability and convergence speed than neural network and is not susceptible to local optimal so that it can be widely used in various fields.

A hypothesis is $\Psi(t) \in L^2(R)$, $L^2(R)$ represents a signal space with limited capabilities, Its Fourier transform is:

$$\Psi(w) = \int_{-\infty}^{\infty} \Psi(t) e^{-iwt} dt \tag{8}$$

When $\Psi(t)$ satisfies the permissibility condition, then:

$$C_\Psi = \int_{-\infty}^{\infty} \frac{|\Psi(w)|^2}{|w|} dw < \infty \tag{9}$$

$\Psi(t)$ is the basic wavelet or maternal wavelet, other wavelets sequences can be calculated by shifting and telescoping the maternal wavelet function $\Psi(t)$. For continuous cases, the wavelet sequence is:

When $\Psi(t)$ satisfies the permissibility condition, then:

$$\Psi(a,b) = |a|^{-\frac{1}{2}} \Psi\left(\frac{x-b}{a}\right), a, b \in R, a \neq 0 \tag{10}$$

In the formula, a is the expansion factor, b is the translational factor.

For discrete cases, the wavelet sequence is:

$$\Psi_{j,k} = 2^{j/2} \Psi\left(2^j x - k\right), j, k \in Z \tag{11}$$

Continuous wavelet transform of the arbitrary function $f(x) \in L^2(R)$ is:

$$W_f(a,b)\langle f, \Psi_{a,b}\rangle = |a|^{-\frac{1}{2}} \int_{-\infty}^{\infty} f(x) \overline{\Psi\left(\frac{x-b}{a}\right)} dx \tag{12}$$

It should be noted that, $\overline{\Psi_{a,b}(t)}$ represents complex conjugate of $\Psi_{a,b}(t)$.

After analysis, we can see that the mother wavelet is not the only function which satisfies the wavelet condition.

Remark. $\Psi(t)$ means wind speed in Formula (8)-(12) of the wind power prediction model.

2.3. RVM model

Relevance Vector Machine (RVM) is a sparse probability model which is proposed based on the Support Vector Machine, RVM uses the self-correlation theory to determine the removal of unrelated vectors; and it is sparse to estimate the regression to get a predictive value. The Relevance Vector Machine has a good predictive precision and a strong generalization capability for small samples.

Establishment of Relevance Vector Machine power forecasting models based on wind power:

The training sample is $D = \{X_i, t_i\}_{i=1}^{N}$:

$$t_i = y(X_i; W) + \varepsilon_i \tag{13}$$

In the formula: $W = [\omega_0, \omega_1, \ldots, \omega_N]$ is the weight, $y(\cdot)$ is nonlinear function; Supposing that ε is compliance with mean 0, Variance for Gaussian distribution is σ^2, that is to say, $\varepsilon \sim N(0, \sigma^2)$.

Nonlinear function can be represented as:

$$y(X_i, W) = \sum_{j=1}^{N} \omega_j K(X_i, X_j) + \omega_0 \tag{14}$$

In the formula, ω_0 is Offset, $K(X_i, X_j)$ is the Kernel function, Kernel function meets:

$$K(X, X_i) = \exp\left(\frac{-\|X - X_i\|}{2\sigma_1^2}\right) \tag{15}$$

In the formula, σ_1^2 is the variance of the additional noise, and ε obeys the normal distribution.

The independent Gaussian distribution with a mean value of 0 is called the prior distribution of RVM, and the hyperparameter α is added. The weight W likelihood function can be written as:

$$p(W|\alpha) = \prod_{i=0}^{N} N\left(\omega_i \middle| 0, \alpha_i^{-1}\right) \tag{16}$$

In the formula: $\alpha = [\alpha_0, \alpha_1, \ldots, \alpha_N]^T$ is $N \times 1$ dimension of hyper parametric vector.

The post-test distribution function of all parameters is obtained by using the Bayes' theorem:

$$p\left(W, \alpha, \sigma^2 | t\right) = \frac{p(t|W, \alpha, \sigma^2) p(W, \alpha, \sigma^2)}{p(t)} \tag{17}$$

The optimal values of super parameters and variance can be obtained by iterative calculation of the following two formulas α_{MP}, σ_{MP}^2:

$$\alpha_i^{new} = \frac{\gamma_i}{\mu_i^2} \tag{18}$$

In the form: $\gamma_i = 1 - \alpha_i^{old} \Sigma_{ii}$

$$\left(\alpha^2\right)^{new} = \frac{\|t - \Phi\mu\|^2}{N - \sum_{i=0}^{N} \gamma_i} \tag{19}$$

Super parameters α_i, the optimal values of variance α_{MP}, σ_{MP}^2, and the post-experimental distribution of the weight vector W is obtained by the above calculation. In the training dataset, type any test X_*, predictive model output forecast t_* is:

$$p\left(t_* | t, \alpha_{MP}, \alpha_{MP}^2\right) = \int p\left(t_* \middle| W, \sigma_{MP}^2\right) p\left(W | t, \alpha_{MP}, \sigma_{MP}^2\right) dW \tag{20}$$

$$p\left(t_* \middle| t, \alpha_{MP}, \sigma_{MP}^2\right) \sim N\left(t_* | y_*, \sigma_*^2\right) \tag{21}$$

Among them, $y_* = \mu^T \phi(X_*)$ is the predicted average value for the corresponding predicted point, $\sigma_*^2 = \sigma_{MP}^2 + \phi(X_*)^T \Sigma \phi(X_*)$ is the predicted variance for the corresponding predicted point.

Remark. X_* means wind speed and y_* means wind power in Formula (13)-(21) of the wind power prediction model.

2.4. Factors influencing uncertainty in wind power forecasting

The surrounding environment information of wind farm, unit operation state, and historical data and NWP data (five-dimensional data of wind speed, wind direction, temperature, atmospheric pressure, and atmospheric humidity) will all have impact on the prediction accuracy. Even with the same forecasting system, if the selected wind farm, the wind farm unit and the accuracy of input data are different, and the prediction error is also different. It is necessary to study the uncertainty by understanding the factors that influence the prediction error. Factors influencing the prediction error include: (1) the accuracy of input data; (2) output power dispersion; (3) unit fault uncertainty; (4) the error of the forecasting model.

Pearson correlation is used to analyze the influence of NWP data on wind turbine output. Table 1 lists the correlation coefficients between NWP data and wind turbine unit power which are calculated by STAT (statistical analysis software).

According to data analysis in Table 1, the output power of wind turbine is the most closely related to wind speed and it is showing a highly positive correlation. Then it is positively correlated with wind direction. It has a micro correlation with pressure and temperature, and a negative correlation with humidity. Based on the above analysis, this paper gives consideration to both the prediction accuracy and the operation efficiency of the algorithm, and selects the wind speed with high correlation to the analysis target as the input of the algorithm for research.

2.4.1. The accuracy of the input data

Factors such as wind speed, wind direction, pressure, and temperature all affect the operation of wind farms. Among all these factors, the influence of wind speed is the most critical. The error probability distribution of NWP data is analyzed.

The screening of training data is crucial and has a greater impact on forecasting accuracy. The real-time wind speed data of January 2010 is selected and compared with NWP data. As can be seen from Fig. 2, the distribution of wind speed error is relatively scattered, and the error in high wind speed is more concentrated and larger, which is corresponding to the histogram of the error frequency distribution in Fig. 3.

2.4.2. Forecasting model error

The error of the forecasting model reflects the accuracy of the forecasting. This paper considers the error of input data and the forecasting error of output power. Select the test data of January (1#) as the research objective, among which there are 192 data points. As can be seen from Fig. 4, more power error is distributed

Table 1
Pearson correlation analysis of each month.

Influence factor	Unit- power				
	January	April	July	October	Average value
Speed	0.946	0.949	0.916	0.910	0.9303
direction	0.334	0.380	0.349	0.296	0.3398
Humidity	−0.401	−0.421	−0.0813	−0.184	−0.2718
Pressure	0.167	0.190	0.112	−0.149	0.0800
Temperature	0.278	0.231	−0.0346	0.100	0.1436

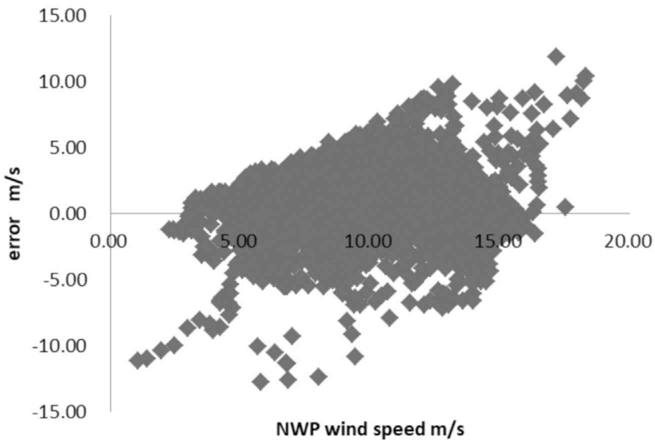

Fig. 2. Scatter plot of actual wind speed and NWP data error.

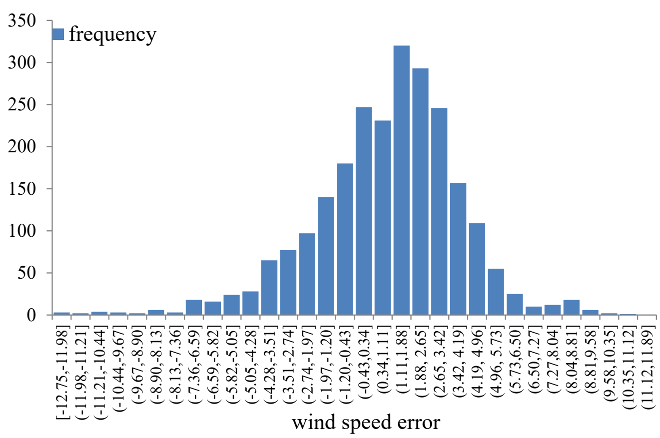

Fig. 3. Wind speed error frequency distribution histogram.

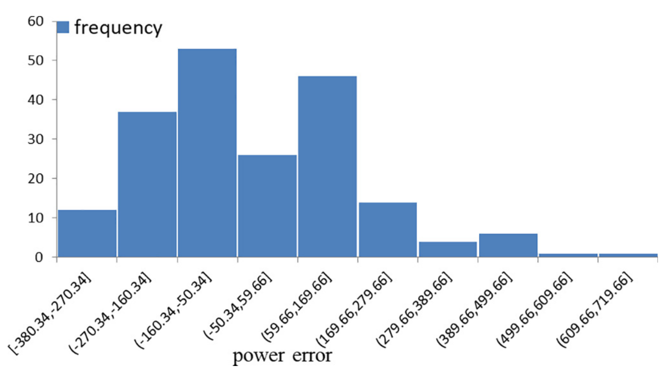

Fig. 4. Frequency distribution histogram of power error.

in the frequency range on the left; the predicted power value is less than the measurements.

As can be seen from Fig. 5, the wind speed error frequency is negatively skewed. The NWP wind speed value is greater than the measured wind speed. In general, the correlation factors are independent of each other, the forecasting error is smaller than the forecasting value, and the predicted power value is slightly lower than the measured power as a whole. Therefore, the wind speed error map corresponds to the power error map. If the forecasting model is chosen differently, its corresponding error distribution

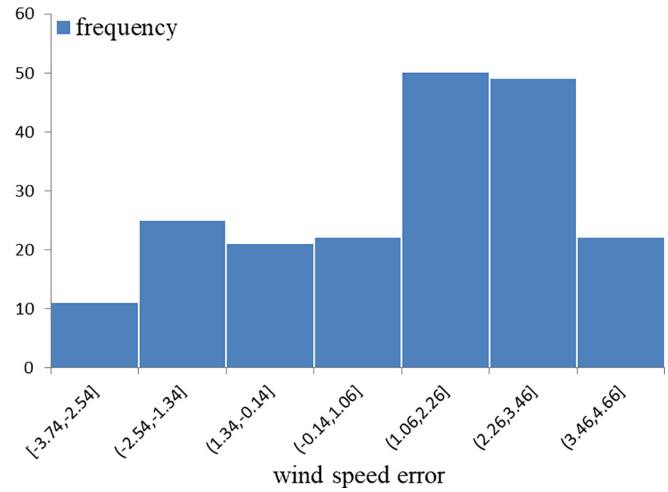

Fig. 5. Wind speed error frequency distribution histogram.

will also be different.

2.5. *Uncertainty analysis of wind power forecasting*

2.5.1. *Error evaluation index*

Root Mean Square Error (RMSE) is a commonly used evaluation index when performing uncertainty analysis. It is sensitive to extreme situations in the forecasting. The formula is defined as follows:

$$e_{RMSE} = \frac{1}{P}\sqrt{\frac{\sum \varepsilon_i^2}{n}} \tag{22}$$

where P is the rated power of the wind farm, n is the number of samples.

2.5.2. *Uncertainty of influencing factors*

Uncertainty of the influencing factors is in a variety of distributions under normal conditions. When it is in a normal distribution, the approximate fluctuation range of the forecasted values and reflect the uncertainty are calculated through the confidence intervals.

The multivariate input wind power forecasting formula can be expressed as:

$$\widehat{\widehat{y}} = f(x_1, x_2, \ldots, x_p) \tag{23}$$

where: $\widehat{\widehat{y}}$ is the forecast mean.

Due to the uncertainties associated with factor $(x_1 \sim x_p)$, these uncertainties can be expressed as:

$$x_i = \widehat{\widehat{x}}_i + \widehat{\varepsilon}_i \tag{24}$$

where: x_i is the actual value; $\widehat{\widehat{x}}_i$ is the forecast average; $\widehat{\varepsilon}_i$ is the forecast error.

When the confidence level is $(1-\alpha)\%$, the confidence interval for x_i is:

$$\widehat{x}_i \in [\widehat{\widehat{x}}_i - \beta\widehat{\sigma}_i, \widehat{\widehat{x}}_i + \beta\widehat{\sigma}_i] \tag{25}$$

In the formula: $\beta = t_{\alpha/2}(n)$ is the proportional coefficient.

The fluctuation range of the forecasted value is:

$$\widehat{\widehat{y}}_{\min} = f\left(\widehat{\widehat{x}}_1 - \beta\delta_1\widehat{\sigma}_1, \widehat{\widehat{x}}_2 - \beta\delta_2\widehat{\sigma}_2, \cdots, \widehat{\widehat{x}}_p - \beta\delta_p\widehat{\sigma}_p\right) \tag{26}$$

$$\widehat{\widehat{y}}_{\max} = f\left(\widehat{\widehat{x}}_1 + \beta\delta_1\widehat{\sigma}_1, \widehat{\widehat{x}}_2 + \beta\delta_2\widehat{\sigma}_2, \cdots, \widehat{\widehat{x}}_p + \beta\delta_p\widehat{\sigma}_p\right) \tag{27}$$

$$\delta_i = \frac{k_i}{|k_i|} \tag{28}$$

The degree of influence of the uncertainty factor on the forecast result can be based on the forecast error and can be reflected by the partial derivative of the forecast value sought. The formula is as follows:

$$k_i = \frac{\partial\widehat{\widehat{y}}}{\partial\widehat{x}_i}\bigg|_{\widehat{X}=\widehat{\widehat{X}}} = \frac{\partial(x_1, x_2, \ldots, x_p)}{\partial\widehat{x}_i}\bigg|_{\widehat{X}=\widehat{\widehat{X}}} \tag{29}$$

In the formula: $\widehat{X}$ and $\widehat{\widehat{X}}$ are the vectors consisting of $\widehat{x}_i$, $\widehat{\widehat{x}}_i$, respectively.

When $k_i > 0$, $\widehat{\widehat{y}}$ increases with the increase of x_i. When $k_i < 0$, $\widehat{\widehat{y}}$ decreases with the increase of x_i. The sensitivity of the forecasting mean $\widehat{\widehat{y}}$ to the forecasting error of the relevant factor x_i will be increased with the increase of k_i, and then it will be significant to improve the forecasting accuracy of relevant factors for the uncertainty research.

3. The combined model of power forecasting of wind power

3.1. A combined wind power prediction model based on entropy weight method

The combined forecasting model is a single wind power forecasting model to predict the wind power, which is assigned reasonable weights to it in order to obtain a more reasonable and accurate combined forecasting model. Shannon used entropy to describe quantitatively the uncertainty or amount of information about a random event in1948. In the process of forecasting, the entropy weight [40]of each forecasting model is calculated by the entropy of information entropy and weighted by the entropy weight, the greater the amount of information are provided by the forecasting model, the more reasonable the forecast results are. The methods for solving the wind power forecasting model based on entropy right are as follows:

(1) Using n-forecasting algorithm to predict the wind power in t-period, the predicted value is p_{tn}:

$$p_{tn}(n = 1, 2, \cdots, N; t = 1, 2, \cdots, T) \tag{30}$$

(2) Establishment of a Matrix for evaluating indicator s

$$R = [p_{tn}]_{T*N} \tag{31}$$

p_{tn} is the forecasting obtained from the forecasting of step t by the n-type forecasting method, and the normalized processing of Matrix R to obtain the standard Evaluation Matrix.

(3) Calculation of entropy

The entropy of the J evaluation index is obtained from the concept of entropy as follows:

$$H_t = -\frac{1}{\ln N}\sum\nolimits_{n=1}^{N} p_{tn}\ln p_{tn}, (n = 1, 2, \cdots, N; t = 1, 2, \cdots, T) \tag{32}$$

In the formula, when $p_{tn} = 0$, $p_{tn}\ln p_{tn} = 0$.

On the basis of obtaining the entropy value, the weight of the Evaluation Index of the J is obtained according to the following formula:

$$w_t = \frac{1 - H_t}{\mathrm{N} - \sum_{t=1}^{T} H_t}, (t = 1, 2, \cdots, T) \tag{33}$$

The forecasted wind power is calculated

$$P_t = \sum w_{tn}p_{tn} \tag{34}$$

P is a combined forecasting value and w is the entropy weight value of the forecasting method of type n in step t and P is the forecasting power value of the wind power at Step t.

The training output of BP neural network, wavelet neural network, RVM algorithms and the corresponding real data are used as the input of maximum information entropy algorithm in this paper. The optimal weight value is obtained through calculation, and the optimal weight value is combined to obtain the final forecasting result.

3.2. A combined wind power prediction model based on average weight method

The combined model uses equal weight to forecasting the results of each single algorithm. Formula (35) shows:

$$P_j = \frac{1}{\mathrm{n}}\sum_{i=1}^{n} p_j^i \tag{35}$$

Through the average distribution of forecasting results of each single algorithm, the influence of single algorithm on the final accuracy of combined prediction is the same.

4. The Gaussian cloud model

4.1. The study of uncertainty

The main factor that affects wind power uncertainty is the strong randomness of the wind speed. Secondly, the uncertainty caused by the wind turbine failure and so on. All of the above factors, if any of the uncertainties of the unilateral study, have one-sided. Therefore, the uncertain characteristics of wind velocity can be extracted from the historical data and have a comprehensive character. At present, it is generally accepted that the uncertainty of wind power should not be described by Gaussian distribution, and the uncertainty of wind power is described based on the Gaussian cloud distribution.

The cloud model is a model of uncertainty transformation between qualitative concepts and quantitative representations proposed by Professor D. Y. Li [41], which effectively combines modularity and randomness. This theory laid the foundation for the uncertainty in the process of predicting the wind power.

The cloud generator has two algorithms, namely the positive and the negative cloud generator. The positive cloud generator is the realization of the qualitative concept to the quantitative representation, while the reverse cloud generator is the opposite.

The cloud model [42] presents its digital features in the expectation (Ex), entropy (En), and superentropy (He). The expectation Ex represents the information center value of the corresponding modular concept in a digital space; The entropy En is known as Modulus, can be accepted in a digital space, entropy is also a measure of the randomness of cloud droplets that represent the concept of modular and stochastic entropy, which is the entropy of entropy (En).

4.1.1. Forward cloud generator

Forward cloud generator is to realize the transformation from qualitative concept to quantitative concept. It is used to obtain the distribution of cloud droplets through one-dimensional forward cloud generator when the three digital features of cloud model are known: expectation (*E*x), entropy (*E*n), and superentropy (*H*e).

The procedure of algorithm is as follows:

Step 1: A normal random number En' with an expectation of Ex, and a standard deviation of He is obtained from the three characteristic parameters of the cloud: expectation, entropy, and superentropy;
Step 2: A normal random number x is a cloud droplet of U, x is generated with the absolute value of expectation Ex and standard deviation En' as the parameter;
Step 3: It can be calculated by 1) and 2) $\mu = e^{-\frac{(x-E_x)^2}{2(En')^2}}$, and the calculated μ represents the membership of x;
Step 4: Repeat step 1 to step 3 until the formation of the set N cloud droplets is completed.

4.1.2. Backward cloud generator

Backward cloud generator is a process of transforming quantitative concept into qualitative concept, which is opposite to the operation process of forward cloud generator. Based on the known distribution of cloud droplets, backward cloud generator is used to calculate the three digital features of the cloud model: Expectation (*E*x), Entropy (*E*n) and Superentropy (*H*e).

The specific algorithm steps are as follows:

Step 1: According to specific historical data, we use the formula $\overline{X} = \frac{1}{n}\sum_{i=1}^{n} x$ to get the mean value of the historical data, first order sample absolute central moment $\frac{1}{n}\sum_{i=1}^{n}|x_i - \overline{X}|$, sample variance $S^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \overline{X}\right)^2$;
Step 2: It can be calculated by Step 1 $E_x = \overline{X}$;
Step 3: Entropy is calculated from the sample mean $E_n = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n}|x_i - \overline{X}|$;
Step 4: Combined Step 1 and Step 3, and we could get $H_e = \sqrt{S^2 - {E_n}^2}$.

4.2. An evaluation system for uncertainty

We use the evaluation system of predictive uncertainty analysis model in the reference [43], which mainly includes three indices: reliability, sharpness, and technical score.

(1) Reliability is an assessment of the deterministic system performance from a probabilistic point of view, that is, if the actual wind power falls within the pre-set confidence interval; if the effective ratio is not less than the intended confidence level, the result is considered reliable.
(2) The sharpness is the precondition of ensuring reliability. If the pre-set confidence interval is smaller and it is closer to the real power curve, it shows that the model has the better performance.
(3) Technical score is a comprehensive index of reliability and sharpness. It is closer to zero, the performance of the analytical model is better. Based on the model satisfying the reliability evaluation, the technical score can be used as the index to judge the sharpness. As a result, the reliability and technical scores are selected as the evaluation indices of uncertainty analysis model.

Other parameters including confidence level is τ, reliability metrics, and technical indicators $Sc^{(\tau)}$ are defined as follows:

$$g^{(\tau)} = \begin{cases} 1, & if \quad w_t^{act} < \widehat{q}_t^{(\tau)} \\ 0, & otherwise \end{cases} \tag{36}$$

$$z^{(\tau)} = \sum_{i=1}^{N} g^{(\tau)} \tag{37}$$

$$r^{(\tau)} = \widehat{a}^{(\tau)} - \tau = \frac{z^{(\tau)}}{N} - \tau \tag{38}$$

$$Sc^{(\tau)} = \frac{1}{N}\sum_{i=1}^{N}\left(g^{(\tau)} - \tau\right)\left(w_t^{act} - \widehat{q}_t^{(\tau)}\right) \tag{39}$$

τ: Preset confidence level or probability level, that is the nominal reliable proportion;
$\widehat{q}_t^{(\tau)}$: At t time, confidence level τ is the limit value of the predicted interval (kW or MW);
$g^{(\tau)}$: Indicator variable, binary variable, which indicates whether the measured power falls into the predicted range;
$z^{(\tau)}$:The number of data in the predicted range of the actual wind power at confidence level;
$Sc^{(\tau)}$:Technical score at confidence level τ.

5. Case studies

This paper analyses the measured data of a wind farm in northern China in 2010. The data mainly includes NWP data, historical wind speed, and measured power. The data are collected every 15 min, after removing the missing and invalid data, which retained up to 96% of the available data. We used 83% of its training data as a predictive model and 17% as test data, using wind turbines 10# and 16# to extract their 1152 sets of data, using 960 sets of data as training data, the 192 groups (2 days data) were used as the testing data. The time of 192 samples is from 00:00 on March 27th, 2010 to 24:00 on March 28th, 2010 in Figs. 6–7 and Figs. 10–15. BP neural networks, wavelet neural networks and RVM (Relevance Vector Machine) are used to separately predict the neural network and then the entropy method are used to predict them. By MATLAB software, simulation experiments are carried out to analyze the results of single forecasting and combined forecasting to verify the superiority of the combined forecasting model.

Table 2
Cloud model parameters for different algorithms.

Unit	algorithm	*Ex*	*En*	*He*
#10	RVM	209.1645	0.1680	0.0099
	Wavelet	206.0622	0.1757	0.0263
	BP	204.3909	0.1612	0.0214
	Combined1	206.4305	0.1687	0.0198
	Combined2	206.5392	0.1683	0.0192
#16	RVM	237.2109	0.1962	0.0514
	Wavelet	240.4128	0.1883	0.0755
	BP	230.6950	0.1832	0.0712
	Combined1	235.8118	0.1895	0.0651
	Combined2	236.1062	0.1894	0.0661

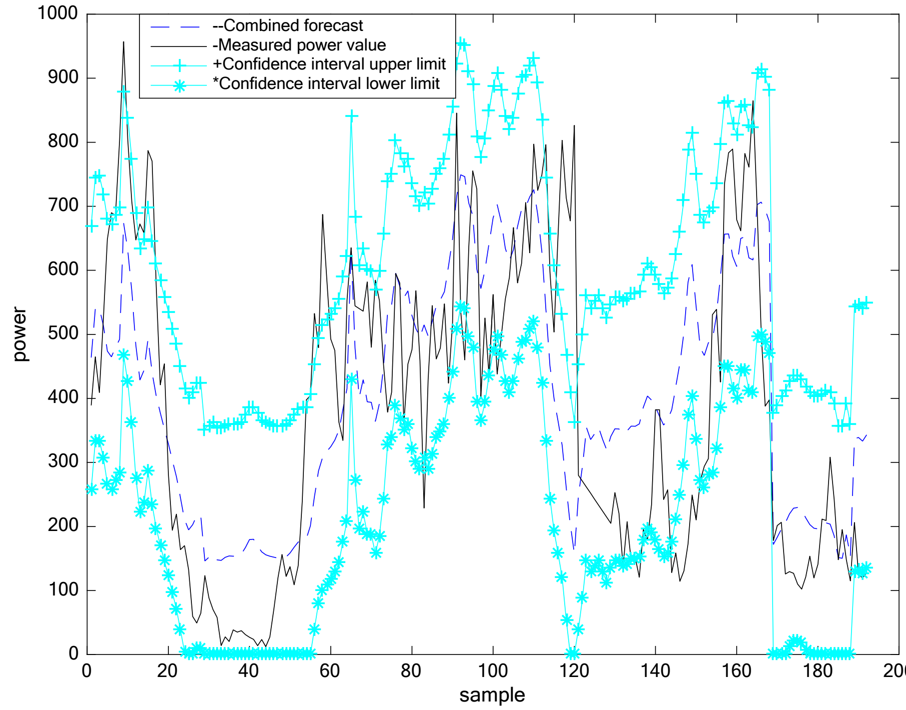

Fig. 6a. Unit #10 forecasting results with 90% confidence level of combined forecasting model 1.

5.1. The case of cloud model

Table 2 is a qualitative representation of the errors of each model by means of the reverse cloud model. On the basis of the combined model of entropy weight whose weights are determined, the qualitative representation of the uncertainty of the combined model is obtained. Combined1 model is the model based on entropy weight method; Combined2 model is the model based on

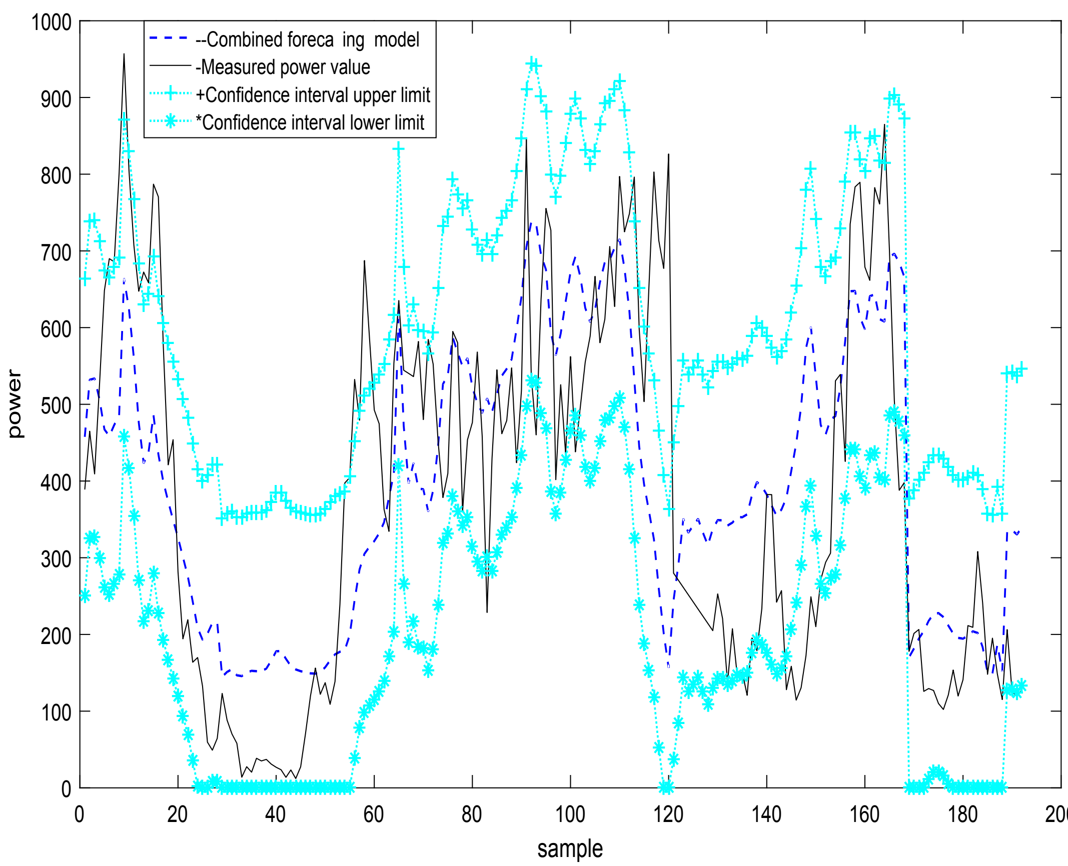

Fig. 6b. Unit #10 forecasting results with 90% confidence level of combined forecasting model 2.

average weight method.

According to the qualitative description of the combined 1 by the cloud model in Table 2, the confidence intervals 90% of the 10 # and 16 # units are [206.4103, 206.4507] and [235.7880, 235.8356], which is shown in Fig. 6(a) and Fig. 7(a); According to the qualitative description of the combined 2 by the cloud model in Table 2, the confidence intervals 90% of the 10 # and 16 # units are [206.5191, 206.5593] and [236.0824, 236.1300], as is shown in Fig. 6(b) and Fig. 7(b):

Fig. 8 and Fig. 9 are the cloud graphs of the uncertainty of the combined model 1of #16 and #10 sets, respectively.

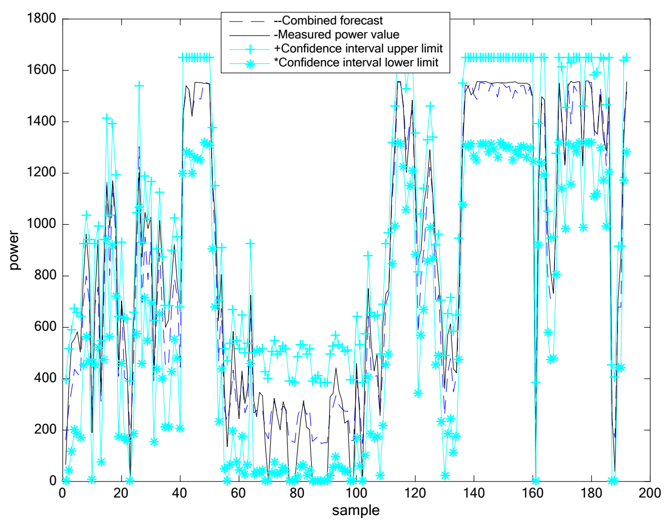

Fig. 7a. 16# unit forecasting results at 90% confidence level of combined forecasting model 1.

Table 2 shows the three parameters of the uncertainty of the combined model. The forward cloud generator of the cloud model is used to convert it from qualitative to quantitative.

5.2. The evaluation result for uncertainty

Firstly, the reliability of the uncertainty analysis model is tested: The ratio of real power to confidence interval is predicted with 90% confidence level in the case of #10 and #16 units, the indicators for the prediction uncertainty evaluation system of the two units are shown in Table 3:

As can be seen from Table 3, the effective ratio of #16 unit is 99%, which is higher than the preset confidence interval, the result is reliable, and the effective ratio of 10 # is only 78% which is less than 90% of the preset level, and the result is not reliable. Secondly, the technical score of 16 # unit is obtained by calculation. The technical score is-0.0488, near zero; the technical fraction of #10 unit is 1.976, which is relatively far from zero. Combined reliability and technical scores indicate that the Gaussian Cloud model can predict uncertainty reliably and qualitatively. Comparing the results of two units, the reason of the unreliability of the results of the 10 # unit is the insufficient data processing in the early period.

5.3. Forecasting of the single model

Fig. 10 and Fig. 11 are the results of the forecasting of the 10 # and 16 # units using the BP neural network, the wavelet neural network, and the RVM Support vector machine single forecasting model, it is not difficult to see that the single forecasting model can accurately predict the basic trend of wind power, but there is still a large error between the forecasting and the measured data.

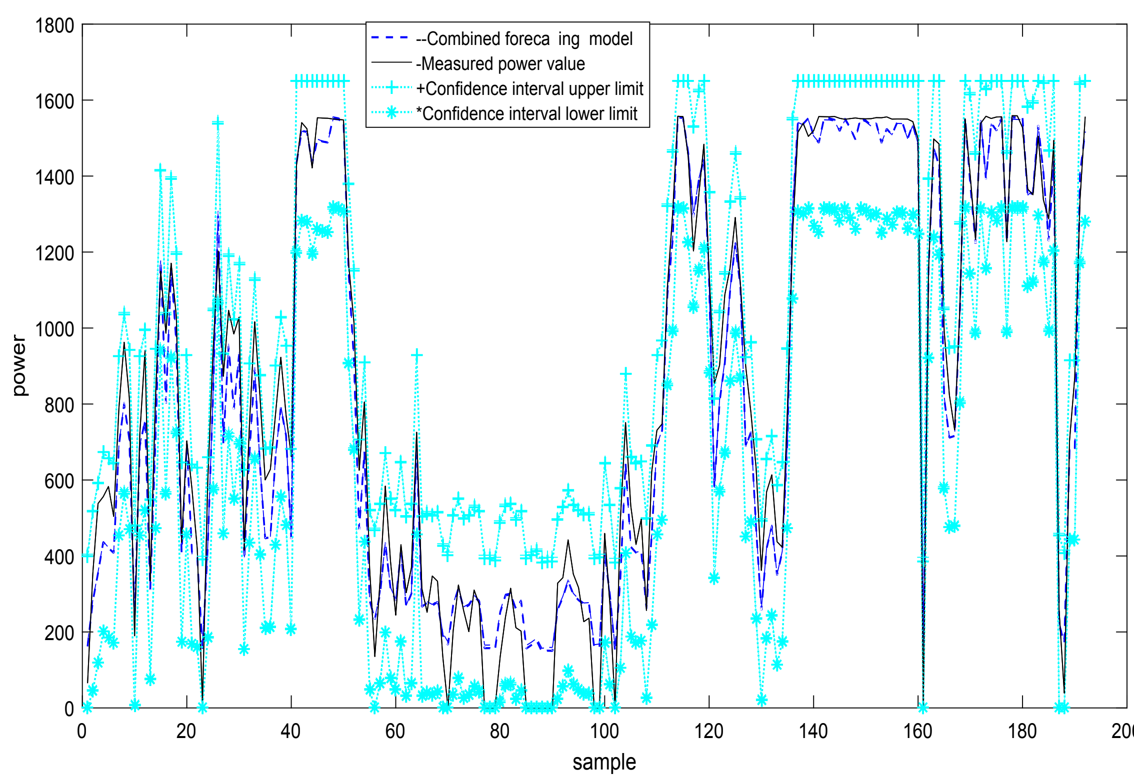

Fig. 7b. 16# unit forecasting results at 90% confidence level of combined forecasting mode 2.

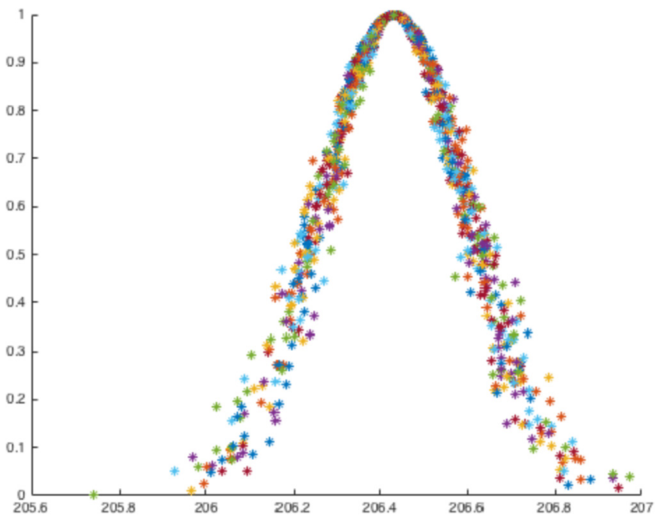

Fig. 8. #10 unit cloud model of combined forecasting model 1.

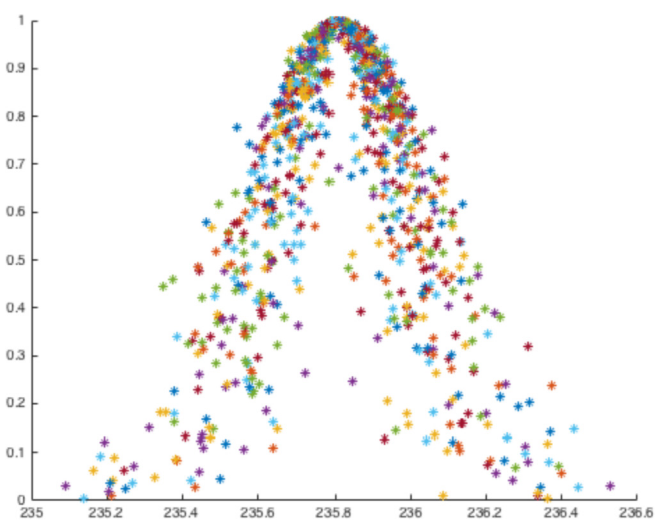

Fig. 9. 16# unit cloud model of combined forecasting model 1.

Table 3
Evaluation indicators of uncertainty evaluation system.

Parameter	10#unit	16#unit
Pre-set letter level	90%	90%
Number of valid values	151	191
Effective ratio	78%	99%
Technical score	1.976	−0.0488

5.4. *Forecasting of the combined model*

The combined forecasting model gives different weights to three single forecasting models by means of entropy method, which makes the forecasting result better fit with the actual wind power curve. Fig. 12 and Fig. 13 show the wind power forecasting of the 10 # and 16 # units through the combined forecasting model, and it can be seen from the diagram that the forecasting results are closer to actual wind power values.

The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of BP, wavelet, RVM, and combined forecasting model are given in Table 4; the MAE mainly focuses on the evaluation of the overall error of the forecasted results of wind power, while the average absolute error focuses on the real-time deviation of the forecast results. Thus, the combined forecasting model is more accurate than the three single forecasting models, which is mainly due to the combined of the statistical information contained in three single-models; the error is relatively small in weight and provides relatively less information, thus avoiding the concentration effect of a single or multiple factors on the accuracy of the forecasting. Table 4 shows that the computational time of the combined forecasting model is more than that of the single forecasting model and the more running time is entropy weight calculation of the three forecasting models, but the forecasting accuracy of the combined model is improved.

5.5. *Forecasting of EVs charge and wind power model*

According to the combined forecasting method, the generating power of a wind farm with 66 (1.5 MW) units in the next 2 days (192 points/48 h) is obtained, and the EVs charge in two regions (EV1 and EV2) are forecasted by RVM model which is trained by the 26 days' history data, as shown in Fig. 14. It can be seen from Fig. 14 that the charging curves of the two regions have an approximate trend. These two curves show that the trough period of charging load is in night and the peak period of charging load is in the day.

In the first day, the wind power is greater than the electric vehicle charge power from 0:00 to10:00, wind power can basically meet EVs charge of the region EV1 or EV2 from 10:00 to12:00, wind power can satisfy most of the EVs charging region EV1 or EV2 from 12:00 to 24:00, but the next day the wind power forecasting from 8:00 to 20:00 cannot satisfy with the EVs charge of region EV1 or EV2, it need other forms of energy to supplement EVs. However, the forecasting value of wind power can meet the EVs charge of region EV1 or EV2 from 20:00 to 24:00. The forecasting curves of wind power and EVs charge can provide the energy complementary scheduling; it can also guide EVs to charge when wind power is abundant according to changes of the electricity price.

The curve in Fig. 15 (a) can be obtained by the expression P_{wind}-P_{EV1}. There are 91 points with positive difference and 101 points with negative value. According to the expression P_{wind}-P_{EV2}, the curve in Fig. 15 (b) can be obtained. There are 105 points with positive difference and 87 points with negative value. As can be seen from Table 5, the difference sum of P_{wind}-P_{EV1} curve is −20595.6kw, and the difference sum of P_{wind}-P_{EV2} curve is 755172.4kw. In Fig. 15(a) and (b), the EVs charging time is mainly concentrated in the case of negative difference, while the wind power is mainly concentrated in the case of positive difference. This difference curve can provide the basis for the power system to make the scheduling plan of peak load shaving. Wind power as a whole does not meet the demand of EVs charging in Fig. 15 (a), EVs charging need to consume power from the system; the overall wind power far meets the changing needs of EVs in Fig. 15 (b), and the excess power can be sent to the power system.

6. Conclusions

The wind power combined forecasting is actually a process of information fusion. Based on the entropy right method, the wind power combined forecasting model has been established, and the following conclusions are obtained:

(1) BP neural network, wavelet neural network, and RVM (Relevance vector machine) can predict the power of wind power, but each individual wind power forecasting has its

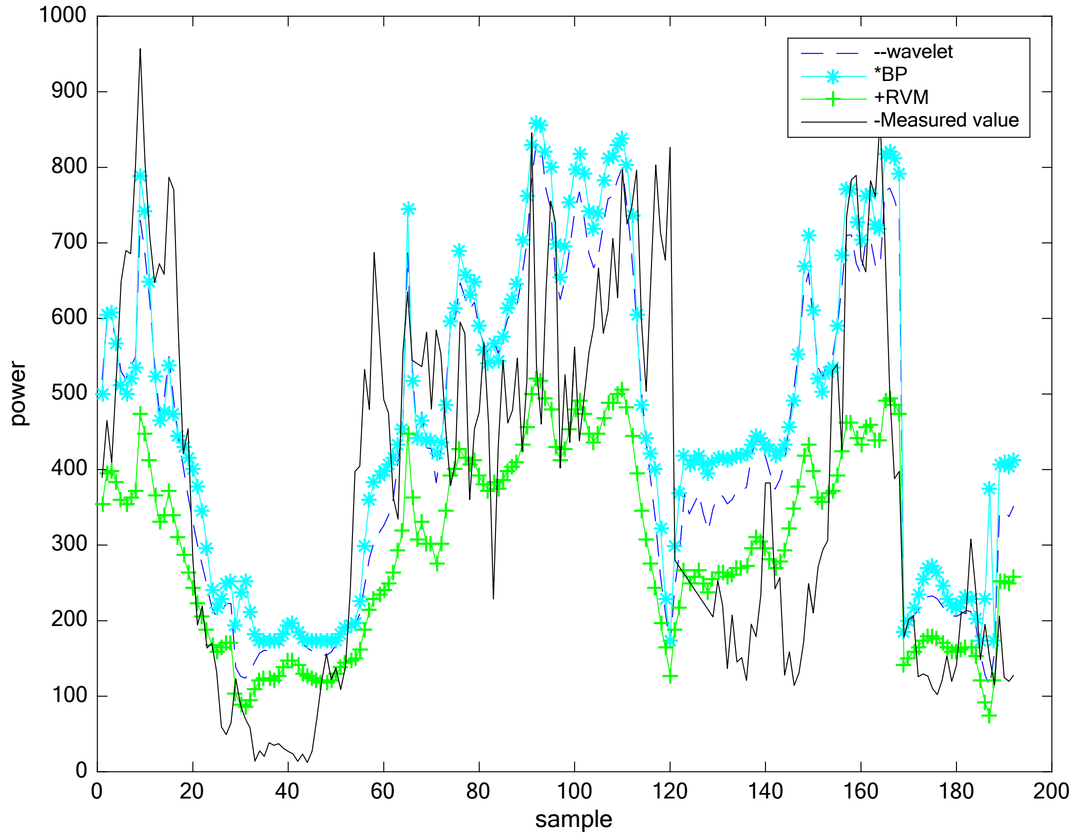

Fig. 10. 10# unit forecasted results of single model.

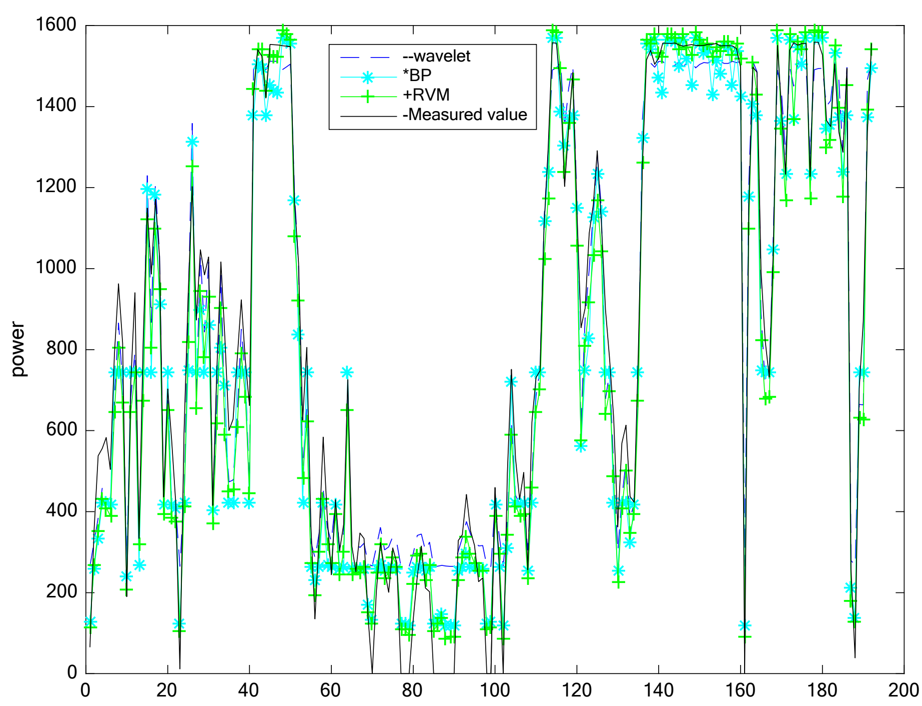

Fig. 11. 16# unit forecasted results of single model.

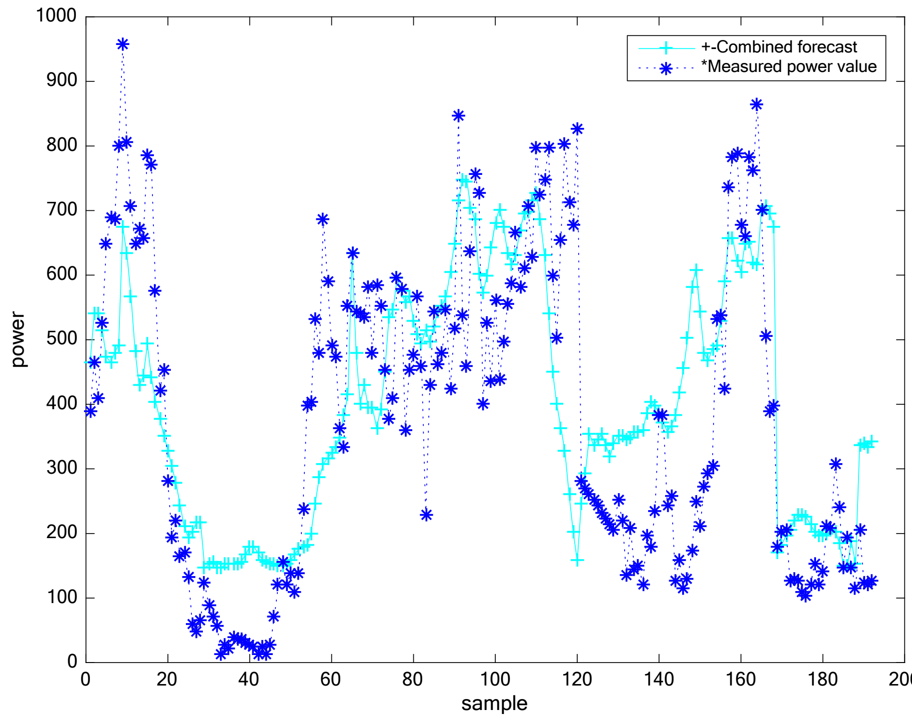

Fig. 12a. 10# unit forecasted results of combined forecasting model 1(Combined 1).

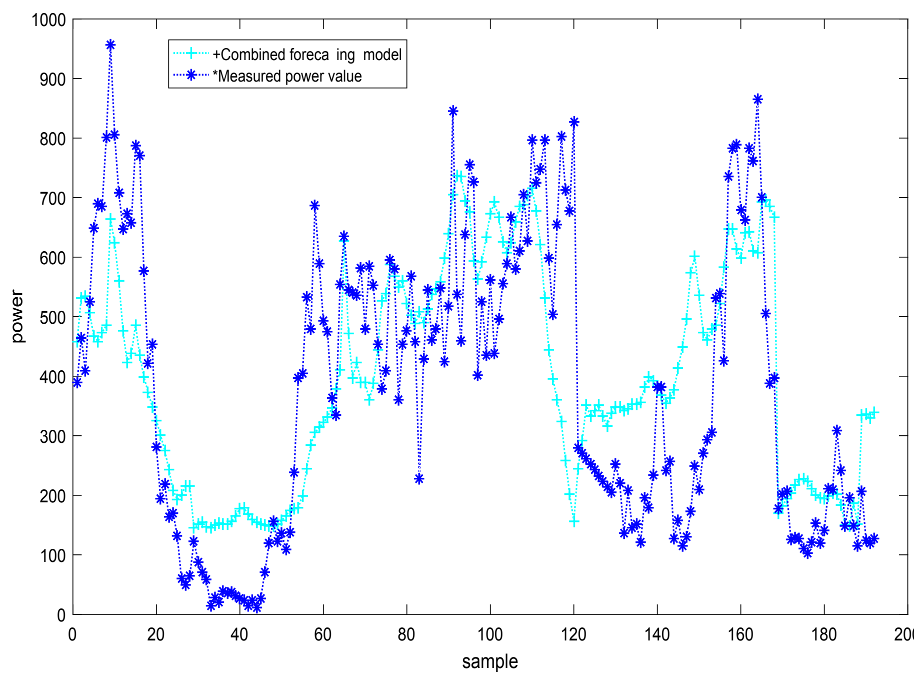

Fig. 12b. 10# unit forecasted results of combined forecasting model 2(Combined 2).

own limitations, which results in a large error. From the simulation results, the accuracy of the combined forecasting model based on entropy weight method is better than that of single forecasting model, which shows the feasibility of the combined forecasting model.

(2) Based on the historical data of wind power generation, the Gaussian cloud model is used to characterize the uncertainty of wind power qualitatively and quantitatively. The uncertainty information of the wind power unit's predicted power interval is provided by the Gaussian cloud model and the optimal combination of conventional units is obtained. Through the estimation of the error risk, the rapid and deep regulation of conventional units can be avoided as far as possible; so as to it can improve the power system economy, reduce the operation risk and reduce the wind abandon.

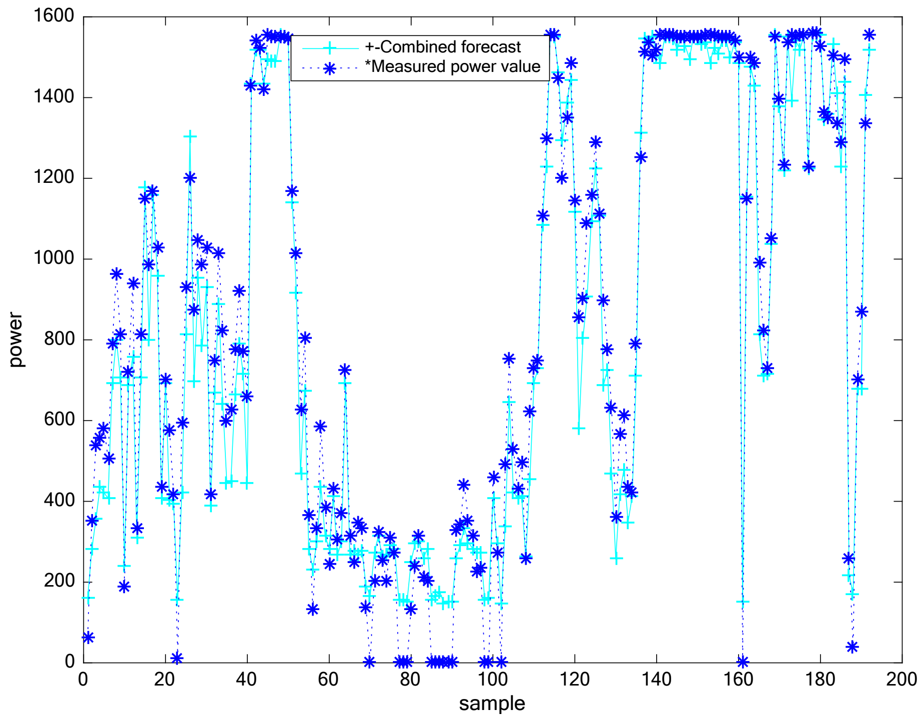

Fig. 13a. 16# unit forecasted results of combined forecasting model 1(Combined 1).

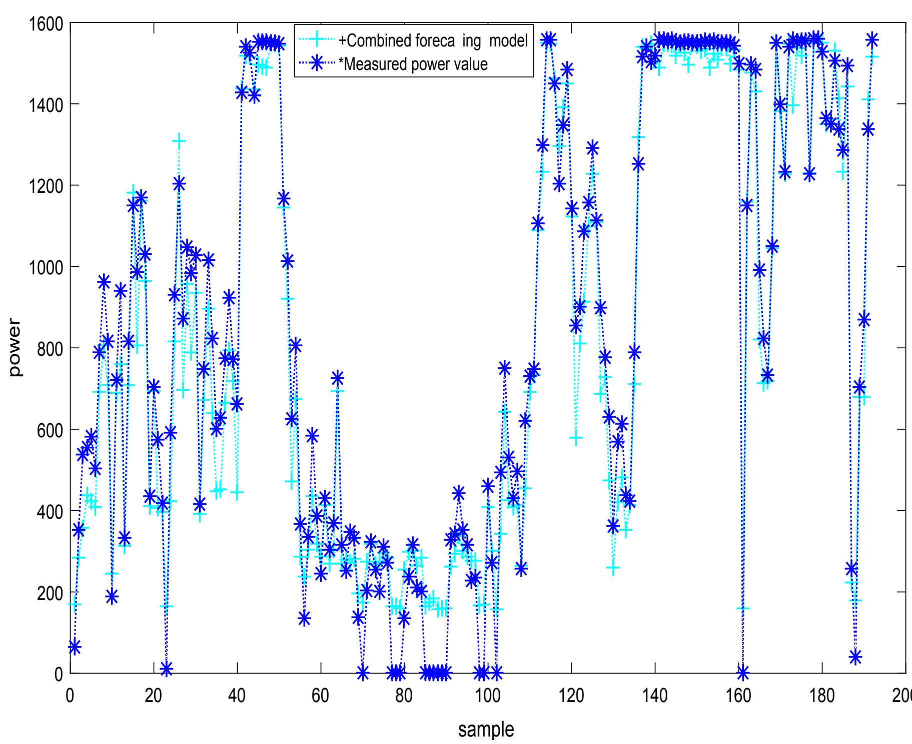

Fig. 13b. 16# unit forecasted results of combined forecasting model 2(Combined 2).

(3) According to the charging curve of EVs, the charging peak of EVs is from 12:00 to 20:00, while the wind power is mainly concentrated at night. The forecasting value of wind power and EVs charging can help coordinate and dispatch the comprehensive energy system, and also guide EVs to choose charging time according to peak and valley electricity price.

(4) In the future research, the multi-source uncertainty of wind power and EVs charging load will be fully considered for short-term forecasting of wind power and EVs charging load. Combined with the scheduling plan of the power system, we will focus on the optimal operation research of wind power generation and EVs charging load.

Table 4
Root mean square error and mean absolute error predicted by each model.

unit	Parameter	BP	Wavelet	RVM	Combined 1	Combined2
	RMSE	13.0157	12.1276	13.0590	11.5140	11.4664
10#	MAE	10.6928	9.5988	9.7567	9.1202	9.0889
	operation time	17.6018s	8.4247s	0.5048s	27.0484s	17.7851s
	Weights of 1	0.3289	0.3751	0.2959	1	
	Weights of 2	0.3333	0.3333	0.3333		1
	RMSE	6.7763	7.3458	6.4551	6.2913	6.3116
16#	MAE	5.1772	5.4671	5.1121	4.8001	4.8100
	operation time	18.4345s	8.7163s	0.4320s	26.0611s	18.6273s
	Weights of 1	0.3520	0.2792	0.3688	1	
	Weights of 2	0.3333	0.3333	0.3333		1

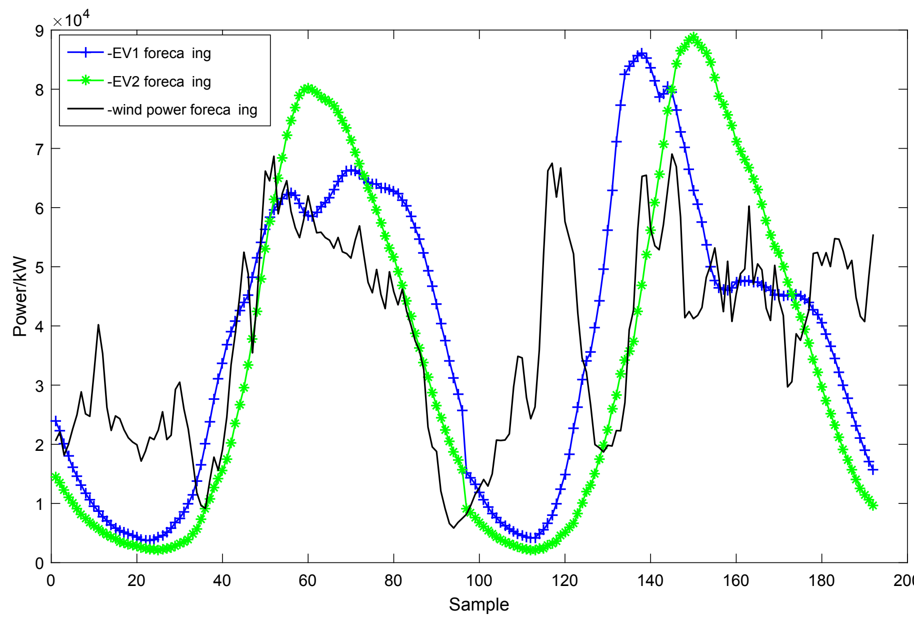

Fig. 14. EVs and wind power forecasting curve.

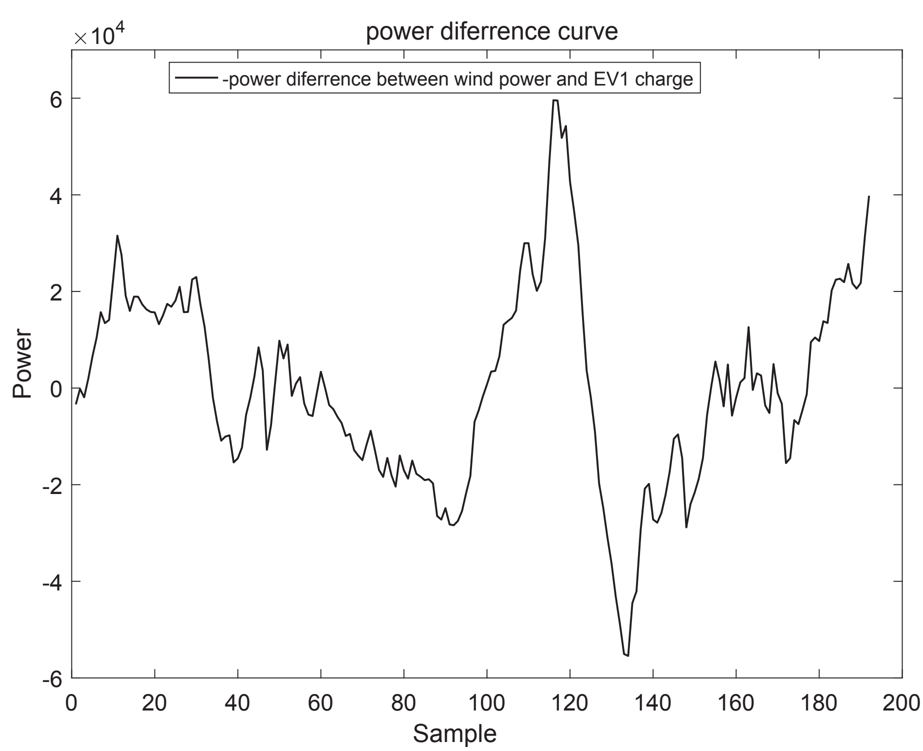

Fig. 15a. Power difference curve of wind power and EV1 charge.

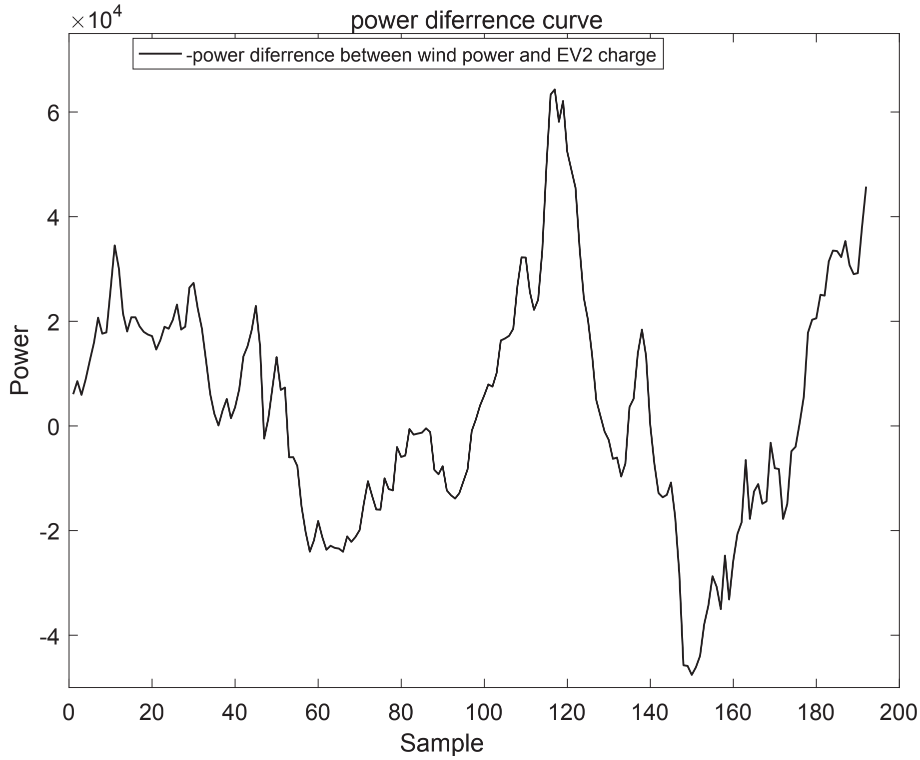

Fig. 15b. Power difference curve of wind power and EV2 charge.

Table 5
Power difference curve.

Curve	>0(Points)	<0(Points)	$\sum_{i=1}^{192}(P_{windi} - P_{EVi})$
P_{wind}-P_{EV1}	91	101	−20595.6 kW
P_{wind}-P_{EV2}	105	87	755172.4 kW

Author's contributions

1. Research concept and design: Jinhua Zhang.
2. Collection and/or assembly of data: Pin Li.
3. Data analysis and interpretation: Jinhua Zhang, Hang Meng, Bo Gu.
4. Writing the article: Jinhua Zhang.
5. Critical revision of the article: Jinhua Zhang, Hang Meng.
6. Final approval of article: Jinhua Zhang.

Declaration of competing interest

The authors (Jinhua Zhang, Hang Meng, Bo Go, Pin Li) declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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