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Ultra-short-term Wind Power Prediction based on Chaos Phase Space Reconstruction and NWP

Yang Gao, Aoran Xu, Yan Zhao, Baogui Liu, Liu Zhang and Lei Dong

Shenyang Institute of Engineering, Shenyang, China
gaoyangsie@163.com

Abstract

Wind power prediction accuracy is important for assessing the security and economy when wind power is connected to the grid, and wind speed is the key factor. This article presents a future four hours prediction scheme that combined chaos phase space reconstruction with NWP method. Historical wind speed data are reconstructed as phase space vectors, which are used as the first input part of prediction model, and the NWP data at the prediction time as the second input part. Wind speed at the height of turbine hub is derived from neural network model output. To test the approach, the data from a wind farm are used for this study. The prediction results are presented and compared separately to the chaos neural network model, NWP ANN model and persistence model. The results show that the method presented in this paper has higher prediction precision.

Keywords: *Wind Power Prediction, Chaos Phase Space Reconstruction, NWP, Ultra-Short-Term, Neural Network*

1. Introduction

Wind power generation has been developing rapidly in recent years as its environmental protection, renewability, and many other advantages, and it has been recognized as an ideal energy. By the end of 2011, the global wind power installed capacity has reached 238 GW, with China in a ratio of 26.3%, becoming the maximum wind power installed capacity [1]. Because the wind has great randomness and uncontrollability, the output power of wind farm also has the characteristics of volatility and indirectness, which resulting in difficulties in power grid pitch peak, reactive power and voltage control, affecting the security and stability of the power grid, and limiting the development of wind power. Therefore, the accurate prediction of wind power can reduce the influence of the wind power uncertainty effectively, thus providing protection for electric power department to make reasonable plan [2-7].

The dispatching department has two basic requirements for wind power prediction [8]: one is the short-term prediction, namely, forecasting the next day at 00:00 within 72 h of the wind farm output power, the time resolution of 15 min, whose purpose is to facilitate reasonable power grid scheduling, to ensure the quality of power supply. The other is the ultra-short-term prediction, that is, implementing schedule of 0~4 h rolling forecasts, which is to control wind turbines, and to advantage the power system real-time scheduling.

The wind speed of fan hub height is the most important determinants of fan power. Therefore, the effective wind speed forecast is a key link in the process of wind power prediction. At present, the main study of wind speed prediction is divided into two categories: statistical method based on historical data modeling and based on the numerical weather prediction and physical methods, such as topography. The former mainly includes the time sequence method [9-10], Kalman filtering [11], neural network [12-16], supporting vector machine (SVM) [11-12], etc. Modeling is relatively simple, and computing speed is fast, but the forecast accuracy declined with the increase of time

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fell sharply. Physical methods mainly include forecasting model based on numerical weather prediction (NWP) [17-19], spatial correlation method [20-21]. The model based on numerical weather prediction can get the wind speed, wind direction, temperature, pressure, humidity etc, of the future 1 to 3 days. This paper will combine the method which is based on historical data and physical method based on NWP, considering both the history of the wind speed information associated with the moment of forecast, and joined the meteorological information of prediction time. Using the nonlinear relation between neural network mapping and the wind speed of prediction moment, hybrid forecasting model is established. Hybrid model overcomes not only the statistical method accuracy decline with the increase of forecast time, also reduced the influence of different altitude meteorological information deviation is larger.

2. Relations between Wind Speed and wind Turbine Output Power

Wind power which wind turbine captured can be represented by type (1):

$$P = C_P A \rho v^3 / 2 \tag{1}$$

Where P is the fan power output (kW), C_P is the wind power coefficient, ρ is the air density ($\mathrm{kg/m^3}$), A is the area rotor swept (m^2), v is the wind speed ($\mathrm{m/s}$).

Fan hub height is usually within 60~80 m. In this scope of the height, it is generally thought that the air density is constant. Although the wind direction is changing, but the fan can aim at the direction of the wind by yaw controlling, and realize the maximum power point of tracking. So for the output power of fan, the wind speed is decisive.

Wind turbine generation power has directly determined relationship with the wind speed. In order to get more accurate wind generation power prediction, the best way is to estimate the fan hub height of wind speed, then through the basic characteristic curve of wind turbine to calculate the wind generation power.

3. Neural Network Prediction based on Chaos Phase Space Reconstruction

3.1 Chaos Phase Space Reconstruction

For a given time series, x_1, x_2, … , x_{n-1}, x_n, we usually extend it to 3 d or more high-dimensional space, in order to show the information contained in the time series, which is the method of delaying coordinate state space reconstruction.

Based on the embedding theorem of takens [22], as long as the embedding dimension is big enough, namely the dimension of delay coordinate (D is the dimensions of the power system), in the embedded dimension it can be put in regular orbits (attractor) recovery, that is, orbit of refactoring space has differential homeomorphism with prime mover system, and its topological structure completely same with the original attractor.

For chaotic time series x_1, x_2, … , x_{n-1}, x_n, If the embedding dimension is m, delay time is τ, then the phase space reconstruction is

$$Y(i) = [x(i), x(i+\tau), x(i+2\tau), ..., x(i+(m-1)\tau)], i = 1,2,...,N \quad N = n-(m-1)\tau \tag{2}$$

Where any phase point contains a component (or state), the number of samples is N after reconstruction. For a pattern which is constructed by N phase points in the phase space, attachment between phase point is to describe evolution trajectory of system in d in phase space.

The selection of the embedding dimension and delay time is very important. There are a variety of methods to choose from. This article adopts mutual information method [19] calculating the amount of delay time, Cao method [23-26] calculating embedding dimension. Checking whether wind power time series have chaotic properties needs to compute the maximum Lyapunov index of the time sequence of [27], which is only available modeling phase space reconstruction method when it is bigger than zero.

Using a certain wind farm 2011-1-1 0:00 to 2011-1-1 23:45 (a resolution of 15 minutes), a total of 1440 sets of data as the training sample, calculate the wind speed time series phase space reconstruction parameters as Table 1.

Table 1. Wind Speed Time Sequence Parameters in a Wind Farm

Embedding dimension m	8
Delay time τ	8
Maximum lyapunov index	0.0097

3.2 GRNN Prediction Model based on Chaos Phase Space Reconstruction

Generalized regression neural network (GRNN) is a branch of RBF neural network, its way to get the relationship of the data is different from the interpolation and fitting, it can change network directly under the same structure through sampling or data by calculated and don't need to recalculate the parameters. Unlike typical BP network, simulation effect of NN network is better than BP neural network. It has better prediction effect, fast calculation and stable results. Only though a simple smoothing parameter, don't need training cycle process [28-29].

GRNN is a feed forward neural network model based on nonlinear regression theory. Unlike typical BP network, it approaches by activation of neurons function, that is, the function of input vector value approximates by a function of neuron vector which corresponding with its neighborhoods map to form it, GRNN network is composed of input layer, hidden layer and output layer, as shown in Figure 1.

The hidden layer radial base layer, adopting Gaussian transformation function to control the hidden layer output, thereby inhibiting activation of output units, in the input space, Gaussian function is symmetrical about acceptance domain. The network output impact by input neurons exponentially attenuate varies with the distance between the input vector. In GRNN network, each training vector has a corresponding radial neurons in the hidden layer, neurons in hidden layer to store each training vector. When a new vector enters the network, the distance between the new vector and each unit weight vector in the hidden layer can be calculated by the next type:

$$dist = \left| X - W^1 \right| \tag{3}$$

Where X is input vector, R is the dimension of X, s^1 is the number of hidden layer unit, W^2 is the unit weight vector of hidden layer, dist is the distance between the input vector and weight vector. The Gaussian function output of hidden layer accord to the following formula:

$$a^1 = \exp\left(-(dist \times |^1 b)^2\right) \tag{4}$$

Distance can be adjusted by the type of computer:

$$b_1 = 0.8326 / s \tag{5}$$

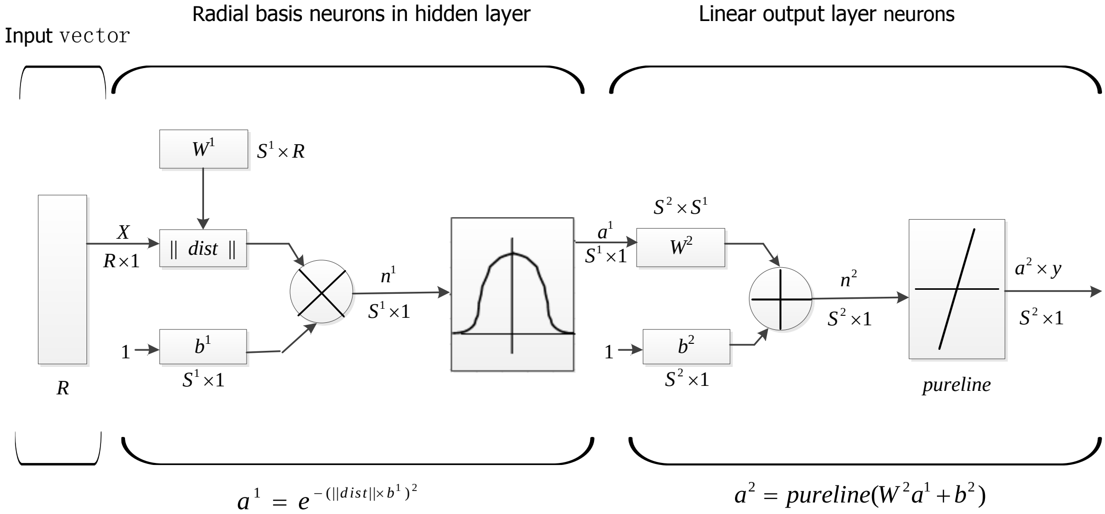

Figure 1. Structure of GRNN

The s is the window width. If dist = s adjusted distance of N1 equals to $|| dist || \times b1$= 0.8326, Gaussian function output a value of 0.5, equivalent to the correlation coefficient is 0.5. If dist is far greater than s, Gaussian function output is close to zero. With the increase of $n1$, output of hidden layer decreases. Variable s play the role of a window, that is to say the size of s plays to activate neuron in output layer. The larger the s, the smaller the $b1$. Distance between neurons in hidden layer and input vector is reduced, so the number of neurons in window which is activated, increased and conversely, the smaller the s, the greater the b. Distance between neurons in hidden layer and input vector is amplified, so output of hidden layer decreases, and the number of neurons in window which is activated declined.

GRNN network output layer is linear with W^2 neuron, whose output calculated according to next type:

$$a^2 = n^2 = W^2 a^1 + b^2 \tag{6}$$

Where W^2 is weight in the second layer.

We can see the GRNN network has less artificial adjustment of parameters with only one threshold s. Network learning all depend on the data sample. This characteristic determines the GRNN network to avoid the effect of subjective assumptions on the result of prediction to best extent possible.

Set the embedding dimension number of GRNN network for input nodes, and the input data correspond to each phase component of wind speed time series after refactoring. Output node number is 1, and the output data corresponding to wind speed value of the next moment. Fig. 2 shows the structure of chaotic neural network prediction model.

The input of the model is the history value of the wind speed time series. In multi-step prediction, the unknown input of model displace by the value predicted. Due to the short-term predictability of chaotic time series, the precision of prediction is on the decline when there are more forecast steps.

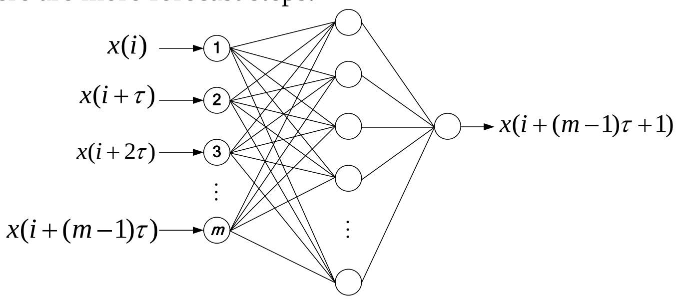

Figure 2. Chaos Neural Network Prediction Model

4. Neural Network Prediction based on NWP

NWP is one of the most important input data of the current mainstream wind power prediction system. The surface wind is affected by complex boundary conditions, such as topography, surface roughness, and atmospheric turbulence.

Figure 3 shows the NWP information as input of neural network prediction model of structure. NWP data information includes wind speed, wind direction, temperature, humidity, air pressure, etc. Here we choose wind speed and wind direction as input of prediction model, and the output of the model is the wind speed of fan hub height.

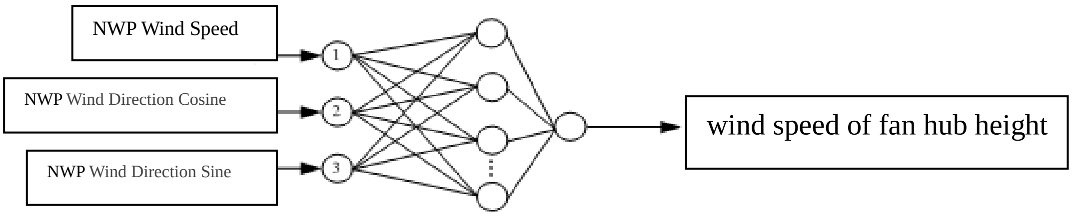

Figure 3. NWP Neural Network Prediction Model

5. Hybrid Forecasting Model

Considering that the wind speed in prediction time point related with both historical wind speed sequence and weather forecast of prediction time. We established Figure 4 neural network prediction model, which is based on history wind speed time series and data of wind speed, wind direction weather forecast.

Input of this hybrid forecasting model is m+3 in total (m is the embedding dimension of the phase space after reconstruction), value m, weather forecast wind speed value of the forecasting moment 1, cosine of weather forecast wind direction values and sine of direction value of each one respectively. The output of the neural network model is fan hub height wind speed of the predict moment. We use the chaotic phase space reconstruction method described in section 2.1 to establish the relationship between historical wind speed value and the wind speed value of predict time, m historical wind speed value are m component of phase point in reconstruction phase space respectively, which has the most close relationship between wind speed prediction time [30-35].

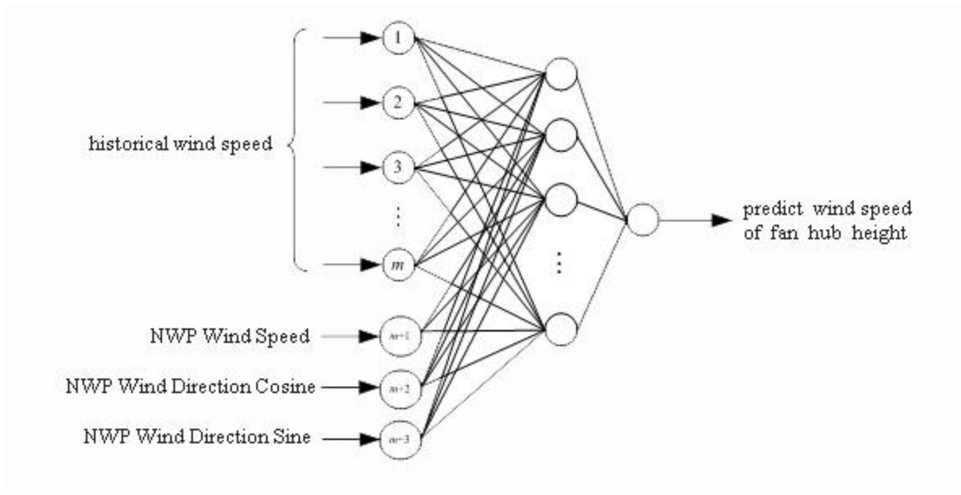

Figure 4. Hybrid Prediction Model

5.1 Sample Introduction and Data Preprocessing

Researching data use the whole line of wind speed data and NWP data from Europe of a wind farm from January 1, 2013 to January 16. We chose a total of 1440 sets of data as the training sample from 0:00, 2013-1-1 to 23:45, 2013-1-15 and a total of 24 hours 96 groups data as predicting sample from 00:00, 2013-1-16 to 23:45, whose data resolution is 15 min.

The corresponding training sample is the data 15 days prior to predict time using 4 hours rolling forecast method, which predict samples selected 4 hours each time.

Due to the unit and magnitude of the sample data are different, in order to calculate conveniently and avoid some neurons reaching supersaturated state, we need to normalize the sample data.

(1) Wind speed normalization

Statistics of extreme wind speed in many years can be used in wind speed data normalization [36-37]. Wind speed data includes wind speed value predict by numerical weather system and fan hub height wind speed value by measured.

(2) Wind direction normalization

Wind direction refers to the direction of the wind that is dividing the circumference into 360, due north direction as 0. To distinguish all of the wind direction, we need to take the wind's two sine and cosine values as the model input.

5.2 Model Training and Prediction

Take a neural network training according to input and output point in the Fig. 5, the first input part is the m dimensional vector after historical wind speed time series phase space reconstruction: the actual wind speed $(m\text{-}1)\tau+1$ time before the predict moment (i), the actual wind speed $(m\text{-}2)\tau+1$ time before the predict moment ($i+\tau$), … , the actual wind speed 1 time before the predict moment ($i+(m\text{-}1)\tau$); the second input part is: weather forecast wind speed value, the cosine and sine of the weather forecast wind direction value of the forecasting moment.

Due to the input of the model contains the historical data of wind speed, for 4 hours 16 step prediction, the historical data used in the point after the second prediction time is also required for the unknown. So we must use estimated value of the time instead of sample input, as shown in Fig. 6.

GRNN network input node number is m+3, output node number is 1, window width parameters of the network s values 0.15.

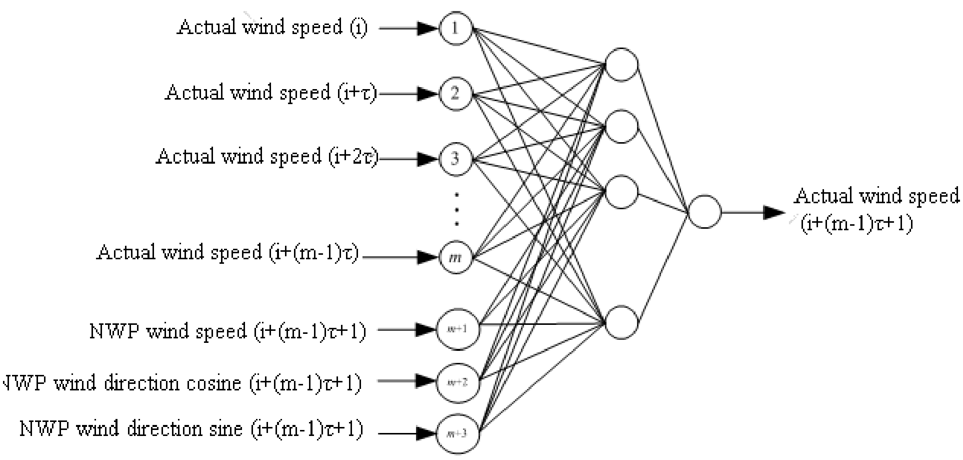

Figure 5. Input and Output of Training Model

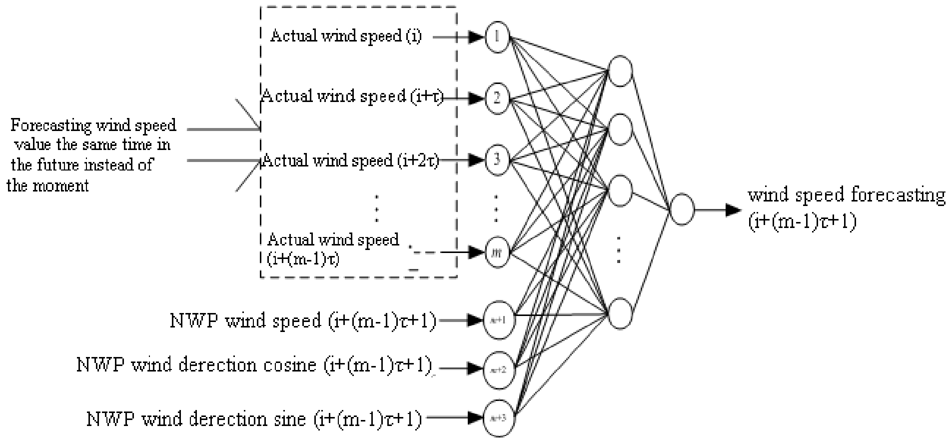

Figure 6. 16 Step Prediction Model

5.3 Predicted Results Comparison

Prediction sample data for the day is divided into six periods, each period of 4 hours prediction respectively. Extract 4 hours prediction data and the corresponding training sample by rolling method. Table 2 lists six time 4 hours prediction error of the hybrid model of chaotic phase space reconstruction and NWP method.

In order to compare the prediction effect, we use the same predicting sample and training sample, getting prediction of rolling 4 hours, a total of 6 hours' chaotic neural network model, NWP neural network model and continuous model respectively. Wind speed curve of comparison between the prediction models are shown in Figure 7.

Table 2 lists the average forecasting error of four different prediction models. NMAE is normalized mean absolute error and NRMSE is the normalized root mean square error. We can see from Table 3, the precision of the hybrid forecasting model is the highest. Prediction accuracy of single NWP neural network model is the worst.

Results show that the hybrid model brings out the advantages of chaotic phase space reconstruction and NWP, both considering the historical wind speed information related to the forecast moment and joining the NWP which is closely related to the wind speed prediction time information, making the prediction accuracy be improved.

Table 2. Wind Speed Error of Four Hours Prediction

Forecast period	NMAE/%	NRMSE/%
00:00~03:45	5.91	7.44
04:00~07:45	2.32	2.94
08:00~11:45	3.73	4.27
12:00~15:45	6.81	7.42
16:00~19:45	7.50	8.25
20:00~23:45	3.09	3.47

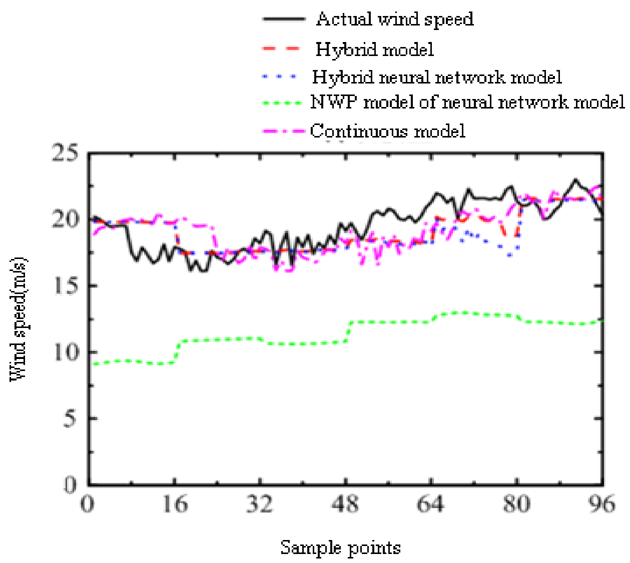

Figure 7. Wind Speed Comparison Curves of Prediction Models

Table 3. NMAE and NRMSE of Four Prediction Models

Prediction model	NMAE/%	NRMSE/%
Hybrid forecasting model	4.89	5.63
Chaotic neural network model	5.77	6.52
NWP neural network model	32.44	32.62
Continuous model	5.67	6.62

6. Conclusion

The text proposes that hybrid model is the combination of chaotic phase space reconstruction model with NWP neural network forecast model. Model input parameters both considering historical wind speed information related to the forecasting time and joining the meteorological information of the prediction time. Combining GRNN neural network, mapping these two pieces of information and nonlinear relationship between wind speed forecasting time, 4 hours multi-step prediction model is established.

Hybrid model not only overcomes the problem that statistical method accuracy declines with the increase of forecast time, but also reduced the impact of meteorological information inaccuracy. Predicted results comparison shows that the hybrid model can be better used in the ultra-short-term wind speed multi-step forecast.

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Authors

Yang Gao, he received the PhD degree in Power System and Automation from Shenyang Agricultural University, Shenyang, China, in 2012. His research interests include fault diagnosis and uncertain theory.

Aoran Xu, he received the M.S degree in Power System and Automation from Beijing Jiaotong University, Beijing, China, in 2008. His research interests include fault diagnosis and uncertain theory.

Yan Zhao, he received the Ph.D. degree in control engineering from Northeastern University, Shenyang, China, in 2008.

He is currently an associate professor with the School of Renewable Energy, Shenyang Institute of Engineering, Shenyang. His current research interests include fuzzy control, neural networks, and intelligent control.

Baogui Liu, he received the M.S degree in Power System and Automation from Wuhan University, China, in 2006. His research interests include wind turbine generator system.

Liu Zhang, she received the M.S degree in Power System and Automation from Northeast Dianli University, Jili, China, in 2008. Her research interests include data set for power performance measurement.

Lei Dong, he received the PhD degree in Power System and Automation from Beijing Institute of Technology, Beijing, China, in 2002. His research interests include fault diagnosis and uncertain theory.