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Wind turbine reliability data review and impacts on levelised cost of energy

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Abstract

Reliability is critical to the design, operation, maintenance, and performance assessment and improvement of wind turbines (WTs). This paper systematically reviews publicly available reliability data for both onshore and offshore WTs and investigates the impacts of reliability on the cost of energy. WT failure rates and downtimes, broken down by subassembly, are collated from 18 publicly available databases including over 18 000 WTs, corresponding to over 90 000 turbine-years. The data are classified based on the types of data collected (failure rate and stop rate) and by onshore and offshore populations. A comprehensive analysis is performed to investigate WT subassembly reliability data variations, identify critical subassemblies, compare onshore and offshore WT reliability, and understand possible sources of uncertainty. Large variations in both failure rates and downtimes are observed, and the skew in failure rate distribution implies that large databases with low failure rates, despite their diverse populations, are less uncertain than more targeted surveys, which are easily skewed by WT type failures. A model is presented to evaluate the levelised cost of energy as a function of WT failure rates and downtimes. A numerical study proves a strong and nonlinear relationship between WT reliability and operation and maintenance expenditure as well as annual energy production. Together with the cost analysis model, the findings can help WT operators identify the optimal degree of reliability improvement to minimise the levelised cost of energy.

KEYWORDS

downtime, failure rate, levelised cost of energy, reliability, uncertainty, wind turbine

1 | INTRODUCTION

Reliability is critical to the success of a wind energy project. Low levels of reliability could result in multiple breakdowns that require extensive maintenance. High levels of reliability can reduce breakdown costs and frequency but may be prohibitively costly to achieve. The breakdown and maintenance costs are significant parts of a WT's operation and maintenance expenditure (OPEX). Additionally, WT reliability affects overall system performance and power output,[1,2] resulting in additional costs from lost revenue.

A common metric used to describe wind farm performance is the levelised cost of energy (LCOE), which is defined as the net present value of the cost to produce a unit of energy. The turbine power output, OPEX, and initial investment cost are all considered in the LCOE evaluation. In the literature, there have been several studies on the LCOE estimation[3-7]; however, the WT reliability has not been considered in such studies. Therefore, it is essential to develop a model for estimating LCOE that incorporates the reliability data of WTs in order to fully understand the effects of reliability.

Wind turbine reliability data comprise the historical failures, repairs, and downtimes of a turbine and its subassemblies. A thorough understanding of WT reliability is critical to the development of effective operation and maintenance (O&M) strategies and to an improved WT and wind farm performance. Several studies have been performed to collect and analyse WT reliability data. The Dutch Offshore Wind Energy Converter project (DOWEC, 1998-2003) provided early research on the need for designing large-scale offshore wind farms and a preliminary reliability study on onshore WTs.[8,9] ReliaWind (2008-2011) is another European project which systematically provided a reliability data taxonomy concept and collected reliability data for a large number of onshore turbines.[10,11] In the ReliaWind project, data from approximately 7000 turbines are collected over a period of more than 10 years from three large databases, including Windstats Germany, Windstats Denmark,[12] and LWK (Landwirtschaftskammer, Schleswig-Holstein, Germany).[13] Data from both DOWEC and ReliaWind projects are now quite old, being before 2001 and before 2006, respectively, and only for relatively small-size wind turbines, but they are, nevertheless, some of the most comprehensive data available publicly. Perez et al[14] present a review of onshore WT subassembly reliability in European countries including the reliability data from six data sources including three from the ReliaWind project.

Offshore wind energy has experienced rapid growth in recent years, and the annual cumulative installed capacity is expected to increase in coming years. Since 2011, the annual cumulative capacity has more than quadrupled and reached 18.8 GW in 2017 (Figure 1). Together with increasing cumulative capacity, advanced and complex turbine technologies have enabled the deployment of larger turbines in further offshore locations. The offshore wind industry is now facing a multitude of operational challenges such as the need to improve component reliability and to apply and develop operation and maintenance strategies to reduce costs.[16]

Compared with onshore wind energy, which is now in a reasonably mature development state, the large-scale offshore wind industry has continued to grow significantly in recent years, in parallel with constant advances in WT and farm technology. Reliability data of offshore WTs are available at different levels as a result from the competitive nature of the industry causing manufacturers and operators to be protective of their data and reluctant to share information about their wind farms and failures openly. Nevertheless, offshore WT reliability data are very useful for reliability, O&M analysis, and performance evaluation and published in many papers such as in the literatures.[17-20] In a review of WT performance and reliability by Pfaffel et al[19] 24 data sources are referenced, but only three of these include data from offshore WTs. Two out of these three offshore sources provide subassembly failure data, while the Wind-Pool database[21] only provides general information on turbine O&M performance. None of the sources in Pfaffel et al[19] report offshore WT downtime. There are some studies in the literature that compare the general operational performance of onshore and offshore wind turbines[19,21]; however, due to the scarcity of offshore reliability data, few studies are available that compare onshore and offshore reliability data. Recently, Artigao et al[20] reviews 13 reliability data sources including two offshore, six onshore in Pinar Pérez et al[14] and five other onshore published from 2011 to 2016. The subassembly reliability data from different sources are normalised and measured in percentage and thus are used to identify critical WT subassemblies for condition monitoring development.
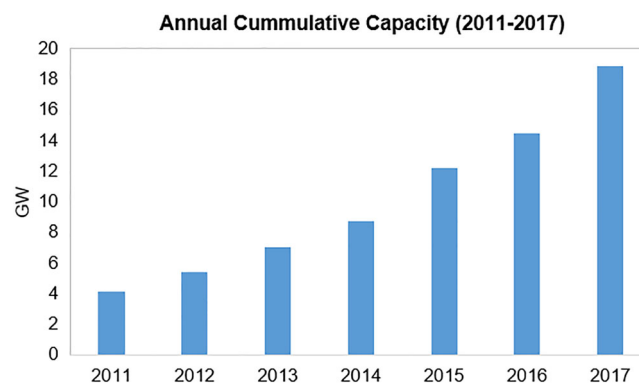

FIGURE 1 Global offshore wind energy capacity in recent years[15] [Colour figure can be viewed at wileyonlinelibrary.com]

This paper summarises the reliability data for WT subassemblies from various sources. The paper analyses additional offshore reliability data that have not been investigated in Pinar Pérez et al, Pfaffel et al, and Artigao et al[14,19,20] in order to identify the critical subassemblies and highlight the differences between onshore and offshore WTs. To the authors' best understanding, this is the most comprehensive review with 18 WT reliability data sources conducted, including more than 18 000 WTs in Europe, Asia, and the USA which correspond to more than 90 000 turbine years; three additional reliability data sources (over 1200 wind turbines, two of them are offshore) have not been included in the previous reviews. The additional offshore databases allow us to do further analysis and comparison between the reliability of onshore and offshore WTs. The reliability analysis in this paper focuses not only on critical subassemblies identification and intersubassembly reliability comparison as in Pinar Pérez et al, Pfaffel et al, and Artigao et al[14,19,20] but also on the failure rate and downtime variations and identification of possible sources of uncertainty. Moreover, the paper presents a new model for LCOE estimation using reliability data, and the surveyed reliability data are employed to evaluate the impacts of WT reliability on LCOE for different populations of WTs.

This paper makes a number of important contributions:

- The paper provides the most comprehensive review of existing onshore and offshore reliability data sources to date and identifies the similarities and differences between the populations of both onshore and offshore wind turbines.

- The paper analyses the failure rates and downtimes of WT subassemblies, based on a common taxonomy, derived from several data sources to identify critical subassemblies (in terms of failure rate and downtime). Moreover, this paper is the first study quantifying reliability data uncertainty and investigating the sources of uncertainty and properly compares the reliability of onshore and offshore populations.

- In addition to quantifying data variations and uncertainty, this paper presents a model for estimating the LCOE using reliability data, which makes it possible to relate WT failure rates and downtime to OPEX and annual energy production. The surveyed reliability data are used to find the optimal reliability improvement required to minimise LCOE for different data sources.

The remainder of this paper is organised as follows. Section 2 provides a methodology for estimating the failure rates and downtimes of WT subassemblies and a common WT taxonomy for collecting and interpreting reliability data. Detailed reviews on several onshore and offshore WT reliability databases are provided in Section 3. Section 4 presents a reliability data analysis of WT subassemblies. Section 5 proposes a model for LCOE estimation using reliability data and numerical analysis for LCOE optimisation for different databases. Section 6 provides conclusions drawn from the survey and analysis.

2 | RELIABILITY DATA COLLECTION METHODOLOGY

2.1 | Failure rate and downtime estimation

In wind farm O&M practice, historical WT events can be recorded from several sources such as condition monitoring systems (CMS), supervisory control and data acquisition (SCADA) systems, failure reports, and maintenance logs. Historical events are commonly summarised for reliability studies and presented in terms of *failure rate*, which is the failure frequency given by the number of failures per turbine per unit time, and *downtime per failure*, which is given as the time during which a turbine does not produce power output due to a failure. The reliability data, including failure rate and downtime, are critical for the design, operation, maintenance, and performance assessment of WTs but are often difficult to acquire or share.

This study looks for all the data sources that contain failure and/or downtime statistics, collectively called reliability statistics, for WT subassemblies. The failure statistics can be either the calculated failure rates per turbine per year or the number of failures in a certain time interval. In both cases, the time between failures is assumed to follow an exponential distribution, with the failure process being a *homogeneous Poisson process (HPP)* with a constant parameter, λ, representing the failure rate. This assumption has been tested and proven to be reasonable for the ReliaWind failure data[22] and is widely accepted for WT reliability data studies.[14,20,23]

With this assumption, the failure rate of subassembly i, λ_i, estimated as the number of failures per turbine per year, can be determined from

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

where $n_{i,p}$ is the number of failures of subassembly i in period p; N_p is the number of WTs considered in period p; and T_p is the time duration of period p in hours. The failure rate of the entire WT is calculated as a summation of all its subassemblies' failure rates:

$$\lambda = \frac{\sum_{i=1}^{I} \sum_{p=1}^{P} n_{i,p}}{\sum_{p=1}^{P} N_p (T_p/8760)} \tag{2}$$

where I is the total number of subassemblies in the turbine. The numerator of Equation (2) represents the total number of failures of the turbine, and the denominator represents the total number of turbine years within the survey. In some databases, this total number of failures and a relative percentage of these resulting from each subassembly are given; the failure rate of each subassembly is derived accordingly.

Similarly to the failure statistics, the downtime statistics are often either average calculated downtime per failure for each subassembly, $\overline{D}_i$, or total downtime in a certain interval. The calculation of $\overline{D}_i$ is shown in Equation (3):

$$\overline{D}_i = \frac{\sum_{p=1}^{P} D_{i,p}}{\sum_{p=1}^{P} n_{i,p}}, \tag{3}$$

where $D_{i,p}$ is the total downtime due to failures of subassembly i in period p. The numerator of Equation (3) is the total downtime caused by failures of subassembly i, and the denominator is the total number of failures in the entire duration of a database.

2.2 | Wind turbine taxonomy

In this study, a common taxonomy is used to report the surveyed WT reliability data. To this end, the WT structure shown in Figure 2 is employed. The common taxonomy, shown in Table 1, is used to streamline the process of surveying the WT reliability data and subsequently estimate the associated failure rates and downtimes and allow comparison of databases.

It is worth noting that, in this paper, only system, subsystem, and subassembly levels (Figure 2) are studied. An example of a subsystem is the turbine rotor, which contains four subassemblies, namely blades, hub, air brake, and the pitch system. Generally, a subassembly may itself be divided into smaller components. For example, the pitch system includes the electric motors used to pitch the blades. Similarly, converters may include individual IGBT/diode components (bidirectional switches). Readers can refer to other general reliability databases, such as Offshore Reliability Databases (OREDA),[24] Nonelectronic Parts Reliability Database (NPRD-2016),[25] and Electronic Parts Reliability Database (EPRD-2014)[26] for reliability data of lower-level components and parts.

In the literature, there is a variation in the ways that WT data are broken down, and many sources of data are not directly comparable for this reason.[19] The taxonomy featured in this paper is based on that used in the ReliaWind project[22,23,27] with some small modifications (Table 1). The ReliaWind turbine taxonomy is also adopted in many other studies on wind turbine reliability data.[19,28-32] Moreover, a subassembly may be named
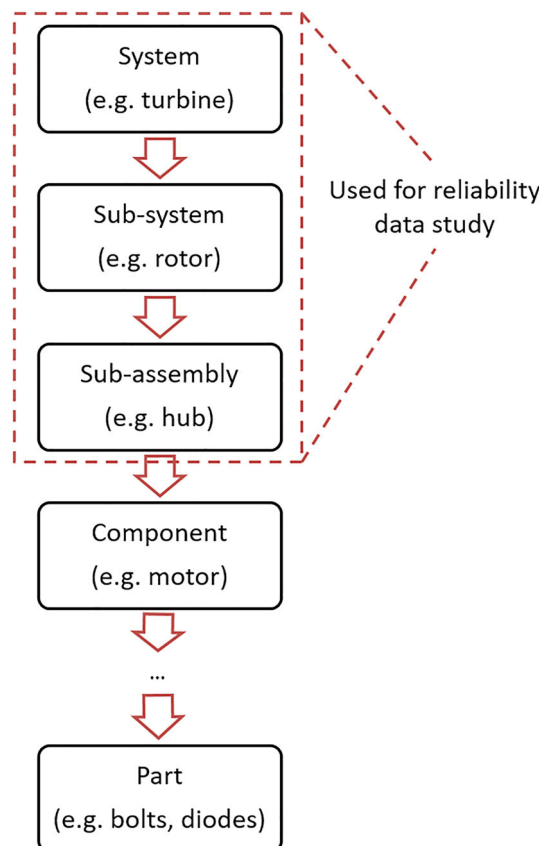

FIGURE 2 Wind turbine breakdown structure [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 WT taxonomy applied in this paper

Subsystem	Subassembly	Alternative Names
Rotor	Blades	Rotor blades
	Hub	Hub unit
	Air brake	Rotor brake
	Pitch system	Pitch control
Drive train	Shafts and bearings	Low-speed, high-speed shafts
	Mechanical brake	Braking system
Gearbox	Gearbox	Speed conversion system
Generator	Generator	-
Hydraulic system	Hydraulic system	Hydraulics
Yaw system	Yaw system	-
Control system	Control system	Electronic control
Electrical	Converter	Frequency converter
	Transformer	-
	Electrical protection and switchgear	Electrical components
Sensors	Sensors	-
Nacelle	Nacelle	-
Structure	Tower	-
	Foundation	-
Other	Other	Other components

differently in different reliability sources. In Table 1, the first two columns include common names of WT subsystems and subassemblies in this paper and the majority of reliability studies; the third column provides alternative names that a subassembly may be called in a few studies in the literature.

In Table 1, the category under subsystems termed "other" is used for equipment in the turbine that could not be associated with any other specific category. For example, some surveys include data marked "unknown" or which are for small components that might not necessarily be associated with the function of the turbine (such as cabinets, lighting, etc.). All such components are included under the "other" category in this paper.

It is noted that there are some papers and reports in the literature that address the reliability of a single subassembly or the overall turbine performance but not the detailed data of all the subassemblies, such as the literatures.[21,33-38] These studies are not in the scope of this survey since no turbine taxonomy is presented, and, as such, the data are insufficient to make a thorough comparison between these studies and other databases.

3 | REVIEW OF WIND TURBINE RELIABILITY DATABASES

Each database is a survey of reliability data; however, the WT characteristics included in each survey vary. In this paper, turbines are classified by four general categories:

- Type I: Fixed speed, induction generator
- Type II: Variable speed/slip, induction generator
- Type III: Variable speed, doubly fed induction generator (DFIG)
- Type IV: Variable speed, fully rated converter (induction/synchronous/permanent magnet generator)

Types I and II are limited to onshore and small-scale wind turbines. These types of turbines have been operating for quite some time. Types III and IV are the dominant configurations and have become standard for all new and recently developed turbines (such as the Siemens SWT-7.0-154, Vestas V164). Depending on the drivetrain configuration, a WT may have an indirect (geared) drive (with a step-up gearbox for connecting the turbine rotor to the generator) or a direct drive (DD) power train (with the low-speed rotor hub directly coupled to the generator). Type IV turbines can be either direct or indirect drive, with some manufacturers now implementing medium speed indirect drive configurations for PMSG machines. DD PMSG turbines (Siemens SG-8.0-167DD, SG-10.0-193DD) are currently being developed for large-scale far offshore applications.

3.1 | Onshore wind turbine reliability databases

In this paper, 14 sources of onshore WT reliability data from all the countries in Europe, Asia, and America that play important roles in the wind energy sector are reviewed (Figure 3). Data from more than 17 000 turbines corresponding to approximately 90 000 turbine years are identified. For each database, the location, number of turbines, turbine ratings (range), type of turbines, survey years, turbine years, references, and key characteristics are given in Table 2.

The majority of the data sources are combinations of small (few hundred kilowatts) to medium (few megawatts) turbines. There may be either a single database for a country, such as in Denmark, Finland, and Sweden, or multiple data sources from the same country, such as in Germany, USA, and China.

The onshore databases are highly variable in terms of their sizes and content. Large databases, such as Windstats, WMEP, and CIRCE, contain data from several thousands of turbines over lengthy periods of time (more than 5 years), and the number of turbine years is more than 10 000. These large databases account for over 70% of the total number of reporting onshore WTs and over 80% of the total reported turbine years. On the other hand, small databases such as EPRI, VTT, East China, Huadian, and Southeast China survey only a small number of turbines or only for short periods of time and, thus, the number of turbine years is less than 1000. These databases, however, do tend to focus on specific turbine types rather than amalgamating data from large numbers of different turbine types. Some medium-sized databases may contain smaller numbers of turbines but for rather long durations, such as LWK, Sweden, CWEA, and CREW.

Since there are several sources of data, there are some disparities between the turbine taxonomies employed and in the way the data have been collected. Generally, a failure is defined as an event that brings the turbine or a subassembly to a failed state that requires a repair action. However, in some databases, such as the CREW (USA) and East China, every stop event is reported, and many of these events can be resolved with a remote or manual reset rather than by a tangible maintenance action. In this case, many stops are not real failures but responses to unusual operating conditions. Occasionally, different databases break down the turbine taxonomy slightly differently. For example, a database may report rotor information in separate categories for blades, hub, air brakes, and pitch systems and present the reliability statistics for all these subassemblies separately, while another database may combine these together and present a single statistic for the rotor subsystem.

3.2 | Offshore wind turbine reliability databases

Data for offshore WTs and wind farms are less prevalent than for onshore. This survey has identified four studies into the reliability of offshore WTs with a total of 1551 WTs, corresponding to over 3300 turbine years in Europe. Details of locations, numbers of turbines, years of data collection, rated power, types, and turbine years from these surveys are presented in Table 3. In addition to the characteristics given in Table 2 for onshore WTs, Table 3 provides the distance to shore and water depth for the offshore surveys.

Unlike onshore reliability data, data sources for offshore WTs contain a relatively small number of WTs and turbine years, and only reliability data of European (including UK) offshore turbines are available (Figure 4). This is well explained by the dominance of European countries in offshore wind. All of these studies are for multimegawatt WTs (2 MW and above). The Strathclyde and SPARTA data are more recent and for a large number of turbines and turbine years, compared with the other two data sources, which cover one or only a few wind farms in their early operation. Just as for the onshore reliability databases, there is also a difference in the way data are presented. For instance, stop/alarm events,
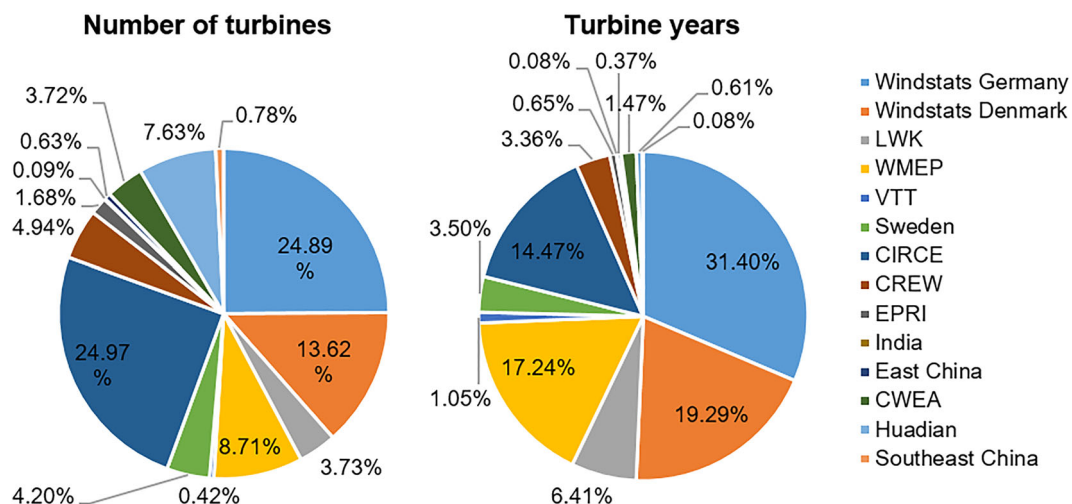

FIGURE 3 Summary of onshore WT reliability databases [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Onshore WT reliability databases

	Name	Location/Country	Number of WTs	WT Rating, MW	WT Type	Years	WT Years	Original Data Ref.	Note
1	Windstats Germany	Germany	4285	0.1-2.5	All	1995-2004	28 000	12	- the largest database with several studies investigated this database[22,23,27,39-41] - failure rate and downtime data, reported quarterly
2	Windstats Denmark	Denmark	2345	0.1-2.5	All	1994-2004	17 200	12	- the second largest databases, often being compared with Windstats Germany - only failure rate data, reported monthly
3	LWK	Germany	643	0.225-1.8	All	1993-2006	5719	13	- data for northern Germany (near coastline) WTs. - failure rate and downtime data, reported annually
4	WMEP	Germany	1500	0.03-1.8	All	1989-2006	15 375	42	- data collected from SCADA alarms and maintenance reports, by the Fraunhofer Institute for wind energy systems[43] - full data for the entire period were updated and presented in Faulstich et al[28]
5	VTT	Finland	72	0.075-3	All	1996-2008	936	44	- failures and WT performance are reported in a conference paper and a thesis in Finnish[45,46]
6	Sweden	Sweden	723	0.055-3	NA	1997-2005	3122	47	- original source in Swedish; data were also summarised in English[31,32] - failure rate and downtime data for the entire period
7	CIRCE	Spain	4300	0.3-3	III, IV	3 y, ~2013	~12 900	29	- data are reported based on failure logs and SCADA alarms[30] - be presented in percentage and estimated using the available total number of WTs and number of failures
8	CREW	USA	800-900	0.05-3	NA	2011-2015	~3000	48	- stop rate (not failure rate) data - original data published in 2011,[48] two subsequent updates in 2012 and 2016[49,50]
9	EPRI	USA	290	0.04-0.6	NA	1986-1987	580	9	- data for California wind farms
10	India	India	15	0.225	I	2000-2004	75	51	- data for Munpadal wind farm (a single wind farm) - only failure data (no downtime) available
11	CWEA	China	640	1.5-6	III, IV	2010-2012	1311	52	- only failure data of seven critical subassemblies (converter, gearbox, generator, pitch, yaw, blades, and brakes) are reported
12	Huadian	China	1313	NA	NA	2012	547	53	- be presented in percentage and estimated using the available total number of WTs and number of failures
13	East China	China	108	1.5-2	NA	2009-2013	331	54	- a single wind farm in Jiangsu Province - stop rate (not failure rate) data
14	SE China	China	134	1.5	III	2011	67	55	- a single wind farm in Southeast China coast - be presented in percentage and estimated using the available total number of WTs and number of failures

TABLE 3 Offshore WT reliability databases

|	Name	Location/Country	Distance to Shore, km	Water Deep, m	Number of WTs	WT Rating, MW	WT Types	Years	WT Years	Original Data Ref.	Note
1	Round 1 UK	UK	3.6-12.8	5-20	120	2-3	III	2004-2007	270	56	- data from four wind farms in early operation - dominant failure of gearbox leading a large number of gearbox replacements
2	NoordzeeWind	Netherlands	10-18	17-33	36	3	III	2007-2009	108	57-59	- Egmond aan zee wind farm - stop rate (not failure rate) data - dominant failures of gearbox and generator
3	Strathclyde	Europe	NA	NA	350	2-4	III	5 y	1768	17	- failures are classified into minor repair, major repair, and major replacement - repair time (not downtime) data
4	SPARTA	UK	Vary	Vary	1045	2-6	III, IV	2015-2016	1219	60	- data from 19 UK wind farms - the monthly average number of repairs (due to failures) data - no downtime per failure data

Number of turbines

Turbine years
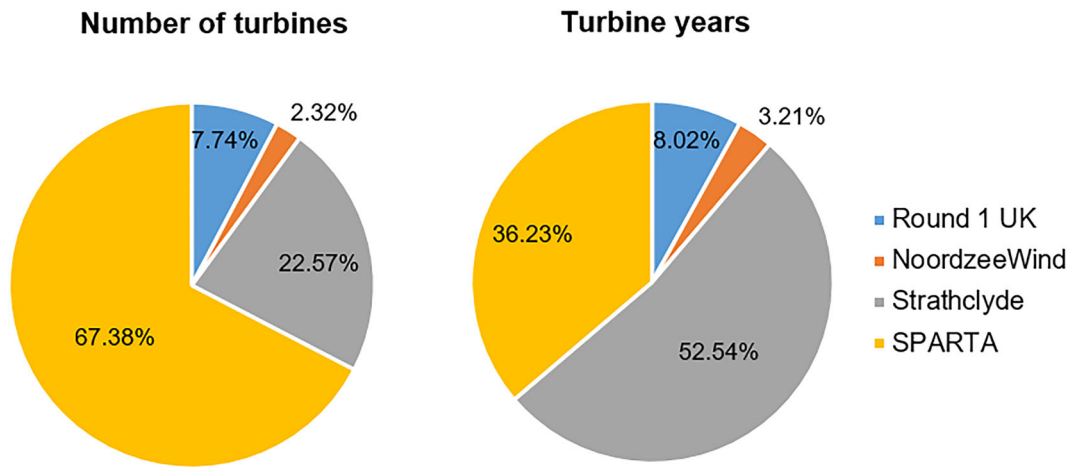
FIGURE 4 Summary of offshore WT reliability databases [Colour figure can be viewed at wileyonlinelibrary.com]

not necessarily real failures, are reported for the NoordzeeWind WTs. The data from this source can be compared with the CREW (USA) and East China onshore databases as these follow a similar reporting approach.

In reliability and performance analysis of offshore wind farms, it may be beneficial to investigate other offshore electrical infrastructure, which is not part of a WT but is essential to energy collection and transmission to shore. The reliability of offshore transmission equipment such as cables (AC and DC), high voltage power transformers, converters, and switchgears can be found in databases and existing surveys such as the International Council on Large Electric Systems (CIGRÉ),[57-59] Offshore Wind Program Board (OWPB),[50] Beddard and Barnes,[61] and Rui et al.[62]

4 | WIND TURBINE RELIABILITY DATA ANALYSIS

In this section, WT subassembly reliability data are presented and analysed in terms of failure rates and downtimes in order to determine the critical subassemblies and to compare the reliability statistics for onshore and offshore WTs. All 18 reliability databases in Section 3, including 14 onshore and four offshore, are analysed. Since there are discrepancies in the manner of data reporting, failure and downtime per failure statistics (from 15 data sources: 12 onshore and three offshore) and stop event and downtime per stop statistics (three data sources: two onshore—CREW and East China, one offshore—NoordzeeWind) are treated separately. It should be noted that in the subsequent analysis, the common taxonomy introduced in Section 2 has been used to group the data.

4.1 | Wind turbine subassembly failure rates and downtimes

In this section, 15 data sources with failure rate and downtime per failure statistics are analysed to the subassemblies reliability and its variations among these data sources. All 15 sources contain failure rate data, but only 10 of them include downtime data: the Windstats Denmark, India, CWEA, UK offshore round 1, and SPARTA data sources do not include downtime information. The boxplots of failure rates and downtimes of WT subassemblies given by different data sources are presented in Figures 5 and 6, respectively.

Based on the median values from Figure 5, subassemblies exhibiting higher average failure rates include

- Electrical
- Control system
- Pitch system
- Blades and hub

Subassemblies exhibiting lower average failure rates include

- Brakes
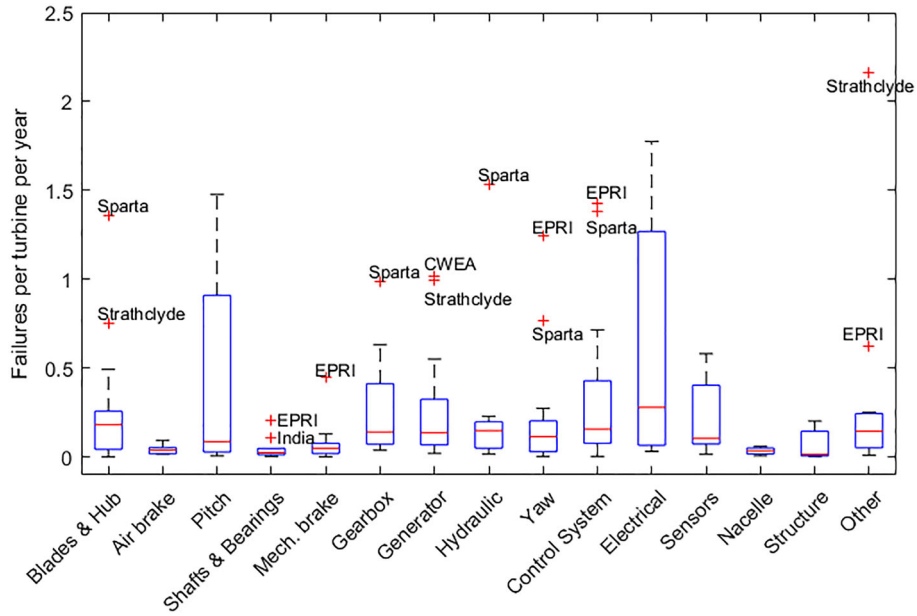- Shafts and bearings
- Nacelle
- Structure

FIGURE 5 Box plot of subassembly failure rates [Colour figure can be viewed at wileyonlinelibrary.com]
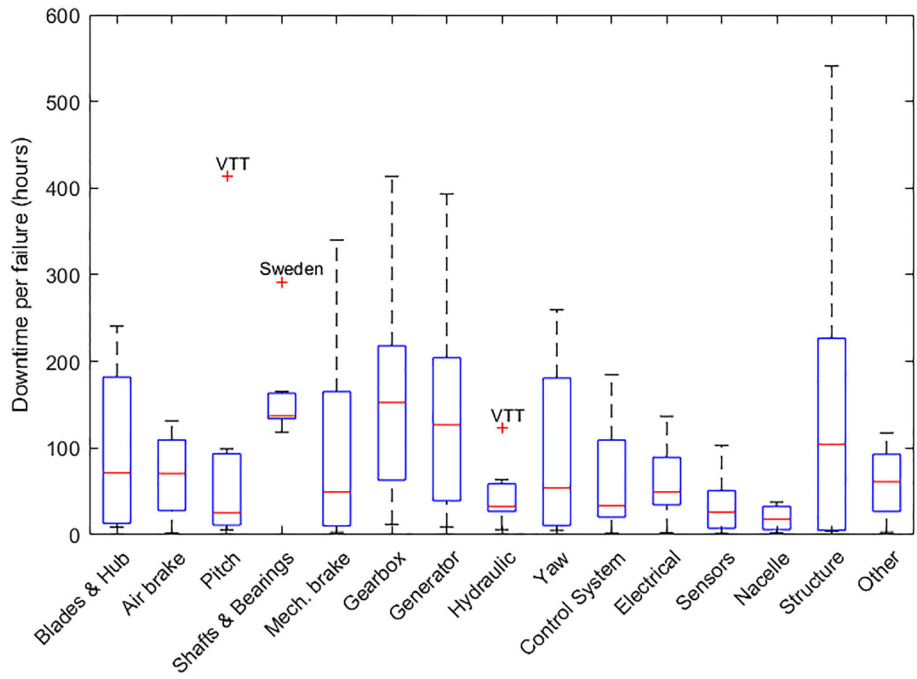

FIGURE 6 Box plot of subassembly downtimes [Colour figure can be viewed at wileyonlinelibrary.com]

Based on the median values from Figure 6, subassemblies with the highest downtimes include

- Gearbox
- Generator
- Shafts and bearings
- Structure

Subassemblies with lower downtimes in all surveys include

- Nacelle
- Sensor
- Hydraulics

It is noted that there are similar types of box plots in Artigao et al[20] compared with Figures 5 and 6. However, the graphs in Artigao et al[20] present normalised data in percentage, while Figures 5 and 6 present absolute failure rates and downtimes values, and thus can provide additional information such as the comparison of reliability data between different subassemblies. In addition, compared with Artigao et al[20] there are more outliers in Figure 5, which can be explained by the use of absolute reliability data instead of normalised percentage reliability data.

Table 4 presents the quartile coefficient of dispersion (COD) for each subassembly, which is used to compare the variations of failure rates and downtimes within different subassemblies. The quartile COD is defined by the ratio $(Q_3 - Q_1)/(Q_3+Q_1)$, where Q_1 and Q_3 are the first and third quartiles, respectively.

Table 4 shows that there are large variations in failure rates and downtimes between different subassemblies. In terms of failure rate, pitch system, electrical, and yaw are the three subassemblies with the largest variations, while air brake, nacelle, and shafts and bearings are the three subassemblies with the smallest variations. The design flexibility is a reason for these statistics since subassemblies with more design options (pitch, electrical, and yaw) often result in disparities in failures experienced. In terms of downtimes, the three highest variability assemblies are structural, yaw, and mechanical brake; the lowest downtime variability assemblies are shafts and bearings, hydraulic, and electrical.

The large variations in failure rates and downtimes result in a number of outliers in the boxplots in Figures 5 and 6. The average CODs for failure rate and downtime are not much different, at 0.67 and 0.65, respectively, but there are only three outliers in the downtime boxplot compared with 15 outliers in the failure rate boxplot. This implies that large failure rates are experienced in some databases while the downtimes widely spread among all databases. The large spread of outliers in Figure 5 is caused by the inclusion of both onshore and offshore datasets. All outliers in subassembly downtime in Figure 6 are from databases in northern Europe (Finland and Sweden), where severe weather condition associated with difficulties in WT accessibility for repair and maintenance may be the reason of the downtime variation.

4.2 | Wind turbine reliability data uncertainty

In order to quantify and identify possible sources of WT reliability data uncertainty, the WT failure rates from different data sources are, first, plotted in Figure 7, where the relative volume of data (the number of turbine years) is indicated by the circle area. Bubble plots of WT failure

TABLE 4 Coefficients of dispersion

	Quartile COD	
Subassemblies	Failure Rate	Downtime
Blades and hub	0.708	0.866
Air brake	**0.478***	0.593
Pitch	**0.938****	0.789
Shafts and bearings	**0.563***	**0.099***
Mech. brake	0.588	**0.882****
Gearbox	0.698	0.552
Generator	0.651	0.678
Hydraulic	0.590	**0.373***
Yaw	**0.740****	**0.888****
Control system	0.693	0.687
Electrical	**0.900****	**0.443***
Sensors	0.631	0.742
Nacelle	**0.496***	0.691
Structure	0.705	**0.955****
Other	0.645	0.552

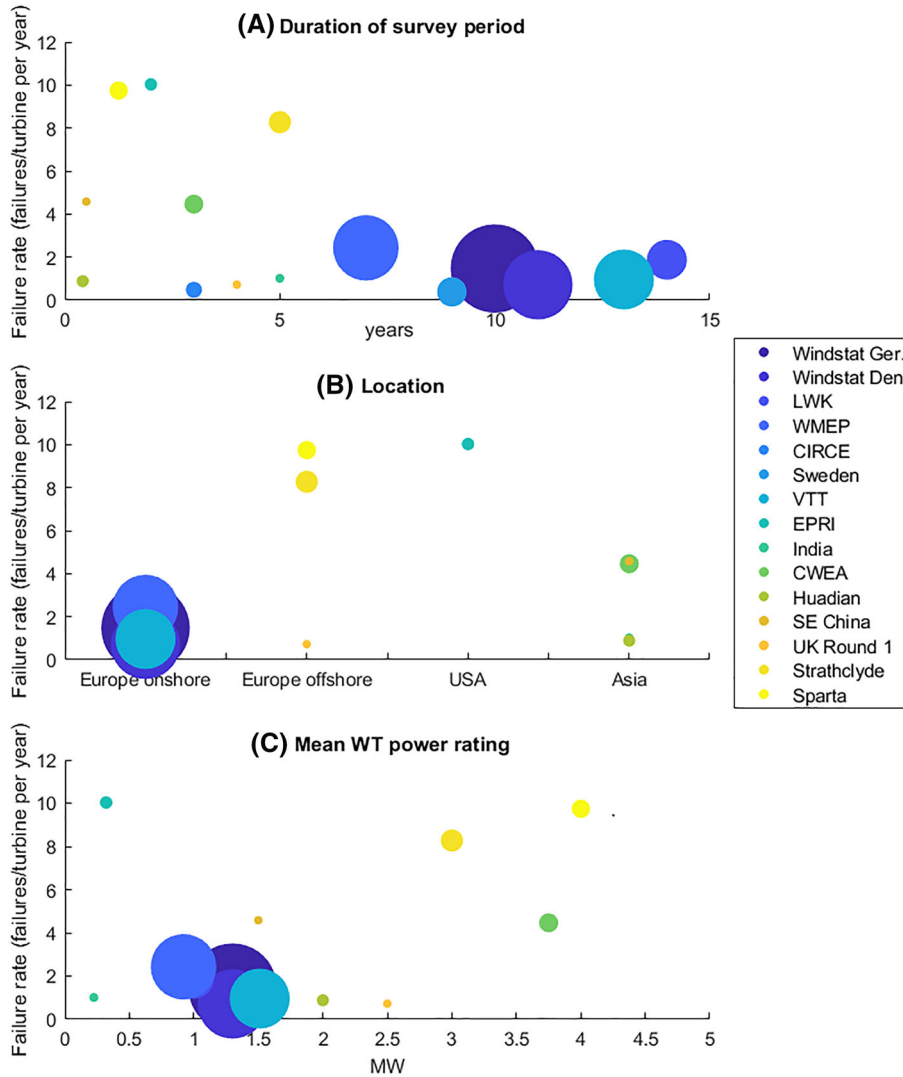*/**: Values in **Bold** indicate the top three low (*) or high (**) CODs.

FIGURE 7 WT failure rate and factors affecting its uncertainty [Colour figure can be viewed at wileyonlinelibrary.com]

against three factors affecting the uncertainty including the survey duration, location, and mean WT power rating are presented in sub-plots 7a, 7b, and 7c respectively. In Figure 7, the WT failure rates from the CWEA and Round 1 UK databases are expected to be higher since the data in Feng et al and Lin et al[63,64] only include failure data of major components in the turbine which included significant types of failures.

The volume of data has a clear influence on the failure rate discrepancy in these databases. It is noticeable that the failures from large surveys such as Windstats, LWK, WMEP, and CIRCE are relatively small and closely grouped, suggesting that larger, more diverse databases may have less uncertainty in their failure rate data. On the other hand, surveys with small WT population or short duration of data collection, such as the EPRI, Chinese, India, Strathclyde, and SPARTA, may produce outlying high or low failure rates. The SPARTA, Strathclyde, SE China, and CWEA all contain type 3 (and some type 4) WTs of similar capacities and times of data collection and yet manage to produce significantly different failure rates. The SE China WTs experienced a specific nontechnical error related to cable missing (human-induced), which explains the high failure rates of WT subassemblies in this source. Together with the data volume, the data survey duration is a related factor as shown in Figure 7A. Large surveys, often associated with long durations (over 5 years), tend to yield low failure rates (to the right of Figure 7A), while failure rates in shorter surveys (5 years or less) tend to be widely spread (to the left of Figure 7A).

Location may be another factor contributing to the failure rate discrepancy. In Figure 7C, all onshore populations in Europe, including Windstats Germany, Windstats Denmark, LWK, WMEP, CIRCE, Sweden, and VTT, are clustered together at a relatively low failure rate level, while other databases in USA, Asia, and offshore Europe have a large spread in WT failure rates. Interestingly, the onshore and offshore locations may be a factor in distinguishing failure rates. The failure rates from SPARTA and Strathclyde (Offshore) feature higher average failure rates than for onshore sources. Additional comparisons of onshore and offshore reliability data are presented in Section 4.3.

In Figure 7C, the WT mean power rating of a survey is determined as an average of the highest WT power rating and the lowest WT power rating presented in the fifth column in Table 2 and seventh column of Table 3. The WT failure rates show relatively less variation for databases

with medium size (average power rating of approximately 1.0-2.5 MW), which mainly include European and Asia databases. For databases with small-size and large-size WTs, the failure rates show a similar pattern to other subfigures 7A,B, and the failure rates vary because of the relationship between data volume/duration and failure rate previously explained.

The majority of databases consist of a mixture of WT types (and configurations), and the failure rates and downtimes are generally not reported separately for different WT configurations. In many databases, such as CWEA, Huadian, and SPARTA, the details of WTs are not revealed due to confidentiality reasons, and thus, the analysis based on WT configuration, eg, geared or gearless, is not performed here due to the ways of reporting data in different surveys. However, there have been some individual studies such as Carroll et al, Reder et al, and Carroll et al[18,29,38] doing this type of comparison, and it is seen that the reliability of gearless WTs is higher than the geared WTs. Thus, the variation in WT type may be another reason for reliability uncertainties within different databases in the literature.

For each database, a failure rate discrepancy, R_d, is defined as the ratio between the deviation and the maximum absolute deviation, presented in Equation (4).

$$R_d = \frac{\lambda_d - \bar{\lambda}}{\max_d\{|\lambda_d - \bar{\lambda}|\}}, \tag{4}$$

where $\bar{\lambda}$ and λ_d are the WT mean failure rate and WT failure rate in database d, respectively. The failure rate discrepancy varies from −1 to 1. Negative R_d indicates that the database failure rate is less than the mean failure rate, and positive R_d indicates that the database failure rate is greater than the mean failure rate. For a group of databases, the mean sum of square of all failure rate discrepancies, $MSS(R_d)$, can be used to measure the variation of that group reliability.

Two ranges of survey duration, namely long (over 5 years) and short (5 years or less) and three ranges of average WT power rating, namely small (less than 1.0 MW), medium (from 1.0 MW to 2.5 MW), and large (over 2.5 MW) are determined, and the $MSS(R_d)$ for each group related to the survey duration, location, and mean WT power rating is presented in Table 5.

Generally, there is less uncertainty among different reliability databases when the mean sum of squares failure rate discrepancy $MSS(R_d)$ is low (or close to zero). The calculated $MSS(R_d)$ values in Table 5 well agree with the bubble plots in Figure 7. The surveys with long durations, onshore Europe, and medium power rating size have the lowest $MSS(R_d)$ in three categories. This result means that the other short surveys in Asia and USA and offshore Europe with small and large WT power rating are the main sources of uncertainty in WT reliability data.

In terms of WT failure rate and downtime distributions, the coefficient of variation, ie, ratio between standard deviation and mean, and skewness are calculated as shown in Table 6.

From Table 6, the coefficient of variation of failure rare is relatively higher than that of the downtime, which reflects the same findings regarding the outliers in Figures 5 and 6. The identified small databases with high failure rates are the major sources that introduce uncertainties to WT failure rates. Besides, the failure rate distribution has a heavy positive skewness that implies the mean value is dominated by large databases with small failure rates. On the other hand, the downtime distribution presents a smaller uncertainty with a much more balance skewness compared with the failure rate distribution.

TABLE 5 MSS failure rate discrepancy

Category	Group	$MSS(R_d)$
Duration	Short (5 y or less)	0.339
	Long (over 5 y)	**0.088***
Location	Onshore Europe	**0.098***
	Offshore Europe	0.534
	Asia and USA	0.259
Mean power rating	Small (less than 1 MW)	0.372
	Medium (1-2.5 MW)	**0.107***
	Large (over 2.5 MW)	0.501

*: The lowest $MSS(R_d)$ in each category.

TABLE 6 Coefficient of variation and skewness

	Coefficient of Variation	Skewness
Failure rate	1.078	1.110
Downtime	0.728	−0.098

4.3 | Critical subassemblies based on failure rate and downtime

This section further investigates the subassembly reliability data using all 18 data sources. The three most critical subassemblies from each data source, in terms of failure/stop rates and downtime/repair times, are identified. Two populations of onshore and offshore WTs are analysed simultaneously to identify the similarities and differences. The critical subassemblies in terms of failure rate are presented in Figure 8.

From Figure 8, top five critical subassemblies in onshore WTs in order of significance include electrical, control system, blades and hub, pitch, and generator. These subassemblies are also critical in offshore wind turbines, but the order of criticality is slightly different. It should be noted that there are fewer offshore data sources (only four rather than 14), and among these sources Round 1 UK offshore is a special case, where a particular gearbox failure required replacements of almost all gearboxes, and where there is a high failure rate of the gearbox and other connected components such as the generator and drivetrain. In fact, the gearbox and drivetrain are not observed to have a high failure rate in other offshore data sources. The pitch system is the most critical subassembly in offshore data sources, appearing in three of the four offshore sources, while the generator is critical in two of the four sources (one of which is Round 1 UK offshore). Additionally, certain subassemblies, such as the control system, electric, blades and hub, and yaw system, appear to be critical in terms of failure rates for both onshore and offshore WTs.

The critical subassemblies in terms of downtime are presented in Figure 9.

Although there are some discrepancies in the average downtime per failure (see Section 4.1) between sources, the criticality ranking of subassemblies in terms of downtime is quite consistent for both onshore and offshore populations. Failures of the gearbox, generator, and blades and hub result in the largest downtimes per failure for both onshore and offshore WTs.

4.4 | Comparison of onshore and offshore WT reliability data

As mentioned in Sections 3.1 and 3.2, there are two ways to report WT subassembly reliability data: reporting either failure data or alarm event (stop) data. In this section, further analysis of the reliability data of onshore and offshore WT subassemblies is performed to highlight the differences between two populations in each way of reporting data.

4.4.1 | Onshore versus offshore failure/stop rates

The weighted average failure rates and stop rates for WT subassemblies in onshore and offshore data populations are calculated and presented in Figures 10 and 11, respectively. Equation (5) is used to calculate the weighted average failure rate of subassembly i, $\overline{\lambda}_i$, from several databases, based on the turbine populations.

$$\overline{\lambda}_i = \frac{\sum_{d=1}^{N_d} \lambda_{i,d} \times Y_d}{\sum_{d=1}^{N_d} Y_d}, \tag{5}$$

where $\lambda_{i,d}$ is the failure rate of component i in database d, N_d is the maximum number of databases, and Y_d is the number of turbine years recorded in database d. The weighted average stop rate of a subassembly i is calculated similarly.

The onshore failure rates in Figure 10 are calculated from 12 onshore data sources with failure statistics while the offshore failure rates are from the Strathclyde data source. Two offshore data sources (UK Round 1 offshore and SPARTA) are not included in this figure since they have
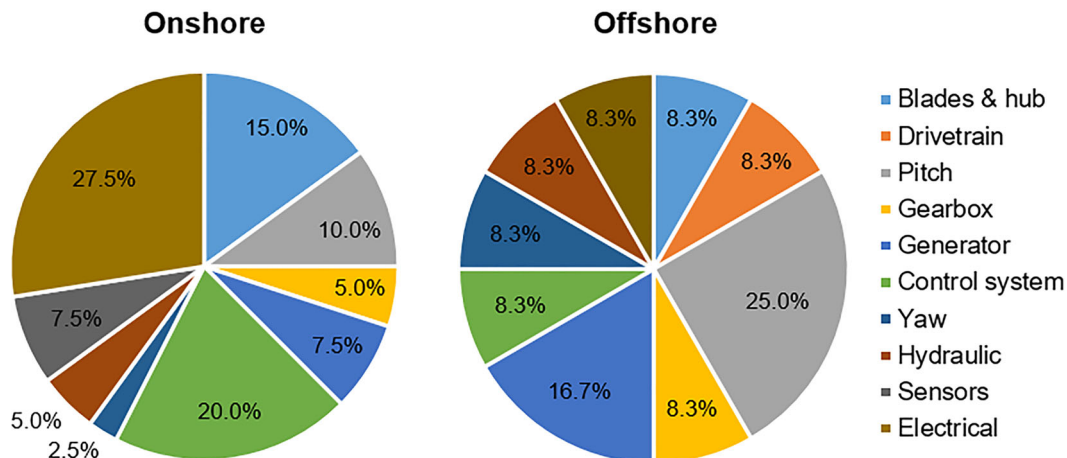

FIGURE 8 Critical subassemblies in terms of failure rate [Colour figure can be viewed at wileyonlinelibrary.com]
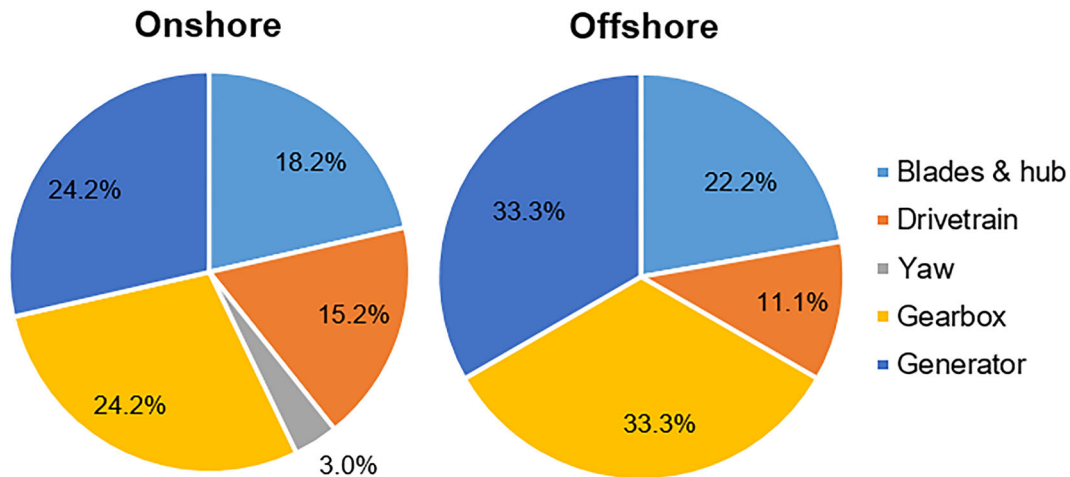
FIGURE 9 Critical components in term of downtime [Colour figure can be viewed at wileyonlinelibrary.com]
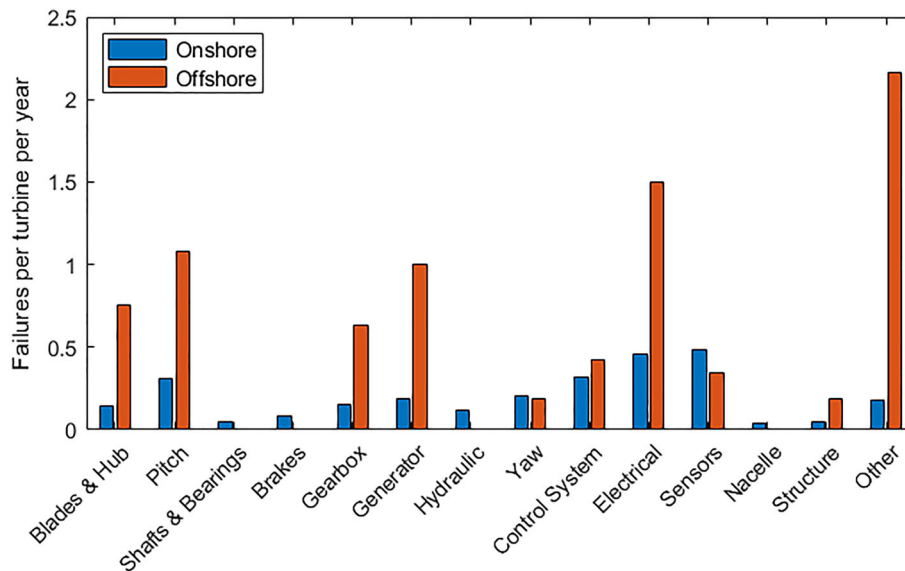

FIGURE 10 Comparison of weighted failure rates between onshore and offshore databases [Colour figure can be viewed at wileyonlinelibrary.com]

some bias and incompleteness. The UK Round 1 source includes a manufacturer error on the gearbox and only reports major failures such as those from the gearbox, generator, and rotor; the Strathclyde source only contains information for the 10 most critical subassemblies, and failures of other subassemblies are not documented.

From Figure 10, it is clear that the failure rates for offshore WTs are generally higher than those for onshore WTs and that this applies for almost all subassemblies. Electrical, control system, generator, blades and hub, and pitch systems all experience high failure rates for both populations, and their average failure rates are higher offshore than onshore. Structure and gearbox subassemblies follow the same pattern, but their failure rates are outside the top five highest failure rate subassemblies. The two interesting and irregular subassemblies are the yaw system and sensors which have higher failure rates onshore than offshore. When individual subassembly data are combined, the offshore WT failure rate is roughly three times the weighted average onshore WT failure rate.

The difference between onshore and offshore failure rates can partly be explained by the offshore severe operating conditions, such as higher mean wind speed and corrosive saltwater. Under the effects of the marine environment, including soil and wave conditions, offshore WT structure is subjected to a larger loading variation in high wind speeds.[63] Thus, the failure rates of many major subassemblies such as blades and hub, gearbox, generator, structure, and electrical components of offshore WTs are higher than onshore WTs'. In addition, larger WTs tend to experience more failures compared with small ones as presented in Figure 7, Section 4.2, and the literature,[20] and thus, the offshore WT power rating in this survey is higher than that of the onshore average.
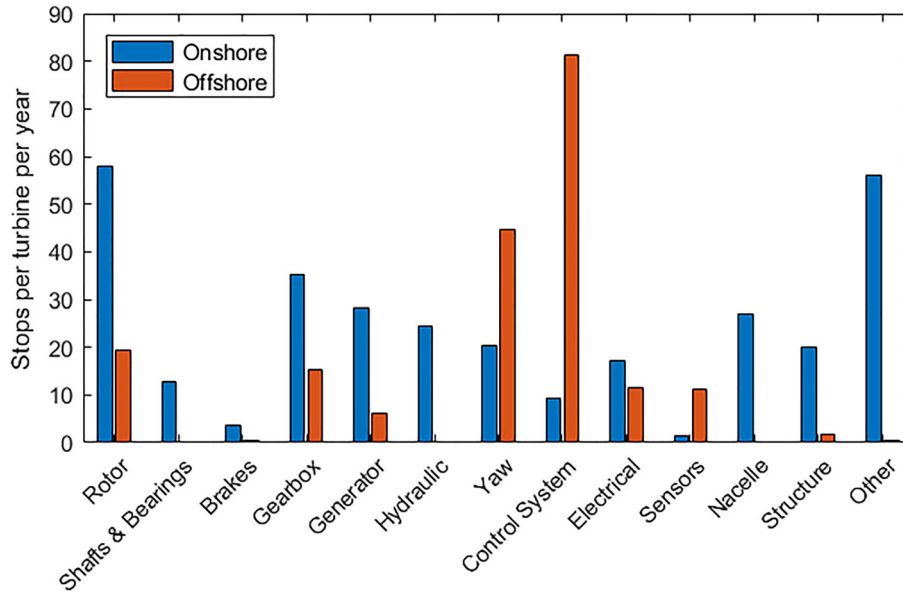
FIGURE 11   Comparison of weighted stop rates between onshore and offshore databases [Colour figure can be viewed at wileyonlinelibrary. com]

In Figure 11, the onshore stop rates are calculated from two databases, CREW (USA) and East China, and the offshore stop rates are from the NoordzeeWind database (Egmond aan Zee wind farm). We observe that the subassembly stop rates are much higher than their failure rates from other sources and, although the failure rates for offshore subassemblies are higher than those for onshore subassemblies, the stop rate comparison shows a different trend. Almost all subassemblies, except control and yaw systems, experience higher stop rates in the onshore population. Control system, yaw, and rotor are the high stop-rate subassemblies offshore, while rotor, gearbox, generator, and hydraulic are the high stop rate subassemblies onshore.

4.4.2 | Onshore and offshore downtime and repair time

Similarly to the failure rate comparison, the weighted average downtimes per failure for different subassemblies of onshore WT populations are calculated. There is only one offshore data source (Strathclyde) that report the repair time per failure. The onshore and offshore downtimes and repair times are shown in Figure 12. The downtime per failure of each subassembly is assumed to include its repair time, lead time, and any logistic delay that may apply to bring a maintenance crew to the turbine to perform a repair and bring the subassembly back to an operational state. Therefore, downtime is larger than repair time. It is noted that the onshore databases report downtime, while the offshore database (Strathclyde)
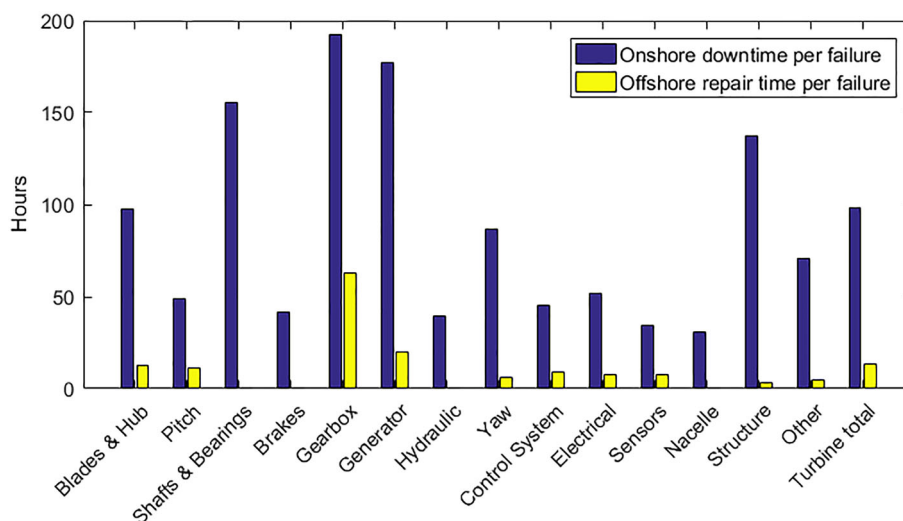

FIGURE 12   Downtime and repair times for onshore and offshore databases [Colour figure can be viewed at wileyonlinelibrary.com]

only reports repair time. There is not enough evidence to conclude which population has a higher downtime or repair time but general trends can be observed.

Figure 13 compares the stop time per event (the duration that a turbine does not generate power due to its stops) based on onshore and offshore data sources[46,57-60] which report alarm event rates.

For a given subassembly, the average stop time per event for offshore WTs is generally higher than that for onshore WTs. Across all subassemblies, on average, stop events last 3.9 hours onshore while offshore events last 7.7 hours. Accessibility is likely to be a reason behind this difference. Also, there are two particular subassemblies, gearbox and generator, which require extremely high stop times in offshore WTs. The offshore WT population in this comparison is on the Egmond aan Zee wind farm, where there is a manufacturer's fault that causes gearbox failure in almost all the turbines, thereby skewing the data. This gearbox failure propagates to the generator and causes the generator to fail,[67,68] which explains the unusual situations observed in Figure 13. However, even without this unusual gearbox failure, the stop rates of major subassemblies, such as the electrical and rotor, are higher offshore than onshore.

It is noted that there is only one offshore data source in the downtime/stop time comparison and that the population of offshore WTs is much smaller than that of onshore wind turbines. The results in this section may change as more offshore reliability data become available, adding to the complexity of precise reliability analysis.

5 | IMPACTS OF RELIABILITY DATA ON LCOE

LCOE and reliability are both common metrics to evaluate the performance of WTs. However, the past reliability data studies have not investigated the relationship between the above two metrics, nor has the literature on LCOE. In this section, a model for estimating LCOE from reliability data and other WT characteristics is presented and analysed to understand the impacts of reliability data on the economics of WTs, and the surveyed reliability data in Section 3 are employed to evaluate the LCOE of different WT populations.

5.1 | LCOE and its traditional estimation

5.1.1 | LCOE and its components

LCOE is the net present value (NPV) of the cost to produce electricity over a WT's lifetime based on the expected power generated. It includes all the life-cycle costs of the turbine that can be classified into two groups: capital investment expenditure (CAPEX) and operation and maintenance expenditure (OPEX). CAPEX includes the cost of the turbine, infrastructure, installation, and other upfront costs for wind farm development, deployment, and commissioning. OPEX covers all the regular costs to operate and maintain the turbine such as leases, insurance, administration, management, scheduled maintenance, unscheduled maintenance, spare parts, and other day-to-day operation costs.[16]

Compared with an onshore WT, an offshore WT requires a higher initial investment as well as regular operational costs. Although the LCOE in offshore wind generation has decreased recently, it is still much higher compared with onshore wind generation. The LCOE of UK offshore wind projects has gradually decreased in recent years, from £142/MWh in 2011 to £97/MWh in 2016.[64] Meanwhile, the LCOE of US offshore wind
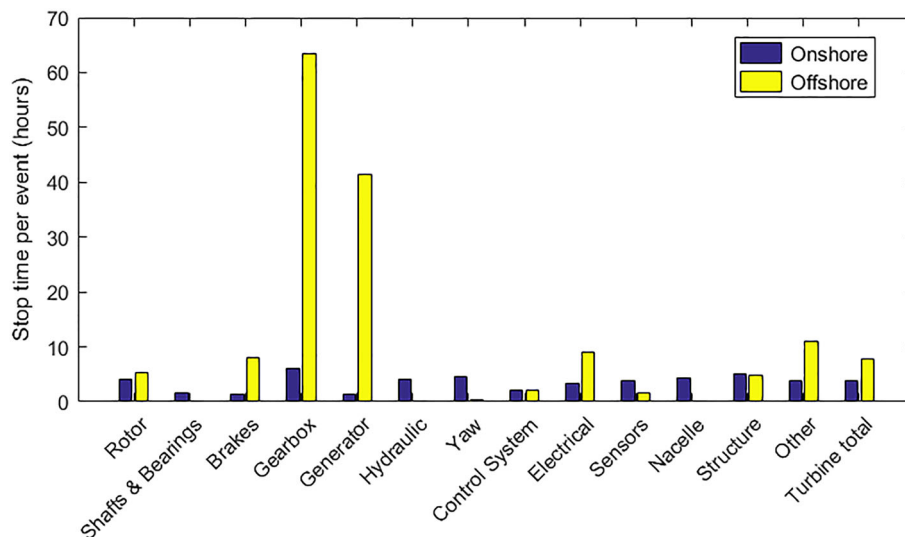

FIGURE 13 Stop time per event for onshore and offshore wind turbines [Colour figure can be viewed at wileyonlinelibrary.com]

energy in 2015 was \$181/MWh, which approximately tripled its onshore counterpart (\$61/MWh).[3] Reducing LCOE is critical in making the offshore wind industry more competitive. Together with the improvement of turbine design and technology to reduce CAPEX, optimising O&M strategy is essential to OPEX reduction and ultimately to LCOE optimisation.

Maintenance cost is a large element in the OPEX, which contributes approximately 20% to 30% to the cost of energy.[16,65] WT maintenance is classified into corrective maintenance (CM) and preventive maintenance (PM).[32,66] CM is defined as an immediate action to fix the turbine once a failure occurs, while PM is a planned action that is performed in advance to prevent failures from happening. PM can be further classified into time-based maintenance (TBM), which is maintenance performed at fixed intervals, and condition-based maintenance (CBM), which is maintenance performed based on the condition of the WT.[67] PM activities, including both time based and condition based, are critical for reliable and efficient WT operation.[14,68]

5.1.2 | Background on LCOE estimation

The following formula is used to calculate LCOE.[69]

$$LCoE = \frac{NPVC}{NPVG} = \frac{\sum_n NPVC_n}{\sum_n NPVG_n}, \tag{6}$$

where $NPVC$ and $NPVC_n$ are the NPVs of the total cost (including CAPEX and OPEX) of the turbine over the turbine lifetime and in year n respectively; $NPVG$ and $NPVG_n$ are the NPVs of the total energy generated by the turbine and in year n respectively.

$$NPVC_n = \frac{CAPEX_n + OPEX_n}{(1+r)^n}, \tag{7}$$

$$NPVG_n = \frac{AEP_n}{(1+r)^n} \tag{8}$$

In Equations (7) and (8), r is a discount rate and AEP is the annual energy production of the WT.

In this paper, it is assumed that CAPEX is generally known, and therefore the focus is on modelling and estimation of WT OPEX and LCOE, particularly on the part of OPEX that is varying with the WT reliability data and maintenance regimes. Conventionally, OPEX is calculated based on the amount of energy generated (£/MWh). Although this method of OPEX estimation is widely used in many studies,[4,7,70-72] it relies on an assumption that allows OPEX to be averaged through the electricity generated without considering the actual failures and maintenance activities on the turbine. There are also research on other cost components in LCOE estimation such as the taxes, royalties paid to land owners, and penalties associated with a power purchased agreements.[73,74] However, the conventional OPEX is used in these studies. The replacement costs of turbine components, whose lifetimes are shorter than the turbine's lifetime, are included in a model presented by the National Renewable Energy Laboratory (NREL) in the USA.[75] This method of OPEX calculation has been used in some later NREL reports,[5,6] but the replacement cost can be included in the general maintenance cost, and this is applied in the most recent NREL publication.[3] The O&M cost is estimated as a product of the failure frequency and repair cost[66,76] and in some cases with additional logistic cost.[77,78] The models in the literatures[66,75-78] can address corrective repair or replacement actions and integrate them into OPEX. However, the actual OPEX may also vary depending on the maintenance strategy, not just the repair or replacement actions when failures occur. For example, a good PM strategy may help reduce OPEX since PM activities can prevent failures, thus reducing repair and other failure-related costs.

5.2 | LCOE estimation using reliability data

As explained in the previous section, two important elements of LCOE are OPEX and annual energy production, both of which vary depending on the reliability and maintenance of the WT. In this section, a model for OPEX and annual energy production estimation using WT failure rate and downtime data is presented.

5.2.1 | Model for OPEX estimation

OPEX includes all cost elements to operate and maintain the WT. In this paper, OPEX is classified into two categories as follows.

- Fixed expenditure—$OPEX_{fixed}$: representing all the cost elements that are generally fixed for a specified turbine at a specified location, such as rental, administration, insurance, etc. These costs may depend on the CAPEX, but they do not depend on the failure and maintenance of the WT.

- Variable expenditure—$OPEX_{variable}$: representing the variable cost elements that not only depend on the turbine capex, but also on the failures and maintenance strategy applied on the turbine. $OPEX_{variable}$ can be further classified into CM cost (the cost of random failures) and PM cost (the cost related to planned maintenance activities).

This gives

$$OPEX = OPEX_{fixed} + OPEX_{variable} = OPEX_{fixed} + C_{CM} + C_{PM}. \tag{9}$$

In detail, CM cost represents the total unplanned maintenance cost when failures occur, that is repair or replacement cost of failures. It depends on the WT reliability data including failure rate and downtime per failure as well as the material cost of a repair and the labour rate per hour. Equation (10) presents a formula to calculate the CM cost given the reliability data of a WT.

$$C_{CM}(\lambda, D) = E[NoF(\lambda)] \times CoF(D) \tag{10}$$

Equation (10) indicates that the CM cost is a product of the annual expected number of failures $E[NoF(\lambda)]$ and the cost of a failure $CoF(D)$ of the WT. The WT expected downtime D can be estimated from the subassembly failure rate and downtime D_i as: $D = {\Sigma_i \lambda_i D_i}/{\Sigma_i \lambda_i}$. The expected number of failures depends on the failure rate of the WT, $E[NoF(\lambda)] = \int_{t=0}^{T} \lambda dt$. The cost of a failure depends on a repair cost per failure, c_r, including materials and spare parts, expected downtime D, and labour rate c_l.

$$CoF(D) = c_r + p_r \times D \times c_l. \tag{11}$$

In Equation (11), $p_r, 0 < p_r < 1$, is the proportion of WT repair time over its downtime.

On the other hand, PM cost represents the cost or investment of a planned maintenance strategy applied to the WT. PM cost of the WT is assumed to be varying depending on its failure rate (λ) with a relationship represented by a power law as in Equation (12).

$$C_{PM}(\lambda) = C_{PM}^0 \left(\frac{\lambda^0}{\lambda}\right)^m \tag{12}$$

In Equation (12), λ^0 is a baseline failure rate that is associated with a baseline PM strategy C_{PM}^0 and m is a positive exponent representing the effectiveness of PM investment on the failure rate of the WT. This equation implies that when more money is spent on PM activities, the reliability of the WT improves and its failure rate λ decreases.

From Equation (9)[12]:

$$OPEX(\lambda, D) = OPEX_{fixed} + \int_{t=0}^{T} \lambda dt (c_r + p_r \times D \times c_l) + C_{PM}^0 \left(\frac{\lambda^0}{\lambda}\right)^m. \tag{13}$$

For simplicity, in the following sections, it is assumed that $m = 1$, ie, the PM cost is inversely proportional to the failure rate of the WT.

5.2.2 | Annual energy production

In this paper, the annual expected energy yield (energy production) of a WT is also estimated using the reliability data. Given the general performance of the WT, the annual energy production can be estimated using Equation (14).

$$AEP = C_f P_{rated}(8760 - D \times E[NoF(\lambda)]), \tag{14}$$

where P_{rated} is the turbine rated power output; C_f is the turbine capacity factor; and $E[NoF(\lambda)]$ is the expected number of failures in a year. The product of $D \times E[NoF(\lambda)]$ represents the expected total downtime in a year.

5.3 | LCOE optimisation

From the analytical representation of OPEX and annual energy production in Section 5.2, it can be seen that LCOE is a function of both WT failure rate and downtime. It is obvious that when wind turbine downtime decreases, OPEX decreases and annual energy production increases, thus decreasing LCOE. On the other hand, the relationship between failure rate and LCOE exhibits a more complex relationship. When the failure rate increases, the total cost may either increase or decrease depending on the CM and PM costs. In this section, the relationship between LCOE and WT failure rate for different databases in Section 4 is investigated in order to find the optimal failure rate that minimises the LCOE.

For each database, the optimal failure rate to minimise the LCOE is determined using Equation (15):

$$\lambda_d^* = \arg \min_{\lambda_d} \{LCOE(\lambda_d)\}, \tag{15}$$

where λ_d and λ_d^* are the failure rate of the WT in database d and its optimal value, respectively. λ_d^* is the value at which minimal LCOE of the WT is attained.

There are 10 databases (nine onshore and one offshore—see Section 4.1) which include both failure rate and downtime data so these are all included in this numerical study. For comparison between onshore databases, the input data for failure rate and downtime are applied to the same exemplar turbine model with similar CAPEX and OPEX. For comparison between onshore and offshore databases, two sets of input data with different CAPEX and OPEX are used in the numerical experiment as shown in Table 7.

In Table 7, the initial investment costs (CAPEX) per MW are average values from the European Wind Energy Association published report for both onshore and offshore WTs.[79] When a failure occurs, downtime of a WT includes repair time, ie, the time for maintenance work to be actually performed, and a logistic delay time, ie, the delay due to weather conditions, transportation, and availability of spares, etc.[23] Due to the difficulties in accessibility, the logistic delay time of offshore WTs is longer than that of onshore WTs, and thus the proportion of repair time over downtime is higher for onshore than offshore. In this paper, we assume that this proportion is double for onshore WTs over its offshore counterpart (40% and 20%, respectively), and this assumption is made based on a result from Figure 13 that the stop time per failure of offshore WTs is approximately double of the stop time per failure of onshore WTs. For the baseline scenarios with the reference PM cost, the fixed OPEX, labour rate, and repair cost are set in the way that the average proportion of the OPEX over the total cost is roughly 30% as reported in Nielsen and Sørensen.[65] The lifetime, capacity factor, and discount rate are assumed to be identical for onshore and offshore WTs.

The value of WT failure rate is varied from 20% to 220% of the reference failure rate λ_0 taken in the reliability survey. Plots of OPEX and LCOE versus change of failure rate for a sample database (Strathclyde) are shown in Figure 14A,B, respectively.

It can be observed that when the failure rate increases the CM cost also increases (the cost of failure increases) and the PM cost decreases (a high failure rate is associated with lower PM investment). Both OPEX and LCOE are convex functions of failure rate. For this database, the baseline scenario gives a LCOE of £93.65/MWh, and the optimal LCOE is £90.37/MWh. The baseline scenario LCOE for offshore WTs is in line with the results by Strathclyde and NREL,[78] in which the LCOE of DFIG offshore wind farms located 10 km to shore is approximately £93/MWh. In Figure 14B, the optimal λ^*/λ_0 is 0.63 (less than 1), which means that WT reliability should be improved to obtain the minimal LCOE.

TABLE 7 Input data for LCOE evaluation

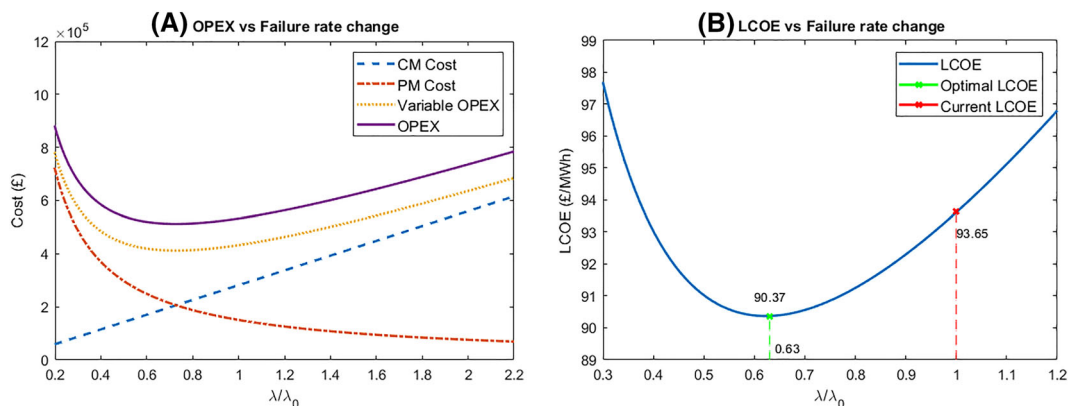| Input Parameter	Onshore	Offshore
Rated power (MW)	2	5
Lifetime (y)	25	25
Capacity factor	0.4	0.4
Initial investment (millions £/MW)	1.07	1.82
Fixed OPEX (% CAPEX)	8	10
Reference PM cost (% CAPEX)	12	15
Labour rate (£/h)	200	300
Repair cost (£ 1000)	20	30
(Repair time)/downtime	40%	20%
Discount rate	10%	10%

FIGURE 14 OPEX (A) and LCOE (B) as functions of failure rate change (Strathclyde) [Colour figure can be viewed at wileyonlinelibrary.com]
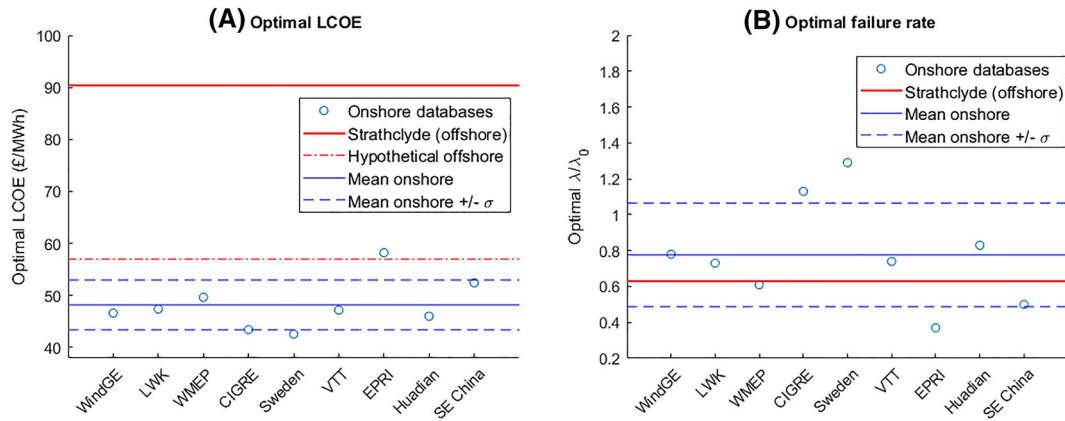
FIGURE 15 Optimal LCOE (A) and failure rate (B) for different databases [Colour figure can be viewed at wileyonlinelibrary.com]
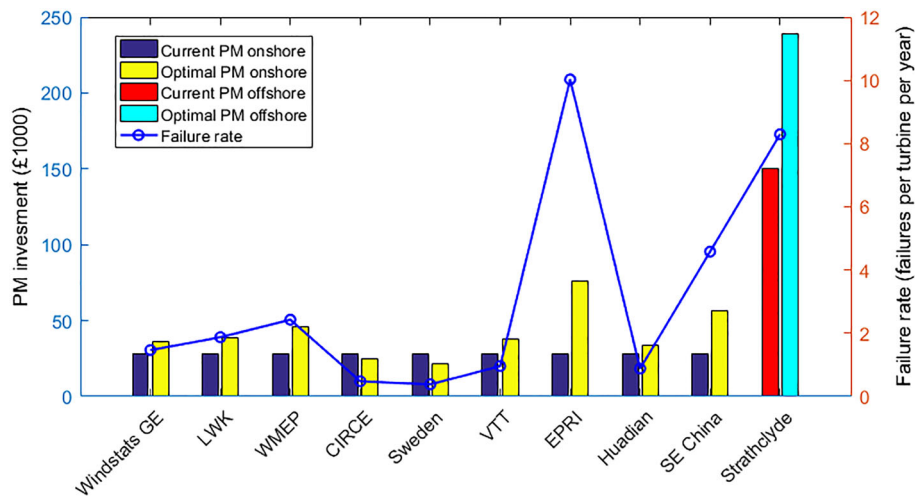

FIGURE 16 PM investment and failure rate [Colour figure can be viewed at wileyonlinelibrary.com]

The shapes of OPEX and LCOE are similar, but actual optimal values of LCOE and failure rate vary for different databases. Plots of optimal LCOE and λ^*/λ_0 for different databases are shown in Figures 15A,B, respectively.

From Figure 15, it can be seen that the optimal LCOE values for onshore databases are quite consistent, while there is a large variation in the optimal λ^*/λ_0. The optimal onshore LCOE is around a mean of £48.2/MWh, which is much smaller than the optimal offshore LCOE at £90.37/MWh. A major reason for this difference is the large investment and OPEX cost set for offshore wind turbines (as shown in Table 7). If the offshore initial investment can be reduced to a hypothetical level that is equivalent to that for onshore WTs, the optimal offshore LCOE can decrease to £56.98/MWh which is only £8.78/MWh higher than the onshore average.

In terms of failure rate, a large variation in the optimal λ^*/λ_0 is observed. This can be explained by the variation in the failure rate data presented in Section 4. The majority of the optimal λ^*/λ_0 are less than 1, which implies that more should be spent on PM to improve the reliability of the WTs. It is also worth mentioning that the mean optimal onshore WT failure rate ratio is higher than the offshore WT failure rate (0.77 compared with 0.63), which suggests that further improvements should be made to improve the reliability of offshore WTs and to minimise their LCOE.

The failure rate and PM investment for different databases are plotted in Figure 16. It can be seen that PM investment to optimise LCOE should be higher for populations with high failure rates. In this case study, PM investment for offshore WTs may rise to approximately £47.7 k per MW per year which is about two times higher than the average PM investment per MW per year for onshore WTs.

6 | CONCLUSIONS

This paper presents an extensive review of the most up-to-date publicly available WT subassembly reliability data. Eighteen data sources for both onshore and offshore WTs are investigated, and the failure and downtime statistics are analysed. In addition, a model for LCOE evaluation using

reliability data is presented. This model allows the estimation of OPEX and annual energy production using the failure rate and downtime of a WT. From the analysis, it can be observed that

- There are significant variations in both the failure rates and downtimes of turbine subassemblies from different data sources.

- The volume of data, collection duration, location, and WT power rating are all possible contributing factors to the WT reliability uncertainty. In addition, the WT failure rate distribution is highly skewed to the right, which infers that the large data sources with low failure rates are dominant and the small to medium data sources with high failure rates are the sources of uncertainty in the population.

- The criticality of subassemblies is quite consistent for different data sources. In terms of failure rates, the electrical, control, blades and hub, and pitch systems are the four most critical subassemblies for onshore wind turbines. These are also among the most critical components for offshore WTs. In terms of downtime, the gearbox, generator, blades and hub, and drivetrain are the four most critical subassemblies for both onshore and offshore WTs.

- The average failure rate for offshore WTs is greater than that for onshore WTs, but the average stop rate onshore is slightly higher than offshore. The downtime per stop of an offshore WT is approximately double that of an onshore WT. The severe offshore operating environment and the difficulty in repair/maintenance accessibility of offshore WTs are possible reasons for these discrepancies.

- In the presented case study, both LCOE and OPEX are convex functions of failure rate. The mean optimal onshore and offshore failure rates to minimise LCOE are both less than 1, which suggests that the reliability should be improved to minimise LCOE.

- In the case study, the optimal LCOE and PM investment of offshore WTs are approximately two times higher than that of onshore WTs.

It is important to highlight that a large population of onshore WTs is surveyed while the offshore population is relatively small. This emphasises the importance of developing a strong understanding of the available data and the sensitivity of LCOE and other calculation to any variations, in order to produce the best quality analysis using the available data. Any results from failure and downtime comparisons between offshore and onshore populations will be much stronger with more extensive input data for offshore WTs; however, a thorough understanding of the nature of the collected data must always be acquired if the best results are to be obtained.

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