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Research Article

Capacity Factor Estimation of Wind Farms Accounting for Outage Probability of Individual Wind Turbines

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ABSTRACT

The power generation sector accounts for a significant portion of GHG emissions, and many countries strive for the large-scale adoption of renewable generation. Although the intermittent nature of renewables brings about complications in energy system planning, the share of renewable generations is increasing to the greatest extent. The wind generation has drawn increasing attention to expanding the use of renewable energy to reduce carbon emissions from the power generation sector, and the estimation of capacity factor is crucial in energy system modeling. This study develops a mathematical model for estimating the capacity factor of a wind farm with the consideration of outage probability of individual turbines. In addition, the power curves and wind speed distribution of the wind farm need to be estimated, which is demonstrated with a wind farm in Korea. It is asserted that the proposed method may render the wind farm capacity factor effectively. Thus, the results from this study can be useful for energy system modeling involving wind generations.

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1. INTRODUCTION

Defined by the ratio of actual output over a given period of time to the rated nameplate capacity over that period, the Capacity Factor (CF) is considered one of the most important measures in wind power generation and its estimation has been under focused investigation over the past decades. The estimation of CF has received significant attention in order to cluster wind turbines or a wind farm even though the derivation of CF for individual wind turbines may be investigated [1-3]. It is well known that the incident wind speed plays a decisive role in the CF estimation. In addition, acquisition of meaningful sample data for individual wind turbines required to assess the variations in wind speed may not be viable mainly due to the lack of spatiotemporal resolution. Authors in [3] argued that the outputs of individual wind turbines could not be modeled as independent random variables and a cluster of turbines needs to be combined into a single equivalent multi-state unit to account for the correlation among turbines, output variability, and forced outages. Recent studies [2,3] have explored the CF estimation and its reliability for a wind farm (not a wind turbine) to provide a higher resolution in order to assess the uncertainty assessment of wind speed data. As proposed in [1], the power curve of a wind farm could be be derived from a simple average of power curves of individual wind turbines and the CF is estimated on the basis of Weibull wind speed distributions. Findings in [1] indicate that the impacts of planned and forced outages are not properly addressed, and the CF estimation was conducted in [2] by taking into account the outage probability (or outage rate) of individual wind turbines. However, it was assumed that the rated capacity and the outage probability were identical for all wind turbines belonging to the same wind farm, which might limit its applicability to the CF estimation of wind farms.

This study intends to develop a mathematical model for CF estimation of wind farms consisting of multiple wind turbines featuring different operating characteristics, namely rated capacity and outage probability. The main input parameters include the wind speed distribution of wind farm site, power curve, rated capacity, and outage rate of individual wind turbines. To the best of authors' knowledge, this study is the first attempt to derive the outage probability of wind farms from those of individual turbines on the basis of probability modeling. The remainder of this paper is organized as follows. First, the derivation of outage probability for wind farms consisting of multiple wind turbines with different rated capacities is discussed. Then, the probability model for CF estimation of wind farms is developed, which is followed by the case study of Hankyung wind farm in the Republic of Korea to demonstrate the applicability of the proposed model. Brief conclusions follow in the last section.

2. DEVELOPMENT OF OUTAGE PROBABILITY OF WIND FARMS

System reliability is defined as the probability that the system will continue to perform its intended function for a certain period of time under stated conditions [4], and the reliability of wind turbines is largely determined by the frequency and duration of planned and forced outages. The outage probability

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q is simply defined as the proportion of downtime, i.e., $q = \text{downtime}/(\text{uptime} + \text{downtime})$ [5,6]. Thus, the annual outage probability is the total downtime measured in hour divided by 8,760 hours (24 hours/day × 365 days). It is intuitive that the planned outages need to be scheduled in advance for maintenance purposes with the consideration of electricity demand. Depending upon system specification, rated capacity, and operating environment, on the other hand, the frequency and duration of forced outages greatly differ from one wind turbine to another. Although determining the precise mechanism of forced outages can be elusive, mainly due to excessive variations in plant operations stemming from the intermittent nature of wind generation, forced outages for individual wind turbines have been assessed by considering individual component failures encountered in the past studies [6,7]. By compiling the data of planned and forces outages for individual wind turbines, the probability of wind turbine outages can easily be derived. For example, Table 1 presents the outage probability of wind turbines in one of the wind farms in Korea. There are 8 wind turbines with the total rated capacity of 19.5MW in the wind farm, three 1.5MW turbines, and five 3.0MW turbines, and it is clear that the outage probability of individual wind turbines differs to a great extent, ranging from 0.0071 to 0.1267. It is noted that the average outage probability of wind turbines is 0.040, which coincides with the usual outage probability of 0.04 ~ 0.12, as reported in [3] and [7]. Presented are the mean time to failure (MTTF) and mean time to repair (MTTR) in Table 1, which can also be used to obtain the outage probability as $q = \text{MTTR}/(\text{MTTF} + \text{MTTR})$ [5].

Table 1. Outage Probability of Individual Wind Turbines at a Wind Farm

Wind Turbine	Downtime	Uptime	Outage Probability	Outage Frequency	MTTF	MTTR
A	507	16,293	0.030	26	627	20
B	2,129	14,671	0.127	28	524	76
C	949	15,851	0.056	27	587	35
D	119	16,681	0.007	8	2,085	15
E	203	16,597	0.012	9	1,844	23
F	960	15,840	0.057	15	1,056	64
G	281	16,519	0.017	18	918	16
H	180	16,620	0.011	16	1,039	11
Average	666	16,134	0.040	18.4	1,085	32

Based on the outage probability of individual wind turbines shown in Table 1, the probability distribution function of outage capacity in a wind farm is derived. Assuming that there are n wind turbines in the wind farm where the state of each turbine is either 'UP' or 'DOWN', the number of possible combinations is 2^n to describe the operation of the wind farm. It is further assumed that the state of a wind turbine is independent of others. Let X denote the random variable designating the total outage capacity of wind farm at a given time point, and its cumulative distribution function can be obtained by solving the recursive formula given in Equation (1) [8].

$$OC_i(x) = OC_{i-1}(x) \cdot (1 - q_i) + OC_{i-1}(x - RC_i) \cdot q_i, \quad \text{for } i = 1, 2, \dots n \quad (1)$$

where the subscript i designates individual wind turbines, RC_i and q_i denote the rated capacity and outage probability of the turbine i, respectively, and $OC_i(x)$ is the probability that X is greater than or equal to x with Turbine 1 through i. It should be noted that $OC_0(x) = 1$ if $x \leq 0$ and $OC_0(x) = 0$ otherwise. Solving the recursive formula in the case of Turbines 1 to n yields the cumulative distribution of the total outage capacity of the wind farm, i.e., $P(X \leq x) = 1 - OC_n(x)$. If both the rated capacity and the outage probability are constant and denoted by RC and q, respectively, for all the wind turbines, the cumulative distribution can easily be derived in a closed form since the number of turbines in outage follows the binomial distribution with parameters of n and q. The cumulative distribution function of outage capacity in the wind farm can now be written as follows:

$$\begin{aligned} P(X \leq x) &= \sum_{k=0}^{\left\lfloor \frac{x}{RC} \right\rfloor} \binom{n}{k} q^k (1-q)^{n-k} \\ &= I_{1-q}\left(n - \left\lfloor \frac{x}{RC} \right\rfloor, \left\lfloor \frac{x}{RC} \right\rfloor + 1\right) \\ &= \left(n - \left\lfloor \frac{x}{RC} \right\rfloor\right) \binom{n}{\left\lfloor \frac{x}{RC} \right\rfloor} \int_0^{1-q} t^{n-\left\lfloor \frac{x}{RC} \right\rfloor - 1} (1-t)^{\left\lfloor \frac{x}{RC} \right\rfloor} dt \end{aligned}$$

where $\lfloor a \rfloor$ denotes the greatest integer less than or equal to a.

Supposing that the outage probability is 0.08 across 8 wind turbines and solving the recursive formula in Equation (1), the probability mass and cumulative distribution of outage capacity of the wind farm described in Table 1 are derived and depicted as bar and solid line in Figure 1, respectively, and its mean and standard deviation are 0.78MW and 1.41MW, respectively. Figure 2 compares the cumulative probability of outage capacity in the wind farm at different values of turbine outage probability (i.e., 0.04, 0.08, and 0.12). It is observed that the total outage capacity of the wind farm tends to increase as the outage probability of individual turbines increases. In addition, the totatl outage capacity of wind farms can easily be obtained for different probabilities of individual turbine outages.

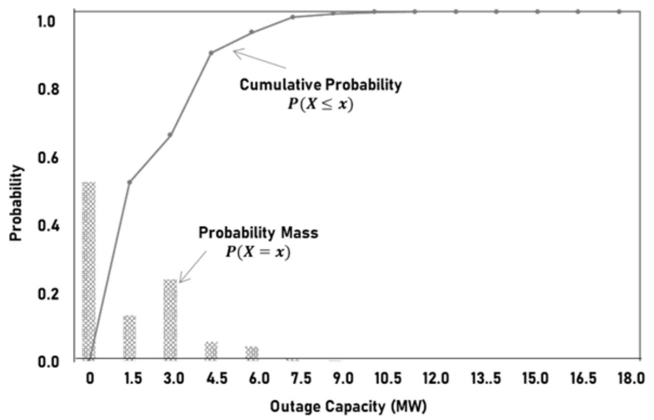

Figure 1. Probability Mass and Cumulative Probability of Outage Capacity in the Wind Farm with the Outage Probability of 0.08

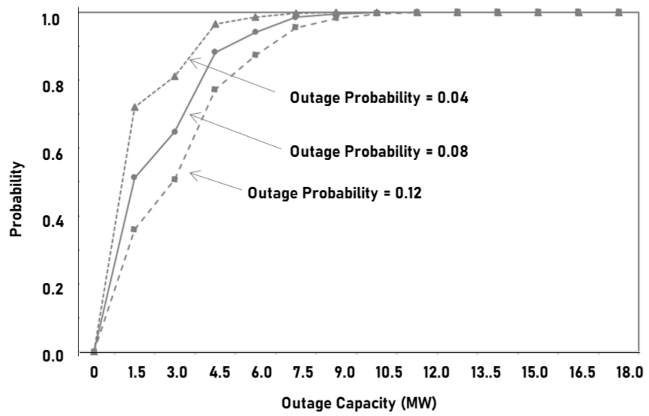

Figure 2. Cumulative Probability of Outage Capacity in the Wind Farm for Different Values of Turbine Outage Probability

3. METHOD

A proper assessment of CF is critical to estimate the power output in energy system modeling involving renewable generations, mainly due to their intermittent nature [9]. The CF of wind generation may be calculated based on the historical data of power production [10], and Figure 3 depicts the nation-wide CF of Korea, the CF of Hankyung wind farm, and the CF of the wind turbine #9 in Hankyung wind farm month by month, displaying a certain degree of variations.

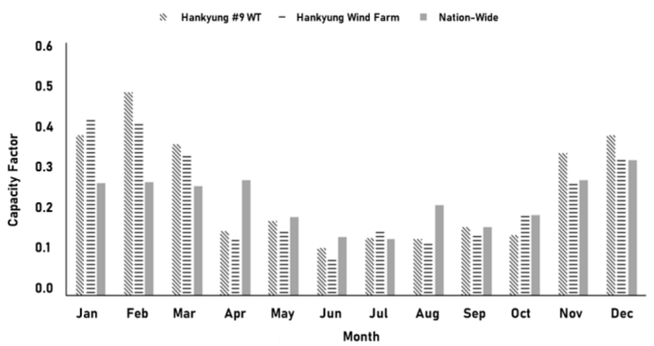

Figure 3. Monthly Capacity Factors of Wind Turbine, Wind Farm, Nation-Wide Consideration

The actual power output of wind generation is determined by the availability of individual turbines, which can be affected by environmental factors such as wind direction and speed, in addition to their potential output. In particular, the wind speed decisively affects the power output and it is generally modeled as a continuous random variable because of its high inherent variability. Affected by the planned and forced outages of individual turbines, the turbine availability in the same wind farm may also fluctuate to some degree. Thus, the CF of the wind farm having a multitude of turbines is defined by the expected output divided by the total rated capacity [11]. The total rated capacity, denoted by RC_{Total}, is simply the sum of rated capacities of individual turbines in the wind farm, i.e., $RC_{Total} = \sum_{k=1}^{n} RC_k$. By denoting the wind farm power output as the random variable PW, we can express the expected power output as follows:

$$E(PW) = \sum_{\forall x} E(PW|X = x) \cdot P(X = x) \quad (2)$$

where $P(X = x)$ is the probability mass function of outage capacity in the wind farm and $E(PW|X = x)$ is the conditional expectation of wind farm power output given that $X = x$. Although the power output of wind farms is influenced by various factors such as wind speed, wind direction, and turbine parameters, it is common to use the power curve based solely on wind speed for projections [12,13]. A typical power curve of wind turbines is depicted in Figure 4, which is divided into 4 regions depending on wind speed. No power is generated below the cut-in speed in Region 1 and above the cut-off speed in Region 4. The power output increases up to the rated power from the cut-in to rated speed in Region 2, while the rated power output is maintained between the rated and cut-off speeds in Region 3.

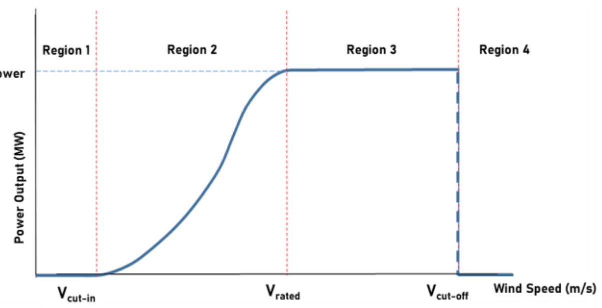

Figure 4. Typical Power Curve of Wind Turbines

The power curve may have a different form for individual wind turbines and the conditional expectation of power output is obtained with the power curves of turbines under operation for the specified outage capacity. However, it can be highly complicated or even infeasible to get the conditional expectation for all the possible combinations of outage capacity since the turbines with different rated capacities may be in the outage state. It is proposed to develop the power output per unit capacity by taking the weighted average of power output of individual turbines as follows:

$$g(v) = \sum_i \alpha_i g_i(v) = \sum_i \frac{RC_i}{RC_{Total}} g_i(v) = \sum_i \left(\frac{RC_i}{\sum_j RC_j}\right) g_i(v) \quad (3)$$

where $g(v)$ and $g_i(\cdot)$ represent the power curve per unit capacity and the power curve of turbine i in the wind farm, respectively, and α_i denotes the weight of individual turbines. It is noted that the proportion of the rated capacity of individual turbines is used as the weight. Then, the conditional expectation in Equation (2) may be obtained by multiplying the rate capacity of turbines under operation, i.e., $(RC_{Total} - x)$, by the expected power output per unit capacity in the wind farm, which can be determined by integrating the power curve per unit capacity over the wind speed distribution in the wind farm site. The conditional expectation in Equation (2) can now be written as follows:

$$E(PW|X=x) = (RC_{Total} - x) \cdot \int_{v\in\Omega_V} g(v)dF_V(v)$$

$$= (RC_{Total} - x) \cdot \int_{v\in\Omega_V} g(v)f_V(v)dv \qquad (4)$$

where $F_V(\cdot)$ and $f_V(\cdot)$ represent the cumulative distribution function and density function of wind speed distribution in the wind farm site, respectively, and Ω_V denotes the domain of power curve. It is often the case that the wind speed follows the 3-parameter Weibull distribution, based on which density function is defined by

$$f_V(x;\lambda,\beta,\tau) = \frac{\beta}{\lambda}\left(\frac{x-\tau}{\lambda}\right)^{\beta-1} \exp\left[-\left(\frac{x-\tau}{\lambda}\right)^{\beta}\right]$$

where λ, β, and τ represent the scale, shape, and threshold parameters, respectively. Then, the conditional expectation in Equation (4) becomes

$$E(PW|X=x)$$
$$= (RC_{Total} - x)$$
$$\times \int_{v\in\Omega_V} g(v)\frac{\beta}{\lambda}\left(\frac{v-\tau}{\lambda}\right)^{\beta-1} \exp\left[-\left(\frac{v-\tau}{\lambda}\right)^{\beta}\right]dv$$
$$= (RC_{Total} - x)$$
$$\times \int_{v\in\Omega_V} \sum_i \left(\frac{RC_i}{\sum_j RC_j}\right) g_i(v)\frac{\beta}{\lambda}\left(\frac{v-\tau}{\lambda}\right)^{\beta-1} \exp\left[-\left(\frac{v-\tau}{\lambda}\right)^{\beta}\right]dv$$

It should be noted that, in addition to the rated capacity of individual turbines, the probability mass function of turbine outage capacity, power curve per unit capacity, and distribution function of wind speed need to be obtained to derive the CF and power output of the wind farm.

4. CASE STUDY

Following the method described above and using Equations (1) to (4), the CF and power curve of a wind farm can be derived. It may seem mathematically simple, but a great amount of operational data is required to assess the outage probability, power curve per unit capacity, and wind speed distribution in the wind farm site. The application of the proposed method described in Sections 2 and 3 is to be demonstrated with the case study of Hankyung wind farm in Korea, which consists of three 1.5MW turbines and five 3.0MW turbines. It is noted that four 1.5MW turbines were originally installed as pointed out by one of the reviewers and it is confirmed from the operation company that one of them has remained shut down since 2018 due to a fatal fire accident. As mentioned earlier, the expected power output per unit capacity and wind speed distribution are crucial for obtaining the conditional expectation in Equation (4). The power curve of wind turbines manufactured by VESTAS in the Hankyung wind farm has been investigated in previous studies [14,15]. The cut-in speed and cut-off speed are 4m/s and 25m/s, respectively, for both 1.5MW and 3.0MW turbines. As reported by authors in [16], the power curves of turbines are usually estimated employing the Weibull distribution function. Using the data of the wind speed and the corresponding power output reported in [14,15], the package 'WindCurve' in the statistical software R is employed to fit the power curves of turbines in the site. The result of fitting the power curves is summarized in Table 2, which also presents the measures of fitting accuracy of Weibull distribution such as the root mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and coefficient of determination R^2. By examining the absolute measure of goodness-of-fit R^2, it is evident that the data are well-suited to fitting Weibull distributions.

Table 2. Weibull Distribution Fitting for Power Curve of Turbines in Hankyung Wind Farm

Turbine Capacity		**1.5MW**	**3.0MW**
Weibull Parameters	Shape	4.6074	5.1846
	Scale	8.7445	9.4622
Measures of Fitting Accuracy	RMSE	0.0190	0.0166
	MAE	0.0096	0.0088
	MAPE	15.7498	5.2571
	R^2	0.9977	0.9981

The power curve per unit capacity in the wind farm can be derived using Equation (3) as follows:

$$g(v) = \begin{cases} 0, & v \le 4m/s \\ \alpha g_1(v) + (1-\alpha)g_2(v), & 4m/s < v \le 25m/s \\ 0, & v > 25m/s \end{cases}$$

$$g_1(v) = 1 - \exp(-v/8.7445)^{4.6074}$$

$$g_2(v) = 1 - \exp(-v/9.6422)^{5.1846}$$

where α is the weight of rated capacity of 1.5MW turbines corresponding to the ratio of total capacity of 1.5MW turbines (i.e., 4.5MW = 1.5MW × 3) to wind farm capacity 19.5MW. The power curves of 1.5MW and 3.0MW turbines are denoted by $g_1(v)$ and $g_2(v)$, respectively, each of which is fitted with Weibull distributions with parameters given in Table 2. The power curves per unit capacity are compared in Figure 5.

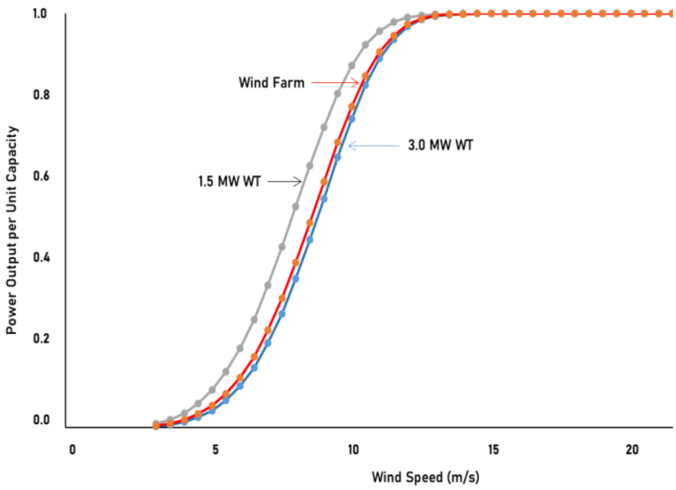

Figure 5. Comparison of Power Curve Per Unit Capacity in Hankyung Wind Farm

The wind speed probability distribution as well as the power curve per unit capacity in the wind farm need to be estimated to obtain the conditional expectation given in Equation (4). The monthly wind speed distribution has often been employed since the variations in wind speed greatly differ month by month [17,18]. For the purpose of clarity, the summarized statistics, including average, max, min, and standard deviation, of the monthly wind speed for the wind turbine #9 are presented in

Table 3. The monthly wind speed data for individual turbines are available upon request with the permission from the wind farm.

Assuming that the wind speed follows the identical distribution within the same month, the sample data from the wind farm are fitted with the 3-parameter Weibull distribution, which is widely used in the literature [19]. The parameters of Weibull distribution for each month are estimated and tested for their significance with Anderson-Darling statistics [20], results of which are summarized in Table 4. Based on the p-values greater than 0.05 for every month, it can be concluded that the monthly wind speed distributions are well-fitted with the Weibull distribution. The corresponding parameters are presented in Table 4. For example, the wind speed distribution for January can be written as

$$f_V(x) = \frac{1.832}{5.042}\left(\frac{x-3.867}{5.042}\right)^{1.832-1} \exp\left[-\left(\frac{x-3.867}{5.042}\right)^{1.832}\right]$$

Table 3. Summarized Statistics for Monthly Wind Speed Distribution of Wind Turbine #9

Year / Month	2018				2019				2020			
	Mean	**Max**	**Min**	**S.D.**	**Mean**	**Max**	**Min**	**S.D.**	**Mean**	**Max**	**Min**	**S.D.**
Jan	9.86	17.50	4.40	3.54	9.20	16.80	5.00	2.78	9.60	17.90	5.30	2.92
Feb	9.04	15.50	3.00	3.70	8.94	23.20	2.50	3.32	9.11	19.10	3.00	4.13
Mar	7.14	18.30	2.00	3.96	8.23	14.70	3.20	3.55	7.29	19.00	4.10	3.81
Apr	7.27	16.10	2.40	3.80	6.01	13.60	2.90	2.61	6.91	14.60	1.70	2.93
May	6.80	13.00	2.30	3.33	6.17	13.20	2.60	3.13	6.03	12.50	2.40	2.81
Jun	4.90	10.80	1.70	2.23	4.72	23.20	2.30	2.94	4.58	12.40	2.10	2.88
Jul	5.67	12.30	2.20	3.23	5.99	15.60	2.30	3.10	6.43	15.00	2.30	3.47
Aug	7.21	25.40	3.00	4.33	6.77	14.10	2.70	3.03	7.60	13.20	2.70	3.53
Sep	6.45	18.00	2.20	3.13	7.29	23.20	2.50	4.57	6.36	23.20	2.50	4.37
Oct	7.90	15.80	2.40	3.41	7.61	16.00	2.70	2.76	8.02	17.10	2.50	3.83
Nov	6.15	12.20	2.80	2.71	8.23	23.20	2.60	4.12	7.22	15.40	4.10	3.81
Dec	9.78	18.00	4.00	3.89	8.97	17.20	3.10	3.61	9.04	19.90	3.30	3.63

Table 4. Monthly Wind Speed Distribution Fitted with 3-Parameter Weibull Distribution

Month	Scale Parameter	Shape Parameter	Threshold Parameter	p −value
Jan	5.042	1.832	3.867	> 0.5
Feb	6.566	2.117	1.733	> 0.5
Mar	5.737	1.756	1.721	0.353
Apr	5.893	2.023	0.912	> 0.5
May	3.799	1.361	1.761	0.345
Jun	3.116	1.412	1.371	0.050
Jul	3.719	1.341	1.527	> 0.5
Aug	4.209	1.282	1.936	0.256
Sep	4.341	1.306	1.759	0.292
Oct	5.941	2.080	1.467	> 0.5
Nov	5.101	1.770	2.056	0.076
Dec	6.071	1.932	2.480	0.400

By using the power curve per unit capacity with parameters in Table 2 and the monthly wind speed distribution with parameters in Table 3, the conditional expectation in Equation (4) can now be derived. The probability mass function of outage capacity $P(X = x)$ needs to be taken into account to obtain the expected power output from the wind farm given in Equation (2). Assuming, without loss of generality, that the outage probability of individual turbines is 0.04 regardless of rated capacity for the sake of simplicity, the probability mass function can be derived by solving the recursive formula given in Equation (1). It should be noted that the outage probability of a wind farm can be similarly derived for actual outage probabilities of individual turbines, if available, as pointed out by reviewers. Summing up the results described above, the monthly capacity factor of Hankyung wind farm can be estimated and compared with the observed capacity factor over the period of 2018-2020, as shown in Figure 6. The annual average of the observed capacity factor of Hankyung wind farm is 0.2510, whereas the estimated annual average is 0.2321, and the difference between the observed and estimated capacity factors turns out to be 7.5%. It is asserted that the capacity factor can be estimated more accurately by improving the estimation accuracy of outage probability of individual turbines, power curve per unit capacity of wind farm, and wind speed distribution.

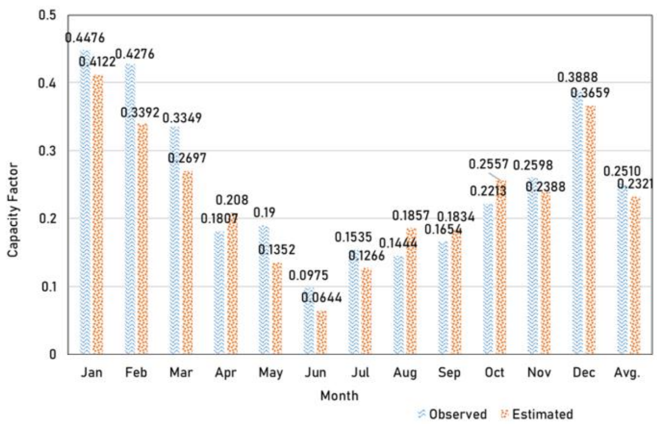

Figure 6. Comparison of Estimated and Observed Capacity Factors by Month

5. CONCLUDING REMARKS

The capacity factor of wind generation is considered one of the most critical measures in assessing the generation performance of wind farm. This study is motivated to develop a mathematical model for estimating the wind farm capacity factor with the consideration of wind speed, power curves, and outage probability. The derivation of outage probability with different rated capacities of turbines is first outlined by the recursive formula. The conditional expectation of output per unit capacity given the specified outage capacity in the wind farm can be obtained with the wind speed distribution and power curves of turbines. The applicability and usefulness of the proposed method were demonstrated with the case study of Hankyung wind farm in Korea. The power curves of individual turbines matched Weibull distributions with different parameters and their goodness-of-fits were also investigated with such fitness measures as root mean squared error, mean absolute error, mean absolute prediction error, and coefficient of determination. The wind speed distributions matched Weibull distributions month by month. Using the fitted functions of power curve and wind speed distribution, the monthly capacity factors of wind farm were calculated and compared with the observed data. Based on the error margin of 7.5%, the proposed procedure might well render the capacity factor estimation of wind farms. It was implied that the proposed method could be effectively employed even when there were a multitude of wind turbines with different rated capacities and outage probabilities. The estimation accuracy of the proposed method can be enhanced with the collection of operational data under different circumstances. More research efforts need to be directed to develop the analysis method of capacity factor estimation involving factors affecting the power output such as power curtailment schedule combined with energy demand.

6. ACKNOWLEDGEMENT

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