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Availability and LCOE Analysis Considering Failure Rate and Downtime for Onshore Wind Turbines in Japan

Yuka Kikuchi and Takeshi Ishihara *

Department of Civil Engineering, School of Engineering, The University of Tokyo, 7-3-1 Hongo, Bunkyo, Tokyo 113-8656, Japan; kikuchi@bridge.t.u-tokyo.ac.jp
* Correspondence: ishihara@bridge.t.u-tokyo.ac.jp

Abstract: In this study, the availability and the levelized cost of energy (LCOE) are investigated considering failure rate and downtime for onshore wind turbines in Japan. The failure mode effect analysis is conducted using the wind turbine failure database collected by the New Energy and Industrial Technology Department Organization (NEDO). The normalized failure rate and downtime between Europe and Japan are comparable. The occurrence rate is similar between Europe and Japan, but the downtime in Japan is much longer than that of Europe. Three cost-reduction scenarios are then proposed to improve availability and to reduce LCOE using assumed failure rate and downtime in each mode based on the industry interview and best practices in Japan. The availability is improved from 87.4% for the baseline scenario to 92.7%, 95.5% and 96.4% for the three scenarios, and LCOE is also reduced from 13.7 Yen/kWh to 11.9, 11.0 and 10.7 Yen/kWh. Finally, the probability distributions of downtime and repair cost are obtained for each failure mode. It is found that the probability distributions of the failure modes with the shortest downtime show similar probability distributions regardless of the size of the assembly. The effects of downtime and repair-cost uncertainties on LCOE are also evaluated.

Keywords: availability; levelized cost of energy; failure mode effect analysis; failure rate; downtime

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1. Introduction

In Japan, the installed capacity of onshore wind power generation was 4439 MW with 2554 turbines at the end of 2020 [1]. In 2016, the levelized cost of energy (LCOE) was reported as 13.9 Yen/kWh (around 10.7 Euro cent/kWh using an exchange rate of 130 Yen/Euro) and the availability as 87.4% by the committee of the Ministry of Energy and Trade Industry (METI) [2], while the cost of energy in Europe was around 4.1 Euro cent/kWh [3] and the availability was above 97% [4]. It is highly required to investigate the reason of long downtime and low availability in Japan.

The wind turbine failure database including failure rate and downtime is generally used to investigate the availability. In Japan, the New Energy and Industrial Technology Development Organization (NEDO) has collected the failure data since 2004 in order to get the overview of accident status all over Japan [5], which collects downtime and repair cost at the assembly level. However, the failure characteristics at assembly and failure mode levels have never been analyzed, and the reason for long downtime and low availability in Japan is not examined.

Pfaffel et al. [6] reviewed the 22 failure databases, and Dao et al. [7] examined the 18 failure databases in the world. WInD-Pool (Wind Energy Information Data Pool) [8] and System Performance, Availability and Reliability Trend Analysis (SPARTA) [9] are the most recent databases, but WMEP (Wissenschaftliches Mess-und Evaluierungsprogramm) [10] and Reliawind [11] have been most widely used for research due to their open accessibility, even though their wind turbines become outdated. Pfaffel et al. [6]

mapped the existing reliability characteristics to a system structure according to the Reference Designation System for Power Plants (RDS-PP) [12] to compare these database characteristics at the assembly level. It was found that the normalized failure rate and downtime in each database showed significant differences. The reason for these differences needs to be investigated further.

These failure databases were mainly categorized into the failure at the assembly level, but the downtime and repair cost are affected by the failure mode. The Reliawind database gave the failure rate and downtime at the failure mode level. Shafiee and Dinmohammadi [13] and Ozturk et al. [14] conducted a failure mode effect analysis-based risk assessment for the wind turbine system and provided the importance of the maintenance plan for each failure mode. Carrol et al. [15] investigated an offshore wind turbine's reliability. The failures were categorized into "No cost", "Minor repair", "Major repair" and "Major replacement", which represent the failure effect on the cost. TNO also analyzed turbine reliability and defined Fault Type Class (FTC) as the group of failure modes having a similar downtime and repair cost [16].

The availability improvement scenarios have been assessed using failure databases. TNO [16] performed the case study to reduce offshore wind farm operation and maintenance (O&M) cost using their developed time-domain Monte Carlo simulation tool named as the ECN O&M Calculator. Maples et al. [17] also investigated the optimum O&M methods for an offshore wind farm in the United States using the ECN O&M Calculator. The availability improvement and LCOE reduction scenarios are highly required in the Japanese wind turbine industry.

The assessment of uncertainty in LCOE is also important. Dao et al. [7] investigated wind turbine reliability data and its impact on LCOE, which makes it possible to relate wind turbine failure rates and downtime with an operating expense (OPEX) and annual energy production. However, the uncertainty of downtime and repair cost and their effects on LCOE are not yet evaluated. Seyr and Muskulus [18] pointed out that the uncertainties of repair time affect the production loss using the stochastic model. Mortstock and Wilkinson [19] evaluated the 90% quantile of downtime for onshore wind farms. The uncertainty evaluation using the failure database in Japan is expected.

In summary, the failure characteristics at the assembly and failure mode levels have never been analyzed in Japan, and the reason for long downtime and low availability is not examined. The failure rate and downtime in the world are compared by Pfaffel et al. [6], but the reason for the difference is not clear. The availability improvement scenario is not yet discussed in Japan based on the reliability analysis. The uncertainty of downtime has never been analyzed using the actual database in Japan.

In this study, the failure rate and downtime in Japan are analyzed using the NEDO database at the assembly and failure mode levels. The difference between Japan and Europe is investigated, and the reason for its difference is clarified by analyzing old and new turbines in the NEDO database in Section 2. The cost-reduction scenarios are then investigated using analyzed failure rates and downtimes with the LCOE database and industry practices in Japan. The probability distributions of downtime and repair cost are examined based on the actual data. The uncertainty of downtime and repair cost are also evaluated from the NEDO database, and the effects of uncertainties on LCOE are analyzed in Section 3. The conclusions are summarized in Section 4.

2. Analysis of Failure Rate and Downtime for Onshore Wind Turbines in Japan and Europe

The failure databases in Japan and Europe are described in Section 2.1. These failure databases are investigated and compared at the assembly level in Section 2.2 and at the failure mode level in Section 2.3.

2.1. Failure Databases in Japan and Europe

New Energy and Industrial Technology Development Organization (NEDO) has collected the turbine failure data since 2004 with the aims of availability improvement and the reduction of turbine failures and accidents. Collection items are described in Table 1. The downtimes are written with 1 h resolution, and repair costs are collected by multiple choice questions from eight categories. The downtime represents the combined time of logistic, repair and weather downtime, and its breakdown is not available in the NEDO failure database. In this study, the data collected from 2014 to 2018 are analyzed because the collection time had changed from the middle of the fiscal year to the end of fiscal year since 2014, which affects the statistical characteristics. The commercial wind turbines are extracted, and the demonstration projects are excluded. The accidents with downtime of more than one year are excluded as an extraordinary exception. After the data cleansing, the number of failure data becomes 1,663.

The assembly is collected by the multiple-choice questions from 21 categories (blade, hub, grid connection equipment, main shaft/main bearing, gearbox, brake, electrical system, control system, yaw, pitch, hydraulic, foundation, general, no failure assembly, unknown). "General", "No failure assembly", "Unknown" failures are excluded from the analysis to make the discussion clear. The assembly category follows RDS-PP (Reference Designation System for Power Plants) as shown in reference [12]. The control system and electrical system are combined as the electrical system. Pitch and aerodynamic brake are combined as pitch system. Flange, wind anemometer, mechanical brake and others are categorized into "others". In the 1,663 failure data, the failures with multiple failure assemblies are 148 data points. The multiple failures are divided into each failure with a weighted of average value of failure with sole assembly. A supplement of less than three days is followed by Okumoto et al. [20]. The absolute value of the failure rate is multiplied by 3.07 to match up to the availability of 87.4% [2] since the short downtime records in SCADA are not included in the NEDO failure database.

Table 1. Description of NEDO failure database.

Item	Sub-Item
Wind farm	Location, Turbine type, Operating start day
Failure data	Assembly, Event, Occurrence data, Root cause, Countermeasure
Downtime	Written question (1 h resolution)
Repair cost	Multiple choice questions in 8 Categories
	1: 0~500,000 Yen (0–3846 Euro)
	2: 500,000–2,000,000 Yen (3846–15,385 Euro)
	3: 2,000,000–5,000,000 Yen (15,385–38,462 Euro)
	4: 5,000,000–10,000,000 Yen (38,462–76,923 Euro)
	5: 10,000,000–20,000,000 Yen (76,932–153,846 Euro)
	6: 20,000,000–50,000,000 Yen (153,846–384,615 Euro)
	7: 50,000,000–100,000,000 Yen (384,615–769,231 Euro)
	8: 100,000,000 Yen–(769,231 Euro–)

For failure databases in Europe, WMEP (Wissenschaftliches Mess-und Evaluierungsprogramm) [10] and Reliawind [11] are used in this study since these databases are public as mentioned in Section 1. The WMEP database contains failure data for up to 1500 turbines over a 15-year period throughout Germany. The Reliawind database contains failure data for 350 turbines, which is smaller than WMEP, but it consists of more modern larger onshore turbines. In this study, the normalized failure rate and downtime of WMEP and Reliawind are extracted from the references [10] and [11]. The characteristics in each database of Japan and Europe are described in Table 2. The data collection periods are 2014–2018, 2008–2011 and 1999–2006 in NEDO, Reliawind and WMEP, respectively. The years of operation for the collected turbines in NEDO and WMEP were less than 20 and 17 years, respectively, while Reliawind collected the new turbines operating 2–4 years since they were built. Rotational speeds were fixed or variable in NEDO and WMEP, while they were only variable in Reliawind. Controls were stall- or pitch-regulated in NEDO and WMEP, but they were only pitch-regulated in Reliawind. Drivetrains were geared or direct in NEDO and WMEP, while they were only geared in Reliawind. Reliawind and WMEP collected the failure data basically from SCADA with the supplement of automated fault-log, O&M reports and a questionnaire, but NEDO collected only a questionnaire, which makes it impossible to compare the absolute value of the failure rate between NEDO and the other two databases of Reliawind and WMEP.

Table 2. Description of characteristics in each database.

	NEDO	Reliawind	WMEP
Collection period	2014–2018	2008–2011	1999–2006
Years of operation	<20 years	2–4 years	<17 years
Number of turbines	780	350	1,593
Rotational speed	Fixed/Variable	Variable	Fixed/Variable
Control	Stall/Pitch	Pitch	Stall/Pitch
Drivetrain	Geared/Direct	Geared	Geared/Direct
Collection method	Questionnaire	SCADA, O&M reports Automated fault-log	SCADA, Questionnaire

For failure mode data in Europe, reference [17] is used, which shows the failure rate and downtime for each fault type class based on the Reliawind database. In reference [17], RDS-PP was used for the assembly categorization for the comparison. Table 3 shows the conversion of taxonomy used for data collection from Reliawind and NEDO database to RDS-PP.

Table 3. Conversion of taxonomy used for data collection from Reliawind and NEDO database to RDS-PP.

RDS-PP Taxonomy	Reliawind Assembly	NEDO Assembly
Rotor system	Blade, Hub, Hub cover	Blade, Hub
Drivetrain	Drivetrain module	Gearbox, Main shaft/main bearing
Generator	Generator assembly	Generator
Hydraulic system	Hydraulic system	Hydraulic system, Pitch system
Yaw gearbox	Yaw system	Yaw system
Control and protection system	Control & communication system, Nacelle sensors, CMS, Auxiliary, Wind farm	Electrical system

In this study, failure rate and downtime are analyzed based on the NEDO failure database in Japan and are used to investigate the characteristics by comparing with European databases.

The failure rate and downtime per assembly are analyzed using the NEDO failure database and are compared with those in the WMEP and Reliawind databases in Section 2.2. The differences among WMEP, Reliawind and NEDO cannot be investigated since each failure datum in the WMEP and Reliawind databases is not available; therefore, the characteristics of failure rate, downtime with operation year, control system and drivetrain existence are investigated using the NEDO failure database.

The failure rate and downtime per failure mode in Japan are analyzed based on the failure mode effect analysis (FMEA) using the NEDO failure database in Section 2.3. FTC is used to categorize the modes because this definition was practical to investigate the failure characteristics with a minimum number of categories compared to discussing a number of failure modes. The characteristics of the normalized failure rate and downtime per failure mode are investigated and compared with those in the WMEP and Reliawind databases.

2.2. Analysis of Failure Rate and Downtime at Assembly Level

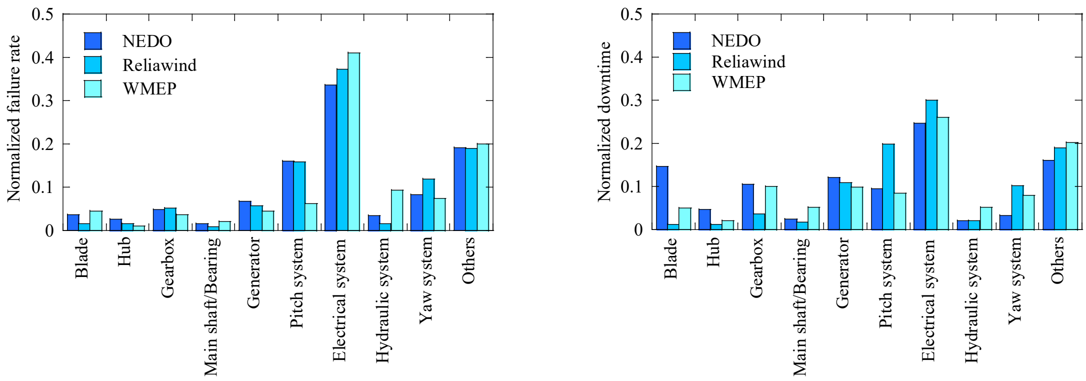
Failure rate and downtime in Japan are analyzed at the assembly level using the NEDO database. The failure rate for each assembly i is calculated using the NEDO database with Equation (1) according to reference [7].

$$\lambda_i = \frac{\sum_{p=1}^{P} n_{i,p}}{\sum_{p=1}^{P} N_p (T_p/8760)} \tag{1}$$

where $n_{i,p}$ is the number of failures of assembly i in period p; N_p is the number of wind turbines considered in period p and T_p is the time duration of period p in hour.

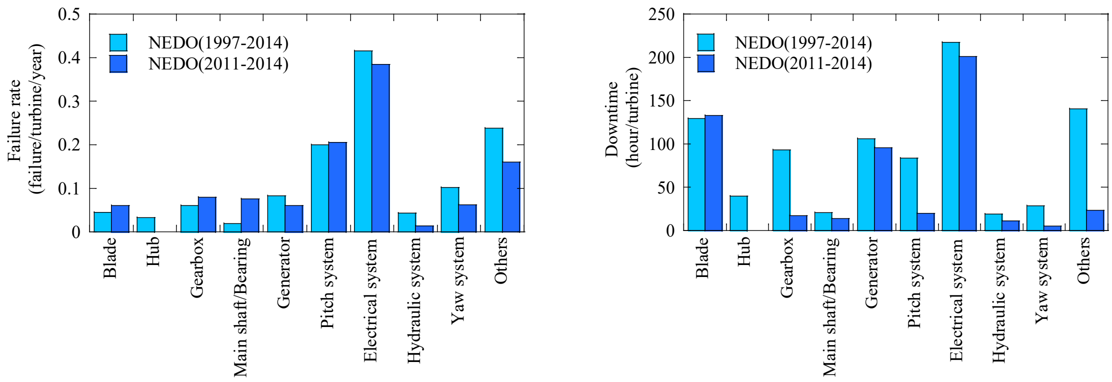
The NEDO, Reliawind and WMEP databases are compared to identify the failure data characteristics in Japan. Normalized failure rate and downtime in the NEDO, Reliawind and WMEP databases are compared at the assembly level. Figure 1 shows a comparison of normalized failure rates and downtime between Europe and Japan. The failure rates of NEDO, WMEP and Reliawind are almost the same, but the downtime of the gearbox and hub in NEDO and WMEP are longer than those in Reliawind.

Figure 2 displays a comparison of absolute failure rates and downtime between the 1997–2014 and 2011–2014 NEDO databases to investigate the reason for differences in NEDO and Reliawind databases. There is only a slight difference in failure rate, but there is a significant difference in downtime, especially in the gearbox, hub, yaw system, pitch system and others. It implies that the years of operation may affect the downtime due to a lack of spare parts for the old wind turbines. The comparison between stalled- and pitch-regulated wind turbines and that between Geared and Gearless drivetrain in the NEDO database are also performed, but the difference cannot be observed in downtime.



(**a**) Normalized failure rate (**b**) Normalized downtime per turbine

Figure 1. Comparison of (**a**) normalized failure rate and (**b**) normalized downtime between NEDO, Reliawind and WMEP databases.



(**a**) Failure rate (**b**) Downtime per turbine

Figure 2. Comparison of (**a**) failure rate and (**b**) downtime between 1997–2014 and 2011–2014 NEDO databases.

2.3. Analysis of Failure Rate and Downtime at Failure Mode Level

The failure mode effect analysis for the failure data in Japan is conducted based on the description of the root cause and countermeasure of each failure. Twenty-seven failure modes are identified as listed in Table 4. The average downtime (DT) and repair cost (RC) of each failure mode are calculated. The corresponding FTC as shown by Maples et al. [17] is identified based on the failure mode description as listed in Table 4.

Table 4. Description of each FTC for NEDO failure database.

No.	Assembly	Description of Failure	DT	RC	FTC [17]
1	Blade	Minor repair	21	140	2
2		Surface repair	780	340	4
3		Failure in blade bearing	682	464	6
4		Failure in blade	2724	3032	14
5	Hub	Minor repair	21	42	2
6		Misalignment of generator iron core	266	76	3
7		Major failure inside of hub	1517	5938	13
8	Gearbox	Minor repair	21	145	2
9		Failure in oil pump motor	267	72	6
10		Failure in medium speed shaft gear	943	419	6
11		Major failure in medium speed shaft	1299	1388	14
12	Main shaft /main bearing	Minor repair	21	95	2
13		Failure in pump motor	263	15	6
14		Misalignment of main shaft/Failure in clutch disk	1810	1813	6
15		Failure in main bearing	1410	4917	14
16	Generator	Minor repair	21	257	2
17		Minor failure in generator	595	234	6
18		Major failure in generator	1179	1982	12
19	Pitch system	Minor repair	21	94	2
20		Malfunction of pitch cylinder	292	91	4
21	Electrical system	Minor repair	21	155	2
22		Defective converter panel controller	310	119	4
23		Failure in IGBT	289	609	8
24	Hydraulic system	Minor repair	21	134	2
25		Hydraulic cylinder	319	83	4
26	Yaw system	Minor repair	21	285	2
27		Break in bolt on yaw gear	323	146	6

Figure 3 shows the comparison of FTC occurrence rates between NEDO and Reliawind. It is found that the percentage of each mode is quite similar between these two databases. Figure 4 illustrates the comparison of downtime between NEDO and Reliawind databases. It is obvious that the downtime in the NEDO database is three times longer than that in the Reliawind database. It is clarified again that longer downtime and lower availability do not come from a higher failure rate, but from a quite longer downtime. The reason for longer downtime is investigated through industry interviews and literature reviews described in Section 3.1.

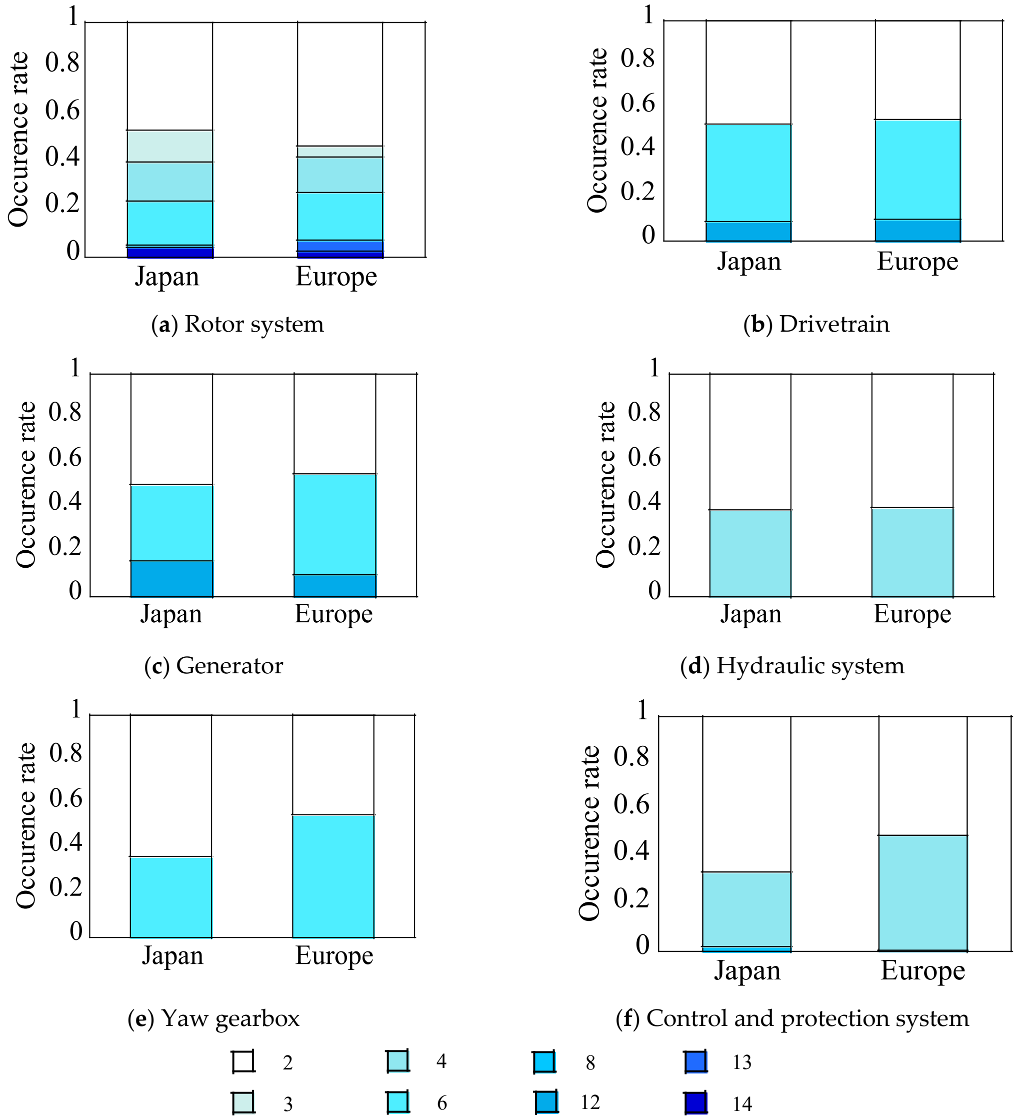


Figure 3. Comparison of FTC occurrence rate between NEDO and Reliawind databases.

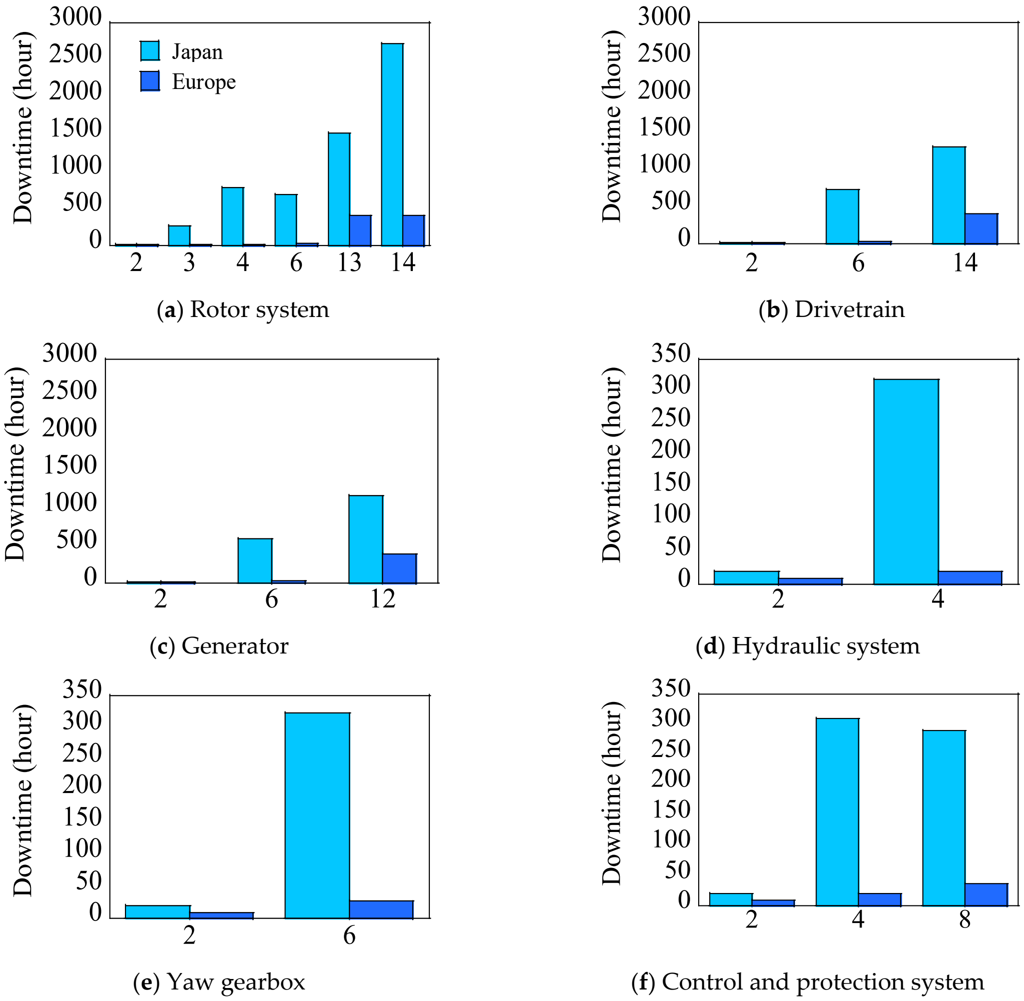


Figure 4. Comparison of downtime between NEDO and Reliawind databases.

3. Availability Improvement and LCOE Reduction

The LCOE and industry practices of onshore wind turbines in Japan are described in Section 3.1. The scenarios for availability improvement and LCOE reduction are investigated in Section 3.2 based on the industry interviews and practices in Japan. The effect of uncertainty of downtime and repair cost on LCOE is discussed in Section 3.3.

3.1. LCOE and Industry Practices of Onshore Wind Turbines in Japan

In Japan, the Ministry of Economy, Trade and Industry (METI) collects the cost data of renewable energy sources from electric utilities under the Feed-in Tariff (FiT) system according to the "Act on Purchase of Renewable Energy Sourced Electricity by Electric Utilities" since 1 July 2012 [21]. The act also applied to wind farms that were installed before the act came into effect. The cost data over the country are collected by METI based on this act with very high accuracy. METI publishes the annual report by analyzing the collected cost data as the base data for the tariff price evaluation [22]. The plot data of CAPEX and OPEX are shown in the figures, and the mean and medium values of the CAPEX, OPEX and capacity factor are described in these reports.

In order to reduce the cost and prepare the transition from the FiT to FiP system since 2021, a "wind power competitiveness strengthening committee" was held in 2018, and the cost data were investigated [2]. The committee analyzed cost data collected by the METI described above. Specifically, 13.9 Yen/kWh was evaluated as LCOE for onshore wind power at that time, and the cost target by 2030 was set as 8 to 9 Yen/kWh, the same as the world average value at that time.

In this study, an industry interview was conducted on 7 August 2015 and was reported by Kikuchi et al. [23]. The technical experts in the major wind power companies and the third maintenance companies joined in this interview. The question was: what is the reason for the longer downtime in Japan. It was found that logistics time was long due to a lack of spare parts. The shipment time was longer because about 70% of the turbines installed in Japan were oversea products, and the main components, such as the blade, were also manufactured overseas, even in domestic wind turbine manufacturers [24]. As a result, the downtime in Japan was much longer than that in Europe due to longer logistic downtimes. The downtime took more than three months if they do not have spare parts even though they are small assemblies such as the yaw controller and hydraulic. However, the downtime reduced to less than three days if they have spare parts. Another interview with two major operators was performed to investigate the downtime composition in detail. Major wind power companies have a capability to prepare spares; however, small-sized enterprises including city municipalities do not. It was also pointed out from this industry interview that the supply chain was immature, and the third parties for O&M were very few in Japan. The troubleshooting also took a lot of time.

The industry practice on onshore wind power was also reviewed, and the maintenance strategy to reduce the downtime in Eurus Energy, a major wind power company in Japan, was considered. It was found that a 25-day downtime was reduced to 10 days by conducting the condition-based monitoring as reported by Takagi [25]. When the major parts of wind turbines are replaced using the crane in the farm land, the permission must be received for the agricultural land conversion according to the Agricultural Land Act in Japan, which usually takes more than one month. This permission procedure can be completed before the failure becomes severe using the condition-monitoring system.

The annual reports named as "current status and challenges of wind power in Hokkaido" published by the Department of Hokkaido Industrial Safety and Inspection of Ministry of Economy, Trade and Industry [26] are used in this study. The collection rate is almost 100% from wind farms in Hokkaido. The averages of the operating time, scheduled downtime and downtime in the Hokkaido region based on SCADA data are shown in this report. The industry interviews by questionnaires about the reason for the higher downtime were also conducted for these annual reports. These reports show that the repair time is longer due to immaturity of the maintenance sector. The third parties for O&M in Japan are very few. The troubleshooting takes time due to a lack of experience. The contract also affects this long downtime. It is necessary to call engineers from oversea manufacturers when a failure occurs since small-sized enterprises and city municipalities do not have availability guarantees.

Availability improvement and LCOE reduction scenarios are conducted based on the data collected above and the NEDO failure database analyzed in Section 2. The baseline case is set based on the data as shown at the wind power competitiveness strengthening committee. The availability improvement scenario is then proposed based on the industry practice in Japan collected from industry interviews and reviews. The strategies, such as spare-parts preparation, condition-based monitoring and industry maturities are used to determine the three reduction scenarios. The cost-reduction potential is calculated using the NEDO failure database. An average annual wind speed is used in this study according to the wind resource map in NEDO [27]. The capacity factor increases only by reducing downtime.

3.2. Scenarios for Availability Improvement and LCOE Reduction

The availability and LCOE in Japan are analyzed using the failure rates and downtime as shown in Section 2.3. Every failure is assumed to be independent. Weather downtime is disregarded since its effect is negligible for onshore wind farms. The downtime is possible to calculate as

$$D = \sum_{j=1}^{N} \lambda_j \times D_j \tag{2}$$

where λ_j and D_j are the failure rate and downtime of each FTC j.

The baseline case and three scenarios shown in Table 5 are assumed to improve availability, to reduce LCOE in Japan and to achieve the world average values. Figure 5 shows the downtime of each FTC for the baseline case and three scenarios. Downtimes described in Table 4 are divided into logistic time and repair time based on the interview with two major operators.

The baseline case is set as the same as the current situation. The downtime for each FTC as shown in Section 2.3 is used. Downtime is divided into logistic time (including transportation time) and repair time based on the industry interview.

As mentioned in Section 2.3, the downtime of small subassemblies was reduced from more than three or four months to less than three days by preparing the spare parts in the country. Scenario 1 is set as that the downtime of minor FTC, reduced to 72 h based on the industry practice.

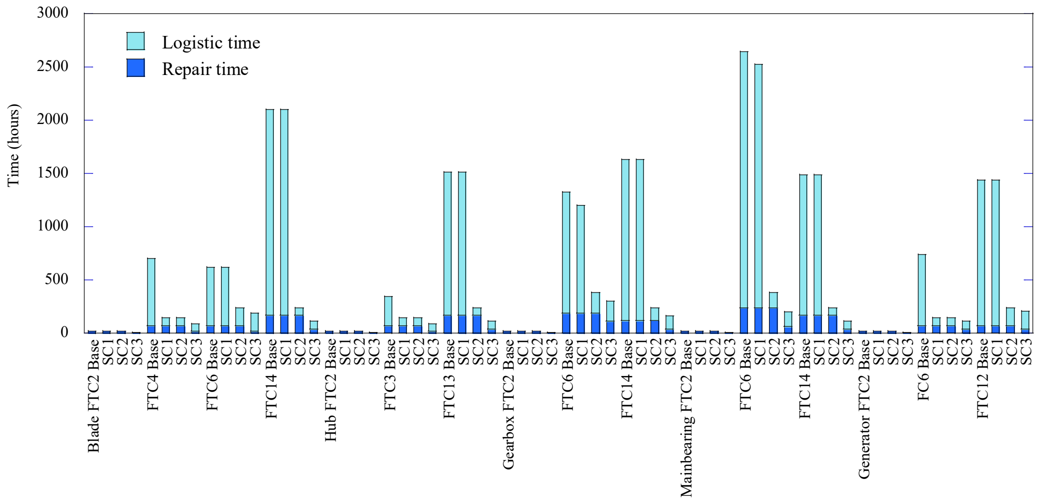
As mentioned in Section 3.1, the condition-monitoring system reduced the downtime from 25 days to 10 days. In addition to reducing the downtime of minor FTC as shown in Scenario 1, Scenario 2 is set such that the downtime of major FTC reduces to 10 days based on the industry practice in Japan.

The repair time in Japan is longer than that in Europe as shown in Section 2.3. It is because the industry maturity is not enough. In addition to reducing the downtime of FTC as mentioned in Scenario 2, an experience curve is adopted in Scenario 3 to reduce the maintenance cost with a learning rate of 18.6% [28] since the learning curve of repair downtime is not available in Japan. The contributions from the maturities of supply chain and the third parties for O&M are taken into account.

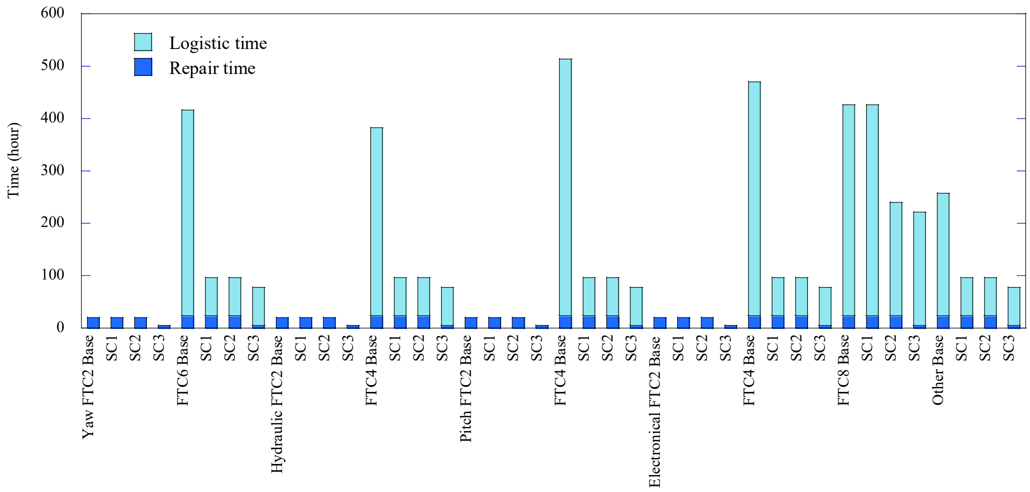
Table 6 summarizes the predicted availability, which is 92.7% for Scenario 1, 95.5% for Scenario 2 and 96.4% for Scenario 3.

Table 5. Cost-reduction scenarios in Japan.

Scenario Number	Scenario Description	Evidence
Baseline	Current failure rates and downtime	Based on NEDO database in Section 2.1
Scenario 1	Prepare spare parts in the country Reduce the logistic downtime to 72 h for minor failure modes (FTC 2,3,4).	Based on the industry practice [23] , which states that logistic downtimes of yaw control and hydraulic were 143 days and 130 days without spares, but 3 days and 1 day with spares.
Scenario 2	Install a condition monitoring system Reduce the downtime to 10 days for major failure mode	Based on the industry report [25] , which states that downtime of large assebly was reduced from 25 days to 10 days using condition monitoring system.
Scenario 3	Reduce the repair time due to industry maturity	Use a learning rate of 18.6% [28]



(**a**) Large assemblies



(**b**) Small assemblies

Figure 5. Downtime of each FTC for the baseline case and three scenarios.

Table 6. Predicted availability for each scenario in Japan.

		Baseline	Scenario 1	Scenario 2	Scenario 3
Downtime	(hours)	970	501	261	181
Scheduled downtime	(hours)	135	135	135	135
Total downtime	(hours)	1,105	636	396	316
Availability	(%)	87.4	92.7	95.5	96.4

LCOE is also investigated for each scenario. The levelized cost of energy is generally evaluated as

$$LCOE = \frac{CAPEX \times FCR + OPEX}{AEP} \tag{3}$$

where *CAPEX* is the capital expenditure; *FCR* is the fixed charge rate; *OPEX* is the operating expense and *AEP* is the annual energy production. *OPEX* is evaluated using Equation (4) with the sum of the repair cost C_{repair}, the labor cost C_{labor} and the other cost in repair C_{other} including land fee and insurance cost. *AEP* is evaluated as the product of power curve $P(f)$, wind speed frequency distribution $f(U)$ and availability as shown in Equation (5). The total downtime can be divided into the downtime $T_{downtime}$ and the scheduled downtime $T_{scheduled}$ due to the scheduled maintenance as shown in Equation (6).

$$OPEX = C_{repair} + C_{labor} + C_{other} \tag{4}$$

$$AEP = \sum P(U) \times f(U) \times Availability \tag{5}$$

$$Availability = \frac{8760 - (T_{downtime} + T_{scheduled})}{8760} \tag{6}$$

Table 7 summarizes the average value used in this study for *LCOE* calculation. The average of *CAPEX* is evaluated as 282,000 Yen/kW from reference [2] reported by the Japanese government. The average of repair cost is evaluated as 2300 Yen/kWh from the NEDO database. The labor cost and the other cost in repair are also identified from Reference [2]. The scheduled downtime is determined based on reference [26], which is collected by the Department of Hokkaido Industrial Safety and Inspection. The fixed charge rate is identified as 6.12% from levelized cost of energy, capital expenditure, operating expense, annual energy production and 20-year lifetime to match the LCOE of 13.9 Yen/kWh as reported in reference [2]. The input values for each scenario are given in Table 7. In addition to three scenarios, the target for 2030 is set, where CAPEX is reduced by the learning rate of 18.6% as proposed by Wiser et al. [21].

Table 7. LCOE parameters in Japan.

	Average	**Reference**
CAPEX	282,000 Yen/kW	[2]
FCR	6.12%	Identified
OPEX	9300 Yen/kW	[2]
C_{repair}	2300 Yen/kW	Identified
C_{labor}	4500 Yen/kW	[2]
C_{other}	2500 Yen/kW	[2]
Capacity Factor	22%	[2]
$T_{downtime}$	970 h/turbine	Identified
$T_{scheduled}$	135 h/turbine	[26]
Availability	87%	[2]
Levelized Cost of Energy	13.9 Yen/kWh	[2]

Table 8 and Figure 6 show the predicted LCOE for each scenario. The downtime $T_{downtime}$ is obtained from Section 2 as described in Table 6. In OPEX, the labor cost C_{labor} assumes to be proportional to the repair downtime, C_{repair} and C_{other} are fixed values. LCOE in Figure 6 is divided into three parts: Production loss, OPEX and CAPEX. The cost reduction in Scenario 1 is 1.9 Yen/kWh, and those in Scenario 2 and 3 are 0.9 Yen/kWh and 0.3 Yen/kWh, respectively. It means that the total reduction of 3.1 Yen/kWh is possible by optimization of O&M strategy optimization. In addition, CAPEX reduction is also required to achieve the national target for LCOE in 2030.

Table 8. Cost-reduction scenarios in Japan.

		Baseline	Scenario 1	Scenario 2	Scenario 3	Target for 2030
CAPEX	(Yen/kW)			282,000		230,180
FCR	(%)			6.12		6.12
OPEX	(Yen/kW)	9300	7124	6011	5640	4603
$T_{downtime}$	(Hour)	970	501	261	181	181
$T_{scheduled}$	(Hour)	135	135	135	135	135
Availability	(%)	87.4	92.7	95.5	96.4	96.4
Capacity factor	(%)	22.1	23.5	24.2	24.4	24.4
Average of LCOE	(Yen/kWh)	13.7	11.9	11.0	10.7	8.7
Reduction	(Yen/kWh)	—	−1.9	−0.9	−0.3	−2.0

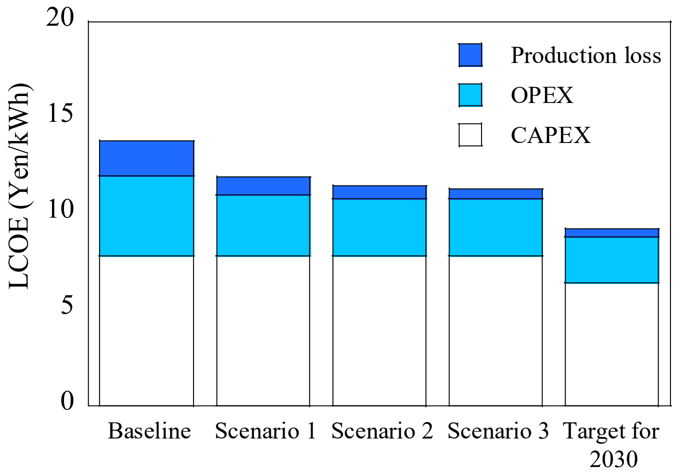


Figure 6. Predicted LCOE for baseline case, three scenarios and the target for 2030.

3.3. Effect of Uncertainty on Levelized Cost of Energy

The effect of uncertainty on CAPEX, downtime and repair cost are considered in this study.

The uncertainty of CAPEX is estimated based on reference [22] reported by the government. Figure 7 shows the probability density distribution of CAPEX. The parameters are identified by moment method. RMSE of beta, log-normalized and Weibull distributions are 1.01×10^{-2}, 1.07×10^{-2} and 0.96×10^{-2}, respectively. The least error distribution of the Weibull distribution is used as shown in Figure 7. The average value is 282,000 Yen/kW, and CoV is 0.27.

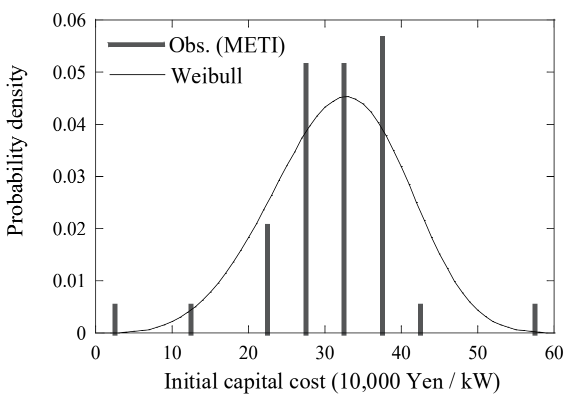


Figure 7. Probability density distribution of CAPEX.

The cumulative distribution of downtime and repair cost for each FTC is analyzed. The beta function is used for the fitting as shown in Equations (7)–(9).

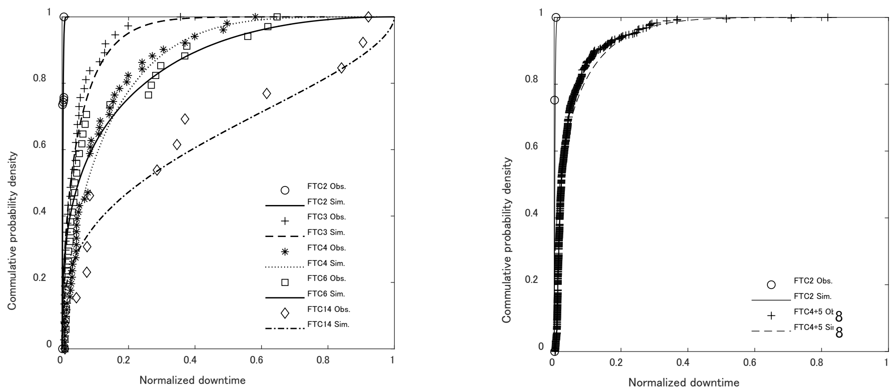
$$f(x|a,b) = \frac{1}{B(a,b)} x^{a-1}(1-x)^{b-1} I_{[0,1]}(x) \quad (7)$$

$$a = (-m^3 + m^2 - mv)/v \quad (8)$$

$$b = \left(\frac{1}{m} - 1\right) \quad (9)$$

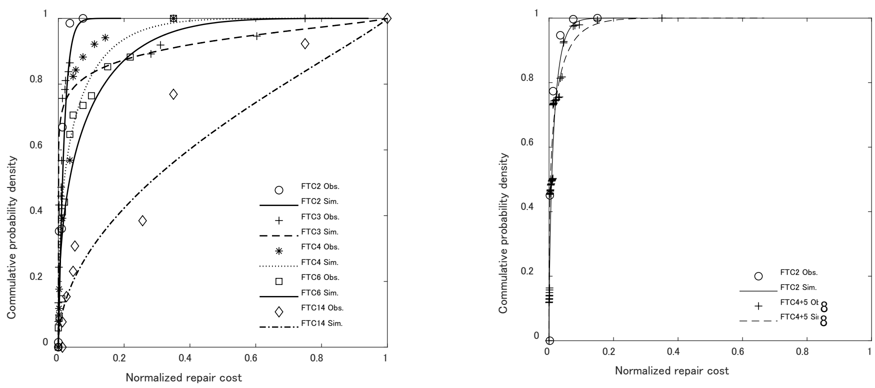
where m is the average value, and v is the standard deviation of data.

The cumulative distributions of downtime for rotor assembly and control assembly are shown in Figure 8, and those of repair cost are shown in Figure 9. The cumulative probability functions of the failure modes with the short downtime show the similar probability distributions regardless of the size of assembly, while those with the long downtime depend on the size of assembly as shown in Figure 8.



(**a**) Downtime of rotor system (**b**) Downtime of control and protection system

Figure 8. Cumulative distribution of downtime for rotor and control systems.



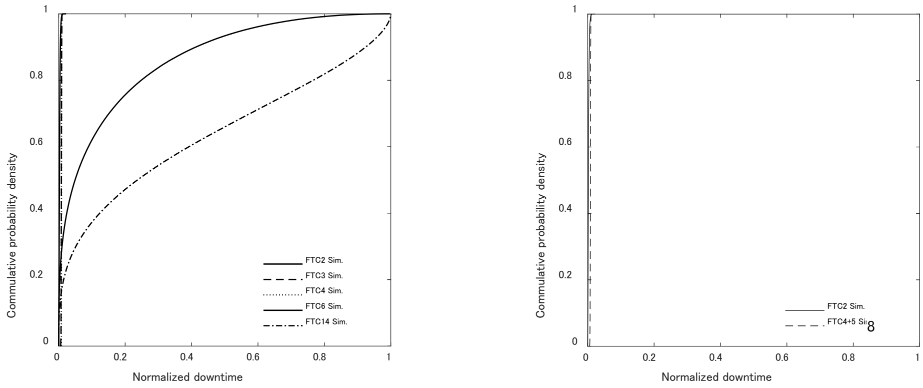
(**a**) Repair cost of rotor system (**b**) Repair cost of control protection system

Figure 9. Cumulative distribution of repair cost for rotor and control systems.

Figure 10 shows the cumulative distributions of downtime for the rotor and control assemblies used in Scenario 1. The downtime of FTC 2, 3, 4 as shown in Table 4 are reduced to 72 h, compared to the baseline case.

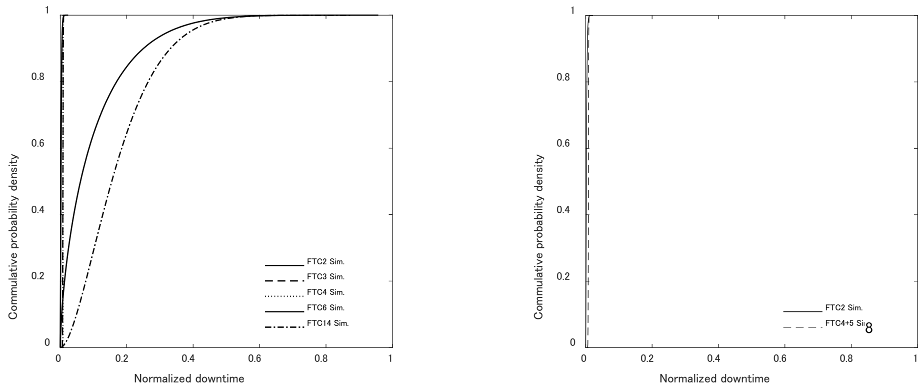
Figure 11 illustrates the cumulative distribution of downtime for rotor assemblies used in Scenario 2. The downtime of FTC 6 and 14 are reduced to 10 days, compared to Scenario 1.

The cumulative distributions of repair cost are not changed from the baseline case as shown in Figure 9.



(**a**) Rotor system (**b**) Control and protection system

Figure 10. Cumulative distribution of downtime for Scenario 1.



(**a**) Rotor system (**b**) Control and protection system

Figure 11. Cumulative distribution of downtime for Scenario 2.

Figure 12 displays the predicted probability density distribution for each scenario, and the predicted median value of P50, the 90th percentile of P90 and those ratios of P90/P50 are summarized in Table 9. This indicates that the uncertainty of LCOE in Scenario 1 reduces from the baseline case, but the uncertainties of LCOE in the three scenarios are similar. It suggests that a reduction in the downtime of small failure modes results in a significant reduction in uncertainty. Reducing the uncertainty is an important aspect to consider OPEX cost reduction, which connects to the reduction in insurance cost included in C_{other} as shown in Equation (4).

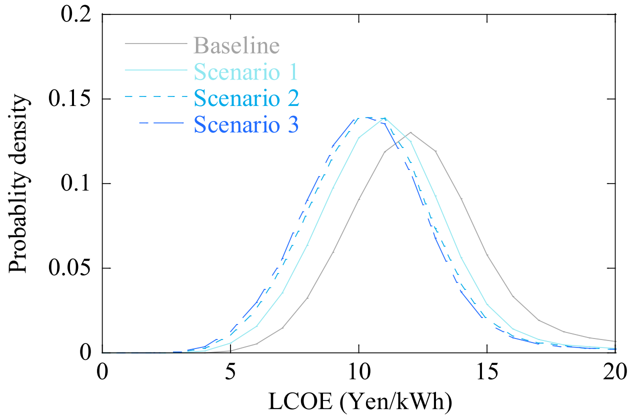


Figure 12. Comparison of predicted probability density distribution for each scenario.

Table 9. Predicted P50 and P90 for each scenario.

	P50 Yen/kWh	P90 Yen/kWh	P90/P50
Baseline	12.52	23.86	1.91
Scenario 1	11.14	15.29	1.37
Scenario 2	10.53	14.10	1.34
Scenario 3	10.36	13.91	1.34

4. Conclusions

In this study, a failure mode effect analysis is conducted based on the failure rate and downtime database for onshore wind turbines in Japan. The availability and levelized cost of energy are analyzed using the failure rate and downtime database. The following conclusions are obtained.

1. The normalized failure rate and downtime are comparable between Japan and Europe for each fault type class at the assembly and failure mode levels. The occurrence rate is similar between Japan and Europe, but the downtime in Japan is much longer than that in Europe. It is clarified that the difference in downtime in each database comes from the operating years of turbines by analyzing old and new turbines in the NEDO database.
2. Availability improvement and cost reduction scenarios are investigated using the failure rate and downtime for each fault type class based on the industry interview and best practices in Japan. The availability can be improved from 87.4% to 92.7, 95.5 and 96.4%, and the levelized cost of energy reduces from 13.7 Yen/kWh to 11.9, 11.0, 10.7 Yen/kWh considering spare parts, condition monitoring and industry maturity.
3. The cumulative probability function of downtime and repair cost for each mode is analyzed. It is found that the cumulative probability functions of the failure modes with the shortest downtime show similar probability distributions regardless of the size of assembly. The uncertainty of LCOE in the three scenarios significantly reduces from the baseline case by about 30% due to a reduction in the downtime of small failure modes, which is an important aspect to consider OPEX cost reduction.

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References

1. Japan Wind Power Association, JWPA Report Detail 2021/02/12. Available online: http://jwpa.jp/page_304_englishsite/jwpa/detail_e.html (accessed on 28 May 2021).
2. Wind Power Competitiveness Strengthening Committee, Final Report, 2016 (In Japanese). Available online: https://www.meti.go.jp/committee/kenkyukai/energy_environment/furyoku/pdf/report_01_01.pdf (accessed on 28 May 2021).
3. Hand, M.M. IEA Wind TCP Task 26–Wind Technology, Cost, and Performance Trends in Denmark, Germany, Ireland, Norway, Sweden, the European Union, and the United States: 2008–2016. NREL/TP-6A20-71844. National Renewable Energy Laboratory, Golden, CO (US). 2018. Available online: https://www.nrel.gov/docs/fy19osti/71844.pdf (accessed on 28 May 2021).
4. Herman, K.; Walker, R.; Wilkinson, M. Availability trends observed at operational wind farms. In Proceedings of the Science & Research Abstract for EWEA 2008 Annual Event, European Wind Energy Conference 2008, Brussels, Belgium, 31 March–3 April 2008.
5. New Energy and Industrial Technology Development Organization. *The Report of Wind Turbine Failure and Accident 2013–2017*; New Energy and Industrial Technology Development Organization: Kawasaki, Japan, 2013–2017. (In Japanese)
6. Pfaffel, S.; Faulstich, S.; Rohrig, K. Performance and reliability of wind turbines: A review. *Energies* **2017**, *10*, 1904, doi:10.3390/en10111904.
7. Dao, C.; Kazemtabrizi, B.; Crabtree, C. Wind turbine reliability data review and impacts on levelised cost of energy. *Wind Energy* **2019**, *22*, 1848–1871, doi:10.1002/we.2404.
8. Faulstich, S.; Pfaffel, S.; Hahn, B. Performance and reliability benchmarking using the cross-company initiative WInD-Pool. In Proceedings of the RAVE Offshore Wind R&D Conference, Bremerhaven, Germany, 14 October 2015.
9. *Portfolio Review 2016*; System Performance, Availability and Reliability Trend Analysis (SPARTA): Northumberland, UK, 2016.
10. Faulstich, S.; Hahn, B.; Tavner, P.J. Wind turbine downtime and its importance for offshore deployment. *Wind Energy* **2011**, *14*, 327–337, doi:10.1002/we.421.
11. Wilkinson, M. Measuring wind turbine reliability—Results of the reliawind project. In Proceedings of the Science & Research Abstract for EWEA 2011 Annual Event, European Wind Energy Conference 2011, Brussels, Belgium, 14–17 March 2011.
12. VGB Standards, RDS-PP—Application Guideline; Part 32: Wind Power Plants, 2014. Available online: https://www.vgb.org/shop/technicalrules/vgb-standards/s-823-0.html?___store=en&___from_store=default (accessed on 28 May 2021)
13. Shafiee, M.; Dinmohammadi, F. An FMEA-based risk assessment approach for wind turbine systems: A comparative study of onshore and offshore. *Energies* **2014**, *7*, 619–642, doi:10.3390/en7020619.
14. Ozturk, S.; Fthenakis, V.; Faulstich, S. Failure modes, effects and criticality analysis for wind turbines considering climatic regions and comparing geared and direct drive wind turbines. *Energies* **2018**, *11*, 2317, doi:10.3390/en11092317.
15. Carroll, J.; McDonald, A.; McMillan, D. Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. *Wind Energ*y **2016** *19*, 1107–1119, doi:10.1002/we.1887
16. Asgarpour, M.; van de Pieterman, R.; Netherlands, E.R.C. *O&M Cost Reduction of Offshore Wind Farms—A Novel Case Study*; ECN: 2014; Available online: https://publicaties.ecn.nl/PdfFetch.aspx?nr=ECN-E--14-028 (accessed on 28 May 2021).
17. Maples, B.; Saur, G.; Hand, M.; van de Pietermen, R.; Obdam, T. *Installation, Operation, and Maintenance Strategies to Reduce the Cost of Offshore Wind Energy*; National Renewable Energy Lab. (NREL): Golden, CO, USA, 2013.
18. Seyr, H.; Muskulus, M. Value of information of repair times for offshore wind farm maintenance planning. *J. Phys. Conf. Ser.* **2016**, *754*, 92009, doi:10.1088/1742-6596/753/9/092009.

19. Mortstock, K.; Wilkinson, M. Data mining to reduce risk and better predict P90 performance, In Proceeding of Wind Europe 2017, Wind Europe Conference 2017, Amsterdam, The Netherlands, 28–30 November 2017.
20. Okumoto, H.; Kato, H.; Niijima, K. Failure rate and downtime analysis for wind turbine by using failure and accident survey. In Proceedings of the 15th World Wind Energy Conference and Exhibition, Tokyo, Japan, 31 October–1 November 2016; pp. 1–4.
21. Ministry of Economy, Trade and Industry. Feed-In Tariff Scheme in Japan. 2010. (In Japanese). Available online: https://www.meti.go.jp/english/policy/energy_environment/renewable/pdf/summary201207.pdf (accessed on 28 May 2021).
22. Committee for Procurement Price. Annual Report from Calculation Committee for Procurement Price. 2012–2021 (In Japanese). Available online: https://www.meti.go.jp/shingikai/santeii/ (accessed on 28 May 2021).
23. Kikuchi, Y.; Saito, R.; Ishihara, T. Assessment of levelized cost of energy for wind energy based on reliability analysis. *J. Wind Energy* **2019**, *43*, 1–12, doi:10.11333/jwea.43.1_A_1. (In Japanese)
24. Wind Power Equipment and Installation Results in Japan, NEDO (In Japanese). Available online: https://www.nedo.go.jp/library/fuuryoku/pdf/05_kaigai_kokusan_dounyuu_suii.pdf (accessed on 28 May 2021).
25. Takagi, K. Towards the availability improvement of wind farm. In *Proceedings of the 38th Wind Energy Symposium 2018*; Tokyo, Japan, 30 November – 1 December 2018. (In Japanese)
26. Department of Hokkaido Industrial Safety and Inspection of Ministry of Economy, Trade and Industry. *Current Status and Challenges of Wind Power in Hokkaido 2013–2015*; (In Japanese) Available online: https://www.safety-hokkaido.meti.go.jp/denki_hoan/h30fy_wp_enq/index.htm (accessed on 28 May 2021)
27. New Energy and Industrial Technology Development Organization, NeoWins, https://appwdc1.infoc.nedo.go.jp/Nedo_Webgis/top.html (accessed on 28 May 2021)
28. Wiser, R.; Jenni, K.; Seel, J.; Baker, E.; Hand, M.; Lantz, E.; Smith, A. Forecasting Wind Energy Costs & Cost Drivers. *IEA Wind* **2016**, *LBNL-1005717*. Available online: https://eta-publications.lbl.gov/sites/default/files/lbnl-1005717.pdf (accessed on 28 May 2021).