Research Article

An RBF Neural Network Combined with OLS Algorithm and Genetic Algorithm for Short-Term Wind Power Forecasting

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An accurate forecasting method for power generation of the wind energy conversion system (WECS) is urgently needed under the relevant issues associated with the high penetration of wind power in the electricity system. This paper proposes a hybrid method that combines orthogonal least squares (OLS) algorithm and genetic algorithm (GA) to construct the radial basis function (RBF) neural network for short-term wind power forecasting. The RBF neural network is composed of three-layer structures, which contain the input, hidden, and output layers. The OLS algorithm is used to determine the optimal number of nodes in a hidden layer of RBF neural network. With an appropriate RBF neural network structure, the GA is then used to tune the parameters in the network, including the centers and widths of RBF and the connection weights in second stage. To demonstrate the effectiveness of the proposed method, the method is tested on the practical information of wind power generation of a WECS installed in Taichung coast of Taiwan. Comparisons of forecasting performance are made to the persistence method and back propagation neural network. The good agreements between the realistic values and forecasting values are obtained; the test results show the proposed forecasting method is accurate and reliable.

1. Introduction

Rising crude oil prices and worldwide awareness of environmental issues highlights the exploitation of renewable energy technologies [1]. The wind power is one of the most attractive renewable energy applications because of its high efficiency and low pollution [2, 3]. However, since the power produced by the WECS is varied with the atmosphere meteorology and wind speed, unexpected variations of the WECS power generation may increase operating costs for the electricity system because the requirements of primary reserves will be increased, and place potential risks to the reliability of electricity supply [4].

The power system operators have to predict the wind power production in order to schedule the spinning reserve capacity and to control and operate the utility grid [4]. To reduce the spin reserve margin capacity and increase the wind power penetration, the accurate forecasting of wind power is needed for power system operations [5]. An accurate wind power forecasting can help to improve competitive market

designs, real-time grid operations, standards of interconnection, ancillary service requirements, and quality of power [6]. In addition, wind power forecasting plays an important role in the allocation of balancing power. Wind power forecasting is used for the day-ahead scheduling of conventional power plants and trading of electricity on the spot market [7].

Although the prediction accuracy of wind power forecasting is lower than the prediction accuracy of load forecasting. Wind power forecasts still play a key role in addressing the operation challenges in electricity supply [8]. Recently, several methods have been employed for the wind power forecasting. Many literatures have been devoted to the improvements of wind power forecasting approaches by researchers with wide experience in the field tests. A number of wind power forecasting methods have been developed and launched on wind farms. The wind power forecasting methods can be generally categorized into six groups: persistence method, physical method, statistical method, spatial correlation method, artificial intelligence method, and hybrid approach.

Persistence method is based on a simple assumption that the wind speed and wind power at a certain future time will be the same as it is when the forecast is made [9]. The persistence method not only is the simplest but also is the most economical wind forecasting method. If the measured wind speed and wind power at t are $v(t)$ and $P(t)$, then the forecasting wind speed and wind power at $t + \Delta t$ can be formulated as the following term:

$$
\begin{aligned}
v(t + \Delta t) &= v(t), \\
P(t + \Delta t) &= P(t).
\end{aligned}
\tag{1}
$$

Physical method is based on numerical weather prediction (NWP) using weather forecast data like wind speed, pressure, temperature, surface roughness, and obstacles. NWP model is developed by meteorologists for large-scale area weather prediction [5]. In general, wind speed obtained from the local meteorological service and transformed to the WECS at the wind farm is converted to wind power [10]. The physical methods are rendered on supercomputers as they need lots of computations.

Statistical methods aim at finding the relationship of the online measured wind power data. For a statistical model, the historical power generation data of the WECS is used. Statistical models are easy to model and cheaper to develop compared to other models. Basically, statistical method is good for short-term forecasting. The disadvantage of this method is that the prediction error increases as the prediction time scale increases [8]. Statistical methods include the autoregressive (AR), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), Bayesian approach, and gray predictions.

The spatial correlation models take the spatial relationship of different sites' wind speed into account. In spatial correlation models, the wind speed time series of the predicted point and its neighboring points are employed to predict the wind speed [5]. A spatial correlation model is used for predicting wind speed at one site based on measurements at another site. Its behavior has been tested with satisfactory verification using data collected over seven years [11].

Based on the development of artificial intelligence (AI), various new AI methods for wind power prediction have been developed. An AI method is to mimic the learning processes of the brain to discover the relations between the variables of a system [8]. The new developed AI methods for wind power prediction include artificial neural network, adaptive neuro-fuzzy inference system, fuzzy logic methods, support vector machine, evolutionary optimization algorithms, and neuro-fuzzy network.

The object of hybrid wind forecasting methods is to benefit from the advantages of individual model and obtain a globally optimal forecasting performance [12]. Since the information contained in the individual forecasting method is limited, hybrid method can maximize the available information, integrate individual model information, and make the best use of the advantages of multiple forecasting methods thus improving the forecasting accuracy [13]. The literatures show that the hybrid methods generally produce good wind forecasting results compared to individual models [8]. The hybrid methods combine different approaches such as mixing physical and statistical approaches or combining short-term and medium-term models [6].

Recently, RBF neural network methods have received a great deal of attention and were proposed as powerful computational tools to solve the forecasting problem. RBF neural network is able to provide universal approximation, and in the hidden layer of RBF neural network, basis functions are utilized. RBF neural network could extract implicit nonlinear relationships among input variables by learning from training data. RBF neural network is applied to forecast the power generation of WECS in this paper.

This paper employs the OLS algorithm to select a suitable set of centers of RBF from the input data. The OLS algorithm is a systematic method that employs the forward regression procedure to reduce the size of RBF neural network [14]. In this paper, the GA is also applied to the training phase of RBF neural network, to obtain a set of weights, centers, and widths that will minimize the error function in competitive time. The weights, centers, and widths are progressively updated until the convergence criterion is satisfied. In the process of searching for the global optimum solution, GA needs neither the information of gradient nor the calculus computing, it can find out the global optimum solution or near-optimal solution in the solution space with high probability, and it could reduce the probability of getting into the local minimum efficiently [15].

This paper deals with the power generation forecasting of WECS and is divided in seven sections. After a brief introduction, Section 2 introduces the principle of RBF neural network. Section 3 is entirely dedicated to OLS algorithm-based optimal hidden layer node number selection scheme. Section 4 describes GA-based RBF neural network training procedure. Section 5 discusses the RBF neural network-based wind power forecasting method. Numerical results are described in Section 6. The conclusions of the paper are summarized in Section 7.

2. Principle of RBF Neural Network

The RBF neural network is a useful methodology for systems with incomplete information. It can be used to analyze the relationships between one major (reference) sequence and the other comparative ones in a given set [16]. In this section, the principle of RBF neural network is described.

The RBF neural network is a forward networks model with good performance and global approximation, and which is free from the local minima problems [17]. It is a multiinput, multioutput system consisting of an input layer, a hidden layer, and an output layer. During data processing, the hidden layer performs nonlinear transforms for the feature extraction and the output layer gives a linear combination of output weights [18]. The structure of RBF neural network is shown in Figure 1.

The network actually performs a nonlinear mapping from the input space R^d to the output space R^m. The mapping
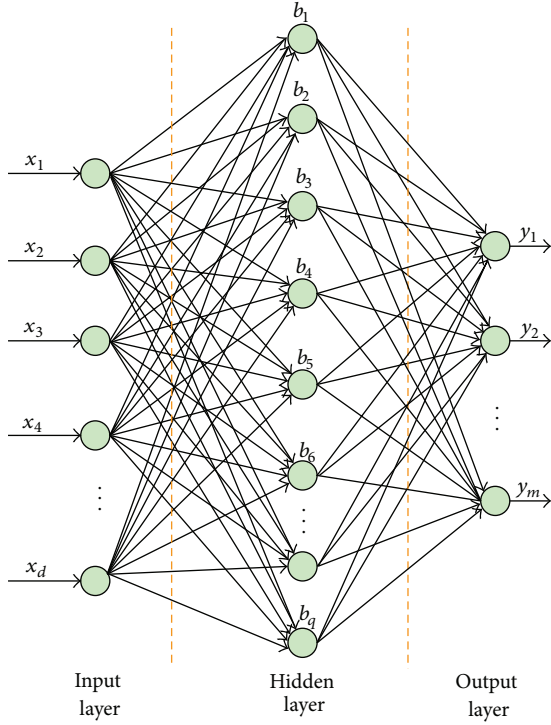
FIGURE 1: Architecture of the RBF neural network.

relationship between input vector and output vector of RBF neural networks is based on the following function:

$$\text{RBF Neural Network} : \begin{cases} R^d \longrightarrow R^m, \\ \overline{x} \longrightarrow \overline{y}, \end{cases} \quad (2)$$

where input vector $\overline{x}_i = \{x_i, \text{for } i = 1, 2, \ldots, d\}$, output vector $\overline{y}_i = \{y_i, \text{for } i = 1, 2, \ldots, m\}$.

Each hidden neuron computes a Gaussian function in the following equation:

$$b_j(\overline{x}) = \exp\left[\frac{-\left(\overline{x}^T - \overline{\mu}_j\right)^2}{2\sigma_j^2}\right], \quad \text{for } j = 1, 2, \ldots, q, \quad (3)$$

where μ_j and σ_j are the center and the width of the Gaussian potential function of the jth neuron in the hidden layer, respectively.

Each output neuron of the RBF neural network computes a linear function in the following form:

$$y_k = \sum_{j=1}^{q} w_{kj} b_j(\overline{x}), \quad \text{for } k = 1, 2, \ldots, m, \quad (4)$$

where y_k is output of the kth node in the output layer, w_{kj} is weight between jth node in the hidden layer and kth node in the output layer, and $b_j(\overline{x})$ is output of the jth node in the hidden layer.

3. OLS Algorithm-Based Optimal Neurons Number Selection Scheme

The OLS algorithm [14] can be implemented by introducing an error term of (4) as follows:

$$y_k = \sum_{j=1}^{q} w_{kj} b_j(\overline{x}) + e_k. \quad (5)$$

Using matrix form, (5) can be expressed as

$$Y = BW + E, \quad (6)$$

where $Y \in \mathfrak{R}^{m \times 1}$ is the vector of the desired network outputs; $B \in \mathfrak{R}^{m \times q}$ can be regarded as a regression matrix with each column vector $b \in \mathfrak{R}^{m \times 1}$; $W \in \mathfrak{R}^{q \times 1}$ is a vector of weights; $E \in \mathfrak{R}^{m \times 1}$ is the vector of errors between the desired and actual network outputs.

By using the Gram-Schmidt orthogonalization [19], the regression matrix B can be decomposed into a set of orthogonal basis vectors as follows:

$$B = DA = \begin{bmatrix} d_1 & d_2 & \cdots & d_q \end{bmatrix} \times \begin{bmatrix} 1 & a_{12} & \cdots & a_{1q} \\ 0 & 1 & \cdots & a_{2q} \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ 0 & 0 & \cdots & 1 \end{bmatrix}, \quad (7)$$

where $A \in \mathfrak{R}^{q \times q}$ is an upper triangular matrix, and $D \in \mathfrak{R}^{1 \times q}$ is a matrix with mutually orthogonal vector d_i such that

$$D^T D = H = \text{diag}\left(h_1, h_2, \ldots, h_q\right), \quad (8)$$

where $h_i = d_i^T d_i = \sum_{k=1}^{q} d_{ik}^2$ is a diagonal element of matrix H.

Aggregating (6) to (8), the desired network outputs can be rewritten as

$$Y = DAW + E = DG + E, \quad (9)$$

where $G = AW$. Since the Gram-Schmidt orthogonalization ensures the orthogonality between E and DG in (9), we have

$$Y^T Y = G^T D^T DG + E^T E = \sum_{k=1}^{q} h_k g_k^2 + E^T E. \quad (10)$$

Therefore, the error reduction ratio (ERR) due to the inclusion of the kth center can be defined as

$$\text{ERR}_k = \frac{h_k g_k^2}{Y^T Y}. \quad (11)$$

The ERR in (11) provides an effective criterion for selecting the RBF centers in a forward regression manner. At every step of the forward regression, an adequate RBF center is selected so that the value of ERR is the maximum. The regression is terminated at the q_1th step when

$$1 - \sum_{k=1}^{q_1} \text{ERR}_k < \Theta, \quad (12)$$

where $0 < \Theta < 1$ is a tolerance value selected by the operators.

4. GA-Based RBF Neural Network Training Procedure

GA is a search method utilizing the mechanism of natural selection and genetics. The application of genetic algorithm to optimization has become a useful tool in many fields. The GA algorithm for training the RBF neural network by tuning the position of RBF centers, the width of RBFs, and the connection weights is described as follows [20, 21].

Step 1 (initialize the parameters of RBF neural network). Randomly produce a population of chromosomes which consist of the three parameters: the output weights, the centers of RBF hidden units, and widths of RBF hidden units. GA is started with 20 randomly generated chromosomes.

Step 2 (evaluation of fitness value). The criterion of mean squared error function defined below is adopted to stand for the fitness value of the RBF network

$$J = \frac{1}{m} \sum_{k=1}^{m} (y_k - \widehat{y}_k)^2, \tag{13}$$

where $\widehat{y}_k$ is the computed output of the RBF network by using (4), y_k is the corresponding desired output, and m is the number of network output nodes.

Step 3 (selection operation). An individual is probabilistically chosen based on the fitness value, and the selected individual is copied into the next generation without any change.

Step 4 (crossover operation). Crossover will introduce a new population of individuals, and mutation is used to randomly alter the allele of a gene. The probability of crossover in this paper is 0.6.

Step 5 (mutation operation). A number of individuals were selected randomly from the population according to a certain probability. The probability of mutation in this paper is 0.02, and the mutation operation is then performed.

Step 6 (stopping rule). Repeat Steps 2 to 5 until the best fitness value can satisfy the minimum requirement or the given count of total generations is reached. The solution with the lowest fitness value is chosen as the best parameter in the RBF network that shall further be applied to wind power forecasting.

5. RBF Neural Network-Based Wind Power Forecasting Method

The proposed RBF neural network-based wind power forecasting method has been successfully implemented for the power generation of WECS-forecasting. The architecture of the RBF neural network-based wind power forecasting method is shown in Figure 2. The RBF neural network model was developed for 10-minute ahead wind power forecasting. The architecture of RBF neural network used in this study contains an input layer, an output layer, and a hidden layer.
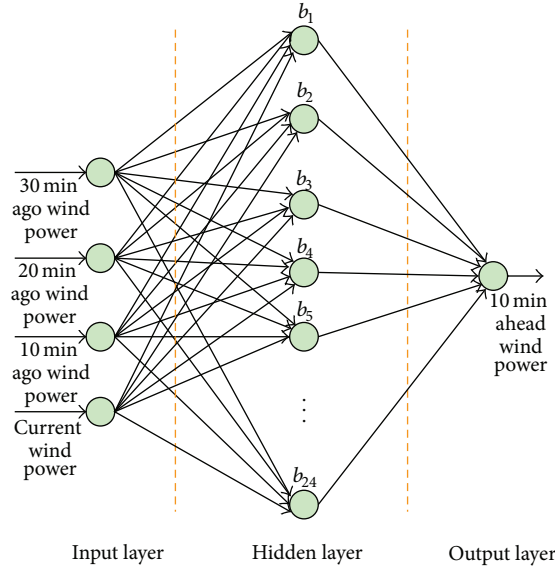

FIGURE 2: The architecture of the proposed RBF neural network based wind power forecasting method.

Input layer has 4 neurons forthe wind power output of 30 minutes ago, 20 minutes ago, 10 minutes ago, and the current wind power output; hidden layer has 24 neurons (the number of neurons is selected by OLS algorithm); and output layer has one neuron for the 10-minute ahead wind power forecasting.

The overall flowchart of proposed RBF neural network-based wind power forecasting method is shown in Figure 3. The proposed forecasting method is described briefly in the following steps.

Step 1. Creating data base of the wind power generation of WECS.

Step 2. Normalize all of the wind power generation data.

Step 3. Prepare the training set for RBF neural network.

Step 4. Use the OLS algorithm to select the optimal number of neurons in hidden layer of RBF neural network.

Step 5. Use the GA to train the RBF neural network for wind power forecasting.

Step 6. Save the Gaussian functions centers, widths and connection weights between the hidden and output layers of trained RBF neural network, as the GA-based training procedure is finished.

Step 7. Use trained RBF neural network to forecast the power generation of WECS.

6. Numerical Results

To verify the proposed forecasting method, the method has been applied for wind power forecasting in Taiwan. The proposed wind power forecast method is compared with the
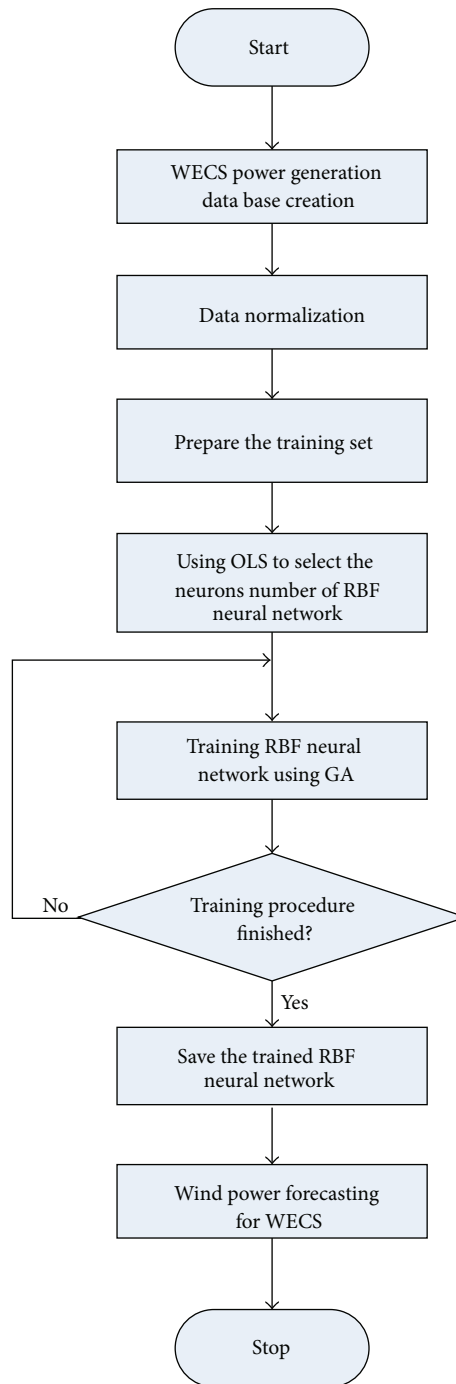
FIGURE 3: The overall flowchart of the proposed wind power forecasting method.

persistence method and back propagation neural network method. Wind power forecasting is computed using the historical wind power and wind speed data every 10 min. of a 2400 kW WECS installed in Taichung coast of Taiwan. The wind power time series data of this WECS are recorded from January 1, 2008 to December 31, 2008 for one complete year. For the sake of clear comparison, no exogenous variables are considered. Due to the seasonal atmosphere weather characteristic, the wind power and wind speed data were divided into 4 categories: spring, summer, autumn, and winter. The four season day test data results are shown below.

In winter day testing, the following days are selected: December 1–5, 2008, corresponding to the typical winter day. The historical data set with 864 patterns are divided into training data set for RBF neural network and back propagation neural network composed of 720 patterns collected from December 1–4, and testing data set composed of 144 patterns collected from December 5. The number of

TABLE 1: The evaluation of the accuracy of the three methods in wind power forecasting.

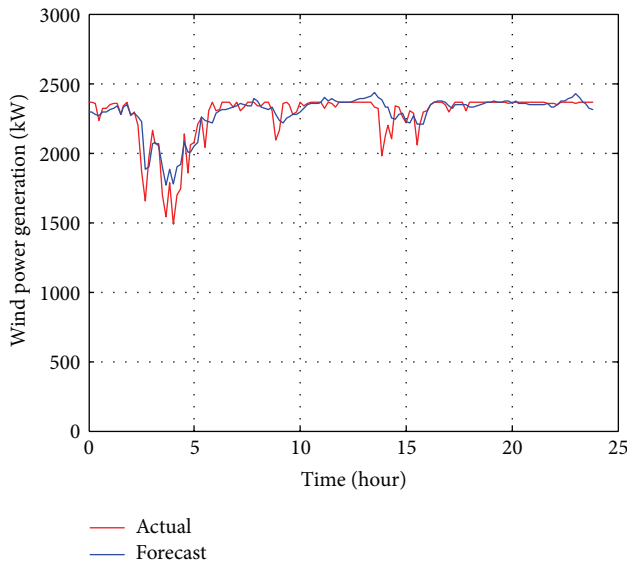| Season	Forecasting method	Maximum absolute percentage error	Mean absolute percentage error
Winter day	Proposed RBF neural network-based method	20.5026%	2.4676%
	Persistence method	21.4370%	2.7579%
	Back propagation neural network method	47.4301%	4.3943%
Summer day	Proposed RBF neural network-based method	57.4755%	15.4433%
	Persistence method	113.0435%	35.4214%
	Back propagation neural network method	108.1397%	25.2375%
Spring day	Proposed RBF neural network-based method	66.9832%	7.3247%
	Persistence method	116.4384%	8.4948%
	Back propagation neural network method	76.1072%	8.4283%
Autumn day	Proposed RBF neural network-based method	121.7294%	29.0453%
	Persistence method	186.6667%	39.5734%
	Back propagation neural network method	146.1742%	36.7328%

FIGURE 4: Numerical results with the RBF neural network-based method for typical winter day.
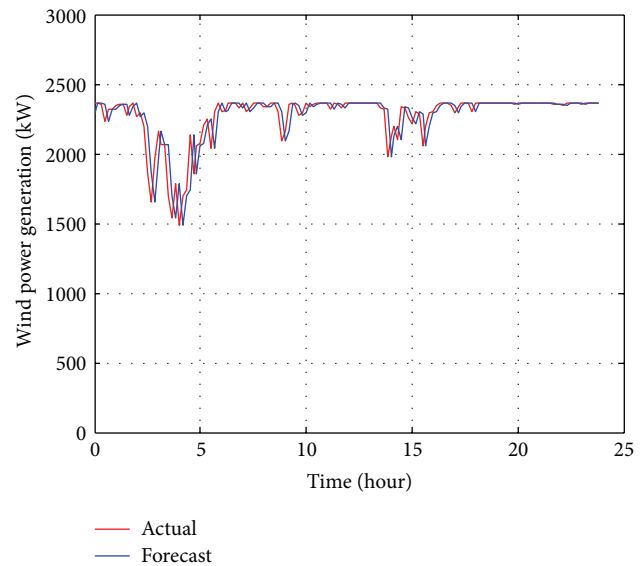

FIGURE 5: Numerical results with the persistence method for typical winter day.

neurons in hidden layer of back propagation neural network is 24. Numerical results with the RBF neural network-based method are shown in **Figure 4**. Numerical results with the persistence method are shown in **Figure 5**. Numerical results with the back propagation neural network method are shown in **Figure 6**. The forecasting error curve of three methods for winter day is shown in **Figure 7**.

In summer day testing, the following days are selected: July 20–24, 2008, corresponding to the typical winter day. The historical data set with 864 patterns are divided into training data set for RBF neural network and back propagation neural network composed of 720 patterns collected from July 20–23, and testing data set composed of 144 patterns collected from July 24. Testing results with the RBF neural network based method are shown in **Figure 8**. Testing results with the

persistence method are shown in **Figure 9**. Test results with the back propagation neural network method are shown in **Figure 10**. The forecasting error curve of three methods for summer day is shown in **Figure 11**.

From the spring day data, the following days are selected: March 1–5, 2008, corresponding to a typical spring day. The training data set is collected from March 1–4, and the test data set is collected from March 5. From the autumn day data, the following days are selected: October 20–24, 2008, corresponding to a typical autumn day. The training data set is collected from October 20–23, and the test data set is collected from October 24.

Table 1 presents the values for the criterions to evaluate the accuracy of the three methods in wind power forecasting. The performance of proposed method is evaluated based on
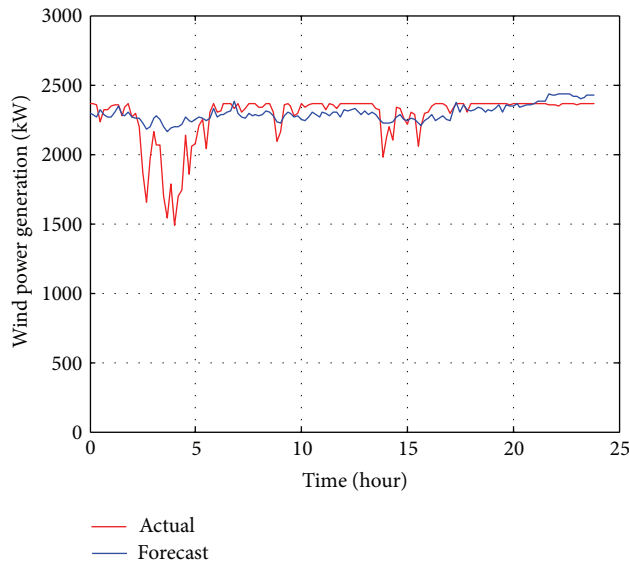
FIGURE 6: Numerical results with the back propagation neural network method for typical winter day.
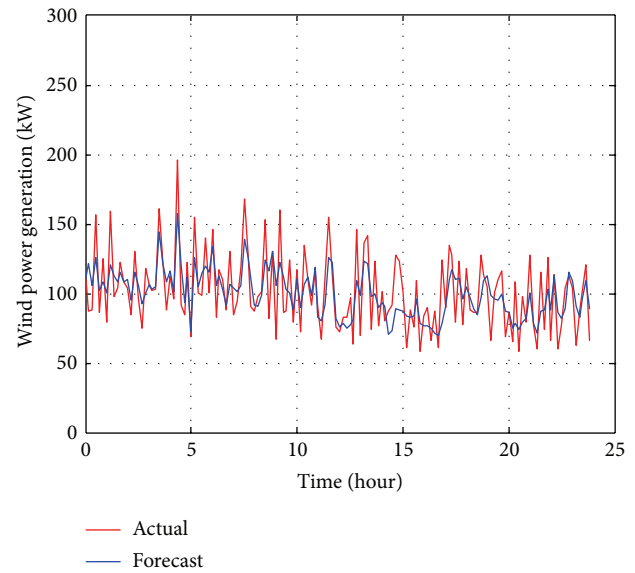

Actual
Forecast

FIGURE 8: Test results with the RBF neural network based method for typical summer day.
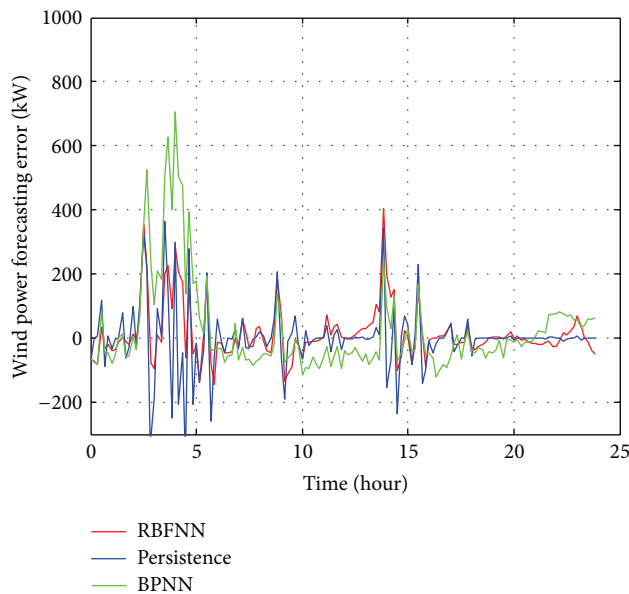

RBFNN
Persistence
BPNN

FIGURE 7: The forecasting error curve of three methods for typical winter day.

Actual
Forecast

FIGURE 9: Test results with the persistence method for typical summer day.

7. Conclusions

A RBF neural network-based method was proposed in this paper for 10-minute ahead wind power forecasting. The proposed method is based on the combination of RBF neural network, OLS algorithm, and GA. The application of the proposed method to short-term wind power forecasting is both novel and effective. The proposed wind power forecast method is compared with the persistence method and back propagation neural network method. Evaluation of the forecast methods is carried out for practical wind power generation information of WECS. The obtained result shows

two indexes, namely, maximum absolute percentage error and mean absolute percentage error. Comparing the three methods, a general conclusion that may be drawn from the obtained results is that three forecasting methods can forecast the wind power accurately. In what relates to the comparison between three methods, we may generally conclude that RBF neural network-based method achieve better forecasts in both mean absolute percentage error and maximum absolute percentage error.
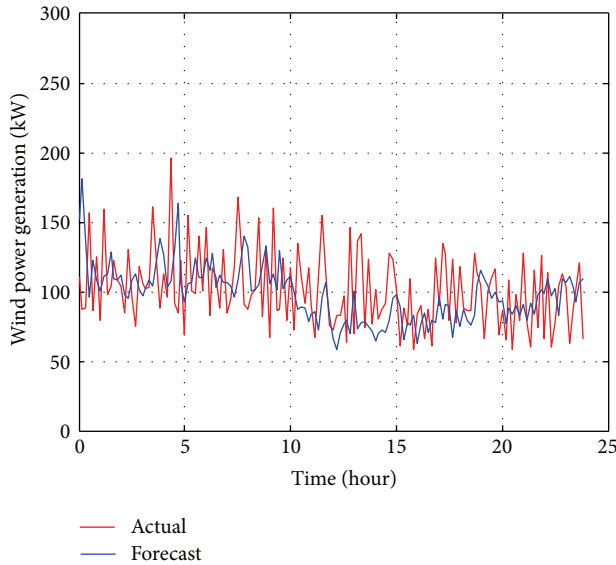
Figure 10: Test results with the back propagation neural network method for typical summer day.
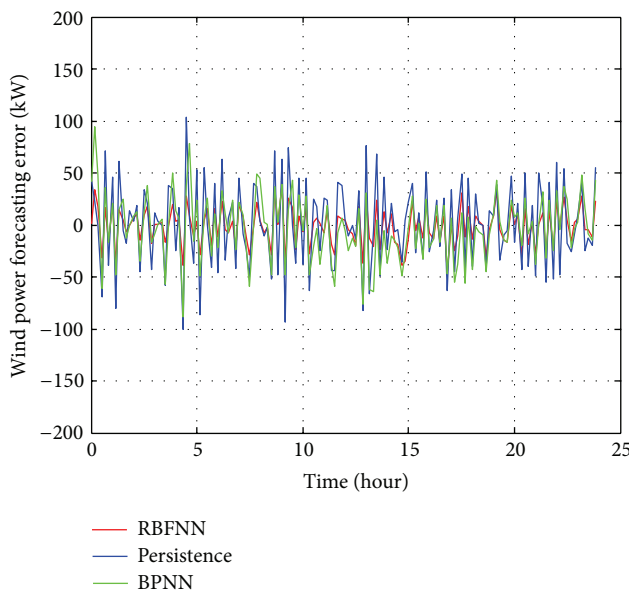

Figure 11: The forecasting error curve of three methods for typical summer day.

effectiveness of the proposed method and this method is capable to enhance accuracy of the wind power forecasting.

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