

## Article

# Evaluation and Long-Term Prediction of Annual Wind Farm Energy Production

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**Abstract:** A comparison and evaluation of the AEP (Annual Energy Production) of a wind farm were conducted in this study with a feasibility study and using the actual operation data from the S wind farm on Jeju Island from January 2020 to December 2022. The free wind speed data were selected from the data measured from a nacelle anemometer, the correlation equation between wind speed and AEP was obtained, and the annual average wind speed for the past 20 years was predicted using the MCP method. As a result, comparing the AEP from the operation data with that estimated in the feasibility study, we found that the AEP was reduced by approximately 2.40% in 2020 and 12.14% in 2021, and increased by 6.76% in 2022. The wind speeds over the 20-year lifetimes of the wind turbines were obtained, and the AEP that could be generated at the S wind farm indicated that it could be used for operation. In the future, the S wind farm will operate at between 25% and 30% availability for the remaining 17 years of operation. If the availability falls below 25%, there will be a need to check the reasons for the deterioration of wind turbine performance and the frequency of failures.

**Keywords:** wind farm; wind turbine; supervisory control and data acquisition (SCADA); annual energy production (AEP); measure correlate predict (MCP)



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## 1. Introduction

Wind power has been highlighted as a sustainable energy source, not only for its contribution to addressing climate change but also for reducing carbon emissions. The commercial viability of wind power has been thoroughly evaluated, and wind power is being developed worldwide at an explosive pace. In Korea, the installed wind power capacity is expected to reach 1934 MW in 2022 and has grown by an average of about 13.5% per year over the past 10 years. It is expected to reach about 34.1 GW in 2036 [1].

As the wind power industry is being developed at an explosive pace, investors in the business are demanding verification of the performance of wind power systems in order to confirm or eliminate risks to their investment return and are conducting performance tests on wind power systems in wind farms.

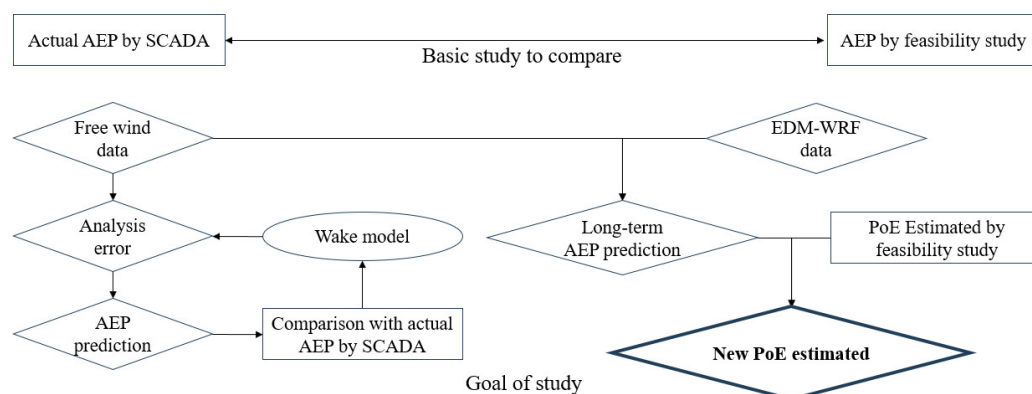
The performance test of a wind power generation system is a test conducted to obtain a power curve by plotting the power produced against wind speed in the actual field. Deviations or abnormalities can be identified by comparison with the power curve guaranteed by the wind power system manufacturer. Based on the power curve obtained in the test, the annual energy production (AEP) of the wind farm can be estimated, and the economic value of the wind farm construction project can be determined. It can also check whether the project will generate the expected return on investment and the risks [2].

However, most of the areas with abundant wind resources in Korea are mountainous with steep slopes and complex terrain with many obstacles, such as mountain valleys and mountain peaks, resulting in high turbulence intensity, up-flow, direction changes, wakes, and wind share [3–5]. Also, there are extreme air temperatures, extreme precipitation,

and typhoons in Korea. They have a negative impact on turbine performance and test results [6].

Especially, it is recommended that the power performance test, which must meet the performance test conditions for wind power generation systems required by IEC 61400-12-1, be conducted under the best conditions with high-quality wind blowing on very flat terrain [7,8]. With complex terrain characteristics, more measuring equipment must be installed and operated than in a general power performance test, and the test period also increases. In addition, the manufacturer's warranty conditions are complex and delicate. In fact, looking at the results of the power performance test conducted at the wind farm analyzed in this paper, it was not possible to secure sufficient data during a test period of about a year. And, it was unclear whether it would be possible to secure data even after more than 10 years, so the power performance test was not completed. It ended with no success.

Figure 1 shows the flowchart of this study. This paper compared and analyzed the annual energy production (AEP) obtained using actual SCADA (supervisory control and data acquisition) data with the annual energy production (AEP) obtained from the feasibility study, such as the output power, wind speed, wind direction, and other environmental variables. With this comparison, we determined whether the power production was at an appropriate level while the wind farm is operating.



**Figure 1.** Flowchart of this study.

The free wind data were selected among the wind data stored in SCADA, and the AEP that considered the wake effect was predicted and compared with the actual AEP to verify whether it could be used for long-term prediction. In addition, the MCP (measure correlate predict) method was used to analyze and evaluate the correlation between measured data and reference data [9]. And, it generated predicted long-term data for periods without measured data. The goal was to use this to estimate a new PoE (probability of exceedance) of power generation that can be produced during the wind farm's operation period.

## 2. Verification of the Feasibility Study

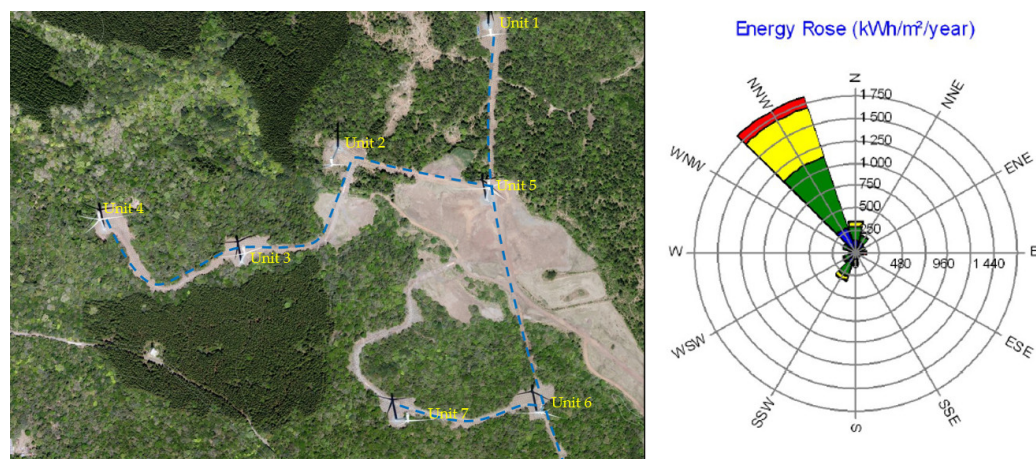
Whether or not to pursue wind farm development is determined through economic feasibility analysis, which is based on sufficient forecasts. It is necessary to secure reliable data on wind resources at the project site and optimize the data by micro-siting wind turbines that can maximize cost efficiency through data analysis. At this time, when multiple wind turbines are installed at the same site, the turbines interact with each other and steal wind energy due to the wake effect generated by the rotors of the wind turbines [10]. These array losses are related to the output of the wind power generation system, and they can be predicted from the configuration of the wind farm. They are analyzed at the business feasibility study stage, where the total power generation is predicted and reviewed based on this.

According to the evaluation of the intended project in this paper, we verified the predicted power generation through a business feasibility study, and the most reasonable

method was evaluating the reliability of the entire project through an analysis of the data on the actual operation of the wind farm, which can be said to be an accurate method.

### 2.1. Status of Wind Farm

The S wind farm is located at an altitude of 400 to 445 m on the mid-mountainous area of Halla mountain in the southeast of Jeju Island. The high-altitude Halla mountain is located in the northwest direction from the wind farm, on terrain where the altitude gradually increases in the direction of Halla mountain. In Figure 2, the wind turbine layout and energy density are presented by direction.



**Figure 2.** Layout of wind turbines and energy rose.

Seven wind turbines of the same type are installed in the wind farm. The rated capacity of one wind turbine is 3.6 MW, and the total capacity of the wind farm is 25.2 MW. Wind turbine unit 1 is located at the top right of the wind farm, and units 6 and 7 are located at the bottom. Unit 4 is located on the left, and units 2, 3, and 5 are located inside the wind farm. The wind rose for energy density is highest in the west-northwest (WNW) direction, so it is believed that the wind turbines were placed with this in mind at the time of wind farm development. The wind turbines with the lowest wake effect from the adjacent wind turbines appear to be units 1 and 4, and those with the highest wake effect appear to be units 6 and 7. The separation distance of the wind turbines was found to be 250 m to 350 m, and when expressed in terms of the blade diameter ( $D$ ) of the wind turbine, it ranges from  $2D$  to  $2.5D$ .

The wind turbines have a rated power of 3.6 MW, a blade diameter of 126 m, a hub height of 117 m, and were made by V Company in Denmark. The cut-in wind speed is 3.0 m/s, the cut-out wind speed is 22.5 m/s, and the design grade of the wind turbine is IEC IIA. They were designed and manufactured under the design conditions of a standard with a 42.5 m/s wind speed and an 18% turbulence intensity [11].

### 2.2. Feasibility Study

At the feasibility study stage, an actual wind measurement mast was installed to measure the wind conditions, and the annual energy production was calculated by substituting the power curve of the wind turbine based on the data obtained.

The wind data obtained from 15:00 on 1 November 2013 to 16:40 on 20 October 2014 were analyzed. According to the analysis results, the average annual wind speed was predicted to be 6.73 m/s at a hub height of 117 m, and the gross AEP was calculated as 79,614 MWh/y. The capacity of the wind farm for this study is 25.2 MW, and 79,614 MWh/y represents a capacity factor of 36.1%. Here, the capacity factor refers to the ratio of energy production to turbine capacity and is used as one of the evaluation indicators of a system or wind farm. The net AEP, considering a loss rate of 19.9%, was calculated at 63,776 MWh/y, with a capacity factor of 28.9%. As shown in Figure 3 and Table 1, the AEP corresponding

to P75 is 58,704 MWh/y, with a capacity factor of 26.6%. And, the AEP corresponding to P90 is 54,138 MWh/y, and the capacity factor is 24.5%. The uncertainty was assessed to be 11.8%. Here, P75 and P90 are the probabilities of exceedance (PoEs), which means that there are 75% and 90% probabilities of generating more than a certain amount of power generation statistically.

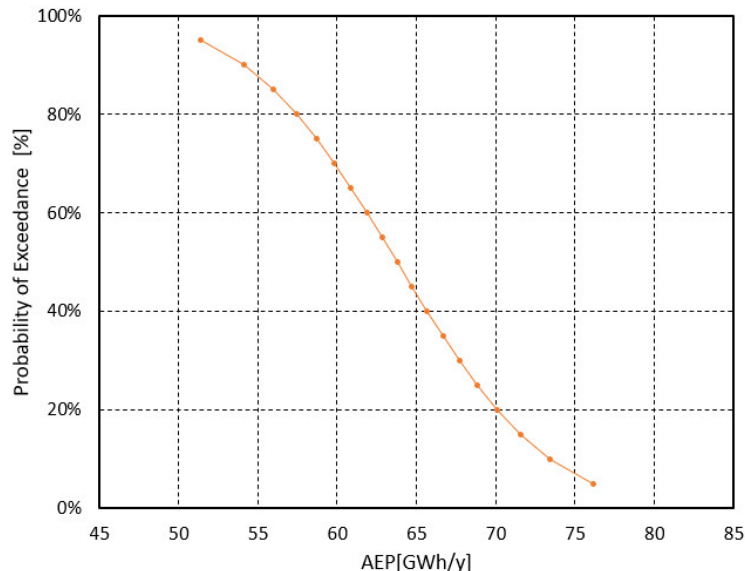


Figure 3. AEP probability of exceedance (PoE) according to the feasibility study.

Table 1. AEP probability of exceedance (PoE) according to the feasibility study.

PoE [%]	5	10	25	30	50	70	75	90	95
AEP [GWh]	76.15	73.41	68.85	67.72	63.78	59.83	58.70	54.14	51.41

As shown in Table 2, the average annual wind speed calculated from SCADA data was compared with the average annual wind speed estimated in the feasibility study. It decreased by approximately 3.7% in 2020 and approximately 8.1% in 2021, and increased by approximately 0.7% in 2022.

Table 2. Comparison of annual wind speed for each wind turbine [m/s].

Year	Unit 1	Unit2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Average
Feasibility study	6.67	6.53	6.61	6.74	6.67	6.99	6.90	6.73
2020	6.61 −0.9%	6.21 −5.2%	6.37 −3.8%	6.75 +0.1%	6.42 −3.9%	6.70 −4.3%	6.35 −8.7%	6.49 −3.7%
2021	6.34 −5.2%	5.90 −10.7%	6.11 −8.2%	6.35 −6.1%	6.14 −8.6%	6.61 −5.7%	6.15 −12.2%	6.23 −8.1%
2022	6.81 +2.1%	6.46 −1.1%	6.78 +2.5%	7.01 +3.9%	6.76 +1.3%	7.13 +2.0%	6.48 −6.5%	6.78 +0.7%

As shown in Table 3, the annual energy production (AEP) calculated from SCADA data was compared with the annual energy production estimated in the feasibility study report. It decreased by approximately 2.40% in 2020 and 12.14% in 2021, and increased by approximately 6.76% in 2022.

In particular, in the case of 2022, the AEP from the SCADA data was higher than the AEP at P30 (67.719 GWh/y) derived from the feasibility study, and it was confirmed that there is a possibility of reaching P30.

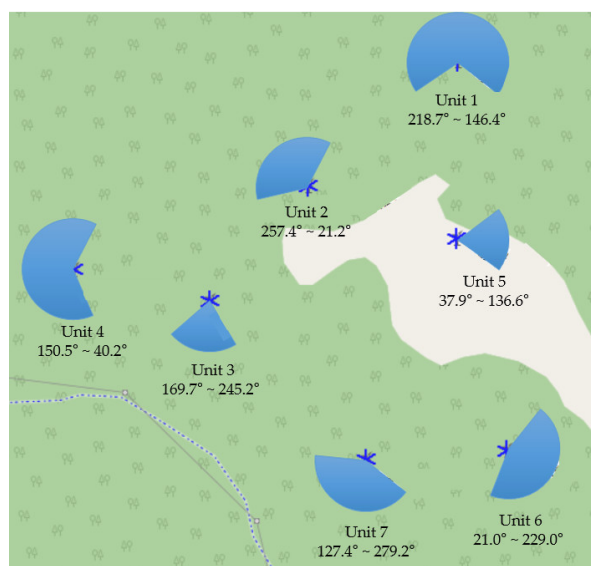
**Table 3.** Comparison of annual energy production with feasibility study [MWh].

	2020	2021	2022
Feasibility study	63,776	63,776	63,776
SCADA AEP	62,248 (−2.4%)	56,033 (−12.14%)	68,085 (+6.76%)

### 3. AEP Prediction and Probability of Exceedance for Wind Farm

#### 3.1. Free Wind Speed Data

In Figure 4 below, the wind speed data measured from a nacelle anemometer within the effective azimuth were selected as the free wind speed data. Free wind speed refers to the wind speed that flows within the effective azimuth range and is unaffected by obstacles or other wind turbines. If there was even one wind turbine abnormally operating due to a breakdown, there would be no free wind speed data, and the selected free wind speed data were used to verify the analysis errors in the wake model and to generate 20-year long-term wind speed data.

**Figure 4.** Valid sector of each wind turbine.

As shown in Table 4, there were 48,500 10 min average data in 2020, 52,355 in 2021, and 51,829 in 2022, and the free wind speed was calculated as 6.78 m/s in 2020, 6.49 m/s in 2021, and 7.02 m/s in 2022. As more than 80% of the data were available for a year, they were judged to be sufficiently representative.

**Table 4.** Average free wind speed and amount of data.

	2020	2021	2022
Wind speed [m/s]	6.78	6.49	7.02
Number of data [Number]	48,500	52,355	51,829

#### 3.2. AEP Prediction Error

After calculating the power production using the free wind speed data and the power curve of the wind turbine, the error in the AEP prediction was evaluated by comparing it with the actual measured data. This error evaluation was used as a correction for the 20-year long-term AEP results.

As shown in Table 5, the power production data of the wind turbine were extracted and used only when seven units were operating normally at the same time. From the SCADA data, 27,351 data in 2020, 29,502 in 2021, and 31,761 in 2022 were classified as valid. Expressing these as percentages, they are 52.0% in 2020, 56.1% in 2021, and 60.4% in 2022. This means that 52.0% to 60.4% of the seven wind turbines operate normally at the same time, and, during the rest of the time, more than one out of the seven units is stopped due to an alarm.

**Table 5.** Amount of SCADA data.

	2020	2021	2022
January	3194 71.6%	2840 63.6%	3248 72.8%
February	2472 59.2%	1613 40.0%	3361 83.4%
March	2375 53.2%	2779 62.3%	1850 41.4%
April	2388 55.3%	2305 53.4%	2062 47.7%
May	1688 37.8%	2406 53.9%	1827 40.9%
June	1485 34.4%	1492 34.5%	2406 55.7%
July	2050 45.9%	2780 62.3%	2311 51.8%
August	2902 65.0%	2616 58.6%	2856 64.0%
September	513 11.9%	2471 57.2%	3197 74.0%
October	2622 58.7%	2925 65.5%	3219 72.1%
November	2746 63.6%	2485 57.5%	2534 58.7%
December	2916 65.3%	2790 62.5%	2890 64.7%
Total	27,351 52.0%	29,502 56.1%	31,761 60.4%

In AEP prediction, power production is calculated by applying the power curve to wind data, and then the final AEP is obtained from a wake model. Therefore, possible errors in AEP prediction are divided into wind data, power curve, and wake model.

Since errors in wind data and power curves are included in the errors of the wake model, only the errors in the wake model were evaluated in this analysis. In order to select a wake model suitable for the analysis target, nine wake models were selected, and the wake model that fit the best accuracy was finally selected.

Figure 5 shows the calculation results of the analysis errors for each wake model, and there were no consistent results by year. So, from Figure 5, the Zong Gaussian model with the lowest absolute value of 0.442% among the three-year averages was finally selected, and the estimated AEP was obtained [12–16].

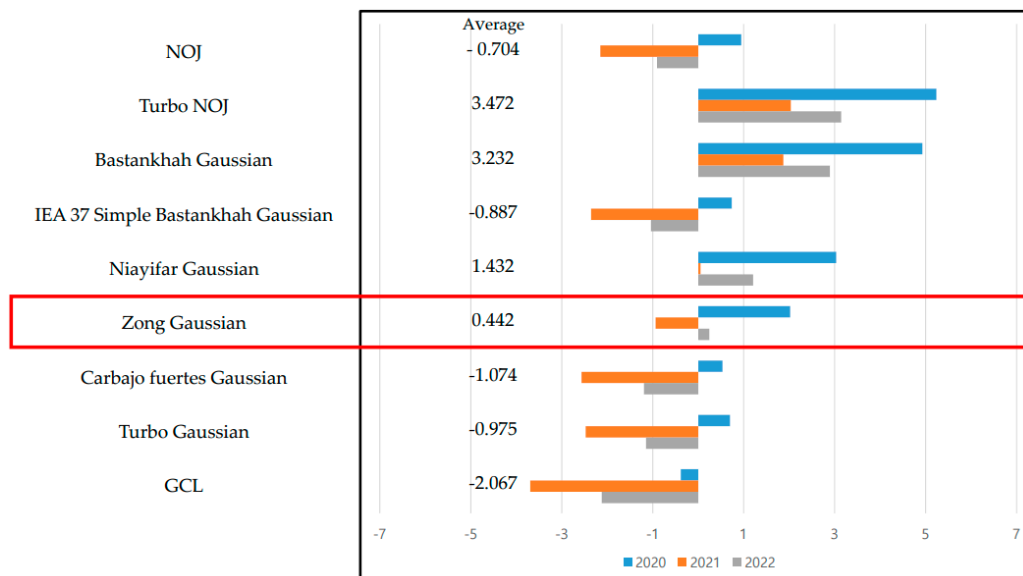


Figure 5. Analysis errors for each wake model.

As shown in Table 6, the total amount of power that can ideally be produced by a wind farm when the operation rate is 100% without an alarm was predicted to be 66,637 MWh in 2020, 59,369 MWh in 2021, and 71,793 MWh in 2022, but the actual total power production (SCADA data) by the wind farm was 62,357 MWh in 2020, 56,302 MWh in 2021, and 68,324 MWh in 2022.

Table 6. Estimated AEP and SCADA AEP results.

	2020	2021	2022	Remarks
Analysis AEP [MWh/year]	66,343	59,107	71,477	
Analysis error [%]		+0.442		3-years average
Estimated AEP [MWh/year]	66,637	59,369	71,793	Operating loss rate: 0%
SCADA APE [MWh/year]	62,357	56,302	68,324	
Operating loss rate [%]	-6.42	-5.17	-4.83	-5.47 (Average)

The difference between the predicted AEP and SCADA AEP can be seen as the amount of power generation lost when the generator stops due to an alarm or other operational reasons, and this loss rate decreased every year by 6.42% in 2020, 5.17% in 2021, and 4.83% in 2022. This means that operation and maintenance have gradually improved each year.

### 3.3. Long-Term Prediction for 20 Years

Since the operation period of an onshore wind farm is generally 20 years, the AEP for 20 years was predicted to confirm the amount of power that could be generated during the operation period to evaluate the probability of exceeding the AEP. To predict long-term AEP, long-term wind speed data were generated using the measure correlate predict (MCP) method [17,18]. MCP (measure correlate predict) is an autocorrelation prediction method that analyzes the correlation between measurement data and reference data to generate predicted data for a period without measurement data. The 20-year AEP was calculated using the generated 20-year long-term wind speed data using the power curve and wake model. The reference data for the MCP were the EMD-WRF data provided by the EMD.

EMD-WRF data are weather data generated using the WRF (Weather Research Forecasting) model and ERA5 (ECMWF Reanalysis v5)-reinterpreted weather data [19].

As shown in Figure 6, the predicted data from four points close to the wind farm were used as reference data, and the results are shown in Table 7. The correlation coefficient of the four points was found to be over 0.8, and the average wind speed was calculated to be 6.59~6.68 m/s. The average wind speed mentioned here refers to the average wind speed for the 20 years after the MCP was performed. The period of the reference data is from 1 January 2003 to 31 December 2022.

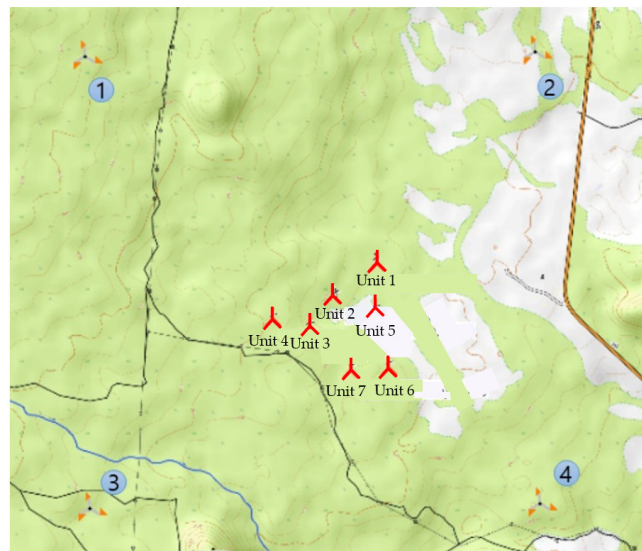


Figure 6. EMD-WRF data point.

Table 7. Correlation of free wind data and EMD-WRF data.

No.	Latitude	Longitude	Coefficient of Correlation (R)	Average Wind Speed
1	126°38'57"	33°22'59"	0.82	6.68 m/s
2	126°40'53"	33°23'00"	0.84	6.65 m/s
3	126°38'58"	33°21'22"	0.80	6.60 m/s
4	126°40'54"	33°21'23"	0.80	6.59 m/s

Figure 7 and Table 8 show the annual average wind speed and AEP calculation results obtained by performing MCP. The lowest annual average wind speed (6.20 m/s) and AEP (54,208 MWh) were found in 2015, and the highest annual average wind speed (7.02 m/s) and AEP (72,092 MWh) were found in 2022. The average annual wind speed and AEP were 6.63 m/s and 62,887 MWh.

When obtaining the annual average wind speed value from the Korea Meteorological Administration or an external agency, the AEP can be estimated according to the annual average wind speed using the estimation equation below:

$$\text{AEP} = 20.981 V - 76.589, \quad (1)$$

Figure 8 shows the AEP compared to wind speed, and the coefficient of correlation is 0.96, which can be said to be highly reliable. However, the AEP estimation equation is limited to the S wind farm, and the effective annual average wind speed range is 6.20~7.02 m/s, so it is inappropriate for other wind speed ranges. In addition, the operating loss rate must be reflected in consideration of the operating performance.



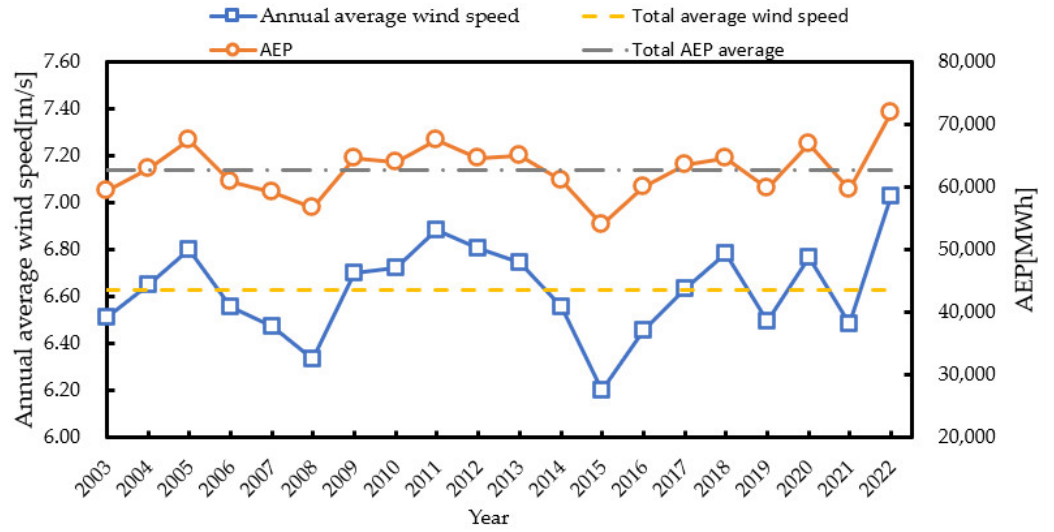


Figure 7. Estimated annual average wind speed and AEP obtained by MCP method.

Table 8. Estimated annual average wind speed and AEP obtained by MCP method.

Year	Annual Average Wind Speed [m/s]	Estimated AEP [MWh/y]
2003	6.51	59,615
2004	6.65	63,211
2005	6.80	67,758
2006	6.56	60,945
2007	6.47	59,471
2008	6.34	56,956
2009	6.70	64,719
2010	6.72	64,228
2011	6.88	67,808
2012	6.80	64,807
2013	6.74	65,159
2014	6.55	61,166
2015	6.20	54,208
2016	6.45	60,310
2017	6.63	63,762
2018	6.78	64,820
2019	6.49	59,900
2020	6.77	67,091
2021	6.48	59,708
2022	7.02	72,092
Average	6.63	62,887

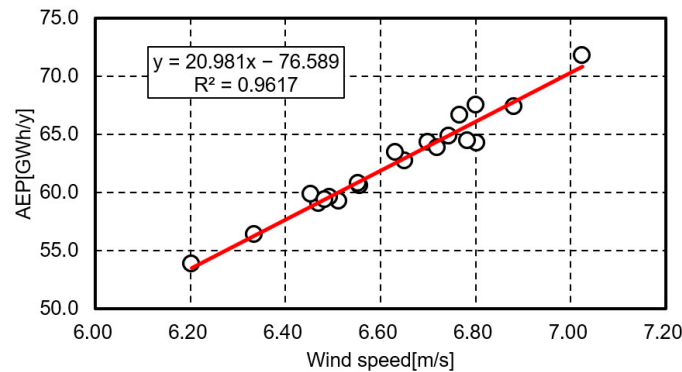


Figure 8. AEP compared to annual average wind speed and coefficient of correlation.

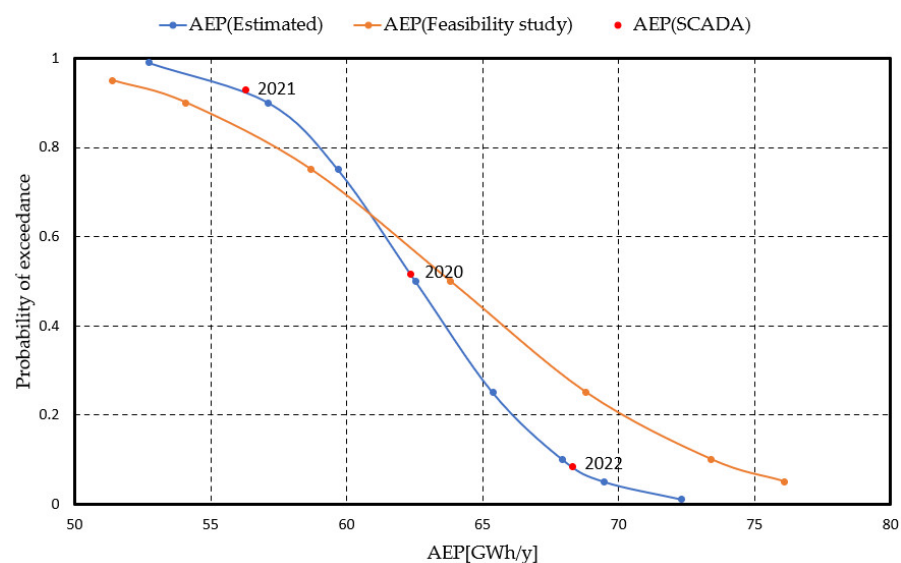
If the recent operating loss rate is estimated to be similar to the  $-5.47\%$  evaluated in this analysis, the result can be added to the result calculated from the above estimation equation.

### 3.4. Probability of Exceedance of the AEP

Based on the previously derived AEP data, the probability of exceedance of the AEP of the wind farm was evaluated and compared with the probability of exceedance of the AEP presented in the 2016 feasibility report (Figure 3, Table 1). As shown in Table 9 and Figure 9, the AEP (estimate) is an estimated result based on 20-year long-term AEP data, the AEP (feasibility report) is the result written in the feasibility study report, and the AEP (SCADA) refers to the AEP actually produced by the wind farm.

**Table 9.** Estimated probability of exceedance.

	P5	P10	P25	P50	P75	P90	P95
① AEP (estimated) [GWh/y]	69.5	67.9	65.4	62.5	59.7	57.1	55.6
② AEP (feasibility study) [GWh/y]	76.1	73.4	68.8	63.8	58.7	54.1	51.4
(② – ①)/② [%]	8.7	7.5	5.9	2.0	−1.7	−5.5	−8.2
③ AEP (SCADA) [GWh/y]	68.3 (P8.4)			62.4 (P51.6)			56.3 (P93.0)



**Figure 9.** Comparison of the results of this study with those of the feasibility study.

As a result, the probability of exceedance on the feasibility report was compared with the results of this study, showing an increase of 2.0% for the average P50 value,  $-1.7\%$  for P75, and  $-5.5\%$  for P90. It is believed that this is a conservative evaluation due to the nature of the feasibility study [20,21].

The probability of exceeding the AEP estimated using the long-term AEP at the S wind farm was compared with the AEP produced by the actual wind farm. The 62.4 GWh actually produced in 2020 was close to the average with a 51.6% probability, the 56.3 GWh produced in 2021 had a 93.0% probability, and the 68.3 GWh produced in 2022 had an 8.4% probability that the power generated was unusually high.

It is judged that during the remaining operating period, the possibility of the capacity factor of the S wind farm exceeding 30% (P25 or lower) is extremely low, and the possibility of the annual capacity factor exceeding 25% (P95 or higher) is considered high. Therefore, if the capacity factor falls below 25%, there will be a need to check whether the performance of the wind turbine has deteriorated or if the frequency of breakdowns has increased.

If there are no abnormal weather events over the next 20 years, the basic target is for 25% of the capacity factor to be reached. To achieve this, continuous management and improvement must be carried out to prevent operational losses from increasing.

#### 4. Conclusions

Based on the SCADA data of the S wind farm from January 2020 to December 2022, the relationship between the AEP calculated at the development planning stage of the wind farm and the AEP generated in actual operation was evaluated. The wind farm capacity is 25.2 MW, and the feasibility study expected an AEP of 63.776 MWh (capacity factor 28.9%) per year. The actual AEP was 62.248 MWh (28.2%) in 2020, 56.033 MWh (25.4%) in 2021, and 68.085 MWh (30.8%) in 2022, meaning that the AEP was between the expected excess probability P90 and P25 in the feasibility study.

The free wind speed data were selected among the data measured by a nacelle anemometer, and it was confirmed that the error of the AEP for wind speed differed depending on the wake model, with the Zong Gaussian model showing the smallest error. The Zone Gaussian wake model is an extended model of the Niayifar Gaussian wake model with improved wake width, and it is thought to have high accuracy only for wind farms built densely with a separation distances of 250 m to 350 m (2D to 2.5D) for wind turbines such as those on the S wind farm.

The long-term AEP was calculated with 20-year long-term wind speed data. In addition, the relation equation between wind speed and AEP was obtained to obtain the reproducible wind speed for the lifetimes of the wind turbines and to estimate the AEP of the S wind farm so that it can be used as a wind farm. However, the AEP estimation formula is not suitable for wind speeds other than the valid annual average wind speed range of 6.20 to 7.02 m/s.

The AEP probability of exceedance of the S wind farm was newly predicted using the long-term AEP, which we compared the AEP produced by the actual wind farm. The 62.4 GWh actually produced in 2020 was close to the average with a probability of 51.6%, the 56.3 GWh produced in 2021 was shown to have a probability of 93.0%, and the 68.3 GWh produced in 2022 was shown to have a probability of 8.4%.

The probability of exceeding the AEP estimated using the long-term AEP at the S wind farm was compared with the actual AEP data. The 62.4 GWh produced in 2020 had a 51.6% probability, the 56.3 GWh produced in 2021 had a 93.0% probability, and the 68.3 GWh produced in 2022 had an 8.4% probability. It is expected that the S wind farm will have a very low probability of producing over 67.9 GWh of power, with around 10% on the exceedance probability curve, and 55.6 GWh of power production lies on the 95% exceedance probability curve. Therefore, it is predicted that the capacity factor of the S wind farm will be over 25% of the capacity factor during the remaining 17 years of its lifetime. If the capacity factor falls below 55.6 GWh (capacity factor of 25%), it will be necessary to investigate the reason for the performance degradation in various ways, such as checking the performance degradation of the components and the failure frequency of the wind turbines.

It is difficult to objectively set conditions for wake effects such as terrain conditions, the roughness coefficient, and the separation distance between wind turbines for each wind farm, so this study is limited to the S wind farm. However, we will continue to study the correlation between wind speed and AEP by conducting an in-depth study of the characteristics and usage conditions of the model in the future.

**Author Contributions:** Conceptualization, S.H.; methodology, S.H.; resources, S.H.; data curation, S.H. and Y.C.P.; writing—original draft preparation, S.H.; writing—review and editing, Y.C.P.; supervision, Y.C.P. All authors have read and agreed to the published version of the manuscript.

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## References

1. Ministry of Trade, Industry and Energy. *The 10th Basic Plan of Long-term Electricity Supply and Demand Korea*; Ministry of Trade, Industry and Energy: Sejong, Republic of Korea, 2023.
2. Power Performance Testing of Wind Turbines. Available online: <https://www.dnv.com/services/power-performance-testing-of-wind-turbines-72084/> (accessed on 23 August 2023).
3. Burton, T.; Sharpe, D.; Jenkins, N.; Bossanyi, E. *Wind Energy Handbook*; Jone Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2001.
4. Ko, K.; Huh, J. *Wind Power Engineering Guide*; Munundang: Seoul, Republic of Korea, 2006.
5. Ko, K.; Huh, J. *Operating, Maintenance, Inspection and Maintenance of Wind Turbine*; Munundang: Seoul, Republic of Korea, 2014.
6. Hyun, S.; Ju, Y.; Kim, K. *A Study on the Effect of Wind Turbulence Intensity on the Power Performance of Wind Turbine System*; The Korean Solar Energy Society: Seoul, Republic of Korea, 2012; Volume 32, No. 4.
7. IEC 61400-12-1; 2022 Wind Turbine Generator Systems Part 12-1: Power Performance Measurements of Electricity Producing Wind Turbines. 3rd ed. IEC: London, UK, 2022.
8. IEC 61400-12-2; 2022 Wind Turbine Generator Systems Part 12-2: Power Performance of Electricity Producing Wind Turbines Based on Nacelle Anemometry. 2nd ed. IEC: London, UK, 2022.
9. Hyun, S.; Jang, M.; Ko, S. *Variability Characteristics Analysis of the Long-Term Wind and Wind Energy Using the MCP Method*; The Korean Solar Energy Society: Seoul, Republic of Korea, 2013; Volume 33, No. 5.
10. Yang, K.; Ko, K. *Analysis of the Effect on Wake Decay Constant of Jensen Wake Model in a Wind Farm*; The Korean Solar Energy Society: Seoul, Republic of Korea, 2024; Volume 44, No. 1.
11. VESTAS. V126-3.6 MW. Features and Performance Are Online. Available online: <https://www.vestas.com/en> (accessed on 7 October 2024).
12. Jensen, N.O. *A Note on Wind Generator Interaction*; Risø-M No. 2411; RISØ National Laboratory: Roskilde, Denmark, 1983.
13. Katic, I.; Højstrup, J.; Jensen, N.O. A Simple Model for Cluster Efficiency. In Proceedings of the European Wind Energy Association Conference and Exhibition, EWEC'86. Proceedings, Rome, Italy, 7–9 October 1986; Volume 1, pp. 407–410.
14. Wu, Y.T.; Porte-Agel, F. Large-Eddy simulation of wind turbine wakes: Evaluation of turbine parametrisations. *Bound.-Layer Meteorol.* **2011**, *138*, 345–366. [[CrossRef](#)]
15. Gögmen, T.; van der Laan, P.; Réthoré, P.-E.; Pena Diaz, A.; Larsen, G.C.; Ott, S. Wind turbine wake models developed at the Technical University of Denmark: A review. *Renew. Sustain. Energy Rev.* **2016**, *60*, 752–769. [[CrossRef](#)]
16. Beaucag, E.P.; Brower, M.; Robinson, N.; Alonge, C. Overview of six commercial and research wake models for large offshore wind farms. In Proceedings of the EWEA Conference, Copenhagen, Denmark, 18 April 2012.
17. Rogers, A.L.; Rogers, J.W.; Manwell, J.F. Comparison of the performance of four measure-correlate-predict algorithms. *J. Wind. Eng. Ind. Aerodyn.* **2005**, *93*, 243–264. [[CrossRef](#)]
18. Sreevalsan, E.; Das, S.S.; Sasikumar, R.; Ramesh, M.P. Wind Farm Site Assessment Using Measure-Correlate-Predict(MCP) Analysis. *Wind. Eng.* **2007**, *31*, 111–116. [[CrossRef](#)]
19. WinPRO 4.0 User Manual. Available online: <https://help.emd.dk/knowledgebase/> (accessed on 23 August 2023).
20. Bolinger, M. *Using Probability of Exceedance to Compare the Resource Risk of Renewable and Gas-Fired Generation*; Energy Analysis and Environmental Impacts Division Lawrence Berkeley National Laboratory: Berkeley, CA, USA, 2017.
21. Lightfoote, S. *Operational Energy Assessments: Updated Methods to Better Predict Long-Term Energy Production*; AWS True Power Webinar: Albany, NY, USA, 2016.

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