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Estimating the Uncertainty of Wind Power Energy Based on the Probability Density Function

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Extended Abstract

The more advantages of wind plants rather than heat power plants causes the development of this valuable energy to generate the electricity. These are including the economic and environmental benefits. However, the intermittent nature of wind causes more risks for wind investors. A new method has been proposed in this article to simulate the capacity value of wind resources based on the probability density function of wind. Then, the amount of the seasonal electricity generation has been calculated in a specific region. Finally, a correction factor has been suggested which is useful for wind investors

Introduction

Challenges related to decrease the fossil fuel, and increase the environmental problems motivate the authority to develop the renewable energy. Because of the fast growth of technology of wind turbines, wind attracts the most attention among the others. Also, Environmental and economic benefits include minimal pollution, no greenhouse gas emissions, low footprint, no water pollution with mercury and no water needed for operation, creation of jobs in rural communities, increased tax revenue and decreased outflow of money to import petroleum products are expanding the wind power development[1-3].

The fluctuations of wind speed effect on the planning and operation of wind plants. The term Capacity Credit (CC) use to estimate the amount of wind energy can be substituted by conventional generation. A simple definition of capacity credit of WECS can be given as[4, 5]: "The amount of conventional generation that could be 'replaced' by generation from wind without making the system less reliable"

Many methods have been given to evaluate the capacity credit of wind turbine generators (WTGs). One of the most famous and widely used reliability-based approaches to evaluate wind capacity credit is Effective Load Carrying Capacity (ELCC). The loss of load expectation (LOLE) is the key factor in determining the capacity credit with ELCC approach. LOLE is the number of hours in a given period (month, year etc.) that generating system cannot respond the overall system demand. At first, the LOLE of original generating system calculate without WTGs. Then the WTGs are added to the system and determine the LOLE and observe the significant drop in LOLE. In the next step the peak load of the system (with WEC) increase gradually until the original LOLE values are obtained. This increased value of the system peak load is called the capacity credit value of the WEC [4, 6, 7].

Doi:

Because of the difficulty of gathering the database to use for the ELCC calculation, interest in simpler approach has grown over the past several years. To assess the capacity value of a wind plant, it would be desirable to have the ability to do the calculation by using the wind data and whatever minimal auxiliary data set. Therefore, in cases where ELCC can't be calculated because of data or other limitations, these methods can be useful. The approach which has been offered in this research is based on the approximation and probability methods. The capacity factor approach is the proportionality of the actual energy output of a wind plant over the output of the plant if it operated at its rated capacity at the same period of time[8]. This approach can be used to measure efficiency of any WTG or any power generating system. PJM and NYISO define capacity credit as the capacity factor during the daily peak load hours of the peak load months[8, 9]. Definition of peak load hours and peak load months may vary for different companies. PJM peak load hours and peak load months are 3-6 pm for the month of June, July and August[10].

The wind speed and wind power output at peak hours for the peak months are measured. With the help of simulation tools, total peak load hour wind power output during the peak load months over a significant period of time is calculated. This summed peak hour wind power output value is divided by wind power that would have been produced if the WTG generated electricity at the rated output to calculate the capacity factor. Wind capacity values in this method will vary with the definition of peak load hours and peak load months.

Derating Adjusted Forced Outage Rate (DAFOR) or the Equivalent Forced Outage Rate (EFOR) is the probability of a unit existing in its complete down state. The DAFOR is obtained using a method in which the residence times of the actual derated states are apportioned between the up (normal) and down (outage) states. The effect of wind variability can be aggregated to produce a DAFOR statistic similar as for conventional generating units. The DAFORW method uses the probability distribution of the annual wind power instead of the particular time period profile used in the Capacity Factor method[8].

In [11] proposed a simplified approach to determine the CC. This approach employs an effective forced outage rate of a wind generator and uses the loss of load probability calculations to estimate the capacity credit of WEC, and the load is kept constant throughout. In this approach, at first, the expected loss of load of a system with conventional generators is obtained. Then, wind generator is added to the system. The decrease in expected loss of load is calculated. After obtaining the expected loss of load with the added wind generator, the wind generator is substituted by a conventional generator and the capacity of the conventional generator is varied until the expected loss of load matches the second value. This capacity is the capacity credit that can be assigned to WTG. In [9] extends the simplified approach to estimate the capacity credit under variable load conditions. It is based on replacing the annual load duration curve by a stepped function and calculating the capacity credit for each of the load steps. weighted average of these values using the probability of the various load steps as weighting factor is proposed as an estimate of the overall capacity credit.

It can be conclude that in the previous methods, the CC should be calculated by any changes in the power system networks. For long term planning the capacity credit should be independent of this variation. In this paper, proposed a method based on the probability distribution function of wind speed to assign the capacity for a wind farm.

The rest of this paper is organized in the following order. Section 2 describes the model of calculating the capacity credit. Section 3 implements the proposed method on a test system. Finally, the last section is devoted to the conclusion.

I. Wind turbine output

Advantages of wind energy conversion systems (WECS) include short lead times in design and installation, less carbon emissions (green energy), most competitive among all renewable energy technologies and no fuel costs; hence reduced operating costs [12]. These advantages cause the wind play an important role for developed countries committed of obtaining the renewable energy portfolio standard. Beside these advantages, the intermittent and fluctuation nature of wind speed can affect on the quality of power system. Also, wind turbine output is directly proportional to the wind speed[13]. Figure 1 illustrates the power curves used to determine power production by each wind turbine. According to Figure 1 a wind generator will begin to generate the electricity at the cut-in speed (Vci) and will trip at the cut-out speed (Vco) for its safety. The maximum power will generate between the rated speed (Vr) and cut-out speed. There is a nonlinear relationship among the power output and the wind between the cut-in speed Vci and the rated speed Vr. Equation 1 given a mathematic expression to calculate the power generated by WTG. A, B, and C are constant value that can be calculated by equation 2, 3, and 4[14-16].

$$P_{Gewind} = \begin{cases} 0 & 0 \le WS \le V_{ci} or WS \ge V_{co} \\ P_r(A + B \times WS + C \times WS^2) & V_{ci} \le WS \le V_r \\ P_r & V_r \le WS \le V_{co} \end{cases} \tag{1}$$

A= $$\frac{1}{(V_{ci}-V_r)^2}\left\{V_{ci}(V_{ci}+V_r)-4V_{ci}V_r\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\}$$ (2)

B= $$\frac{1}{(V_{ci}-V_r)^2}\left\{4(V_{ci}+V_r)\left[\frac{V_{ci}+V_r}{2V_r}\right]^3-(3V_{ci}+V_r)\right\}$$ (3)

C= $$\frac{1}{(V_{ci}-V_r)^2}\left\{2-4\left[\frac{V_{ci}+V_r}{2V_r}\right]^3\right\}$$ (4)

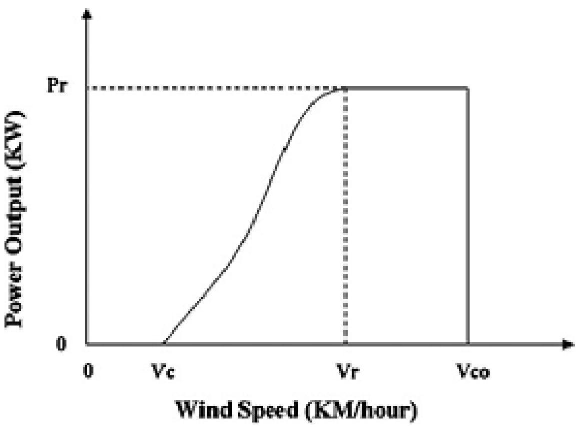

Figure 1.: Power curve of wind turbine

II. Wind probability distribution function

As mentioned in previous section the generated power of wind depends on the wind speed intensively. Wind speed distribution, when required in the model is calculated in RETScreen as a Weibull probability density function. In some cases, Rayleigh wind speed distribution also uses for modeling, which is a special case of the Weibull distribution, where the shape factor (described below) is equal to 2.

Nevertheless, wind speed distributions are often characterized by Weibull distributions [14]. Equation 5 shows the Weibull distribution function. The Weibull probability density function indicates the probability P_w to have a wind speed (w) during the year, as follows[17]:

$$P_w=\left(\frac{k}{c}\right)\left(\frac{w}{c}\right)^{k-1}\exp\left[-\left(\frac{w}{c}\right)^k\right]$$ (5)

Where ,

This expression is valid for k > 1, w ≥ 0, and c > 0. k is the shape factor, specified by the user. The shape factor will typically range from 1 to 3. For a given average wind speed, a lower shape factor indicates a relatively wide distribution of wind speeds around the aver-age while a higher shape factor indicates a relatively narrow distribution of wind speeds around the average. A lower shape factor will normally lead to a higher energy production for a given average wind speed. c is the scale factor, which is calculated from the following equation [16, 17]:

$$c=\frac{\overline{x}}{\Gamma\left[1+\frac{1}{k}\right]}$$ (6)

In this research, c and k are determined based on the historical data obtain from Canada's national climate archive [18]. These factors are estimated in MATLAB statistical toolbox.

III. Modeling the capacity value of wind

Capacity value is one of the most important parameters to evaluate the feasibility of wind power. In the introduction summarized the concept of capacity credit and factor. And also, reviewed the various methods used to determine them.

In this article, an approach is given to determine the capacity value based on the concept of expected value and probability density function of wind speed.

Expected value is one of the fundamental concepts in probability. The expected value of a real-valued random variable gives a measure of the center of the distribution of the variable. More importantly, by taking the expected value of various functions of a general random variable, we can measure many interesting features of its distribution, including spread and correlation.

If the probability distribution of P_w as wind admits a probability density function $f(P_w)$, then the expected value of wind power can be computed as follows:

$$E[P_{Gewind}]=\int_0^{V_{c-o}} P_{Gewind}\times f(P_w)d_x$$ (7)

Where

P_{Gewind} wind power generation

Since, the aim of this paper is to give a method to determine the capacity value in order to use it in long term planning. In the first step, the prediction of wind speed is compulsory. In this article, the data for Swift Current in Canada [18] is used. These data are collected for ten years from 2000 to 2009 from the Canada's National Climate Archive. And also, Billinton wind speed model has been used to predict the wind speed. This model is based on the ARMA time series. Once the wind speed time series modeled by equation (8) the simulated wind speed can be determined by (9).

$$y_t = (OW_t - \mu_t) / \delta_t \tag{8}$$

$$SW_t = \mu_t + \delta_t \times y_t \tag{9}$$

Where

OWt is the observed wind speed at hour t
μt is the mean observed wind speed at hour t
δt is the standard deviation of observed wind speed at hour t
SWt is the simulated wind speed at hour t

After modeling the wind speed based on the historical data, each year is divided into four seasons. Then, determining the Weibull probability density function's parameters include shape and scale factors for each seasons. And then, the total amounts of wind power calculate by the following equation annually.

$$P_{Gewind} = \sum_{0}^{V_{c-o}} \sum_{1}^{S=N} P_w \times f(P_w) \times 2190 hrs \tag{10}$$

IV. Case study

The Centennial Wind Power Facility is a SaskPower facility situated in the hills 25 kilometres southeast of Swift Current, Saskatchewan. Table 1 shows the technical specific of Swift current wind farm.

Table 1: Centennial wind power facility

Generating capacity	150 MW
Mean annual output	540 GWh
Mean annual wind speed	30 km/h (8 m/s)
Wind turbine model and number	Vestas V-80, 83 turbines
Rated output	1.8 MW/turbine
Operational wind speed	15–90 km/h (4–25 m/s)
Speed at which full power achieved	50 km/h (14 m/s)
Number of blades and blade length	3, 39 m
Rotor diameter	80 m
Rotor weight	35 tonnes
Rotor speed	17 rev/min
Overall height to blade tip	107 m
Height of support tower	67 m
Diameter at base	4 m
Diameter at top	2.3 m
Weight of support towers	117 tonnes

V. Results and Discussion

As mentioned before, the Swift Current wind speed data are used to demonstrate the validity of this model. In the first step the amount of wind power generation (WPG) has been determined seasonally based on the proposed model in this article. And then, to evaluate the accuracy of the proposed model, the annual wind power generation for years 2007, 2008, and 2009, that simulated by WAsP, has been compared with the results of the proposed model. These results are given in Table 2 and 3.

Table 2: WPG seasonally based on the wind speed historical data (2000 to 2009)

	Year			
	First Quarter	Second Quarter	Third Quarter	Fourth Quarter
E(Pw)	0.835862	0.736054	0.544428	0.918585
WTG (GWh)	151.2409	133.1816	98.50888	160.4143

Table 3.: WPG for 2007, 2008, and 2009

	2007	2008	2009
Proposed Model(GWh)	511.043	479.070	496823.3
WAsP simulation(GWh)	570.599	532.918	548.713
Error percentage	10.4375	10.1044	9.4566

The average error for proposed model determined for 2007 to 2009 is 9.99%. This error can be so useful in economic studies of electricity market. It can be referred as an Error correction factor for wind (ECFW). This correction factor indicates the amount of risk for wind investors who want to invest in this specific area.

The result of annual wind power generation has been indicated in Table 4. The wind speed is predicted based on the wind speed historical data from 2000 to 2009 by using ARMA time series.

Table 4: Total WPG based on the wind speed historical data (2000 to 2009)

Proposed Model(GWh)	543288.6
WAsP simulation(GWh)	541.126

The wind power generation model diagram for 2007, 2008, and 2009 has been given in figures 2, 3, and 4.

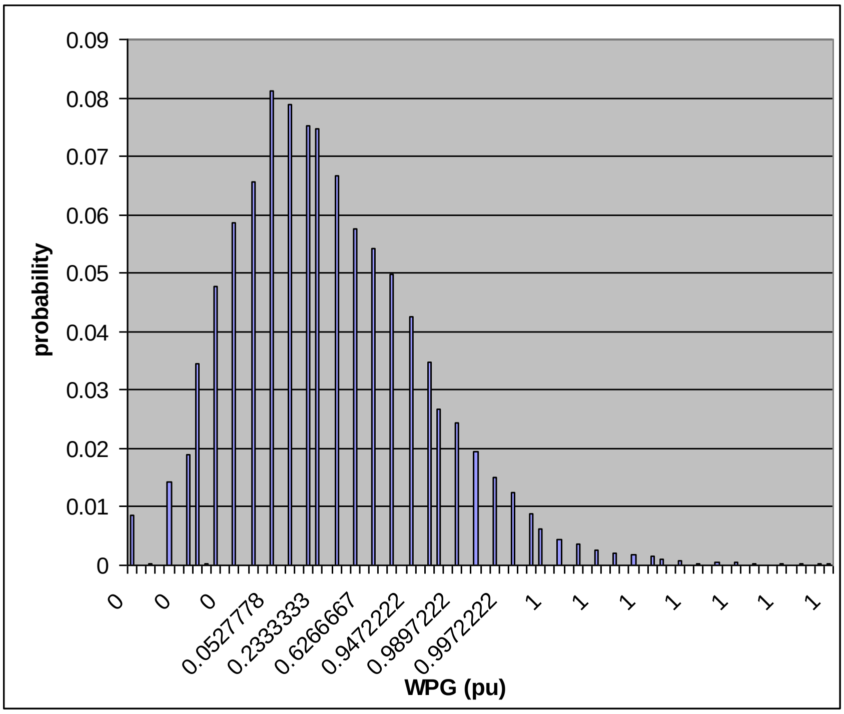

Figure 2: WPG for 2007

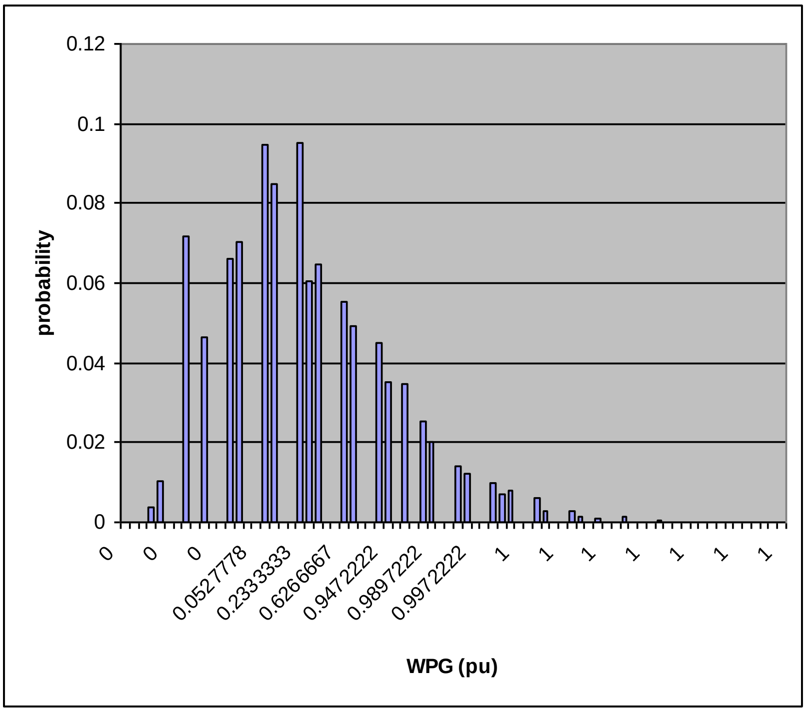

Figure 3: WPG for 2008

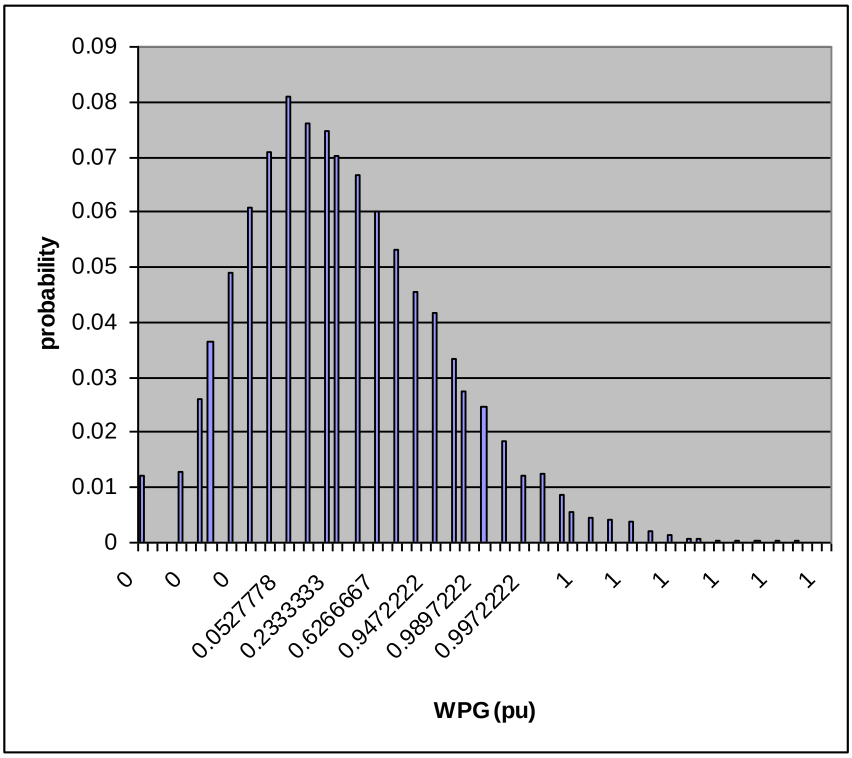

Figure 4: WPG for 2009

Conclusion

Modeling the wind power generation in Swift Current wind farm was conducted in this paper. In this paper, in addition to reviews the previous methods for calculating the CC the new model has been proposed based on the probability distribution function of wind speed and the concept of expected value. The ECFW which given in this study can be so useful to determine the risk of investment in wind power market. The advantage of this model can refer to simplicity and universality than the other method. According to the results of this article this model can be feasible for any other area.

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