MODEL AND PROCEDURES FOR RELIABLE NEAR TERM WIND ENERGY PRODUCTION FORECAST

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ABSTRACT

Accurate and reliable prediction of wind energy production is important for the operational management of wind farm as well as for the stability of electrical grid with renewable energy integration. This paper describes a model and procedure that accurately predict wind energy production using weather forecast. An aerodynamic model is used to predict the wind speed distribution with elevation from the 24 hour forecasted wind speeds at three hours intervals. The model considers the effects of factors such as ground topology, land cover, etc. on the wind speed distribution. Therefore, it is applicable for different types of territories. The simulated wind speed, at time interval of 15 minutes, is then used together with the factory or calibrated turbine production curve to predict the energy production in 24 hours. The model and procedures for wind energy production forecast are validated on a 100kw prototype research wind turbine installed on the campus of CWRU. The actual energy production data in different seasons from the prototype wind turbine was analyzed and compared with that by model forecast. It was found this new model-based forecast method provide more reliable and accurate prediction of wind energy production, compared with alternative methods. The potential application of this wind energy forecast method include to improve the management of wind farm operations, to evaluate the electric power storage demand, to optimize the market values of wind energy , and to assist the electric grid integration of renewable energies.

1. INTRODUCTION

Being clean and renewable, wind energy arouses significant research all around the world. According to the report form U.S. Department of Energy, the total electricity produced from wind power in the United States is 163.85 terawatt-hours, or 4.06% of all produced electrical energy by the end of 2013. This number is expected to continue to grow [1]. However, as commonly known, a major issue for efficient utilization of wind energy is its instability [2]. This makes it complex to integrate the wind energy with the electricity network. This poses demand on energy store capacities, causes the waste of wind energy, and decreases the efficiency and stability of the electric grid. Model to accurately predict wind energy production will play an essential role to increase the efficiency of wind energy utilization.

To this end, this research aims to develop a reliable forecast model for wind energy production. The performance of the model is verified on a utility scale wind turbine.

2. PROTOTYPE WIND TURBINE

The wind turbine used in this research is a 100kW utility scale wind turbine (Northern Power® 100) located on the campus of CWRU (Figure 1). The key parameters of the turbine are shown in Table 1. The manufacture power curve is shown in Figure 2. The wind turbine was installed in November 2010 with financial support from the Ohio Third Frontier Program. The primary role of the turbine is to serve as a research test-bed for electrical and mechanical research. A Campbell-Scientific data acquisition system (DAQ) is installed in the wind turbine to collect its operation data continuously, which include data on the wind speed, direction, output power, etc.

Table 1 Prototype wind turbine parameter

Configuration	Description
Model	Northern Power® 100
Design Class	IEC IIA
Design Life	20 years
Hub Heights	37m
Power Regulation	Variable speed, stall control
Rotor Diameter	21m
Rated Wind Speed	14.5m/s
Rated Electrical Power	100kw, 3 phase, 480 VAC, 60/50 Hz
Cut-In wind speed	3.5m/s
Cut-out wind speed	25m/s

Figure 1 Wind turbine on CWRU campus

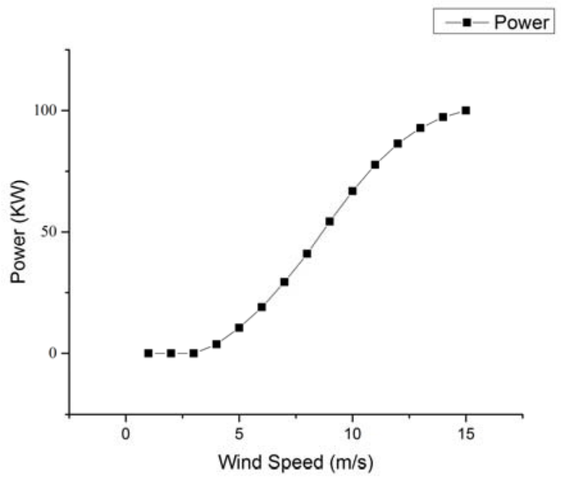

Figure 2 Northern Power® 100 power curve

3. MEASURED WIND TURBINE POWER CURVE

3.1. Measured curve

The DAQ system described above is connected to a data storage system installed at the bottom of the wind turbine tower, which can be accessed directly from a terminal computer. Among the instrument signals the DAQ system collects are the power output versus wind speed. Data collected on the wind turbine power produce history is analyzed to develop the relationship between power production and wind speed. Example data over one month period, from August 20th through September 20th, is shown in Figure 3. Plot of wind speed versus power production is shown in Figure 4.

The equation from regression analyses is shown as

$$P_w = 0.215 - 0.962v + 0.199v^2 + 0.073v^3 \qquad (1)$$

where P is output power (kW) and v is wind speed (m/s).

The Pearson product-moment correlation coefficient (PPMCC or PCC) is used to measure the degree of linear dependence between two variables [3], i.e., wind speed and power output. The value of PPMCC ranges between -1 to +1, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation. PPMCC is calculated via Eqs (2-4). [4]

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{X_i - \overline{X}}{s_X}\right)\left(\frac{Y_i - \overline{Y}}{s_Y}\right) \qquad (2)$$

$$S_X = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \overline{X})^2} \qquad (3)$$

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad (4)$$

where r is Pearson product-moment correlation coefficient, S_X is sample standard deviation and $\overline{X}$ is sample mean.

Table 2 Correlation and Pearson coefficient [5]

Correlation	Coefficient
None	0~0.09
Low	0.1~0.3
Middle	0.3~0.5
High	0.5~1.0

Pearson correlation of power and wind speed is 0.816. According to Table 2, there is a high correlation between wind speed and power output.

By comparing the manufacture curve and measured curve shown in Figure 5, it shows that from wind speed 0 to 4 m/s, power output of simulation curve is higher than manufacture curve and from 4m/s to 8m/s, simulation curve is lower than manufacture curve. The measured curve exceeds 8m/s may not reliable because there is no real measured wind speed as shown in Figure 4.

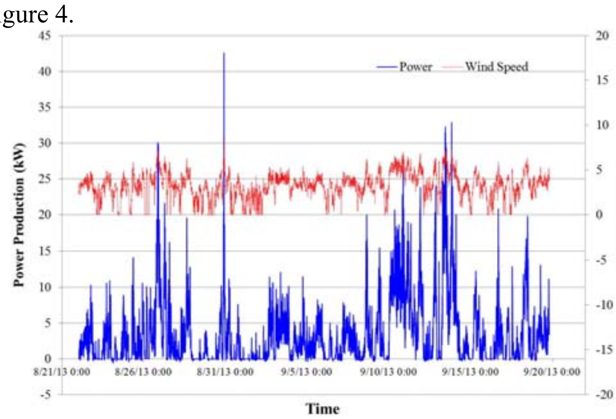

Figure 3 Wind speed and power production over one month

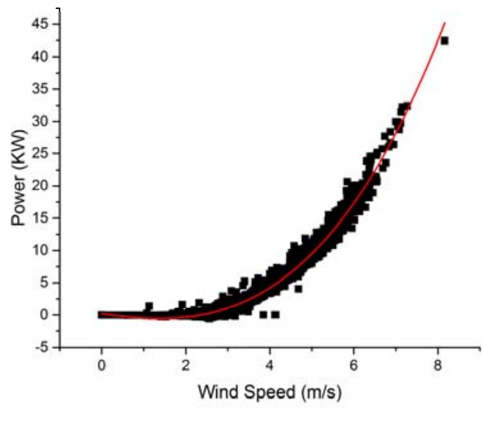

Figure 4 Measured curve of wind speed and power output

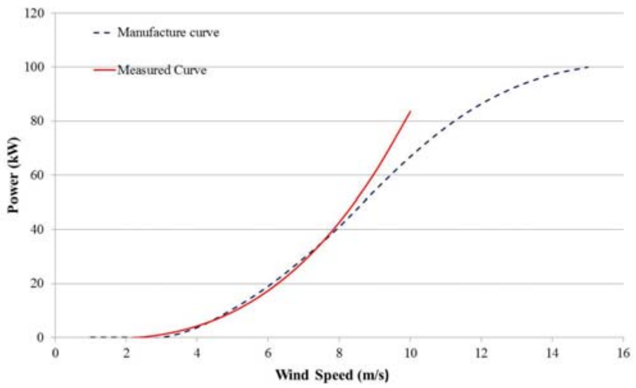

Figure 5 Manufacture curve and measured curve

3.2. Temperature

The temperature affects the power production by changing the density of air. According to the theoretical wind power and wind speed relationship [6]:

$$P_w = \frac{1}{2}\rho A v^3 \qquad (5)$$

where P_w is power output; ρ (kg/m^3) is air density; v (m/s) is the wind speed, A (m^2) is the intercept area.

The density of air changes with temperature know as ideal gas law, as shown in the following Figure 6 for pressure at 1 atm: [7]

$$\rho = \frac{p}{R_{Sp} \times T} \qquad (6)$$

where ρ (kg/m^3) is air density, p is absolute pressure, R_{Sp} is specific gas constant for dry air, 287.058 J/(kg·K) and T (°C) is temperature

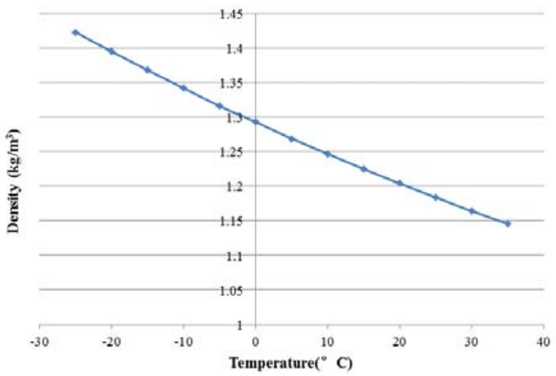

Figure 6 Air density and temperature relationship under 1 atmosphere

Use the temperature data collected form the sensor near the wind turbine, the density change for the same period as power output versus wind could be calculated. The old power data divide by the density will come out with a set of new power data as shown in Eq. 7.

$$P_{w1} = \frac{P_w}{\rho(T)} \qquad (7)$$

Making regression analyses of the new corresponding power and wind speed data, taking both temperature and wind speed into consideration, the power equation from measured data becomes:

$$P_{w1} = 0.1732 - 0.7799v + 0.1726v^2 + 0.0542v^3 \qquad (8)$$

Because the lack of temperature predicts data, the DAQ recorded temperature is used in this research to predict power and to determine the importance of the temperature as shown in Table 3 and Table 4. The time column refers to 3 hours interval for different date and thee temperature column is the corresponding temperature.

Figure 7 shows the power curve under different temperatures using Eq. 8. It shows that from wind speed 2 to 8m/s, the power output and temperature has inverse relationship.

Table 3 Temperature recorded data in 2013. 9

Time 9.26 (Hour)	**TEMP (°C)**	**Time 9.27 (Hour)**	**TEMP (°C)**	**Time 9.30 (Hour)**	**TEMP (°C)**
0-3	16.96	0-3	17.63	0-3	20.17
3-6	16.15	3-6	16.72	3-6	19.00
6-9	14.45	6-9	15.95	6-9	18.44
9-12	12.99	9-12	15.38	9-12	18.13
12-15	15.08	12-15	17.14	12-15	18.40
15-18	18.89	15-18	20.17	15-18	18.94
18-21	21.46	18-21	21.91	18-21	18.54
21-24	20.31	21-24	20.54	21-24	18.82

Table 4 Temperature recorded data in 2013. 2

Time 2.19 (Hour)	**TEMP (°C)**	**Time 2.20 (Hour)**	**TEMP (°C)**	**Time 2.21 (Hour)**	**TEMP (°C)**
0-3	6.27	0-3	-5.37	0-3	-5.18
3-6	8.46	3-6	-6.97	3-6	-4.84
6-9	6.69	6-9	-7.64	6-9	-5.02
9-12	5.09	9-12	-7.35	9-12	-6.17
12-15	3.76	12-15	-6.78	12-15	-6.47
15-18	0.06	15-18	-5.8	15-18	-5.03
18-21	-1.38	18-21	-5.21	18-21	-4.01
21-24	-3.21	21-24	-5.27	21-24	-4.8

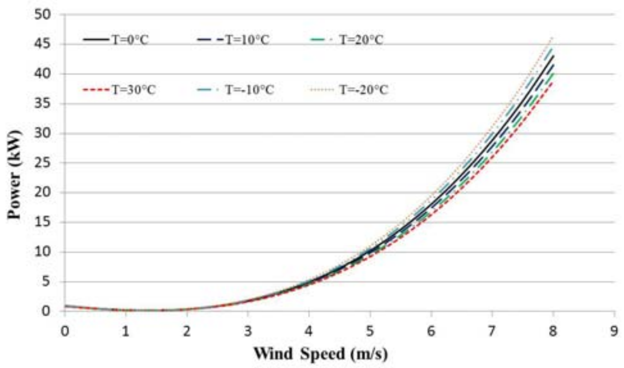

Figure 7 Power curve under different temperature

4. MODEL FOR WIND ENERGY PRODUCTION PREDICTION

4.1. Wind speed forecast data

The wind prediction data was obtained from a commercial weather forecast website [8]. It provide 24 hour weather forecast at 3 hour interval. Predicted wind speed data in Cleveland from different time periods of a year were used. Examples of the predicted wind speed data is shown in Table 5 and 6.

Table 5 Wind predict data in September 2013

Time 9.26 (Hour)	Wind speed (m/s)	Time 9.27 (Hour)	Wind speed (m/s)	Time 9.30 (Hour)	Wind speed (m/s)
0-3	4.10	0-3	3.00	0-3	2.62
3-6	3.45	3-6	3.42	3-6	3.41
6-9	0.01	6-9	2.75	6-9	3.70
9-12	0.01	9-12	3.65	9-12	2.79
12-15	0.10	12-15	2.55	12-15	3.30
15-18	2.77	15-18	3.90	15-18	3.01
18-21	3.55	18-21	3.76	18-21	0.45
21-24	3.74	21-24	4.17	21-24	1.86

Table 6 Wind predict data in February 2013

Time 2.19 (Hour)	Wind speed (m/s)	Time 2.20 (Hour)	Wind speed (m/s)	Time 2.21 (Hour)	Wind speed (m/s)
0-3	7.68	0-3	6.60	0-3	5.24
3-6	8.44	3-6	6.19	3-6	4.60
6-9	8.77	6-9	6.04	6-9	4.78
9-12	8.68	9-12	5.89	9-12	5.69
12-15	7.11	12-15	6.84	12-15	4.95
15-18	7.19	15-18	6.63	15-18	3.73
18-21	7.60	18-21	6.49	18-21	2.90
21-24	6.45	21-24	5.58	21-24	1.89

4.2. Model for wind load simulation

The forecasted wind speed data at 3 hours interval is apparently not sufficient in both time and space resolution for accurate wind power prediction. In order to increase the accuracy of power output prediction, a model is developed to improve the prediction results.

Wind speed mainly contains two parts: mean wind speed and turbulent wind speed. Wind speed history can be very complex because it is affected by terrain, elevation, land cover, and many other factors. All of these are considered in wind speed simulation.

4.2.1. Transient Wind Simulation

The transient wind velocities include two components: (1) mean wind speed and (2) turbulent wind speed, i.e.:

$$U_{tot}(t,z) = U_z(z) + u_z(t,z) \tag{9}$$

where $U_{tot}(t,z)$ is the total wind speed; $U_z(z)$ is mean wind speed component which varies with height z above ground and $u_z(t)$ is the fluctuating turbulent wind speed that varies with time t at a height of z above ground.

a) Mean wind speed component

The NOAA (National Oceanic and Atmospheric Administration) provides mean hourly wind speed which must be converted to an instantaneous speed to produce transient wind simulations. For example, for the prototype wind turbine in Cleveland, the mean annual wind speed is 4.69m/s at a height of 10.0 meters under open terrain [9]. This wind speed needs to be adjusted for averaging time and height exposure before it is used in the model.

The *Durst curve* [10] (Fig. 8) is often used to convert wind speed data measured and averaged over one time interval to another time interval.

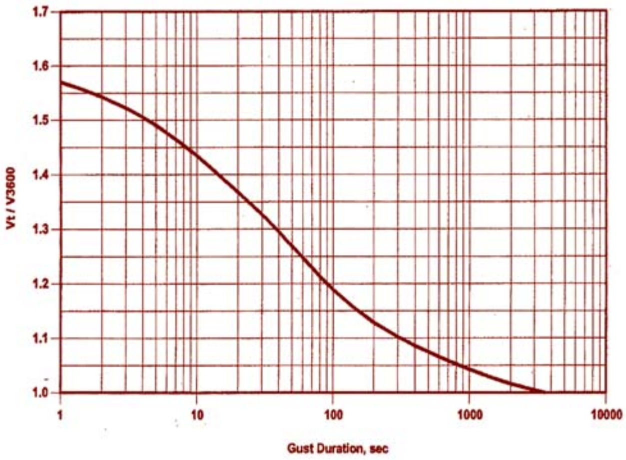

Figure 8: Durst Curve [10]

For example, taking the hourly mean wind speed value of 4.69m/s to an instantaneous value requires an amplification factor from the *Durst curve* of 1.57 and thus the site wind speed at the reference height (10.06 meters) is equal to:

$$U_{ref} = 4.69m/s \times 1.57 = 7.36m/s \qquad (10)$$

Two empirical relationships are commonly used to describe the variation of mean wind speed with elevation above the earth's surface within the atmospheric boundary layer: *The Logarithmic Law* and *the Power Law* [11]. The Logarithmic Law generally considered is more accurate for large heights, but is more complex. T*he Power Law* is more frequently used in structural engineering. It is used here to calculate mean wind speed over the turbine height.

Using *the Power Law*, the wind speed at any height above the ground can be determined using the following expression [11]:

$$U_z(z) = U_{ref}\left(\frac{z}{z_{ref}}\right)^{\alpha_0} \qquad (11)$$

z_{ref} is reference height above the ground equals to 10m [10] and U_{ref} is the reference wind velocity measured at reference height. The exponent, α_0, in Eq. 11 will change with the terrain roughness, and also with the height range, when matched to the logarithmic law.

A relationship that can be used to relate the exponent to a constant of integration, with the dimensions of length, known as the roughness length, z_0, is as follows [12]:

$$\alpha_0 = \frac{1}{\log_e(z_{ref}/z_0)} \qquad (12)$$

Table 7 Drag coefficient for various terrain types [12]

Terrain type	Roughness length (m)
Very flat terrain(dessert)	0.001-0.005
Open terrain(grassland)	0.01-0.005
Suburban terrain(buildings 3-5m)	0.1-0.5
Dense urban (buildings 10-30m)	1-5

For the 100kW wind turbine on CWRU campus, z_0 is taken as 0.3 for a site surrounded with medium rise buildings [11]. The chosen of coefficient can be referring to Table 7. Wind turbine hub-height of the turbine is 37m. Therefore, the mean wind speed at the hub height is equal to 9.03m/s.

b) Turbulent wind speed component

The model used here to simulate turbulent wind speed was developed by [13] and utilizes the wind turbulence spectral density $S_k(k,z)$ proposed by [14]:

$$S_k(k,z) = \frac{\left(200 \times U_1^2 \times z\right)}{U_z(z) \times \left[1 + 50 \times f_k(k) \times \frac{z}{U_z(z)}\right]^{\frac{5}{3}}} \qquad (13)$$

where $f_k(k)$ and U_1 are intermediate variables defined by:

$$f_k(k) = k \times \Delta f \qquad (14)$$

$$U_1^2 = K \times U_{ref}^2 \qquad (15)$$

$$K = \left(\frac{0.4}{\log(10/z_0)}\right)^2 \qquad (16)$$

where Δf is frequency increment; k is the number of frequency increment; K is the surface drag coefficient. 0.4 here is an experimentally value known as von Karman's constant.

The random turbulent wind speed component is simulated using Eq. (17) [15]:

$$u_z(t,z) = \sum_{k=1}^{n}\left\{\sqrt{(2 \times S_k(f_k) \times \Delta f} \times \cos[(2 \times \pi \times f_k(k) \times t + \phi_k]\right\} \qquad (17)$$

where ϕ_k is Gaussian random number distributed uniformly between 0 and 2π which is chosen for each central frequency; t is time value in the simulation, and n is the number of frequencies for which the given spectrum $S_k(k,z)$ has been evaluated for specific frequencies f_k.

The equations above have been evaluated by [15] and have been found to generate accurate wind histories when compared to measured wind histories. Finally, a 180 minutes wind history was simulated, the resulting simulated wind record, including the adjusted mean wind speed, is given in Figure 9. In the Figure, for a given mean wind speed of 3.1m/s, the wind velocity is predicted to vary between 2m/s to 4m/s. This means the fluctuating turbulent wind speed varied from -1.4m/s to 1.1m/s. Finally, with this model, the wind speed data at 3 hour time interval was transformed into 18 data point at ten minutes time interval.

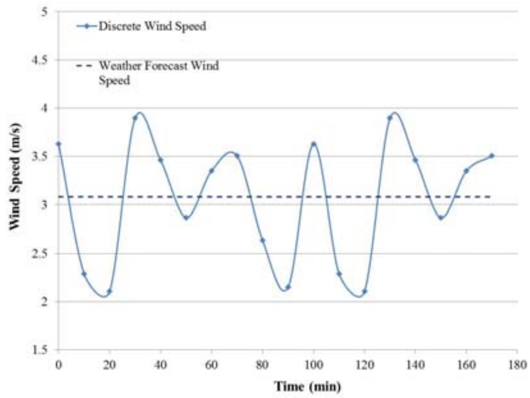

Fig. 9 Simulation wind speed over time

However, the real relationship between power output and wind speed is very complex [16]. A lot of other factors like humidity, rain and other components. For the reason that the influence of these factors is relatively small compare to wind speed. In this research, the other factors other than wind speed and temperature was ignored.

5. METHODS FOR WIND ENERGY PRODUCTION FORECAST

Several methods are evaluated on the performance to forecast 24 hour wind power output, i.e., (Method 1) prediction using weather forecast directly with manufacturer turbine production curve; (Method 2) prediction using weather forecast directly with measured turbine production curve; (Method 3) prediction using simulated wind speed from weather forecast data and manufacturer turbine production curve; (Method 4) prediction using simulated wind speed from weather forecast and measured turbine production curve; and (Method 5) prediction using discrete weather forecast data and measured turbine production curve considering temperature effects. The measured actual power output data is used as the comparison basis. The results are summarized in Table 8 and 9. The difference refers as

$$\text{Difference}=\left|\frac{\text{Predicted-Actural}}{\text{Actural}}\right| \tag{18}$$

From table 8, it is observed that predict use Method 4, i.e., prediction using simulated wind speed from weather forecast and measured turbine production curve, gives best result with an overall less than 3% from real power production. This method is about 10% more accurate than Method 2, i.e., prediction by directly using weather forecast. This method is also more accurate than Method (5), which considers both wind speed and temperature.

Energy production prediction directly using manufacturer production curve and weather forecast data (Method 1) is unsatisfactory. The prediction difference is about 118% on September 26th, 60% difference on September 27th and 70.39% difference on September 30th from actual energy production. Using simulated weather data from weather forecast data improved the accuracy, but still more than 30% difference.

Table 8 Wind energy production prediction by different methods for warm weather

Date	*9/26/13*	*9/27/13*	*9/30/13*
Actual energy production (kW)	273.56	394.8	185.44
Predicted Energy production by Method (1)	596.84	155.13	54.91
Difference	118.18%	60.71%	70.39%
Predicted Energy production by Method (2)	248.27	341.95	154.11
Difference	9.24%	13.39%	16.89%
Predicted Energy production by Method (3)	649.41	238.42	125.38
Difference	137.39%	39.61%	32.39%
Predicted Energy production by Method (4)	280.08	389.87	186.76
Difference	2.38%	1.25%	0.71%
Predicted Energy production by Method (5)	265.25	368.06	176.65
Difference	3.04%	6.77%	4.74%

Table 9 illustrates that the most accurate method is the use of simulated wind speed and manufacture curve which is overall 3% more accurate than predict directly using manufacture curve and weather forecast. Prediction using discrete weather forecast data and simulation curve in this case shows overall 8% difference than real number. The reason for the inaccuracy of method (4) in cold weather is that the measured curve is based on lower wind speed. But as shown in Table 6, the wind speed for chosen days is relatively high. In such case, the manufacture curve is more accurate. Method (5), which considers both wind speed and temperature in this case is more accurate than method (4) but less accurate than method (3).

Method (5) in both Table 8 and Table 9 takes wind speed and temperature into consideration. It is the second accurate way in both warm and cold weather however not the most accurate way. This might be due to the reason that the ambient temperature also affects the efficiency of the wind turbine. Another reason is because the curve was simulated mainly based on lower wind speed level while the average wind speed is relatively high in the three chosen days.

Table 9 Wind energy production prediction by different methods for cold weather

Time	*2/19/13*	*2/20/13*	*2/21/13*
Actual Energy Production (kW)	5375.04	3328.22	1119.67
Predicted Energy production by Method (1)	5640.40	3273.10	995.70
Difference	4.94%	1.66%	11.07%
Predicted Energy production by Method (2)	5696.13	2925.14	965.83
Difference	5.97%	12.11%	13.74%
Predicted Energy production by Method (3)	5536.24	3276.93	1061.97
Difference	3%	1.54%	5.15%
Predicted Energy production by Method (4)	5846.74	3051.12	1037.26
Difference	8.78%	8.33%	7.36%
Predicted Energy production by Method (5)	5736.08	3122.72	1063.53
Difference	6.72%	6.17%	5.01%

6. CONCLUSION

Wind power output depends decisively on the unpredictability of the wind speed, unexpected variations of wind farm output may increase operating costs of the electricity grid as well as set potential threats to the reliability of electricity supply [17]. Without the ability to accurately predict wind energy generation, it is very unlikely that wind energy will become a major contributor to the total energy market [18]. A sophisticated method to predict energy output of wind turbine is presented in this research. The method is based on the real data from a prototype wind turbine and using statistical analysis tools to produce a simulation power curve. In the study, both wind speed and temperature were taken into consideration to produce different power curve. A simulation discrete wind speed method was then introduced in order to increase the accuracy of the power output prediction. Finally, by using both weather forecast data and real data record from DAQ system in the turbine, the results based on different methods of power output prediction were carried out. By analysis the results, following conclusions can be drawn after analyzing:

1. The power output curve of a same wind turbine is different under different temperature. In a certain range, the power output and temperature has an inverse relationship at same wind speed. However, the temperature has less effect on wind turbine power output compare to wind speed. In this research, the method take temperature into consideration is less accurate than the method take only temperature into consideration.
2. In order to increase the accuracy of wind power predicts, different power curve should be used around the year. In this study, the manufacture power curve is more accurate to use in winter and simulation curve is more accurate to use in summer time.
3. By comparing Method (1) and Method (3); Method (2) and Method (4), the discrete wind speed method developed in this research can increase the accuracy of energy forecast effectively. Using the simulation wind speed method shows great advantage if compared to a prediction by directly using weather forecast.

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