Wind Power Plant Prediction by Using Neural Networks

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Wind Power Plant Prediction by Using Neural Networks

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***Abstract*--This paper introduces a method of short term wind power prediction for a wind power plant by training neural networks based on historical data of wind speed and wind direction. There are two steps in the process of wind power prediction. In the first step, raw data collected by plant information system is filtered by probabilistic neural network. This step prepares valid data to be used for building a prediction model. In the second step, a complex-valued recurrent neural network is applied to build a model to predict wind power. The test results of the prediction model are presented and analyzed at the end of the paper. The model proposed is shown to achieve a high accuracy with respect to the measured data.**

***Index Terms*--wind power plant, wind power prediction, probabilistic neural network, complex-valued recurrent neural network.**

I. Introduction

WIND plant has lower cost of energy compared to other renewable energy sources for large scale application. Due to the different geographical patterns, weather, and properties of the wind turbines, a wind turbine may have various performance given different situations. If the total output of a wind power plant (WPP) can be predicted with high accuracy, more useful information can be provided to the power companies to help in scheduling power generation. This information will allow a more flexible and intelligent control of a WPP (e.g., improve the working schedule of wind turbines, reactive power control, etc). Methods for predicting wind power generation can be categorized into physical methods, statistical methods, methods based on neural networks, and hybrid methods [1]. The physical methods rely heavily on numeric whether prediction, which is confined by the sensors and monitoring devices placed within the WPP. The quality of hardware chosen, the parameter settings, the computation time, the time delays, and the sampling rates influence the accuracy of data collected from the WPP. It is easier to predict a single wind turbine's performance rather than a whole WPP's power generation. Statistical and neural network methods are based on the historical data and have a low prediction cost. The relationship between input data and output data based on historical measured data is learned and then a nonlinear relationship model between them is built. But when new data not previously included in the training data set is used as input into this kind of model, the prediction error might be large, which is a disadvantage. Different prediction methods mentioned above can be combined as hybrid methods to achieve better prediction results. But this will increase the complexity of the model. In this paper, several neural network methods are applied to predict power generation of a WPP located in northeast Colorado.

In this WPP, data of wind information, such as wind speed, wind direction, wind power generation, humidity and air pressure are collected by a Plant Information (PI) system, and the output of the entire WPP is monitored by the utility's supervisory control and data acquisition (SCADA) system. Raw data from the WPP is processed by a probabilistic neural network (PNN) and then a complex-valued recurrent neural network (CRNN) model is built to predict the total output of the WPP with the following considerations [3]:

- The raw data set will be screened by probabilistic neural network to prepare high quality data for building neural network models;
- The model's inputs do not rely on the data of wind speed and wind direction from all turbines; representative wind turbines can be found to compress the length of the input data;
- The inputs are expressed as complex-valued data (vector representation) which combine wind speed and wind direction;
- The complex-valued recurrent neural network model's time series inputs are generated based on the historical data values of the WPP rather than the predicted values by the model at the previous steps;
- The result to be predicted is the total power generation of the whole WPP rather than outputs of some single wind turbines;
- The models are trained based on the data collected within the year of 2010; the prediction accuracy of the model is tested by the data of 2011.

The rest of the paper are arranged as follows. In section II, the data preparation process of wind power plant by using PNN is introduced. In section III, we show the process of wind power prediction model design by using complex-valued recurrent neural network. In section IV, prediction results using CRNN are discussed and analyzed. The conclusion of the paper is summarized in section V.

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II. DATA PREPARATION

A data preparation process is a very important step in mathematical modeling, since the quality of raw data acquired by PI system may contain errors.

A. Raw Data Description and Analysis

There are two kinds of wind turbines in this WPP. There are 53 turbines in Group 1 with each turbine's rated power at 1.5 MW; there are 221 turbines in Group 2 with each rated at 1MW. The rated power of the whole WPP is 300.5 MW. The layout of wind turbines and two meteorological towers (MET1&2) is shown in Fig. 1.

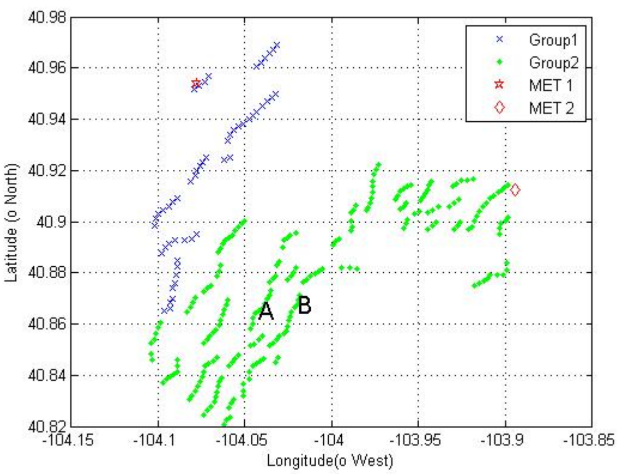

Fig.1. Wind power plant distribution

The data of wind speed (m/s), wind direction (degree, 0^o~360^o), total metered plant-output power (MW), temperature (^oC) and air pressure is monitored by the sensors installed at the two MET towers. From individual wind turbines, data of wind speed, wind direction and power output is also collected. The data of total metered WPP output power is recorded at the point of interconnection and is very useful to a utility company as a reference to compute power revenue. Following the IEC standard, all the data acquired except the turbine status is averaged over a 10-minute period for turbine power curve measurement [1]. Fig. 2 shows a raw scatter plot of WPP output and wind speed data from MET 1. The raw data set (8486 dots) contains some invalid data which is not useful for power prediction and has a minor effect on the power grid. The raw data can be classified into five types as shown in Table I.

TABLE I
RAW DATA CLASSIFICATION

Type	Description
1	data points following the main power stream
2	data points in low wind speed period with high power generation
3	data points with negative value wind speed
4	data points with negative value power generation
5	data points with low power generation at high wind speed period

The existence of type 2 data might be due to some physical problems, disabled sensors or data distortion in communication channels. Type 3 data does not exist in reality and may be caused by anemometer that needs to be calibrated. Type 4 data is due to the fact that sometimes the wind turbine cannot generate enough power to offset the electrical consumption of the turbine itself and was drawing (consuming) power from the grid. The existence of type 5 data might be due to the fact that not all turbines are always online during high wind speed period (especially near cut-off wind speed) and some wind turbines maybe disabled during that period. Another reason can be derived from [4], because a strong wind from wrong direction can make a turbine work at low efficiency. In sum, all types of data except type 1 data should be filtered out.

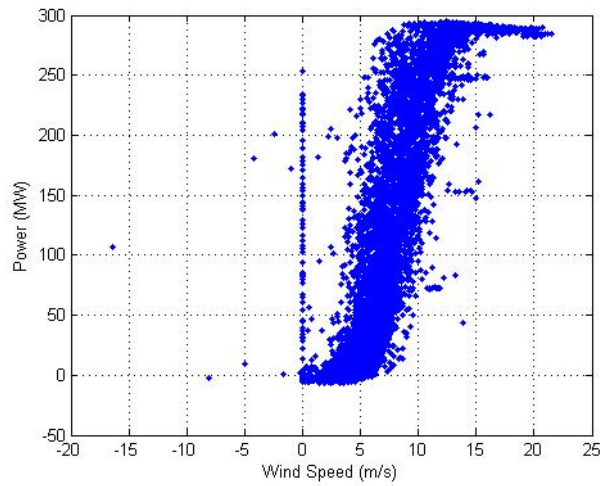

Fig.2. Scatter plot of total output of WPP and wind speed from MET1 (2010 Jan-Mar)

B. Data Selection Process

Probabilistic neural network (PNN) is a feed-forward neural network with supervised learning using Bayes decision rule and Parzen window [3]. PNN can be used for data classification. The structure of PNN is usually a two-layer model as shown in Fig. 3. In the pattern units, the distance between the input vector and the target vector will be calculated. A new vector will be generated to indicate how close the input is to the target vector. The summation units add these distances for each type of inputs to produce a vector of probabilities as the output of the network. The output unit generates a 1 for the target class and a 0 for the other classes with the use of a competing transfer function, which picks the maximum the vector of probabilities [4].

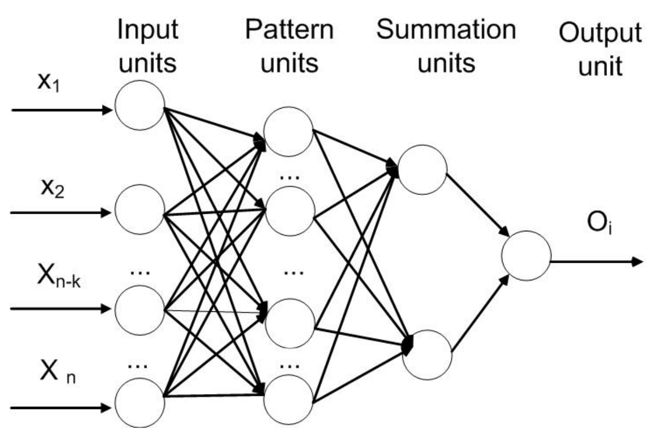

Fig.3. Structure of PNN

In this paper, PNN was applied to filter out invalid data in the raw data set. For example, data points in Fig.2 were classified into five types and the portion for each type of data is different based on statistical analysis. The order of proportion from the largest to the smallest is type 1, type 4, type 5, type 2, type 3. In the process of building PNN model, about 20% of the data points in Fig. 2 (1700 data points) were selected as training data set. The PNN model was trained using the sampled data.

Since only type 1 data is the useful information and should be kept, there are two strategies in training PNN model. Method 1 is simpler, for which the classification results of PNN are assumed to have only two types. PNN is trained based on two groups: the first group is type 1; the second group includes type 2-5. 1700 data points are selected, among which 1540 were randomly selected from type 1 data points, the rest 160 data points were from type 2-5. In the training data set, the input data vector includes data of wind speed and wind power generation, and the target vector has only two elements, which are 1 (group 1) and 2 (group 2). And then, the rest data points (about 80%) were used as testing data set as input to be classified by the PNN model already built. The number of neurons in the input layer is equal to that of the output layer, which is 2. The training results are shown in Fig. 4 and Fig. 5.

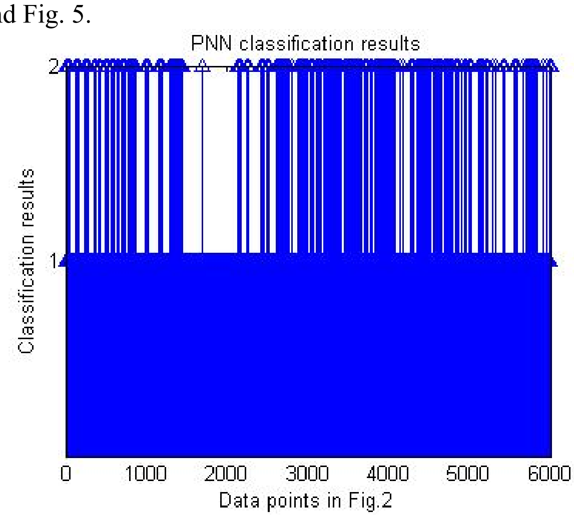

Fig.4. Classification results of data in Fig.2 by method 1

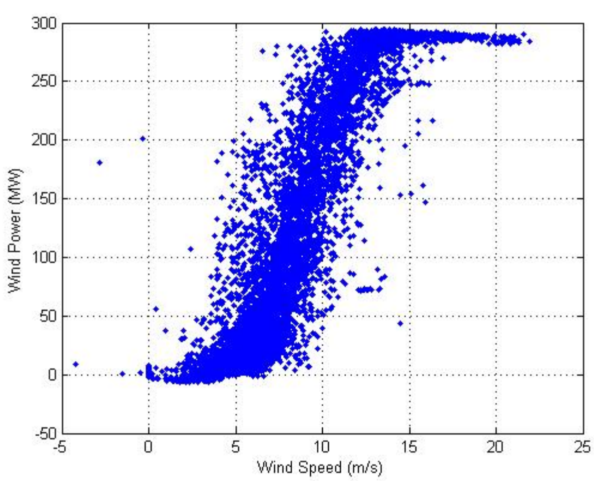

Fig.5. Filtered scatter plot of Group 1 data points classified by method 1 (2010 Jan-Mar)

As shown in Fig. 5, the classification result using method 1 is not ideal; PNN model could not succeed in diagnosing all the unwanted data. And the classification accuracy is 92.7%, which means the number of the correctly classified data points versus the number of type 1 data as shown in Fig. 2.

In method 2, there are five classification results of PNN, which are type 1, type 2, type 3, type 4, type 5. PNN is trained based on five types of data points as shown in Table I. In the 1700 selected data points, 1540 data points were sampled from type 1 data. For the rest 160 data points, according to the portion of each data type, number of data points sampled from type 2, 3, 4, 5 were 20, 10, 70 and 60 respectively. The number of neurons in the input layer is 2 and the number of neurons in the output layer is 5. And results done by testing the rest of the data set can be seen in Fig. 6 and Fig.7.

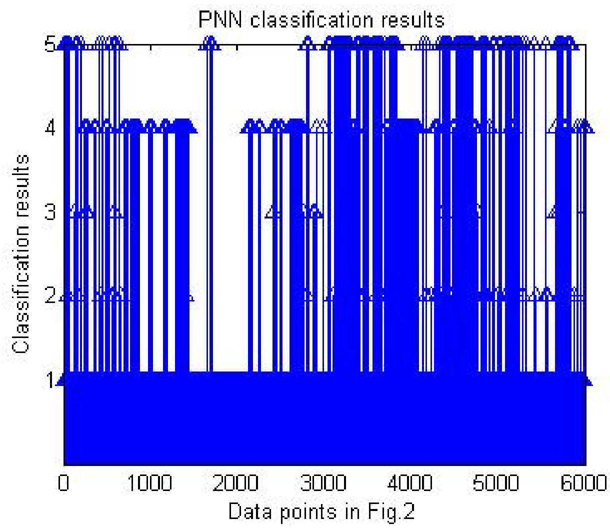

Fig.6. Classification results of data in Fig.2 by method 2

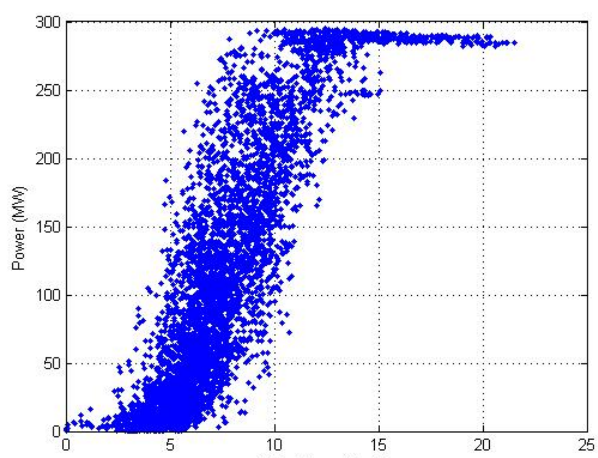

Fig.7. Filtered scatter plot of type 1 data points classified by method 2 (2010 Jan-Mar)

In Fig. 6, type 1 data can be separated from the testing data set as shown in the classification result and were plotted in Fig. 7. And PNN model built by method 2 could succeed in screening the raw data even though the power curve is not totally smooth. The classification accuracy is 96.5%, which is higher than that of method 1. The classification result using method 2 has a better accuracy than the one performed using method 1, because simply combining type 2-5 data pints into a group will disturb the process of building PNN and it creates confusions in dividing the line between type 1 data and type 2-5 data.

Wrong classification data points will decrease the accuracy of the prediction model. In the data preparation process of the WPP power prediction model, we adopted method 2 to train PNN model and the problem of wrong classification can be solved by improving the PNN's training data set. For example, after the PNN is built, data points with wrong classification results from testing data set can be added into the training data set. And then PNN model should be trained again with the expanded training data set in order to have more accurate classification ability.

C. Data for Building Models

In this paper, the power prediction result of the WPP is based on wind speed and wind direction. At first, wind speed factor is a key point in determining the available power generated from a single wind turbine with a certain cross-sectional area [5]. The wind speed experienced by individual wind turbines is acquired by the anemometer and comes from the direction of horizontal axes of turbine's hub. The hub is behind the blades, which has an effect of decreasing the natural wind speed. The wind speed acquired from the MET towers represents the natural wind speed at the location on the tower. Even though the height of the hub and MET tower are the same, they have different physical meanings. When we predict wind power generation, wind speed from turbine should be adopted as input information of the model.

Secondly, wind direction (direction from which the wind blows) is another kind of useful information to predict wind power based on previous research results [6]. Wind can come from every direction when the wind speed is low. The higher the wind speed, the more uniform and more focused the wind direction. So during the same wind speed period, wind turbines can have different efficiencies due to different wind directions. But it is not convenient to predict the total power generation of the whole WPP by processing data information from all the turbines. It is better to find wind turbines from which the wind speed and wind direction can be most representative of the WPP area's wind situation. The wind speed situation (after data selection process) of the whole year of 2010 is shown in Table II. The data from 2010 Apr-Jun covers a wide range and has the largest mean value of wind speed, which is suitable for training neural network model and was researched in this paper.

TABLE II
2010 WIND SPEED DATA ANALYSIS

Wind Speed (m/s)	Avg.	Std.	Maximum
2010 Jan-Mar	6.945	3.919	21.362
2010 Apr-Jun	8.812	3.927	22.635
2010 Jul-Sep	6.371	3.212	19.552
2010 Oct-Dec	7.330	4.117	21.912

Wind directions of the two groups of wind turbines at 3/18/2010 10:00 pm and 4/10/2010 8:40 am are shown in Fig. 8 and Fig. 9 respectively. The arrows indicate the direction of the wind. The wind directions of Group 2 turbines are focused on a certain direction. The reason of the messy direction of Group 1 turbine is likely to be the data distortion due to the data transmission channel or bad performance sensors. The total output of WPP can be predicted according to only one or two turbine's information [1]. Based on the filtered data set, the average wind speed of all the wind turbines can be acquired. By correlation method, the wind turbine which has the highest correlation value with the average wind speed can be found (turbine A as indicated in Fig.1) and thus turbine A is the one which has the most representative wind speed. Following the same method, the turbine which has the most representative wind direction can also be found (turbine B as indicate in Fig.1). In this paper, data acquired from turbine A and B will be used to predict the total output of the WPP.

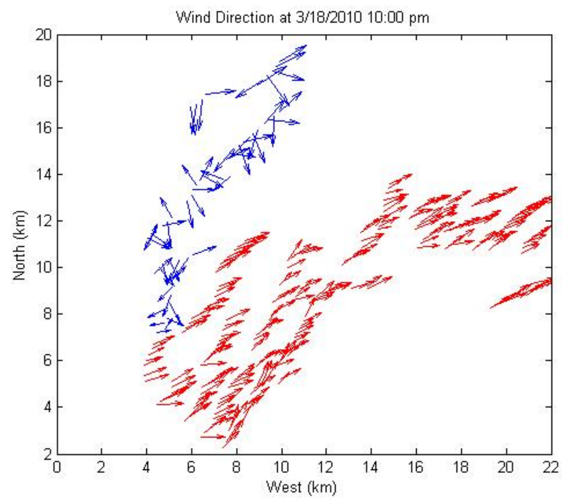

Fig.8. Wind direction at 3/18/2010 10:00 pm

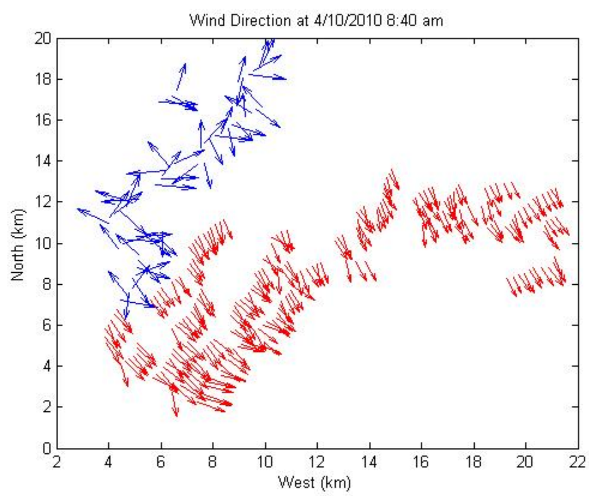

Fig.9. Wind direction at 4/10/2010 8:40 am

III. MODEL DESIGN

A. Complex-valued Recurrent Neural Network Model Structure

Data of wind speed and direction from turbine A and turbine B can be combined and expressed as a vector on a two-dimensional complex coordinates as shown in Fig. 10.

The wind vector can be expressed as equation (1). Paper [7] demonstrates that the prediction effect by using complex-valued neural network outperforms that of using real-valued neural network.

$$\vec{v} = v\cos\theta + i\, v\sin\theta \tag{1}$$

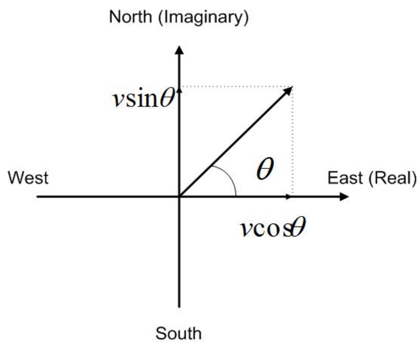

Fig.10. Wind vector

Inputs of recurrent neural network can be either a series of historical measured data or simulated data generated by the model as shown in Fig. 11. The advantage of this kind of model is that the output signal does not just rely on the current input signals of the system but it also has an internal memory in its training process. The disadvantage is that the training time of the recurrent neural network is longer than that of the static neural network. In this paper, we built a complex-valued recurrent neural network (CRNN) to predict the WPP's power generation. The CRNN can be trained under two kinds of modes— Parallel (P) mode and Series-Parallel (SP) mode, as seen in Fig.11. In the former mode, the simulated outputs $\tilde{p}(n-2), \tilde{p}(n-1), \tilde{p}(n)$ are fed back as input signals. In the SP mode, actual outputs in the previous time step $p(n-2), p(n-1), p(n)$ are used. Paper [8] demonstrates that prediction model with parallel mode inputs will result in accumulation of error if the previous prediction results are not accurate.

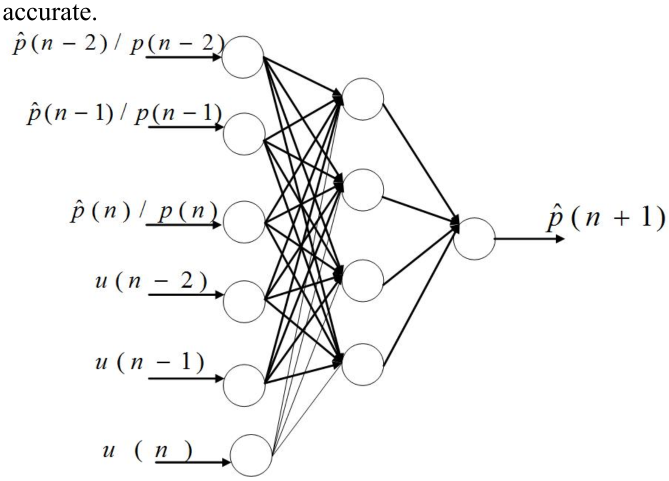

Fig.11. Recurrent neural network training structure

B. *Basic Algorithm*

In this paper, p indicates the power readings from MET tower, which represents the value of the effective power amount of the whole WPP transmitted to the grid. The u includes the wind speed vectors from representative wind turbines (turbine A and B). And, n indicates the time step of 10 minutes period. Usually a two-layer NN model can reasonably approximate any nonlinear function [9]. In this paper, a single hidden layer NN with fifteen neurons and one output was used. A bias of 1 was set initially. The longer the length of delay, the heavier the load of the training process has, which will also inevitably increase the training time of the model. In this paper, we trained the complex-valued recurrent neural network in 10-min, 20-min, 30-min, 40-min, 50-min, 60-min time delay modes. For the transfer function, log-sigmoid function was selected to be the hidden layer's transfer function due to its efficiency; linear transfer function was used in the output layer as a convention. Levenberg-Marquardt back propagation algorithm is used as the training function for the whole recurrent neural network model. This method is typically used in minimization problems because it appears to be the fastest method in terms of convergence. The weights of each connection between neurons are adjusted in the training process until the errors are within the pre-determined range. To compare the performance of the two modes of recurrent neural network, the accuracy of the model can be evaluated by mean absolute error (MAE), as shown in (2), root mean squared error (RMSE), as shown in (3) and mean absolute percentage error (MAPE), as shown in (4). In (2) (3) (4), x_i and $\tilde{x}_i$ are the ith component of the actual power and predicted wind power respectively. And, n is the length of the vector.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |x_i - \tilde{x}_i| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \tilde{x}_i)^2} \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{x_i - \tilde{x}_i}{x_i}\right| \times 100\,\% \tag{4}$$

IV. Comparison and Analysis of Prediction Results

Based on section II, data as shown in Table III was selected to finish the WPP's power prediction model. Data of each group consists of wind speed, wind direction and wind power generation.

TABLE III
DATA DESCRIPTION

Data Group	Start time	End time	No. of data points	Description
A	4/1/2010 0:00	5/8/2010 23:50	5474	Training data set
B	4/1/2011 0:10	5/8/2011 23:50	5362	Testing data set

In the modeling process, the Group A's data is used for training the model; the Group B's data is used for testing and validation of the model. In the training process of neural network, according to the principle of the neural network, training set data will be divided into two parts randomly, one part is for learning the relationship between input data and output data and building the model, which occupies 60% of the total data, the rest 40% data is reserved for validation of the model and for further adjusting value of its weights. So models built by a same training data set could be different due to neural network's randomness in training. In order to get more accurate results, each model was built by Group A data repeatedly for three times and the prediction results were tested by Group B data repeatedly for three times and then average values are computed. Results from the proposed model were compared with the actual values of the historical data. The error statistics of the prediction results by different time series SP mode CRNN is shown in Table IV and Table V. Model 1 denotes SP mode CRNN with only wind speed as input, Model 2 denotes SP mode CRNN with wind vectors as inputs. Table VI shows the error analysis of prediction results by complex-valued neural network (CVNN) and real-valued neural network model (RVNN).

TABLE IV
ERROR ANALYSIS I

(MW)	MAE		RMSE	
Input type	Model 1	Model 2	Model 1	Model2
10min	9.901	7.874	13.613	9.408
20min	10.156	8.635	14.067	9.677
30min	11.205	9.258	16.268	10.502
40min	13.371	9.422	16.331	10.845
50min	13.931	9.423	18.256	11.111
60min	14.691	9.58	18.584	11.374

TABLE V
ERROR ANALYSIS II

	MAPE (%)		Std. of Error (MW)	
Input type	Model 1	Model 2	Model 1	Model2
10min	12.163	11.204	10.722	9.408
20min	14.549	12.091	11.801	11.221
30min	18.149	12.753	13.834	11.474
40min	22.777	13.872	15.362	12.385
50min	24.448	17.772	17.255	12.722
60min	29.192	18.091	19.522	13.044

TABLE VI
ERROR ANALYSIS OF CVNN

	MAE	RMSE	Std. of Error	MAPE
CVNN	14.149	14.994	14.635	14.867%
RVNN	16.210	17.086	30.672	22.535%

From Table IV, V and VI above, the results show that the 10-min delay mode of Model 2 has the best performance in the CRNN models and can be adopted to build power prediction models for WPP. The accuracy suggested by MAPE is 11.204%, which also outperforms the prediction results of CVNN and RVNN as shown in Table VI. In the CRNN models, the accuracy of CRNN's prediction results decreases with the increasing of the delay length in the model training process. The reason is that the wind is changing rapidly, so it is better to predict the wind power by referring the wind status in the nearest previous time. Apparently, the accuracy of prediction results and its consistency for different delay length are improved when the direction of wind is combined into input signals of the neural network. The prediction results of CVNN and RVNN models, which do not include time delay in their training data set, have worse prediction results even compared to Model 2 with 40-min delay. Fig. 12 shows the prediction results from 4/1/2011 1:20 am to 4/2/201110:40 am, where the predicted power generation points are very close to theose actual ones. Additionally, there are always some prediction data points with large relative errors, which are larger than 100%. The characteristic of those data points are always generated during low wind speed period (below 4m/s) which is not important for wind power integration and can be ignored.

The whole prediction is shown in Fig. 13. Overall, most of the prediction values are smaller than the actual values. According to the errors of the prediction results, the power company can compensate the errors by allocating proper power reserve and make some adjustment in scheduling the wind power generation.

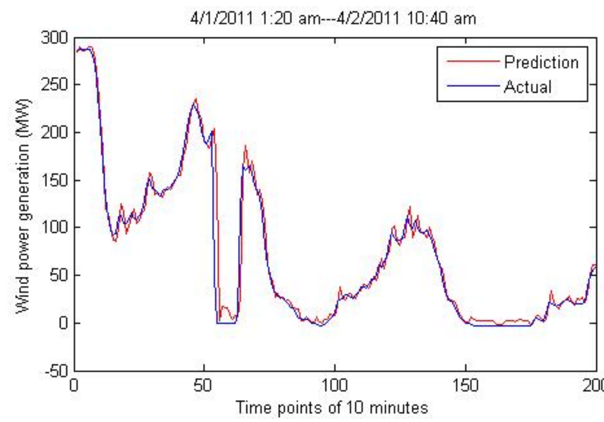

Fig.12 Prediction results by 10-min time delay SP mode RNN

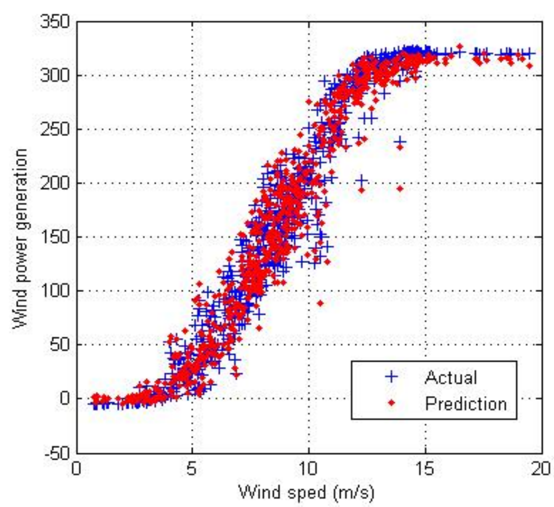

Fig.13 Predicted wind power vs. actual wind power of 2011

V. CONCLUSION

This paper describes a procedure of predicting total output of wind power plant (WPP) by neural networks. Probabilistic neural network (PNN) was applied to classify and screen the raw wind data for the training of neural network prediction models. And then certain representative wind turbines were selected as an input data source for modeling and to simplify the input signals to the model. In the last step, based on the previous wind power prediction experience [2-6], complex-valued recurrent neural network (CRNN) model was chosen to predict the total output of WPP with high accuracy.

VI. Acknowledgment

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VIII. Biographies

Ziqiao Liu received the M.S. degree from Beijing Institute of Technology, School of Automation, Beijing, China, in 2010. She is currently working toward the Ph.D. degree in the Department of Electrical and Computer Engineering, University of Denver, Colorado, USA. Her current research interests include wind power prediction, wind farm supervisory control.

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Yih-huie Wan received the B.S. degree from National Cheng Kung University, Taiwan, R.O.C., and the M.S. degree from Southern Illinois University, Carbondale, IL, in 1973 and 1979, respectively, both in electrical engineering.

He is a Senior Engineer with the National Renewable Energy Laboratory (NREL), Golden, CO. His main expertise is in electric power system engineering, planning, and operation. Before joining NREL, he worked as an Electrical Engineer for an electric power company in Oklahoma for ten years in substation and distribution feeder design, transmission system planning, and bulk power transaction analysis. His work at NREL includes renewable energy technology assessment and integration of renewable energy technologies with the electric utility grid. He has also done work in renewable energy policy analysis, renewable energy resource assessment, and distributed generation.

Mr. Wan is a Registered Professional Engineer in the State of Oklahoma.

Eduard Muljadi (M'82, SM'94, F'10) received his Ph.D. in electrical engineering from the University of Wisconsin at Madison. From 1988 to 1992, he taught at California State University at Fresno. In June 1992, he joined the National Renewable Energy Laboratory in Golden, Colorado. His research interests are in the fields of electric machines, power electronics, and power systems, with an emphasis on renewable energy applications. He is a member of Eta Kappa Nu and Sigma X, and a fellow of the Institute of Electrical and Electronics Engineers (IEEE). He is involved in the activities of the IEEE Industry Application Society (IAS), Power Electronics Society, and Power and Energy Society (PES), and an editor of the IEEE Transactions on Energy Conversion.

Dr. Muljadi is a member of various committees of the IAS, as well as a member of the Working Group on Renewable Technologies and the Task Force on Dynamic Performance of Wind Power Generation, both of the PES. He holds two patents in power conversion for renewable energy.