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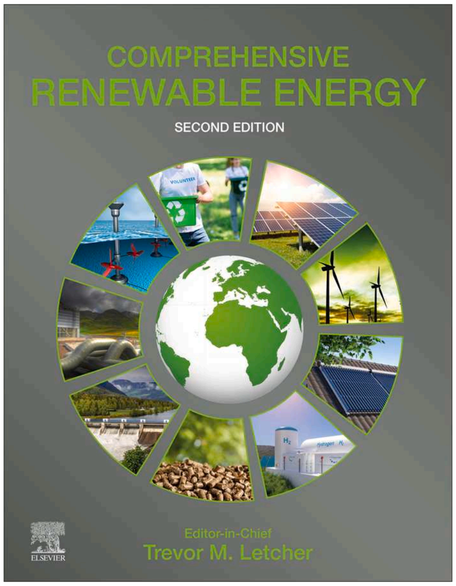

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2.11 Wind Turbine Reliability - Maintenance Strategies

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Abbreviations

AI Artificial Intelligence
AM Asset Management
CAPEX Capital Expenditure
CBM Condition-based Maintenance
CMS Condition Monitoring System
FM Field Management
FMEA Failure Modes and Effects Analysis
HM Health Monitoring
HPP Homogenous Poisson Process
IM Information Management
MM Maintenance Management
MV Medium Voltage
OEM Original Equipment Manufacturer
O&M Operations & Maintenance
OM Operations Management
OPEX Operational Expenditure
PLP Power Law Process
RCM Reliability-Centered Maintenance
SCADA Supervision Control and Data Acquisition
SCIG Squirrel Cage Induction Generator
SPARTA System Performance, Availability and Reliability Trend Analysis
WF Wind Farm
WT Wind Turbine

Nomenclature

$\lambda(t)$ Failure intensity function
t Time
N_i Number of wind turbines
T_i Total time period (hours)
$n_{i,k}$ Number of failures of subassembly k
β Shape parameter

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λ	Failure rate
ϱ	Scale parameter

2.11.1 Introduction

The remarkable growth in the installed wind power capacity worldwide over the last two decades poses significant technical and economic challenges. As wind turbines (WT) are rapidly evolving in complexity and size, as well as moving to more remote and harsh offshore environments, there is an urgent need of high reliability and cost-effective Operations and Maintenance (O&M) strategies to increase the profitability of wind power assets. Unplanned downtime, associated to extended overhauls or replacements of major components, represents one of the main cost drivers of the Operational Expenditure (OPEX) in a modern wind farm (WF). Timely and effective detection, diagnosis and prognosis of developing damages in the most unreliable WT components are essential for minimizing unplanned downtime. They enable operators to adopt preventive maintenance strategies rather than proceed with corrective actions. Hence, a thorough understanding of when and how WT components fail is crucial for developing profitable preventive maintenance approaches. WT reliability statistics, in terms of frequency of failure occurrences and downtimes, can be obtained from statistical analysis of historical failure databases and maintenance logbooks provided by manufacturers and WF operators.

This Chapter outlines the current knowledge in the field of WT reliability and maintenance. Firstly, recent published WT reliability studies are summarized and the subassemblies that are of most concern for O&M are identified. This is followed by a description of the state of the art of WT maintenance, looking at new emerging techniques currently being researched, with a particular focus on the economic benefits of maintenance strategies optimization. In the Conclusions, the main points, lessons and opportunities are summarized.

2.11.2 Wind turbine reliability

Reliability is critical for the economic success of wind power assets throughout their entire lifecycle. Quantitative reliability assessment allows past performance assessment as well as future performance prediction (Billinton and Allan, 1992). It indicates how a system may fail, shows the consequences of failures and provides information to enable stakeholders to relate the system quality to economics and capital investment. Reliability and Failure Modes and Effects Analysis (FMEA) analyses provide feedback for identifying weak areas in parts and subassemblies needing reinforcement and improvement, thus leading to better and more economic designs (Arabian-Hoseynabadia et al., 2010). Poor reliability can increase capital expenditures (CAPEX) due to overdesign, excessive prototyping and testing, together with warranty and insurance requirements (Sheng and O'Connor, 2017). It also directly affects projects' revenue streams through reduced availability and increased OPEX, leading to reduced annual energy production. A thorough understanding of the main WT components' reliability is instrumental in achieving cost-effective O&M best practices, especially in offshore installations.

If appropriate reliability statistics are available, their systematic and thorough assessment can bring considerable technical and economic benefits to the O&M wind power industry.

This Section first provides a brief introduction to the basic reliability theory and metrics. Then, it presents a comprehensive and systematic overview of publicly available knowledge on WT reliability, both onshore and offshore, followed by the analysis of fundamental data trends, highlighting the main issues and bottlenecks as well as the current initiatives and standards that aim to achieve their alleviation.

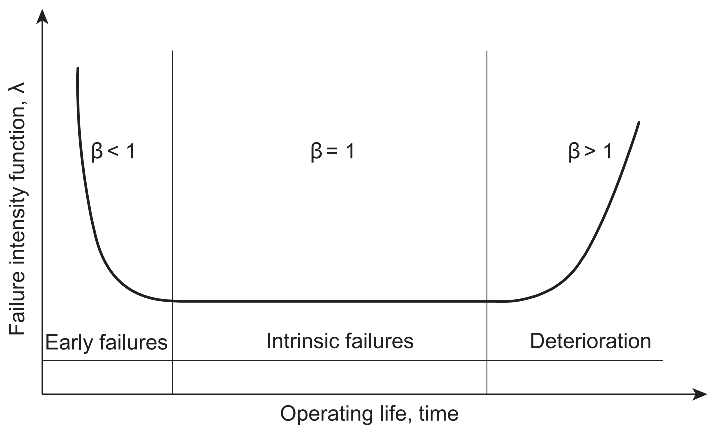

Fig. 1 Bathtub curve (Tavner, 2021). From Tavner PJ (2021) Offshore Wind Power - Reliability Availability and Maintenance, 2nd edn. London, UK: The Institution of Engineering and Technology.

2.11.2.1 Elements of reliability engineering theory

The reliability of an item is defined as the *probability that it will perform a required function without failure under stated* (environmental and operating) *conditions for a stated period of time* (O'Connor and Kleyner, 2012). In our context, the item can be the entire WT or a turbine component. A WT is a complex machine and its reliability is affected by the reliabilities of its subsystems, including both hardware and software and how they are interlinked. When predicting or measuring reliability it is important to distinguish between non-repairable and repairable systems. A non-repairable system is one which is discarded the first time it fails. Examples are small batteries or light bulbs. A repairable system is one that, when a failure occurs, can be restored into operational condition after any action of repair, other than replacement of the entire system. Examples are WTs, car engines and electrical generators (Tavner, 2021). The fundamentals of classical reliability theory for both repairable and non-repairable systems can be found in Billinton and Allan (1992) and O'Connor and Kleyner (2012).

In some applications, it is practical to evaluate the unreliability or probability of system failure rather than evaluating the reliability or probability of system success, where system success and system failure are complementary events. For repairable systems, such as WTs, the unreliability variation throughout their lifetime can be modelled in terms of the failure intensity function, (t), by the bathtub curve shown in **Fig. 1** and described by the Power Law Process (PLP):

$$\lambda(t) = \varrho\beta t^{\beta-1} \tag{1}$$

where ϱ is the scale parameter, β is the shape parameter and t is time (Spinato, 2008). $\lambda(t)$ usually expresses the failures per item (e.g. an entire WT or a sub-assembly) per year. The bathtub curve is a conceptual and mathematical model that represents three different phases of engineering systems dynamic behavior, as shown in **Fig. 1**. The shape parameter β can model these three different phases of the failure intensity function:

(a) Early failure phase ($\beta < 1$): During this period, also known as infant mortality phase, failures typically occur because of improper design, manufacturing flaws or poor understanding of operating conditions. Failure rates at the beginning of this stage are high, but then decrease with time as the early failures are removed. This first section of the bathtub curve shows rapid reliability improvement with time, with the rate mainly depending on the maturity of the design and the manufacturing process. During its early development, the wind power industry has suffered of early failures and struggled to change the image.

(b) Intrinsic failure phase ($\beta = 1$): This is the bottom of the bathtub curve, also known as useful life period or normal operating phase, where the intensity function of the PLP is constant and equal to ϱ. In this case, the process becomes an Homogenous Poisson Process (HPP), meaning that the failures are caused by randomly occurring defects. The failure rate, λ, is generally defined as the failure intensity during the intrinsic failure phase, where the failure intensity is approximately constant and largely dependent on random failures. In this case, the time-periods between failures are considered independent and identically distributed exponential random variables. This is the most significant phase for reliability prediction and evaluation activities. The majority of the currently operating WTs lie in their useful life phase. It is difficult to assess precisely the length of the useful period for WTs because, as is also valid for other repairable systems, they undergo continuous component maintenance. Adequate maintenance actions effectively move the system backwards in its operational life.

(c) Deterioration phase ($\beta > 1$): This is the final phase of the bathtub curve, also known as wear- out phase, where the failure intensity function increases rapidly with time as the components begin to wear out and break down. In this phase, components start to deteriorate to such a degree that they reach the end of their useful life. The wear-out period for entire WT systems is not yet upon the industry as machines are designed for a 20- or 25-year life.

Systems should be designed for reliability such that the useful life period is extended and so that the early life and wear-out failure periods are reduced in time or, ideally, removed entirely.

More details on the reliability theory used to analyze failure data can be found in Billinton and Allan (1992) and, for the particular case of WTs, in Spinato (2008) and Tavner (2021).

2.11.2.2 Wind turbine reliability databases

Understanding WT reliability statistics is difficult because of the variety of designs and sizes now in service worldwide but also because studies available in literature are conducted independently under various operating conditions in different countries (Pinar Pérez et al., 2013). As discussed in the previous Section, most of the currently operating WTs are at the bottom of their bathtub curve modelled by the HPP and characterized by a constant failure rate, which represents the likelihood of a system to fail within a specific time-period. Based on this assumption, reliability studies collecting data from a large number of WTs refer to average failure rates at a given time interval. In particular, the failure rate per WT per year, λ, is given by (Tavner et al., 2006):

$$\lambda = \frac{\sum_{i=1}^{I}\sum_{k=1}^{K} n_{i,k}/N_i}{\sum_{i=1}^{I} T_i/8760} \tag{2}$$

where I is the number of intervals for which data is collected, K is the total number of subassemblies in the WT, $n_{i,k}$ is the number of failures of subassembly k, N_i is the number of WTs and T_i is the length (in hours) of the total time-period. The numerator of Eq.

(2) represents the total number of failures in all periods per WT and the denominator represents the total number of years within the survey.

Another important reliability performance indicator is downtime, defined as the total time between stop and restart of operation of a considered unit while the unit is in a down state (Pfaffel et al., 2017). It represents the time during which a WT is not operational (i.e. is not producing energy) due to a failure. It includes various subcategories such as the time delay due to mobilization and logistics, the time delay to attain a favorable weather window, the administrative delays, the transportation time, the failure detection and finally the repair time.

In contrast with the well-established standardization practices for data collection in the oil and gas industry (ISO 14224:2016), the wind power industry has not yet standardized its methods for reliability reporting. Stemming also from the commercial sensitivity of such data, for a long time, WT reliability data, including failure rate and downtime, were difficult to obtain, share and compare, with only a few publicly available databases for onshore WTs (Spinato, 2008). Only recently a wider variety of initiatives have rendered available reliability data for modern and, in some cases, offshore WTs. The main characteristics of the reliability databases that can be fully accessed in the public domain to date are given in the synoptic Table 1, for both onshore and offshore WTs. Internal company initiatives as well as initiatives lacking any publications are not considered. For each database, the location, the number of WTs, the WT type and rating, the reporting period and the key characteristics and reference(s) are given in Table 1, where databases are listed according to their size. Database and the population size are reported to provide an indication of the statistical significance of the data collected. Some databases present a low level of detail which does not allow to provide a sufficient description of some quantities in Table 1. The WT type is defined according to the nomenclature reported in Tavner (2021):

(a) Type A: fixed – /dual-speed, stall-regulated WT with a geared-drive squirrel cage induction generator (SCIG);
(b) Type B: fixed – /dual-speed, stall-regulated/variable-speed, controlled-stall-regulated WT with a geared-drive wound rotor induction generator (WRIG) with variable rotor resistance;
(c) Type C: variable-speed, variable-pitch WT with a geared-drive doubly fed induction generator (DFIG);
(d) Type D: variable-speed, variable-pitch WT with a direct-drive (DD) wound rotor synchronous generator with exciter/permanent magnet synchronous generator/SCIG with a fully rated converter connected to the stator.

Table 1 lists 15 reliability databases for onshore WTs out of which most refer to machines located in Europe (including UK), with either a single database per country (Denmark, Finland and Sweden) or multiple databases from the same country (Germany). Only two databases (CIRCE and EPRI) are from the Unites States and five from Asia, i.e. four (CWEA, Huadian, Nanjing, SE China) from China and one (Muppandal) from India. The majority of the data refers to combinations of small (few hundred kW) to medium (few MW) WTs. Only four offshore databases are currently publicly available as listed in Table 1. Unlike onshore data, the offshore databases contain a relatively small number of WTs and only reliability data from Europe (including UK). This reflects the dominance of European countries in offshore wind power installations. The most recent are the Strathclyde (offshore) and SPARTA databases and refer to a larger WT population and reporting period, compared with the other two sources, which refer to one or only a few WFs in their early operation. Among the offshore databases, of particular relevance is SPARTA (System Performance, Availability and Reliability Trend Analysis) a collaborative ongoing initiative between ORE Catapult, The Crown Estate and offshore WF owners/operators, started in 2013 in the UK (Catapult, 2020). SPARTA gathers reliability data at subsystem level from the participating operators and outputs monthly benchmarks. The databases reported in Table 1 present some inconsistencies, together with different levels of data quality and availability, due to the lack of an harmonized practice for WT reliability data collection, processing and publication, as discussed in detail in Sheng and O'Connor (2017) and Leahy et al. (2019). For example, in some cases, they adopt different definitions for failure/downtime and lack of an homogenous WT taxonomy. Failure is generally defined as an event requiring a repair action, hence a visit to the WT for a maintenance activity, as in Carroll et al. (2016). However, in some studies, only events associated to downtime over a certain time threshold are classified as failures (Wilkinson, 2011). Conversely, in other databases, such as the CREW (USA) and the one of the University of Nanjing (China), every stop event is reported. Some of these events might be only due to unusual operating conditions and can be resolved by remote reset without requiring a visit to the WT to perform a proper maintenance action.

When counting remote resets, the failure rates recorded are normally higher. Similarly, the NoordzeeWind OWEZ database reports stop/alarm events and not all of them are necessarily real failures. In some cases, it is unclear whether repairs, replacements or both are considered in the results (Pfaffel et al., 2017). Another contributor to the database inconsistencies has been identified in the use of project-specific or undocumented taxonomies, as in the case of the CREW and Muppandal initiatives, respectively. In other cases, slightly different WT taxonomies are adopted. For example, some statistics report rotor data in separate categories for blades, hub, air brakes and pitch systems, as in the case of CIRCE, while others combine them together presenting single reliability data for the whole rotor subsystem, as in the case of the Muppandal and the University of Nanjing initiatives (Pfaffel et al., 2017).

This variation in the way WT data are broken down makes many sources of reliability statistics not feasible to be directly comparable. Several efforts have been made in the past to develop a WT taxonomy to facilitate the categorization and comparison of failure statistics (Reder et al., 2016). Richardson (2010) discussed the differences between some of the proposed taxonomies and the problems associated with non-uniform data treatment in failure analyses.

Two of the most recent and widely accepted initiatives are the ReliaWind taxonomy (Wilkinson, 2011) and the Reference Designation System for Power Plants (RDS-PP) taxonomy (VGB Powertech, 2012). The first was developed by the EU FP7

Table 1 Onshore and offshore WT reliability databases.

	Size of survey No of WTs		*Reporting Period*		*WT Rating (MW)*		*Onshore/ Offshore*	*WT Type, see Tavner (2021)*	*Database Name*	*Country*	*Data collection*	*References*
	From	*To*	*From*	*To*	*From*	*To*						
1	4300	4300	2013	2016	0.3	3.0	Onshore	C, D	CIRCE	Spain	Large database Based on failure logs and SCADA alarms from 14 wind turbine manufacturers. No absolute values provided. Failures normalized to the total number of recorded failures. Downtimes expressed as component's contribution to the overall downtime.	Reder et al. (2016) and Gonzalez et al. (2016)
2	1295	4285	1995	2004	0.1	2.5	Onshore	A, B, C	WSD WindStats	Germany	Large database. Failure rate and downtime data collected manually by maintenance technicians. Quarterly reports.	Windstats newsletter (1987–Present), Spinato (2008), and Tavner et al. (2006)
3	851	2345	1994	2004	0.1	2.5	Onshore	A, B, C	WSDK WindStats	Denmark	Large database Only failure rate data collected manually by maintenance technicians. Monthly reports.	Windstats newsletter (1987–Present), Spinato (2008), and Tavner et al. (2006)
4	2222	2222	2009	2014	1.5	2.5	Onshore	C, D	Strathclyde	UK	Failure rates only of generators and converters for two turbine configurations & not downtime. From OEM work order and inventory databases. Failures broken down into severity categories depending on material cost of repair or replacement.	Carroll et al. (2015)
5	1347	1347	2013	2021	2.0	6.0	Offshore	C, D	SPARTA	UK	Monthly average repairs from 19 UK wind farms due to failures only, not downtime data.	SPARTA (2021)
6	800	900	2011	2015	1.3	1.4	Onshore	A, B, C	CREW	USA	Stop rate data not failure rate only Data originally published in 2011, with two updates in 2012 and 2016.	Peters et al. (2011, 2012) and Karlson et al., (2016)
7	527	723	1997	2005	0.5	1.5	Onshore	A, B, C, D	Elforsk/ Vindstat	Sweden	Failure rate and downtime data for the entire period. Original source in Swedish, data also summarized in English.	Ribrant (2006) and Ribrant and Bertling (2007)
8	158	643	1993	2006	0.225	1.8	Onshore	A, B, C	LWK	Germany	Failure rate and downtime data for WTs in the Northern Germany (Schleswig- Holstein) Manually reported annually.	Tavner et al. (2008), Spinato et al. (2009), and Pettersson et al. (2010)
9	1500	1500	1989	2006	0.03	1.8	Onshore	A, B, C	WMEP	Germany	SCADA alarms and maintenance reports collected by the Fraunhofer Institute for wind energy systems Data collected manually by maintenance technicians.	Hahn et al. (2007) and Faulstich et al. (2008, 2011)
10	1313	1313	2012	2012	-	-	Onshore	-	Huadian	China	No absolute values provided, data reported in percentages and estimated based on number of failures and total number of available WTs.	Ma et al. (2015)
11	640	640	2010	2012	1.5	6.0	Onshore	C, D	CWEA	China	Only failure data of 7 critical subassemblies (converter, gearbox, generator, pitch, yaw, blades, and brakes) from 47 manufacturers.	Lin et al. (2016)

(*Continued*)

Table 1 Continued

	Size of survey No of WTs		*Reporting Period*		*WT Rating (MW)*		*Onshore/ Offshore*	*WT Type, see Tavner (2021)*	*Database Name*	*Country*	*Data collection*	*References*
	From	*To*	*From*	*To*	*From*	*To*						
12	350	350	2011	2016	2.0	4.0	Offshore	-	Strathclyde	UK	Only repair time not downtime reported from maintenance inventory and cost databases Failures broken down into severity categories depending on material cost of repair or replacement.	Carroll et al. (2016)
13	290	290	1986	1987	0.04	0.6	Onshore	A, B	EPRI	USA	Data reported for some Californian wind farms.	Calvert et al. (1997)
14	134	134	2011	2011	1.5	1.5	Onshore	D	SE China	China	No absolute values provided Data from a single coastal wind farm in SE China. Reported in percentage and estimated with the available total number of WTs and number of failures.	Bi et al. (2014)
15	120	120	2004	2007	2.0	3.0	Offshore	C	Round 1 UK	UK	Data from 4 wind farms in early operation. Dominated by gearbox failures, which lead to large numbers of gearbox replacements. Compare with Noordzee experience.	Feng et al. (2010)
16	108	108	2009	2013	1.5	2.0	Onshore	A, B, C	University of Nanjing	China	Only stop rates & no failure rates reported from a single wind farm in Jiangsu Province.	Su et al. (2016)
17	72	72	1996	2008	0.075	3.0	Onshore	A, B, C, D	VTT	Finland	Failure rate data reported in a conference paper and thesis in Finnish.	Stenberg and Holttinen (2010) and Stenberg (2010)
18	36	36	2007	2009	3.0	3.0	Offshore	C	NoordzeeWind OWEZ	Netherlands	Only stop rate, not failure rates reported from Egmond aan zee wind farm. Dominanted by gearbox and generator failures.	NoordzeeWind (2008, 2009, 2010)
19	15	15	2000	2004	0.225	0.225	Onshore	A	Muppandal	India	Only failure data, no downtime reported from a wind farm at Muppandal, South India.	Herbert et al. (2010)
Totals, Minima, Maxima	16078	21343	1986	2021	0.03	6.00						
	From	To	From	To	From	To						
	Size of survey, No of WTs		Reporting Period		WT Rating (MW)							

Adapted from Pinar Pérez JM, García Márquez FP, Tobias A, and Papaelias M (2013) Wind turbine reliability analysis. *Renewable and Sustainable Energy Reviews* 23: 463–472; Pfaffel S, Faulstich S, and Rohrig K (2017) Performance and reliability of wind turbines: A review. *Energies* 10(11): 1904; Artigao E, Martín-Martínez S, Honrubia-Escribano A, and Gómez-Lázaro E (2018) Wind turbine reliability: A comprehensive review towards effective condition monitoring development. *Applied Energy* 228: 1569–1583; Dao C, Kazemtabrizi B, and Crabtree C (2019) Wind turbine reliability data review and impacts on levelised cost of energy. *Wind Energy* 22: 1848–1871; Cevasco D, Koukoura S, and Kolios AJ (2021) Reliability, availability, maintainability data review for the identification of trends in offshore wind energy applications. *Renewable and Sustainable Energy Reviews*, 136: 110414.

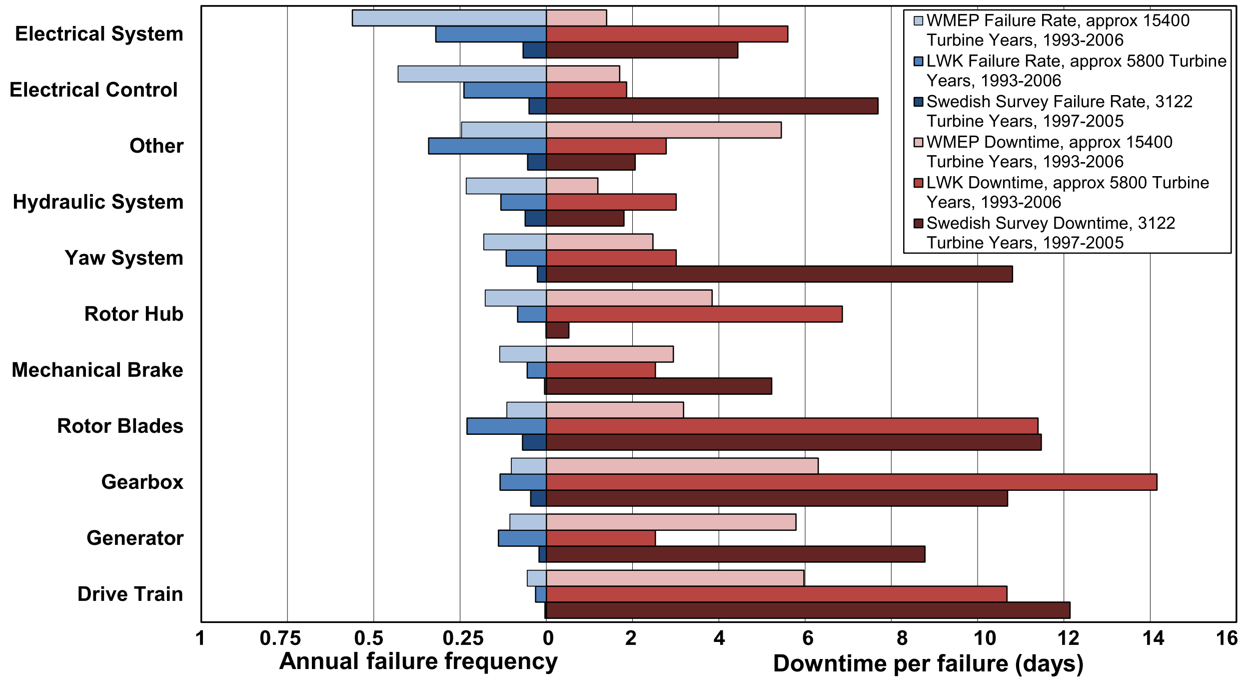

Fig. 2 Failure rates and downtime for onshore WTs from the WMEP, LWK and Elforsk/Vindstat (Swedish survey) initiatives (Ribrant and Bertling, 2007; Tavner et al., 2010). From Ribrant J and Bertling L (2007) Survey of failures in wind power systems with focus on Swedish wind power plants during 1997–2005. *IEEE Power Engineering Society General Meeting*, 1–8.; Tavner PJ, Faulstich S, Hahn B, and Van Bussel GJ (2010) Reliability & availability of wind turbine electrical & electronic components. *EPE Journal*, 45–50.

ReliaWind Consortium for an extensive failure data study and comprises of a total of 257 components. This is a reliability-oriented, simple to apply and internationally recognized taxonomy that has been adopted by several studies on WT reliability such as (Faulstich et al., 2011; Reder et al., 2016; Gonzalez et al., 2016; Pfaffel et al., 2017; Dao et al., 2019). A full description is provided in Chapter 11 of (Tavner, 2021). The RDS-PP taxonomy has been adapted from similar industry taxonomies and was designed to be consistent with designations of other power systems. It provides a high level of detail for both system and subsystem identification and components' technical information. It is currently employed for offshore data collection such as the SPARTA and WinD-Pool (Fraunhofer and Dresden, 2021) initiatives.

The different degrees of granularity of the information provided by the reliability databases make a straight cross-comparison between them difficult. However, several quantitative studies have been performed to map initiative-specific reliability data to homogeneous standardized statistics and taxonomies with the aim to identify trends in the data (e.g. according to WT location, population size and mean power rating), draw universal conclusions and/or carry out comparisons. In the next Section, some of the main results of these review studies based on publicly available data are presented.

2.11.2.3 Trends in the reliability statistics

The Dutch Offshore Wind Energy Converter (DOWEC) research project (1998–2003) was a pioneer in the quantitative analysis of WT reliability, emphasizing its crucial role for the offshore development (DOWEC, 2002). A group of experts analyzed reliability data from WTs located in northern Germany, recorded by WSD, WSDK, LWK and WMEP up to 2001, and estimated an onshore average failure rate per WT per year equal to 2.20 (van Bussel and Zaaijer, 2003). The study did not include the EPRI dataset in the comparative study due to the outdated technology of the WTs surveyed in it.

Three of the largest and oldest databases of European onshore WTs, the WMEP, LWK and Elforsk/Vindstat, are compared in Fig. 2. Failure rates and downtime, categorized by WT subassembly, refer to a period of 13 years (between 1993 and 2006). These databases are quite old and present some important limitations, such as they refer to mixed and changing WT populations, with outdated technologies and a much lower power than modern WTs. However, they are among the most comprehensive data publicly available so far and show significant similarities, giving valuable insights into the reliability of the drivetrain components. A common feature is that the highest failure rate subassemblies in onshore installations do not necessarily cause the most downtime. While electrical subassemblies appear to have higher failure rates and shorter downtimes, mechanical subassemblies, including blades, gearbox and generator components, tend to have relatively low failure rates but the longest downtimes. The long downtime of the mechanical subassemblies is clearly not due to their unreliability but rather to the complex logistical and technical repair procedures in the field (such as the acquisition time for the spare part and for the required maintenance equipment). This will be aggravated particularly in offshore applications, where any maintenance actions require favorable weather windows, special lifting equipment and vessels. In particular, **Fig. 2** shows that the gearbox is among the top-three contributors to WT downtime per failure, being one of the most critical subassemblies for onshore WT availability.

An interesting study by (Faulstich et al., 2011) shows that, in onshore installations, 75% of failures are responsible for only 5% of the WT downtime, whereas only 25% of failures cause 95% of downtime. A few large faults, many of which associated with gearboxes, generators and blades, dominate onshore downtime as they usually require complex and costly maintenance actions. The replacement of major WT components, such as the gearbox, has been shown to be responsible for up to 80% of the cost of corrective maintenance (Besnard, 2013). This suggests that large drivetrain subassemblies require the most attention. The 75% of faults causing 5% of the downtime are mainly electrical faults, and in the majority of the cases, can be easily fixed via remote/local resets. However, the effect of these failures on the WT availability can be amplified when moving offshore due to the limited accessibility, the longer time delay and the travel and repair times, leading to increase of the downtime contribution of these subassemblies (Tavner et al., 2010).

Similar results have been later confirmed by (Pinar Pérez et al., 2013) who brought together and compared data from a selection of major reliability surveys in the literature, i.e. Elforsk/Vindstat, VTT, LWK, WSD, WSDK and the results from the DOWEC and CONMOW (Braam and Rademakers, 2004) European projects.

One the first extensive surveys of wind reliability from the European experience was compiled by the ReliaWind project (European Commission, 2013), between 2008 and 2011, which developed a systematic and consistent approach to deal with the WT taxonomy and detailed data collected from operational WFs. This included the analysis of 10-min average Supervision Control and Data Acquisition (SCADA) data, fault logs and O&M reports. In the ReliaWind project, in order to compare an homogenous WT population, only WFs with at least 15 WTs and variable-speed, pitch-regulated machines with rating greater than/equal to 850 kW were included. Data from around 350 WTs from multiple manufacturers were collected, over a period of more than 10 years, from various databases, including WSD and WSDK. For confidentiality reasons, the results of the ReliaWind project do not show the actual failure rate and downtime but only the percentage distribution (Wilkinson, 2011). Despite of the diverse technologies and power ratings, they are broadly comparable with the WMEP, LWK and Elforsk/Vindstat (Swedish survey) shown in **Fig. 2** and the same failure rate trend emerges.

However, the downtime shows much greater emphasis on the rotor and power modules because it is believed that the variable-speed WTs analyzed in this study have not yet experienced major gearbox, generator or blade failures to-date in service (Tavner, 2021).

Four more recent studies have contributed to compare available onshore, and in some cases offshore, data with the latest study published in 2021. Since a detailed description of the WT location, type and manufacturer is missing in most of the single initiative listed in **Table 1**, the independence of the single results compared in these review studies cannot be fully assessed.

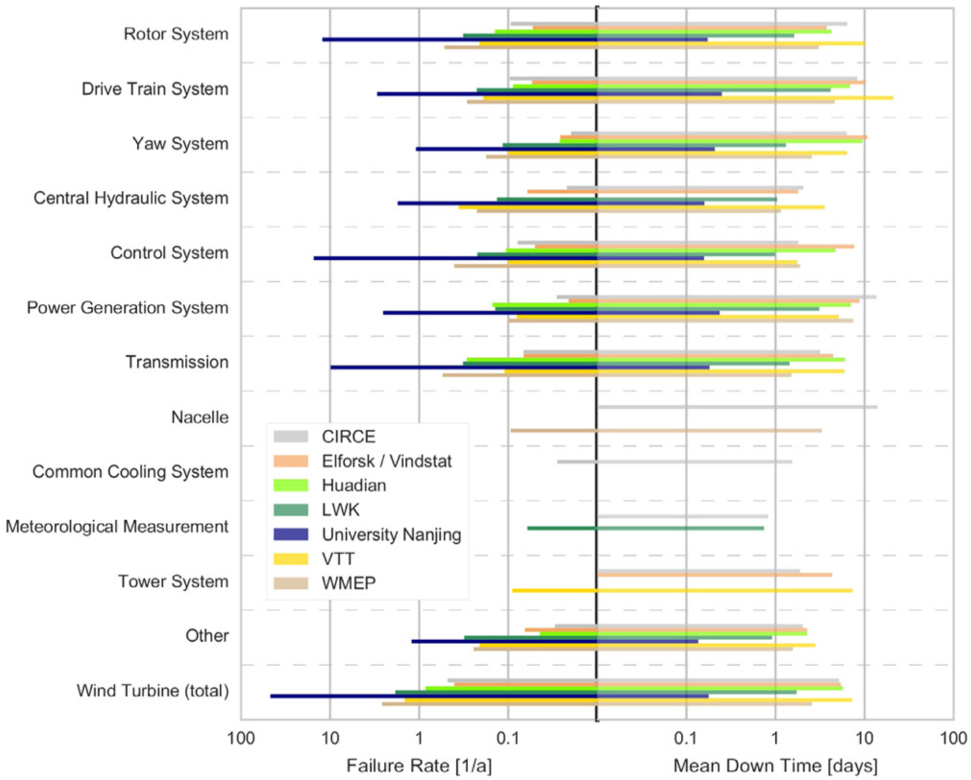

Fig. 3 Failure rates (failure per WT per year) and mean downtimes (weighted according to their occurrences) per failure of onshore WTs according to seven (7) publicly available databases (Pfaffel et al., 2017). From Pfaffel S, Faulstich S, and Rohrig K (2017) Performance and reliability of wind turbines: A review. *Energies* 10(11): 1904.

The review by (Pfaffel et al., 2017) collates results from to-date available reliability statistics, both onshore and offshore, including data from outside Europe. Failure data from 15 initiatives is harmonized according to the RDS-PP taxonomy. Based on the considered time-period and the country/region they refer to, as well as on their expertise, the authors state that overlaps between databases are likely between LWK and WMEP as well as SPARTA and Strathclyde (Offshore). Only seven (none of them offshore) data sources provide also downtime information; results are summarized in Fig. 3. Due to the different levels of data quality and availability, a comparison between initiatives is difficult. The mean WT downtime per failure, shown in Fig. 3, varies significantly between 0.18 and 7.29 days per failure. This is mainly caused by diverse failure definitions adopted by the data sources, as discussed in the previous Section. However, overall Fig. 3 confirms previous studies as it shows that the (mechanical) drivetrain of onshore WTs, although presenting a quite low failure rate, has on average the largest share of downtime and it is responsible for about a fourth of the total downtime. On the other hand, electrical components, such as the transmission and control system, cause more failures but lower total downtime. The highest failure rates and lowest downtimes shown by the University of Nanjing database are related to the way reliability statistics are collected, as in this case, every stop event is reported.

The work by (Artigao et al., 2018) cross- compares 13 reliability statistics, out of which two are offshore (Strathclyde (Offshore) and NoordzeeWind OWEZ), six are onshore as in (Pinar Pérez et al., 2013) and the remaining 5 are from sources published between 2011 and 2016. Data refer to WTs ranging from 100 kW to 4 MW located in Europe, China and the United States. To facilitate the comparison between the datasets, the authors adopt a common taxonomy, breaking down the WT components in thirteen categories, and uniform the data into normalized percentages, both for failure rates and downtime.

The normalization does not allow the comparison of absolute failure rates or downtimes between different WT configurations, size and location, but gives an overview of the most critical components for maintenance. In line with previous studies, even if the analysis is now extended to a larger number of data sources, results show that the assemblies with the highest failure rates are the electrical and control systems, whereas the hub and blades and the gearbox show the highest downtime. Studies from CREW, NoordzeeWind OWEZ, LWK, Strathclyde (Offshore), WSDK, WSD and WMEP, for which downtime figures are also available, show that the highest contributor to the hours lost per WT per year is due to the presence of the gearbox. Overall, mechanical components cause higher amount of downtime when compared to electrical/control ones, reaching more than 75% of the total downtime. Failures of mechanical components, such as the gearbox, are hence critical for WT availability and attention should be paid to them, together with the hub and blades, when developing effective WT monitoring systems. Similarly, (Dao et al., 2019) surveyed averaged reliability statistics, but expanded the analysis by including additional onshore and offshore sources. In particular, this study takes into account 18 data sources, including all the onshore databases listed in Table 1, with the exception of Strathclyde (Onshore) which only reports generator and converter failure rates, and all the four offshore databases. A more robust dataset allows the authors for a reliability comparison between onshore and offshore WT populations. The ReliaWind taxonomy, with some small modifications, is adopted to collate and harmonize the surveyed reliability data. Discrepancies between the volume of data collected, the duration, the WT location and the power rating are identified as the main contributing factors to the significant variations in both failure rates and downtimes from different, individual data sources.

Overall, the criticality of the WTs subassemblies is shown in Figs. 4 and 5 in terms of failure rates and downtime, respectively. In onshore installations, the electrical and control system, the blades and hub, the pitch and the generator show the highest failure rates. This is also confirmed for offshore WTs, but with a slightly different order of criticality, where the pitch system is the most critical subassembly. The higher gearbox, generator and drivetrain failure rates observed in offshore installations might be due to the fact that fewer datasets are analyzed and they include the Round 1 UK database, which, unlike the other three sources, reports high failure rates of the gearbox and interrelated components. This is because many WTs experienced severe gearbox failures requiring, in most of the cases, its replacement. For both the onshore and offshore populations, failures in the gearbox, the generator and the blades and hub result in the largest downtimes per failure. These results support further the trends already identified in previous studies. The study also shows that, in offshore installations, the downtime per stop is approximately double the one of onshore installations, most likely due to the more complex offshore maintenance procedures adopted as opposed to the onshore ones.

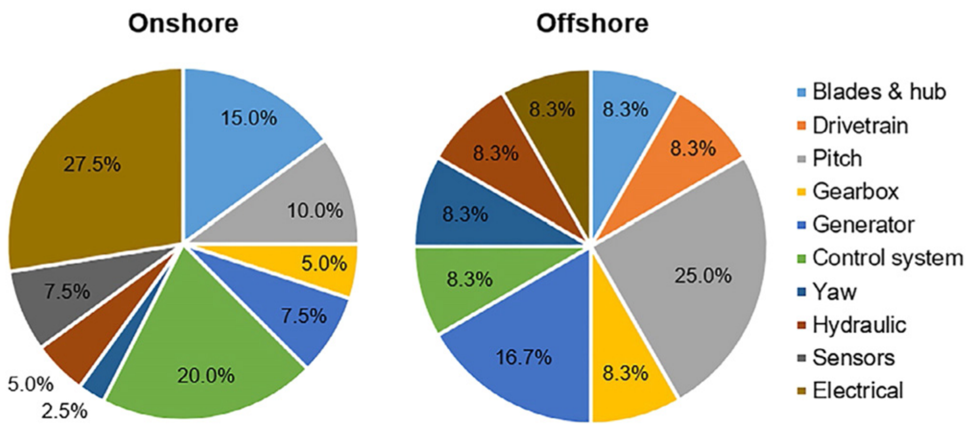

Fig. 4 Failure rate distribution among the main WT components for 14 onshore and 4 offshore reliability databases (Dao et al., 2019). From Dao C, Kazemtabrizi B, and Crabtree C (2019) Wind turbine reliability data review and impacts on levelised cost of energy. *Wind Energy*, 22: 1848–1871.

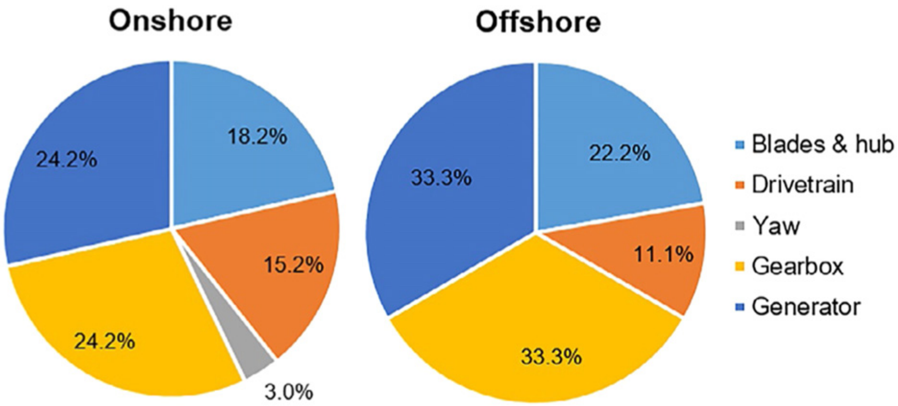

Fig. 5 Downtime distribution among the main WT assembly/components for 14 onshore and 4 offshore reliability databases (Dao et al., 2019). From Dao C, Kazemtabrizi B, and Crabtree C (2019) Wind turbine reliability data review and impacts on levelised cost of energy. *Wind Energy* 22: 1848–1871.

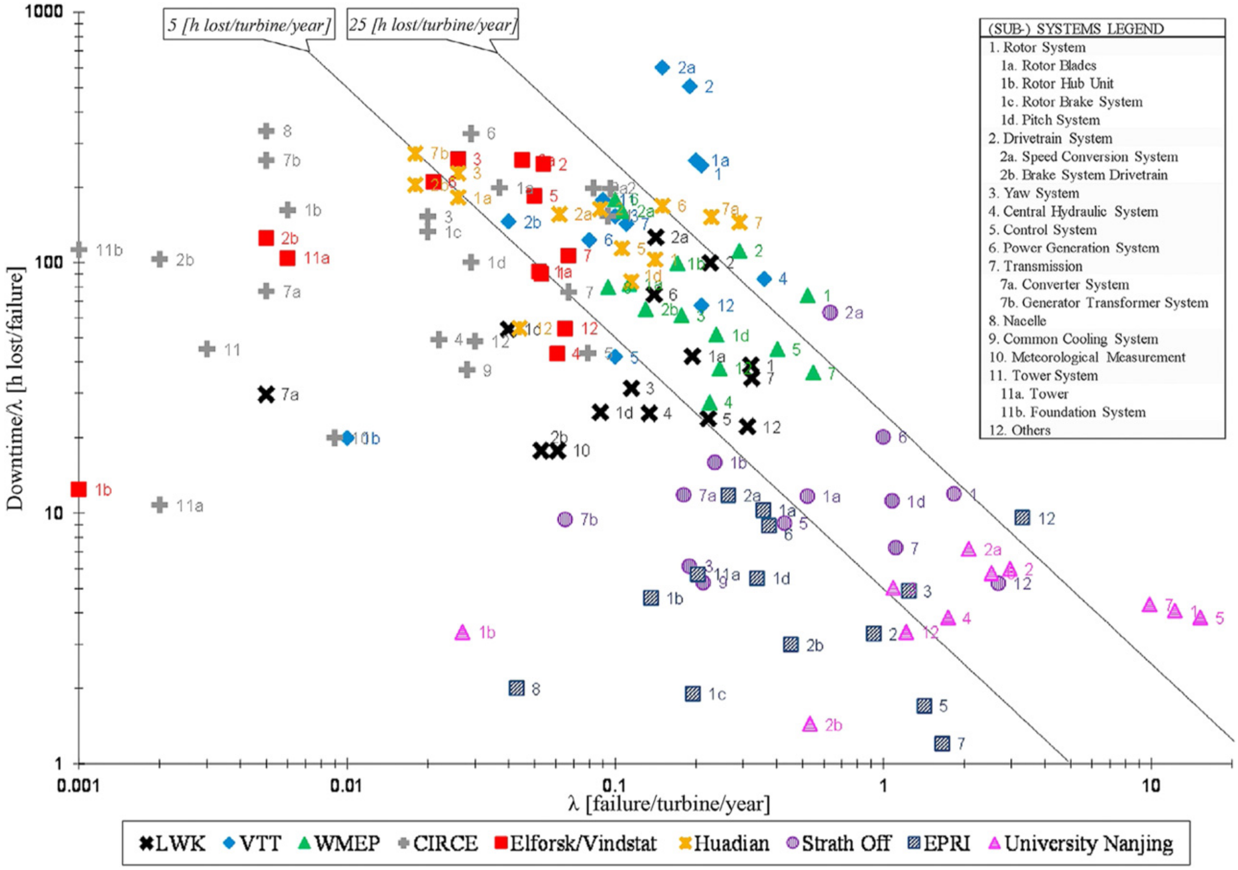

Fig. 6 Failure rate vs. downtime per component according to Cevasco et al. (2021). From Cevasco D, Koukoura S, and Kolios AJ (2021) Reliability, availability, maintainability data review for the identification of trends in offshore wind energy applications. *Renewable and Sustainable Energy Reviews* 136: 110414.

Cevasco et al. (2021) is the most recent WT reliability review to-date and provides an interesting all-in-one comparison of the average reliability figures of 9 databases, which represent the most complete and accessible initiatives so far. The RDS-PP taxonomy is adopted to allow the coherent comparison of the reliability statistics. Fig. 6 shows the failure frequency against the time lost to restore the system after failure and allows to compare key reliability aspects of early-stage and modern assets. Although there is a significant spread across the averaged data, mainly due to inconsistencies in terms of data quality and availability between the data sources, most of the components are characterized by less than 25 h lost per WT per year.

While the WMEP and Huadian databases are mainly characterized by lost hours per failure of the component ranging between 5 and 10 h/WT/year, the other databases show a wider spread of values. However, some clustering in the data according to the analyzed population and the way the data have been collected, can be observed. The oldest database, EPRI, which refers to outdated configurations and small rated WTs, shows high values of failure rates. They can be associated to the early maturity stage of the industry, where WTs were still in their infant mortality phase. On the other hand, the more recent CIRCE database show lower failure rates compared to older datasets, which can be attributed to the higher maturity level reached by the industry in recent years. The University of Nanjing database shows an outlier behavior that can be attributed to the fact that, unlike other populations, stop rates are recorded, implying higher failure rates and lower downtime mainly due to the contribution of remote resets. The Strathclyde (Offshore) results also show a peculiar, skewed behavior which can be explained by the fact that this database reports the mean active repair time (i.e. the expected effective time to repair) as an indicator of downtime. This differs from the mean downtime definition (i.e. time interval during which an item is unavailable due to a failure, including all the delays between the component failure and the restoration of its service) adopted by other databases, except EPRI and Huadian.

Overall, failure rates statistics show a significant improvement compared to the first WT generation, while downtime is still quite long for high criticality components such as the drivetrain and the rotor systems. Overhauls or replacements of such major components, which are infrequent but typically associated with long downtime, together with frequent failures of other components with a shorter downtime, lead to high O&M costs.

2.11.2.4 Toward reliability data standardization

The wind power industry recognizes the broad significance of reliability data collection and analysis for profitability of WF assets optimization. Currently, there are wide variations among different reliability data collection and analysis efforts and there is a need for the wind power industry to develop and adopt a standardized approach. The lack of internationally recognized standards is currently seen as one of the main obstacles for enhancing the industry's progress in addressing the reliability issues. A variety of guidelines and recommendations for data harmonization and standardization have been suggested by several initiatives and the most recent are IEA Wind Task 33 (Hahn et al., 2017) and two industrially-led databases, SPARTA in the UK (SPARTA, 2021) and WInD-Pool in Germany (Fraunhofer and Dresden, 2021). Recommendations for developers, owners and operators are:

(a) Adopt a common taxonomy to map all WT components to one internationally recognized designation system (RDS-PP is seen as the most promising designation system for equipment data in the wind power industry).
(b) Align operating states to those specified in standards for a WT time- and production-based availability assessment.
(c) Automate data collection to reduce the risk of human error as well as improving data quality.
(d) Collect reliability data from the early development stages throughout the WF asset lifetime.
(e) Share data by engaging in external initiatives (such as SPARTA and WInD-Pool) to align collection methodologies and achieve statistically significant populations for reliability and performance analyses.

Achieving an harmonized approach for reliability statistics collection will result in the improvement of the data quality and availability and, consequently, of the valuable information that can be derived from it for all stakeholders involved in the management of the WF asset. The adoption of data collection and reporting standards across the industry will require time and the commitment of all stakeholders. The value, as realized in other industries such as oil and gas, lies in safer and more effective and efficient maintenance policies, strategies and practices. Failure to do this will restrict the pace at which opportunities to improve O&M costs can be identified and consequently implemented. The adoption of a systematic and internationally recognized approach in which and how reliability data should be collected will render feasible to optimize the use of operational experience to improve O&M, as well as to improve design and manage the risk. This process will require time and commitment of all stakeholders, but is essential in order to optimize the WF profitability, as already shown in other industries such as oil and gas by the OREDA database, while protecting competitive advantage and intellectual property of owners and operators.

2.11.3 Wind turbine maintenance strategies

O&M plays a key role in the cost-effective development of WF projects, especially the offshore ones. While the cost of wind energy reduces due to smaller upfront costs and improved performance, O&M activities represent a major contributor to total expenditure, with offshore O&M costs estimated to account for up to 35% of the total cost of wind energy (Stehly et al., 2020).

Operations represent a small proportion of O&M expenditure and refer to activities contributing to the high-level management of the asset, such as the environmental monitoring, the remote monitoring, electricity sales, marketing, administration and other back-office tasks.

Maintenance represents a large portion of O&M effort, cost and risk. The purpose of maintenance is to achieve the desired component performance by maintaining the component's ability to function correctly. The component failure rates, as well as the maintenance duration, the vessel availability and the operational weather limits have the greatest effect/impact on O&M costs (Martin et al., 2016).

Maintenance strategies are typically classified as corrective and preventive, as shown in Fig. 7, according to when maintenance is conducted. The primary difference between these two strategies is that a problem in the system must exist before corrective maintenance actions are taken, while preventive tasks are intended to prevent occurrence of a problem in the first place.

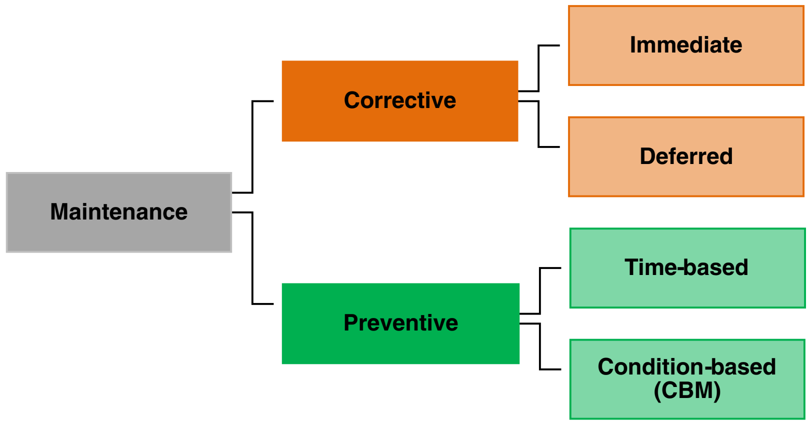

Fig. 7 Classification of maintenance strategies.

Corrective maintenance is the traditional maintenance approach, being undertaken after a failure occurs. For critical component failures, this should be performed immediately. For offshore wind power installations, this approach requires planning action as soon as a failure occurs, otherwise long unscheduled downtime and significant production losses can occur. For failures that are of small consequence to the comprehensive system function, the maintenance actions can be deferred to a better suited time.

Thus, corrective maintenance has the advantage that useful asset life is available without loss of capacity. On the other hand, it has two disadvantages:

(a) it requires fast response to avoid significant downtime;
(b) it can lead to greater damage and direct costs, for example due to consequential failure of components other than those initially failed (Koukoura et al., 2021).

Preventive maintenance is performed to avoid major failures and can be further subdivided into time-based and Condition-Based Maintenance (CBM).

Scheduled time-based WT maintenance is done at fixed intervals between maintenance visits, independent of the WT operating status. This generally takes 2–3 days per WT and is suitable for age-related failures where a failure probability distribution is known. It includes, tests of safety systems, gearbox oil sampling and analysis, oil and filter changes, inspections for oil or water leakage, generator brush and slip-ring checks, brake pad renewal, bolt strength testing/re-tightening and blade visual inspections. These tests are usually based on manufacturer recommendations but may be modified based on the operator's experience.

In onshore installations, preventive time-based maintenance is generally performed every 3 months during the first year of operation and later every 6 months depending on the WT service type and model. However, in offshore installations, due to the higher transportation and production loss costs, WTs are routinely serviced only once a year during spring or summer (Besnard, 2013). A preventive time-based maintenance strategy has the main advantage that assets deliver more predictable and reliable electricity, optimizing the financial return. However, compared to CBM, it results in higher costs and the risk of over-maintenance, since tasks may be completed more frequently than needed before the nominal component life end.

CBM is performed based on the physical machine component conditions, requiring monitoring systems with warning/alarm limits to alert attention if a condition exceeds specified accepted levels. Advanced and reliable monitoring and analysis techniques are needed to plan CBM using WT SCADA and Condition Monitoring Systems (CMS) data (Crabtree et al., 2015).

Information about machine component condition must be accurate if effective CBM strategies are to be implemented. The objective is to detect the presence and type of incipient faults at an early stage and monitor their evolution, allowing estimates to be made for the residual life, then taking remedial action by planning the most viable economic maintenance intervention using a dynamic schedule (Bengtsson, 2004). In this way, any planned maintenance activity should not be production-critical and could be carried out during low wind periods, when access is easier and electricity demand low.

A comparison of maintenance strategies, showing the advantages and disadvantages of each category, is given in Hameed et al. (2010).

Wind power industry maintenance strategies are evolving rapidly, particularly for offshore applications. The increasing impact of O&M costs, especially in offshore installations, is encouraging WF operators to shift from scheduled corrective to preventive CBM approaches (Mérigaud and Ringwood, 2016; Rinaldi et al., 2021). This should reduce significant financial loss by avoiding long failure downtimes. Corrective maintenance costs have been estimated to be approximately four times higher than those of preventive activities (Scheu, 2012). The economic benefits of implementing preventive CBM strategies are substantial, in terms of maintenance costs minimization, operational performance and safety improvement, preventive part replacement reduction when effective life has not been reached, as well as the reduction of the number and severity of in-service failures (McMillan and Ault, 2008; Byon and Ding, 2010; Zhigang et al., 2011).

A comprehensive understanding of WT reliability, identifying the most critical components and their failure modes, is essential for implementing appropriate CMSs to achieve the full economic benefits of CBM.

2.11.3.1 Overview of wind turbine condition monitoring

With the development of advanced condition monitoring, diagnostics and prognostics, CBM has attracted much attention in the offshore wind power industry in recent years. Modern WTs are equipped with SCADA systems and CMSs for the active remote monitoring and control of their components (Tavner, 2021). SCADA systems provide a range of low frequency (typically 10-min averaged values) measurements, such as for the active power, the wind speed and the pitch conditions and temperatures. The data recorded includes alarms, fault logs, environmental and operating conditions leading up to fault occurrences. These systems were designed for operating purposes but have given valuable insights into impending WT malfunctions, attracting extensive research attention as in Feng et al. (2010), Qiu et al. (2011), Schlechtingen et al. (2013), Feng et al. (2013), Schlechtingen and Santos (2014), Tautz-Weinert and Watson (2016), Maldonado-Correa et al. (2020) and Zhang et al. (2020). Potentially, SCADA records could help WT operators to understand key WT components health. However, this requires considerable analysis for interpretation of the large volume of data generated. Furthermore, the low resolution of the data does not usually permit an in-depth analysis, generally agreed as necessary for accurate diagnosis and prognosis (Crabtree et al., 2015).

CMSs provide high-resolution monitoring of WT high-risk subassemblies. The majority of CMSs currently available are based on drivetrain high-frequency vibration monitoring, with special focus on main bearing, gearbox and generator bearings. In some cases, these measurements can be used in combination with oil particle counters and fiber-optic strain gauges to enhance their monitoring capabilities. No commercial CMS is offered for electrical and power electronic components or for the yaw and pitch systems, beyond that monitored by the SCADA system (Tavner, 2021). This is a gap that needs to be addressed because, as shown in Section 2.11.2, the reliability of electrical components is being increasingly recognized as a growing concern, especially in offshore installations, where electrical component deterioration could be accelerated by enhanced corrosion and erosion rates due to the harsh environment. A number of non-destructive monitoring techniques applicable to WT CMS are reviewed in Garcia Marquez et al. (2012), Yang et al. (2014), and Hossain et al. (2018). According to the survey carried out by Crabtree et al. (2014) there is a wide variety of commercially available CMSs for industries other than wind, mainly relying on established rotating machine industry techniques, where they have become an integral part of asset management. However, the adaptation of these techniques to wind power plants has proved challenging, due to their peculiar variable operating conditions (Yang et al., 2009).

The application of WT state identification to fault detection, diagnosis and prognosis uses both physics-based and data-driven approaches (Qiao and Lu, 2015; Luo, 2017; Stetco et al., 2019). SCADA systems and CMS collect large, complex volumes of data, requiring a high degree of expert manual analysis. Leveraging the full potential of this data and extracting actionable and timely insights to optimize O&M strategies require systems that automatically analyze and interpret large volumes of monitoring data (DNV, 2019). The development of reliable and cost-effective analysis methods, with automatic damage detection, diagnosis and problem prognosis on the most critical WT components, could play a crucial role in establishing technically and economically viable CBM strategies for offshore wind power installations. In the last decade of the wind power industry, data-driven decision-making for effective CBM has evolved rapidly, from applying conventional signal processing and physics-based methods in 2010 to the application of artificial intelligence (AI) and especially deep learning in 2020. While AI techniques have been game-changers in other fields, such as healthcare and finance, they are still at an embryonic stage in industrial wind power engineering.

This is probably due to the lack of a clear perspective and the limited trust in these methods. Despite their enormous potential, there are key challenges for the offshore wind power industry in adopting data-driven decision-making techniques that need to be addressed, as they have been identified by (Chatterjee and Dethlefs, 2021):

(a) Lack of quality data access;
(b) Problems in deploying AI models for real-time decision support;
(c) Lack of black-box approach transparency.

These are critical areas where researchers should focus soon to develop advanced solutions for reducing offshore wind power O&M costs. The main objective will be to develop a platform for the analysis and management of offshore WTs' data and use the data collected in the design of cost- efficient CBM strategies.

2.11.3.2 Toward an offshore wind integrated maintenance strategy

Historic design and reliability information together with on-line monitoring data must play a key role for the optimization of O&M planning and the management of WF assets, especially in offshore installations. Effective asset management of a WF is crucial for the optimization of the future cost of wind energy. That must be based upon data to close the gap between prior knowledge and current operational experience, with the data coming from:

(a) A logical classification of maintenance methods, Fig. 7;
(b) WT and WF Design, e.g. prior FMEA, Fig. 8;

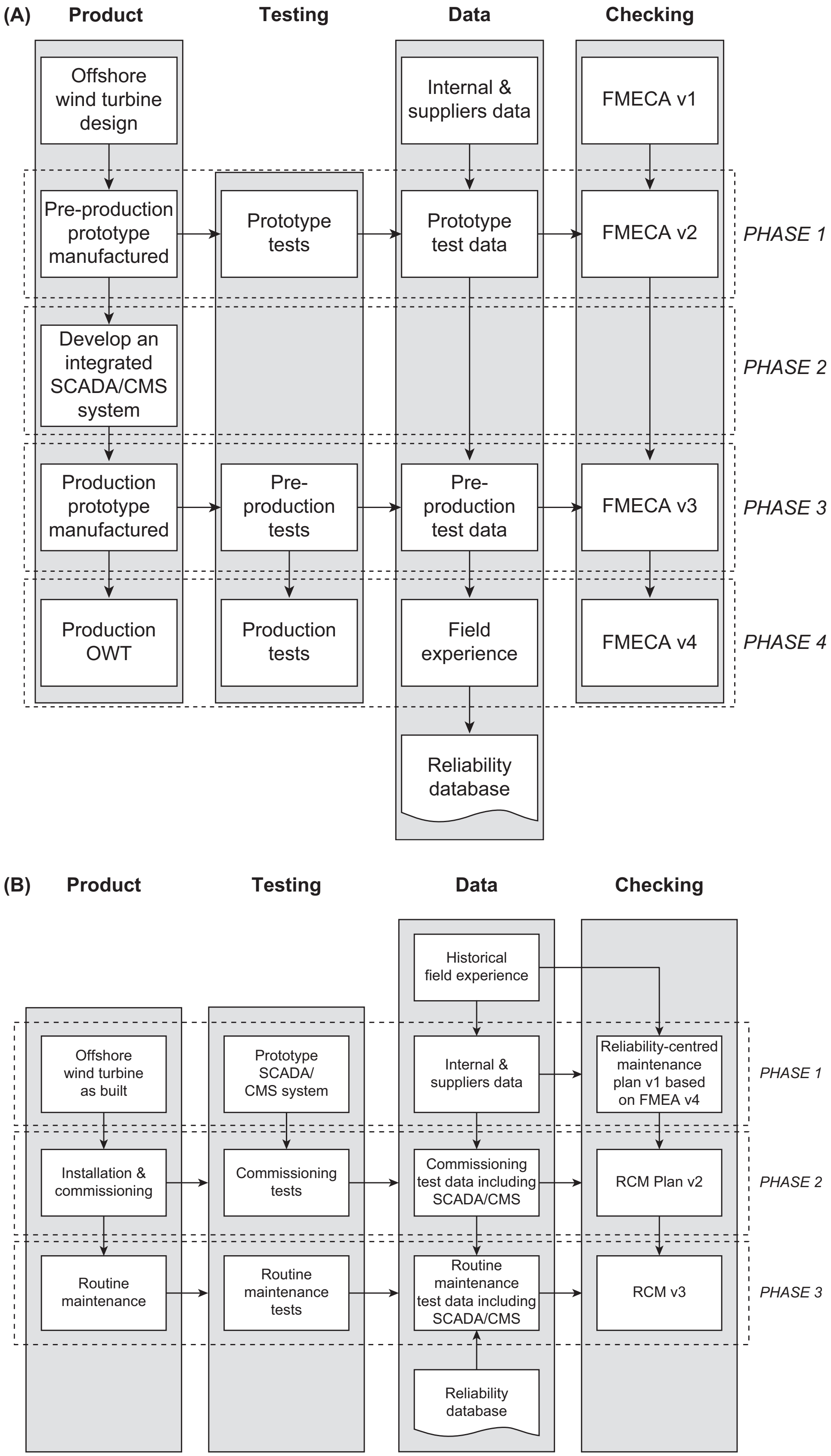

Fig. 8 Proposals to use of FMEA and Reliability-Centered Maintenance (RCM) as Review Tools during Offshore WT Design and Manufacture for improved WF O&M outcomes (Tavner, 2021). (A) FMEA as a Design Review Tool; (B) FMEA and RCM together as an O&M Review Tool. From Tavner PJ (2021) Offshore Wind Power - Reliability Availability and Maintenance, 2nd edn. London, UK: The Institution of Engineering and Technology.

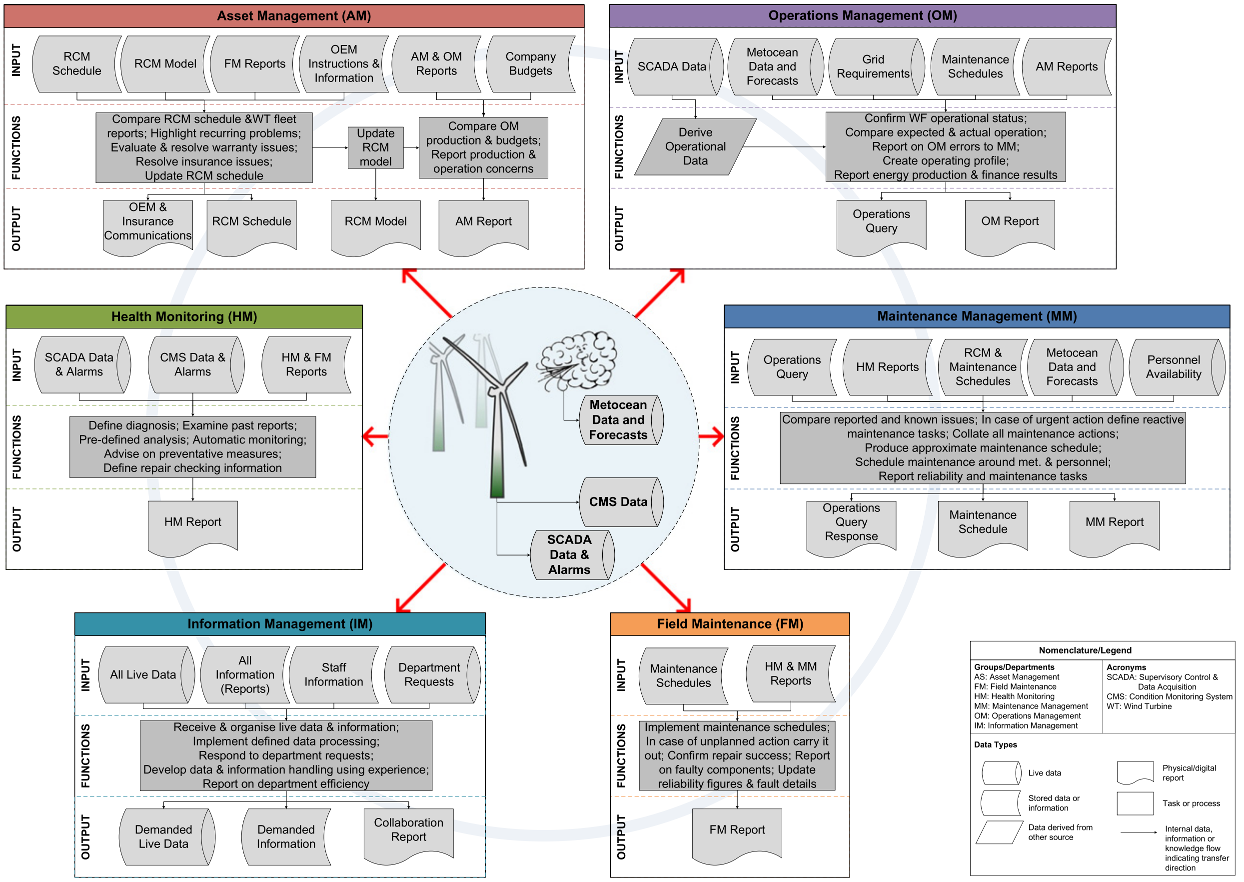

Fig. 9 Offshore WF Knowledge Management System. Modified from the original version produced by Christopher J. Crabtree with contributions from Peter J. Tavner, Bindi Chen, Yanhui Feng, Yingning Qiu and Donatella Zappalá in Tavner PJ (2021) *Offshore Wind Power - Reliability Availability and Maintenance*, 2nd edn. London, UK: The Institution of Engineering and Technology.

(c) Historic operation, i.e. prior failure rate and downtime surveys, summarized in Table 1 and Figs. 2–6;
(d) Current operational experience on this and similar WFs, operator/manufacturer information;
(e) On-line WF operational data, integrated from both SCADA and CMS.

The challenge is to integrate this information so that it can be exploited by WF operators and maintenance teams to operate and maintain the assets in the most cost-effective manner.

Fig. 9 proposes a framework for the implementation of an optimal offshore WF maintenance strategy by managing and integrating the available knowledge. It collates live SCADA and CMS monitoring data, as well as met-ocean data and forecasts with available reliability data, then correlates them with maintenance logs to provide an integrated system upon which optimal planned maintenance strategies can be implemented. Fig. 9 represents a simplified version of an earlier framework proposed by (Tavner, 2021). Its implementation would require the adaptation of original equipment manufacturers (OEM) and operators' data structures to the conditions of individual WFs. There are various closely interlinked stakeholders involved in offshore WF O&M and they can be grouped into six specific departments shown in Fig. 9 with their live data inputs, stored information, functions, maintenance actions, report outputs and key interactions.

(a) Health Monitoring (HM): Responsible for the continuous WT health monitoring, via automated SCADA alarm and signal data, the CMS alarm and signal data processing and the examination of historical reports to alert other groups via generated HM reports, which include fault development, severity, expected time to failure and advice on preventive measures.
(b) Asset Management (AM): Concerned with ensuring that assets are operated in the most cost- efficient and valuable manner to secure the longest life cycle of profitable operation. RCM activities are driven by a clear understanding of subassembly history and performance provided by the exchange of information with the other departments.
(c) Operations Management (OM): Concerned with achieving the required WF operation, given the available operational and met-ocean information, meeting AM, maintenance schedule and grid requirements.
(d) Maintenance Management (MM): Related with the implementation of the AM requirements, via OM outputs, responding to concerns raised by HM and producing cost-effective maintenance schedules, including preventive CBM, reactive and RCM responses, based on met-ocean forecasts, resources, equipment and personal availability.

(e) Field Maintenance (FM): Responsible for the implementation of maintenance schedules, for reporting and resolving any faults (or potential faults) discovered during maintenance, for the confirmation of repair success against advice in HM reports and for updating reliability figures and fault details from MM report and integrating them in the FM reports.
(f) Information Management (IM): responsible for handling the WF data and information, including live data, department reports, staff information and department requests, providing on demand data and information based on department requests and realizing effective communication between departments and integrating them in a collaboration report.

2.11.4 Summary

2.11.4.1 Main points

This Chapter shows that both historic and current field data provide invaluable information for WF operators, assisting in the planning of repairs and maintenance, reducing operational expenditure (OPEX).

The larger sizes of future onshore and offshore WFs, both fixed and floating, renders future OPEX reduction important.

WFs collect a large amount of operational data to manage their O&M. These data can provide effective, cost-saving information but require careful handling.

The results of this Chapter's analysis suggest that while data management methodologies are essential to the OPEX costs' reduction, predictive analysis will also be essential to hold down those costs over a large WF life, whether an onshore or offshore one, a fixed or a floating installation.

The following is a summary of Lessons and Opportunities from this Chapter aimed at improving the OPEX cost control.

2.11.4.2 Lessons

(a) The Chapter has revealed an extensive list of international reliability surveys, assembled between 1986 and 2021 from more than 11 countries, reporting failure rates, downtime and repair strategies from more than 21,000 WTs, onshore and offshore ones, rated between 30 kW and 6 MW.
(b) It reports a clear and consistent distribution of failure rates and downtimes among WT components, confirmed from a number of different sources. These figures can be extrapolated or developed to the larger WTs now being installed onshore and/or offshore, both fixed and floating.
(c) It shows how the collection of failure rate and downtime information has been improved. The latest data, Fig. 6, show a combined presentation of failure rates and downtime allowing WF operators to predict future likely operational performance for larger, more complex wind power developments.
(d) Machine reliability experience has shown that such data will be an invaluable information source for future large WF maintenance and OPEX reduction, regardless of the size and complexity of future installations compared to the ones of these surveys.
(e) Both CMS and SCADA data analyses have been demonstrated as valuable for detecting faults early and initiating the appropriate repair. The limitations of CMS and SCADA are their large data volume, the widely differing time intervals and the difficulties of translating their information into suitable engineering action.
(f) This Chapter gives clear guidance on the varying methodologies available for predicting future WT and WF performance, ranging from monitoring data-based field information to employing design-based FMEAs and other techniques to plan onshore and offshore WF maintenance for future installations.
(g) The application of CBM, using CMS and SCADA and data- and design-based methodologies will, in time, improve the reliability performance of future larger, fixed and floating offshore wind power installations, where currently there is a lack of operational data, but where capability and profitability are encouraging development.
(h) Based on the current world net-zero carbon plans, it is likely that other renewable energy industries must learn the reliability lessons from the onshore and offshore wind power. For example, the failure rate, the downtime and the repair strategies developed and successfully deployed by the wind power industry could be employed in the future development of wave and tidal power.

2.11.4.3 Opportunities

(a) The reliability surveys reported in this Chapter deal with WTs of lower rating than those currently being installed in new WFs, somewhat limiting the applicability of that data.
(b) Current publicly available data sources lack a common and harmonized practice for reliability statistics collection. This makes cross-comparison between them difficult. To enable comparability, facilitate the exchange of information between parties and make better use of operational experience, standard approaches to WT taxonomy and reliability data collection should be adopted.
(c) The data from WTs reported in this Chapter do not include the most modern drivetrains currently being deployed in offshore installations. There is a lack of data on the reliability of direct or indirect-drive large Medium Voltage (MV) permanent magnet generators, fully rated converters or the use of MV converters, now being advocated for the largest WTs.

(d) The industry continues to struggle to integrate data from CMS and SCADA to become fully effective tools for failure and repair management. This is because of the differences in the data rate and the scope of these different systems. The integration of these systems into the overall management systems of large WFs is an important future goal, particularly in offshore installations, where site access is more difficult.
(e) There is limited operational data available from fixed offshore WTs and no operational data yet published from floating offshore WTs, their mooring and collection cables, substations/converters and export cable systems. Such data will be of future importance to ensure the reliability and profitability of this important and growing technologies. The current lack of information limits the industry's ability to accurately predict and control operational reliability for future large floating offshore assets. However, experience demonstrates that the judicious use of data from existing sources, either onshore and/or offshore, can give reasonable approximations for future trends.
(f) Most surveys reported in this Chapter originate from National or Regional Government data schemes aimed at encouraging renewable energy dissemination, for example in Germany, Denmark, the Netherlands, the UK and Sweden. It appears that only the SPARTA survey in the UK involved National, Regional and Commercial collaboration.
(g) The wind power industry is still very cautious about making data available for reasons of commercial confidentiality. This differs from other more developed industries, for example the healthcare, the railways, the aviation, the motoring and the oil and gas, where reliability data have been made readily available in the public domain. These industries have found ways to collaborate in sharing information of mutual benefit to safety and profitability, without sacrificing Intellectual Property. That must be possible for the wind power industry too.

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