Forecast of Wind Turbine Power Using Deterministic and Non-Deterministic Methods

Zulati Litipu, Kazuma Hanada, Bahman Kermanshahi, and Chi-Hung Kelvin Chu

***Abstract*—This paper presents and compares two different methods using in the forecasting of wind power turbine (WPT) outputs. These two forecasting methods, which utilize different types of input to forecast the output of WPT, are the Meteorology Forecasting Method (MFM) and the Observational Forecasting Method (OFM). The MFM determines the unit output from the forecasted wind speed at the WPT installation site, using the input from a composite data set created from the original annual-hourly weather data. Three different techniques can be used in MFM to forecast the wind speed, and the best result is selected for conversion calculation of the output of WPT. OFM, however, forecasts the unit output based on five observed annual-hourly data obtained from the operation of target WPT. Two different techniques can be used in the OFM simulation. The results from these techniques for each method are compared and the best one will be used for the final forecast of the WPT outputs. This paper presents and compares the forecasting results of WPT output obtained from MFM and OFM. Furthermore, in order to increase the result precision and decrease the forecast error, a new composite data system is also developed and proposed.**

The methodologies proposed in this paper will be very useful for designers, planners and operators of the wind power turbines.

***Index Terms*—Composite data system, MFM forecast, OFM forecast, simulation, WPT output forecast.**

I. INTRODUCTION

IN A SYSTEM consisting of both wind power and traditional fuel-fired units, there are two issues that need to be addressed:

1. How to make full use of wind energy to obtain the highest benefit from wind power system;

2. How to accurately control the introduced capacity of the wind power units in an existing power system in order to maintain the stability of the power system.

Recent literature shows that WPT output forecast is playing an important role in the stable and economical operation of a Wind Power System (WPS – defined here as a power system that are connected to wind power units) [1]. This paper presents and compares two forecasting methods, namely Meteorology Forecasting Method (MFM) and Observational Forecasting Method (OFM) in basis of weather data and operational data for the forecast of WPT output. The brief principle and concept of mentioned two methods are explained as follows.

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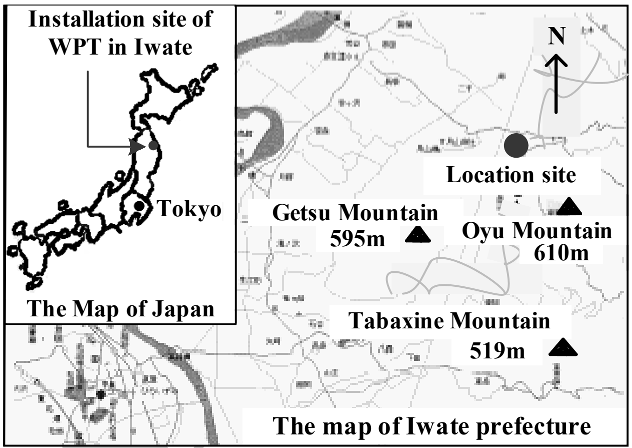

Fig. 1. Geographical position of the 490 kW WPT in Iwate prefecture of Japan.

A. Meteorology Forecasting Method (MFM)

WPT output forecasting of this method involves two separate steps; at first forecast the wind speed and then convert the forecasted wind speed to the output power. Inputs used in this forecast are based on the annual weather data measured from the installation site of target WPT by the Meteorology Agency of Japan. Since different weather data exerts different degree of influence on wind speed, therefore, it is difficult usually to achieve high precision results in wind speed forecast; therefore, this paper proposes a more relevant composite weather data set, which is generated from the original data. To compare the efficiency of this composite data set with the original hourly data, a special testing simulation of wind speed forecasting is conducted. The testing results show that the composite data set provides better precision of prediction. Based on this composite data set, three different methods, namely the Jacobean method, the Lorenz method and the Chaos-ANN, are operated in MFM to predict the wind speed. The results from these three techniques are compared and the best one is selected and used to be converted to the WPT outputs in the second step. Here, converting calculation is realized by the Output Characteristic Equation, which is derived from the Output Characteristics Curve of target 490 kW WPT.

B. Observational Forecasting Method (OFM)

In OFM, the WPT output is directly forecasted by using the inputs of observed annual-hourly data; which are composed by historical observational data of 490 kW WPT and the weather data in WPT located site. In data measurement, required weather data including wind speed data are collected from the sensors placed on the top of the WPT, and the observational data are measured from meters

TABLE I
TYPES AND NUMBERS OF ORIGINAL ANNUAL-HOURLY DATA

Data orders	Data Type	Data numbers
1	Pressure	8760
2	Temperature	8760
3	Humidity	8760
4	Forecasted wind speed of previous hour	6

in controlling unit. Since the weather sensors are located at the same height level as the generator of WPT, the height conversion of observed weather data needs not to be considered.

The mentioned data above are put into two forecasting techniques, known as Radial Basis Function Network (RBFN), which is atypical neural network model and Multiple Regression Method (MRM) [2] to forecast the wind speed. Here, the interesting point is that historical observed output data is separately taken as one of the inputs and only input to forecast the WPT outputs, and it provides very excellent result than we desired one. Finally, the results obtained from the MFM are compared and appraised with the results obtained from OFM. Fig. 1 shows the location position of target WPT.

II. OUTPUT FORECASTING BY MFM

Wind speed is the main parameter to be used in estimating and planning the output of WPT in wind power system. Very often, the collection of wind speed information is very costly and requires a long working time. This paper proposes the methods to estimate the wind speed in certain degree but may be not so high in precision by using the relevant weather data only; instead of using actual measurement by equipments. This method provides a flexible means of approximately knowing wind speed in expected places.

A. Data Processing

Table I shows the original data proposed by the Meteorology Agency of Japan, these are composed by the annual data of air pressure, air temperature and air humidity. Each data type consisted by 8760 hourly data. Because the forecast time is arranged from 1 hour to six hours ahead, the forecasted wind speed of previous hour (by taken hourly average value from 10 minutes output) is possible and also used for input as shown in Table I.

The composite data set proposed in this paper includes all the original hourly data and several additional generated data. The original hourly data in Table I is taken as basic input data, and D_4, D_8, D_{12}, and D_{24} are additional data generated from the original hourly data in Table I. The additional data are generated by the ways mentioned as follows:

Take an example, by extract any one out from three types of data in Table I, we have:

1) The Hourly Data

$$D_1 = \sum_{i=1}^{8760} \left(d_1 + d_2 + d_3 + \cdots + d_i \right) \quad . \tag{1}$$

Here, D_1 is the number of annual hourly data that is 8760 as given in Table I. d_1, d_2 and d_i are data of first

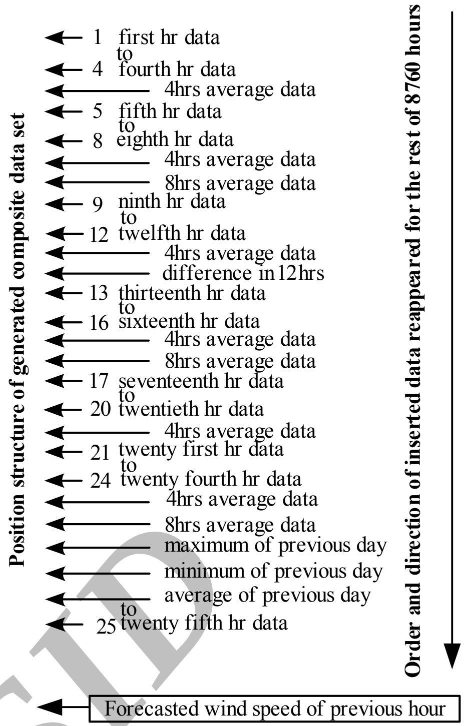

Fig. 2. The structure of composite data set generated from original hourly data (hr =hour, data in red color are new generated data).

hour, second hour, and i -th hour.

2) The 4-Hour Average Data

This data is derived from (2) and is inserted after every fourth data.

$$D_4 = \sum_{i=1}^{2190} \left(\frac{d_1 + d_2 + d_3 + d_4}{4} \right)_i \tag{2}$$

Here, D_4 is the numbers of annual 4-hour average data that equals to 2190, the meaning of d is same as (1).

3) The 8-Hour Average Data

This data is obtained from (3) and is inserted after every eighth data.

$$D_8 = \sum_{i=1}^{1095} \left(\frac{d_1 + d_2 + d_3 + \cdots + d_8}{8} \right)_i \tag{3}$$

Here, D_8 is the number of annual 8-hour average data that is 1095, the meaning of d is same as (1).

4) The 12-Hour Difference Data

This data is the difference between two consecutive average values of 12 hourly data. The initial value of this data is assumed to be zero. This data is inserted after every twelfth data; which is given by

$$D_{12} = \sum_{i=1}^{730} \left(D_{12\,(i+1)} - D_{12\,i} \right)_i \tag{4}$$

where $D_{12\,(i+1)} = (d_1 + d_2 + d_3 + ... + d_{12})/12$ is the average value of 12 consecutive hourly data that equals to 730 in one year.

5) 24-Hour Data

For every 24 hours, an additional set of data consisting of the maximum, minimum and average values of the previous 24 hours is added to the data set. This data can be

TABLE II
TYPES AND NUMBERS OF GENERATED COMPOSITE DATA OF ONE YEAR

Data types	Data names	Data numbers
Pressure	Hourly 4 Hours average 8 Hours average	7160 2190 1950
Temperature	Hourly 4 Hours average 8 Hours average	7160 2190 1950
Humidity	Hourly 4 Hours average 8 Hours average	7160 2190 1950
Difference with previous 12 hour	Hourly 4 Hours average 8 Hours average	730 730 730
Maximum value of previous day	Hourly 4 Hours average 8 Hours average	360 360 360
Minimum value of previous day	Hourly 4 Hours average 8 Hours average	360 360 360
Average value of previous day	Hourly 4 Hours average 8 Hours average	360 360 360

expressed by

$$D_{24} = \sum_{i=1}^{365}(D_{\max}) + \sum_{i=1}^{365}(D_{\min}) + \sum_{i=1}^{365}(D_{av}) \qquad (5)$$

Here, D_{24} is numbers of maximum, minimum and average values of the previous 24 hours.

Now, the number and structure of original data have changed. Define the new data set as composite data set, the structure of composite data set may be shown in Fig. 2. By defining D_{all} is the number of annual composite data obtained from one type of original data, and then it may be expressed by

$$D_{all} = D_1 + D_4 + D_8 + D_{12} + 3D_{24} \; . \qquad (6)$$

Equation (6) yields the quantity for D_{all}

$$D_{all} = 8760 + 2190 + 1095 + 730 + 3 \times 365 = 13870 \, .$$

For the three types of original weather data in Table I, the number of annual composite data would be: $3 \times 13870 = 41610$.

The forecasted wind speed of previous hour derived from 10 minutes output is also included in the composite data set. The names, types and numbers of generated composite data set are shown in Table II.

In order to verify the superiority of composite data set, the wind speed for a selected location site is forecasted separately based on the original data in Table 1 and derived composite data in Table II by using the Jacobean method [2]. In this forecast, forecasting times are arranged in accordance with time length of input data as follows:

- 3 hours ahead forecast by three months data.
- 4 hours ahead forecast by six months data.
- 5 hours ahead forecast by nine months data.
- 6 hours ahead forecast by 12 months data.

Table III shows the percentage of average absolute error obtained from the test. The results in Table III shows that it is possible to make reasonable change in type and number based on original data in forecasting wind speed, increment of the numbers and types of inputs is the important reason to improve the forecast precision.

TABLE III
PERCENTAGE OF AVERAGE ABSOLUTE ERROR IN TEST BASED ON HOURLY AND COMPOSITE DATA SYSTEM

Forecast time (length of data)	Average absolute error [%] (hourly data)	Average absolute error [%] (compound data)	Difference
3 Hours ahead (3 months data)	38.36	33.58	4.78
4 Hours ahead (6 months data)	36.25	31.76	4.49
5 Hours ahead (9 months data)	35.83	29.31	6.52
6 Hours ahead (12 months data)	34.23	28.22	6.01

This method can be used to select the target sites by estimating wind speed in order to make preparing of equipments measuring, and it shows nimble particularly in complex land shape such as mountain and sea area.

B. Wind Speed Forecast Using Three Different Techniques

Three different methods [3] are applied to forecast the wind speed. The forecasting methods used in this paper are

1. The Lorenz method of analogues,
2. The Jacobean matrix procession estimation method,
3. The Artificial Neural Networks-Chaos (ANN-Chaos).

Software for forecasting the wind speed using these three techniques was developed for the calculation. The forecasting software was designed using C^{++} program. A beginning screen of the developed software is shown in Fig. 3. The main feature of this software is to forecast wind speed by using weather data as input. In simulation, the data are put into software by the defined order and number of composite data set.

Fig. 4 shows the input structure of the software. The neuron number of hidden layer is 15 based on the theory of neural network. In forecasting, the feedback data of previous hour is obtained from generator that converts the 6 of 10 minutes outputs to hourly average data as shown in Fig. 4. The output result is also obtained by 10 minutes interval, in the obtained results, the values in accordance with 1, 2, 3, 4, 5 and 6 hours are considered and they are given in Figs. 5-7. In these figures, the value points are based on 10 minute-intervals by the way shown in Fig. 4. Table IV shows the percentage of average absolute error of the forecasting [4].

From Table IV it is known that the Jacobean method yields the best result among the three mentioned methods. Therefore, the forecasted result from the Jacobean method is converted to the output of the target WPT. The conversion calculation is based on Output Characteristic of the 490 kW WPT. Equation (7) is derived from the *P*-*V* (*P* is power, *V* is wind speed) output characteristic curve [5] as shown in Fig. 8 and is expressed by

$$Y = -0.4773x^3 + 13.5384x^2 - 85.776x + 157.0368 \, ,$$

where, Y is the output power with the unit kW, and x is the wind speed with the unit m/s.

In this calculation, Y is calculated with special method by substituting the forecasted value x to (7), Fig. 9 shows the converted output. The curve shown in Fig. 7 is not very

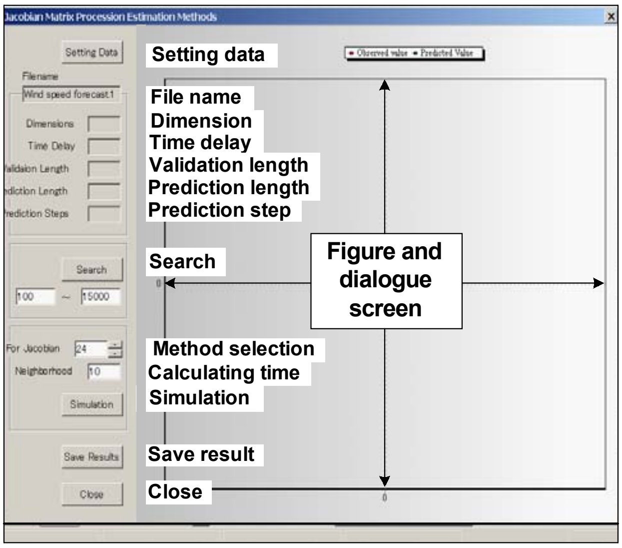

Fig. 3. Developed simulation package for wind speed forecast.

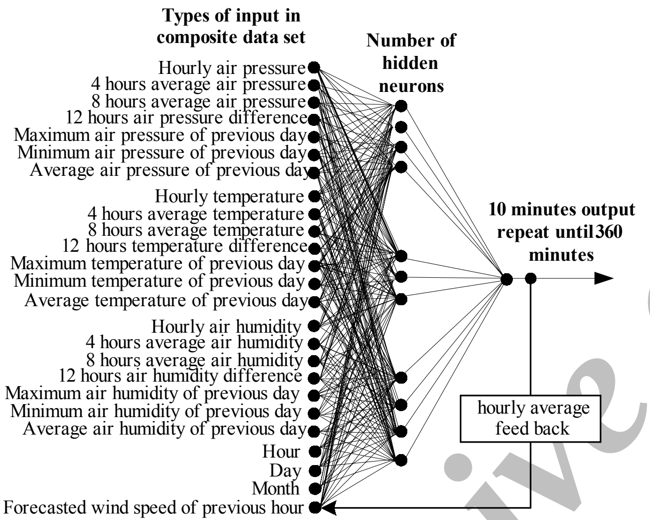

Fig. 4. Architecture in the neural network used in *MFM*.

smooth as it is affected by the change of wind speed and wind direction. Table V shows the percentage of average absolute error.

C. Analysis and Appraisal of the MFM Results

Wind speed can be forecasted by using weather data so as to WPT output may be converted. Generating additional weather data, as was done in the composite data set, is one way to improve the forecast result. Table V shows the errors of output which is smaller than those of wind speed shown in Table IV. The reasons are denoted as follows:

The influence of the natural changing characteristics of wind speed causes a relatively big difference between the forecasted speed and the measured one. In wind forecasting, Table IV shows that data quantity and forecast time are two important factors to obtain good forecast result.

1. The output power value may be corresponding to multiple wind speed values or vice versa, for example, 260 kW output may be generated by wind speed at 11 m/s, 9 m/s and even 7 m/s. This characteristic of the WPT characteristic curve acts like a filter and smoothes out the errors from the forecasted wind speed.

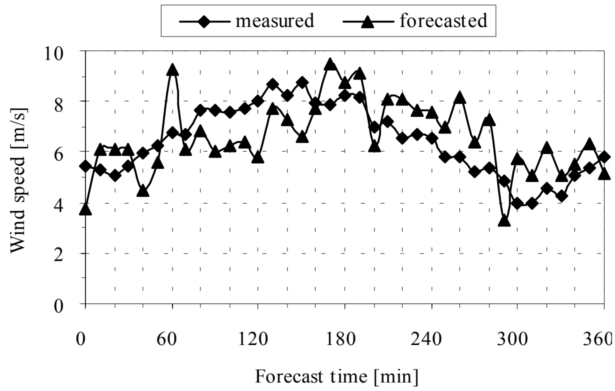

Fig. 5. Forecasted wind speed by Jacobean method.

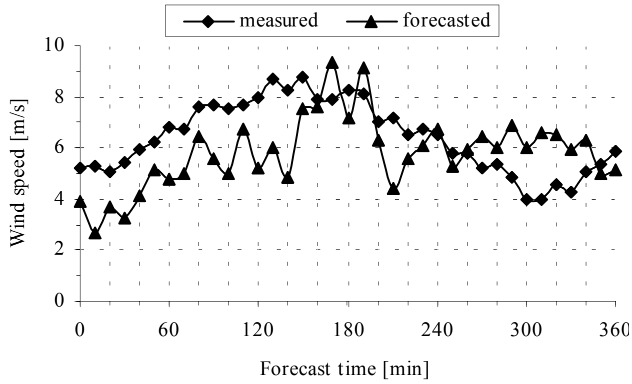

Fig. 6. Forecasted wind speed by Lorenz method.

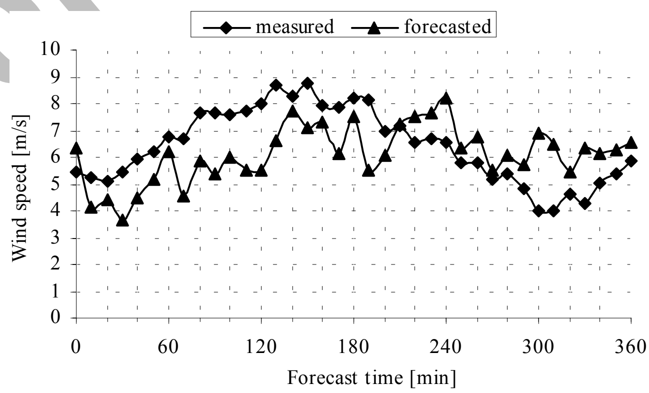

Fig. 7. Forecasted wind speed by ANN-Chaos method

2. Many large sized WPT have automatic blade pitch changing system. When wind speed changes to a certain range, WPT will keep running at a (or near one) working point by changing the attack angle of their blades. This characteristic of WPT also decreases the possible error caused by the forecasted wind speed, especially in the range of low wind speed. Fig. 10 shows the relationship of the torque coefficient, C_m, and velocity ratio k of target WPT under different attack angles. When wind speed changes from 9.6 m/s to 8.8 m/s, C_m can be kept at 0.04 by changing blade attack angle from 0.5 degree to 3.6 degrees.

It is confirmed that the converted output is not significantly influenced by the precision of the forecasted wind speed within a limited range. The forecasted wind speed with relative large error may therefore be used in the conversion of outputs.

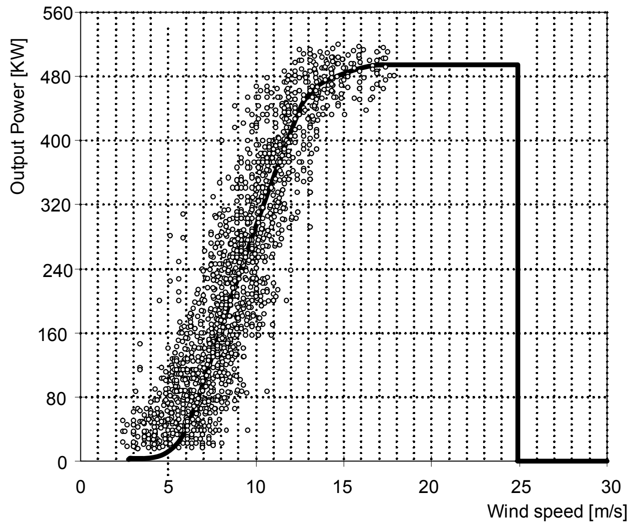

Fig. 8. The Output Characteristic Curve used in conversion of forecasted wind speed to output of *WPT* (Note: *WPT* is 490 kW in capacity. Dots spread around curve are operation points.)

TABLE IV
PERCENTAGE OF AVERAGE ABSOLUTE ERROR BASED ON THREE METHODS

Forecast time	Lorenz method	Chaos-ANN method	Jacobean method
1 Hours ahead	22.65%	25.48%	20.59%
2 Hours ahead	23.23%	28.12%	20.68%
3 Hours ahead	26.74%	27.24%	24.45%
4 Hours ahead	30.25%	31.03%	26.66%
5 Hours ahead	33.56%	32.18%	28.52%
6 Hours ahead	33.50%	35.14%	30.32%
In average	28.32%	29.87%	25.20%

III. OUTPUT FORECASTING BY OFM

In OFM, two techniques, namely *Radial Basis Function Network* (*RBFN*) [7] and *Multiple Regression Method (MRM)* are applied based on the observed data from the target WPT.

A. Input Data for MRM and RBFN

Table IV shows the five types of observed annual-hourly data that are considered in this method. These data include the output power (OP), the power energy (PE), the wind speed (WS), the maximum wind speed (MS) and the wind direction (WD), these five inputs are also used in RBFN. Here, two necessary points need to be emphasized:

1. The observed historical output is applied as one of the inputs to forecast the output.
2. Selected five inputs have strong influence on the output power, which can be accurately or approximately expressed by a linear equation. They can be easily used in predicting the output results.

B. The Application of MRM in Wind Speed Forecast

1) The Structure and Principle of MRM

The relationship between the inputs and the output is linear for MRM.

For one variable x_1 (as input), the MRM defines a line to output Y by

$$Y = b_1 x_1 + a_{01} \quad . \tag{8}$$

For two variables x_1 and x_2 (as inputs), MRM will yield a surface defined by

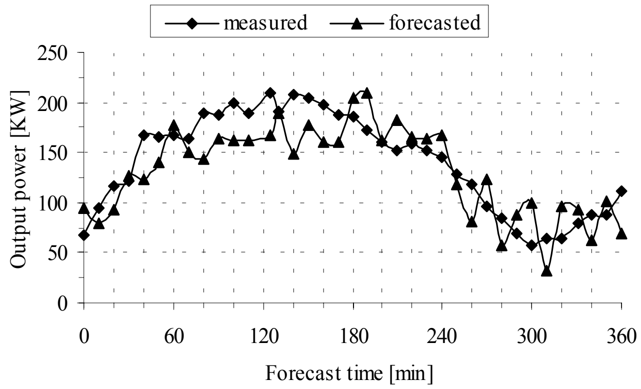

Fig. 9. The converted output power from forecasted wind speed.

TABLE V
PERCENTAGE OF AVERAGE ABSOLUTE ERROR IN CONVERTED OUTPUT POWER SIX HOURS AHEAD IN MFM

Time	Average absolute error	Maximum absolute error
1 Hours ahead	15.33%	39.23%
2 Hours ahead	10.86%	33.12%
3 Hours ahead	18.55%	36.49%
4 Hours ahead	18.84%	32.62%
5 Hours ahead	16.82%	30.65%
6 Hours ahead	15.20%	42.60%
In average	15.93%	35.78%

surface defined by

$$Y = b_1 x_1 + b_2 x_2 + a_{02} \tag{9}$$

For N variables $x_1, x_2 ...... x_{n-1}, x_n$ (as inputs), MRM will yield multiple surfaces defined by

$$Y = b_1 x_1 + b_2 x_2 + ... + b_n x_n + a_{0n} \, . \tag{10}$$

Fig. 11 shows relationship of the actual value, the forecasted value and the error value in surface for a two-variable system. In MRM, the inputs, WS, MS and PE, are linear to the WPT output. Wind direction also has a strong influence on the WPT output.

Fig. 12 shows a P-D (output and direction) chart of the target WPT. It shows the influence of wind direction on the output of the WPT. The wind direction centers at around 60 and 240 degrease. The relationship of wind direction and WPT output is calculated statistically in this paper.

Based on the mentioned reason, in our case the output is able to be expressed by four selected input data and forecasted by MRM, This will be a interesting test in this paper also.

2) The Forecasting Procedure of MFM

Here, first define $x_1, x_2, x_3,$ and x_4 as the input variables and let: x_1 relates to MS, x_2 relates to WD, x_3 relates to WS, and x_4 relates to PE. Then, extract 8754 data out of the 8760 data for each type of data to forecast the constants b_1, b_2, b_3 and b_4. The results are shown in Table VII.

In this table, b_1, b_2, b_3, and b_4 are shown in column $\mathbf{B}$, β and t are the coefficients generated from calculation process. The linear output equation of Table VII may be expressed as

$$P = 4.852 x_1 + 8.43 \times 10^{-2} x_2 + 5.548 x_3 + 0.629 x_4 - 15.877 x_5 \tag{11}$$

where, the unit of P is kW.

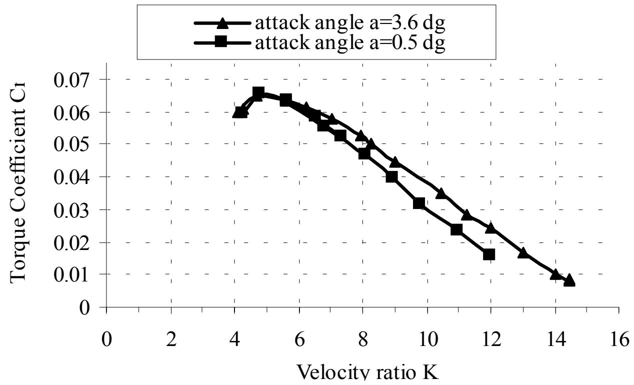

Fig. 10. Relationship of moment coefficient and velocity ratio of 490 kW WPT in different attack angles.

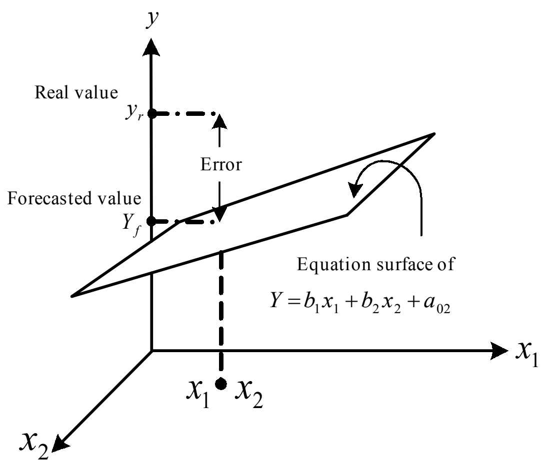

Fig. 11. The relational curve of actual value, forecasted value and error in surface of two variables.

TABLE VI
THE TYPES AND NUMBERS OF ANNUAL-OBSERVATIONAL DATA OF WPT USED AS INPUTS IN OFM

Input names	Input numbers
Output Power (OP)	8760
Power Energy (PE)	8760
Wind Speed (WS)	8760
Maximum Value of Wind Speed (WS)	8760
Wind Direction (WD)	8760

TABLE VII
THE COEFFICIENTS AND VALUES OBTAINED FROM LINEAR MULTIPLE REGRESSION METHOD IN OFM

Regression model	Unstandardized coefficient		Coefficient β	Coefficient t
	B	Error		
Constant	-15.877	1.832	---	-19.584
Variable x_1	4.582	0.262	0.136	14.159
Variable x_2	8.43E-02	0.006	0.025	3.808
Variable x_3	5.548	0.354	0.158	15.654
Variable x_4	0.629	0.01	0.598	65.651

Now, the issue is determining the values of input variable x_1, x_2, x_3, and x_4. By determine forecast time from 1 to 6 hours, the each hour forecasted values of x_1, x_2, x_3, and x_4 are obtained from the forecast by neural network. The forecast results are shown in Table VIII. Table IX shows the simulated results obtained from (11) and Table VIII. Fig. 13 shows the output curves converted from the forecasted results.

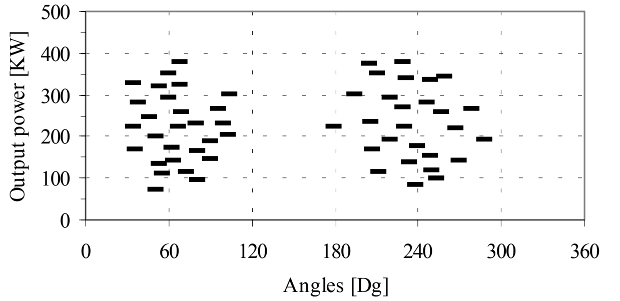

Fig. 12. The output of target WPT under different degree of wind direction (Note: this figure takes North direction as 60 degree in calculation.)

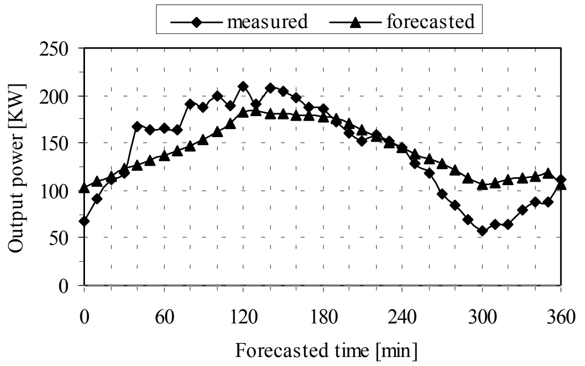

Fig. 13. The Output of WPT converted from forecasted equation by *MRM* in *OFM*.

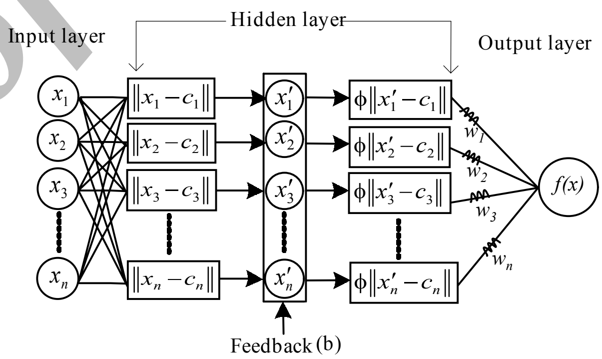

Fig.14. The structure of RBFN with n inputs.

TABLE VIII
VARIABLE COEFFICIENTS IN EACH HOUR OF FORECAST TIME IN MULTIPLE REGRESSION METHOD OF OFM

Forecast time	Variable x_1	Variable x_2	Variable x_3	Variable x_4
1 Hours ahead	7.50	206.00	5.90	90.00
2 Hours ahead	8.81	280.08	7.70	150.00
3 Hours ahead	8.60	231.04	7.50	150.00
4 Hours ahead	7.80	213.58	6.20	120.00
5 Hours ahead	7.00	69.27	5.50	80.00
6 Hours ahead	7.20	68.50	5.60	82.00

C. The Application of RBFN to Wind Speed Forecast

1) The Structure and Principle of RBFN

Fig. 14 shows a neuron model with n inputs in RBFN. Each neuron contains a parameter vector called center $\mathbf{w}$, and the unit calculates a square distance between the center and the network input vector $\mathbf{x}$. The squared distance is then divided by a parameter called a bias and the result is passed through a nonlinear function.

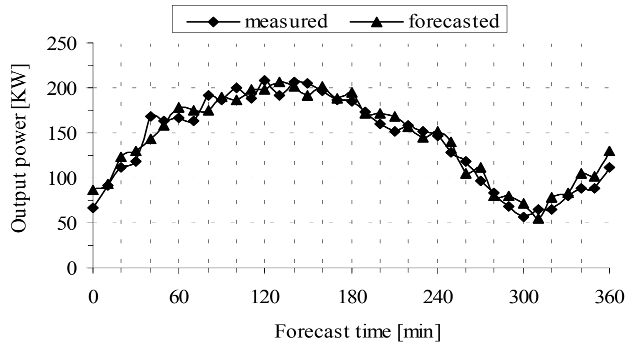

Fig. 15. Forecasted output power by Radical Basis Function network in *OFM*.

In Fig. 14, $\|x_i - c_i\|$ calculates the distance between $\mathbf{w}$ and $\mathbf{x}$. The transfer function ϕ is the radial basis function and is usually a Gaussian function. The radial basis function acts as a detector which produces 1 whenever the input $\mathbf{x}$ is identical to its weight vector $\mathbf{w}$. b is bias which allows the sensitivity of the radial basis function to be adjusted. The response of the RBFN is given by

$$f(x) = \sum_{i=1}^{n} w_i \phi \left(\|x_i - c_i\|^2 / b_i \right) \qquad (12)$$

2) The Forecasting Procedure of RBFN

Here, it will be shown the calculation steps of RBFN for forecasting the WPT output. *Neural Connection* Version 2.1 software is used in this forecasting. Five types of data, including 8760 historical output data of our target WPT, are used to forecast the future output. In the calculation, the best result is obtained by dividing the input data as follows:

1. The numbers of training data is 5×6395.
2. The numbers of validation data is 5×1315.
3. The numbers of testing data is 5×1050.

Fig .15 shows the forecasted outputs obtained from the RBFN simulation.

Table X shows the percentage of average absolute error of the forecasted output. The result shows that the errors are much smaller than that of other methods.

D. Analysis and Appraisal on the Results of OFM

From the previous analysis of the OFM, it is obvious that:

- Taking observed data as input is useful for improving the precision in output forecast, particularly when input and forecasted output are same type. In RBFN, Table 10 shows that the percentage of absolute error is about 3.66% in average.
- It is necessary to know what relationship exists between the input and output (forecasted target). This relationship is useful in the selection of the best forecast method. The selection process of MRM described previously is an example.
- In Multiple Regression Method, the percentage of average absolute error ranges from 4.48% to 28.52%. The forecast result can be changed by changing and testing arrangement order of input data, this is a topic of another research and will not be discussed here.

TABLE IX
PERCENTAGE OF AVERAGE ABSOLUTE ERROR IN FORECASTED OUTPUT POWER SIX HOURS AHEAD BY *MRM*

Forecast time	Average absolute error	Maximum absolute error
1 Hours ahead	18.45%	38.83%
2 Hours ahead	20.06%	42.11%
3 Hours ahead	15.35%	26.29%
4 Hours ahead	4.48%	8.62%
5 Hours ahead	26.21%	43.56%
6 Hours ahead	28.52%	48.42%
Average of six hours ahead	18.80%	34.63%

TABLE X
PERCENTAGE OF AVERAGE ABSOLUTE ERROR IN CONVERTED OUTPUT POWER BY RBFN

Forecast time	Average absolute error	Maximum absolute error
1 Hours ahead	4.50%	10.003%
2 Hours ahead	4.62%	8.00%
3 Hours ahead	3.52%	7.50%
4 Hours ahead	2.80%	9.00%
5 Hours ahead	2.36%	6.50%
6 Hours ahead	4.18%	15.33%
Average of six hours ahead	3.66%	9.39%

IV. CONCLUSION

This paper shows that it is possible to forecast the output power of WPT with certain degree of precision. The same technique can be used to forecast output power of a complex wind farm with multiple types of WPT. From results of this paper, the following points could be summarized:

1. The output of a WPT can be estimated by using relevant weather data besides the wind speed. The weather data can be modified to form a new composite data set. This study proposes several practical ways to estimate the WPT output; these techniques are very useful in planning and operation of WPS.
2. For a WPT under operation, it is possible to forecast its output by using the historical operation data at the site, the precision of forecast result relates not only to the number of data, but also to its relationship with the output to be forecasted. RBFN is very useful in forecasting the same type of data (as discussed in RBFN). The relative low error (in relative condition) in forecasted result also makes it possible to be used in practical situation.
3. This paper shows that RBFN method based on five observed data set yields a better result than the MRM method, which utilizes four sets of the observed data. RBFN is also better than the MFM, which is based on the weather data only. The forecasted result from MRM has almost the same degree of precision as the MFM.

The results and experiments obtained from this paper can also be applied to predict the output of a wind power farm with multi-type of WPT on complex land shape.

REFERENCES

[1] H. S. Hong, L. Hong, "Wind turbine simulation," *Journal X. J. Technology*, vol. 2, no. 1, pp.32-38, Dec. 2000.

[2] H. Y. Shi and K. Nagasaka, *Wind Speed Forecasting by Special Method*, Master Dissertation, Dept. Elect. Eng. Univ. TUAT. Tokyo, 2002.

[3] R. Capone and S. Kimbrough, "Using a neural network to predict electricity generation," in *Proc. 1994 Neural Network Conf.,* pp. 324-329, 1994..

[4] S. T. Chen, D. C. Yue and A. Moghaddamjoo, "Weather sensitive short-term load forecasting using non-fully connected artificial neural network," *IEEE Trans. Power Delivery*, vol. 7, no. 3, pp. 198-205, Aug. 1992.

[5] J. T. Conner and L. E. Atlas, "Recurrent neural networks and load forecasting," in *Proc.1991 Applications of Neural Networks to Power Systems Conf.*, pp. 22-25, 1991.

[6] X. J. Wind Power Company, *Wind Power Technology*, Urumqi: New-energy, pp. 5-35, 1999.

[7] S. I. Mura, *Analysis of Time Serious Forecast*, Tokyo: Pub. Corp., 1999 p. 80-126.

[8] T. S. Dillon and S. Sestito, "Short-term load forecasting using an adaptive neural network," *Electric Power Energy Systems*, vol. 13, no. 4, pp. 186-1921991.

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