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An Intelligent Failure Feature Learning Method for Failure and Maintenance Data Management of Wind Turbines

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Abstract: This paper introduces an intelligent feature learning framework for the failure and maintenance data management of the wind energy sector. The framework employs Bidirectional Encoder Representations from Transformers and the Conditional Random Field model to intelligently identify failures in wind turbines. Additionally, a transfer training model is constructed to infer offshore wind turbine failures based on knowledge learned from onshore devices, which can address the insufficient knowledge of the offshore sector. The accuracy of the feature learning is enhanced by creating an adaptive resampling mechanism to detect features of rare failures often overlooked by high-frequency ones. Two failure and maintenance datasets, LGS-Onshore and LGS-Offshore, are collected and analysed to recognise differences in failure and maintenance between onshore and offshore wind turbines. The results demonstrate that this innovative data analysis framework outperforms existing methods, contributing to the wind energy sector's data foundation by providing essential datasets and new insights into wind farm operation and maintenance.

Keywords: Data management; Wind turbines; Failure identification; Maintenance.

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1. Introduction

The offshore wind energy sector is well established in many countries, with many years of operation of wind turbines, mostly bottom-fixed, although there is an important push for moving toward floating platforms [1]. During this time of operation, failure and operation data have been collected. The operation of the systems is monitored by several sensors and is recorded as operational data [2]. Mathematical models can extract failure information from numerical operation data, such as degradation models for reliability investigations [3, 4], deep learning models for fault diagnosis and prognosis [5, 6]. On the other hand, failure data are textual, recording failure modes and corresponding maintenance actions [7, 8]. Effective wind farm resource management leads to reduced operation and maintenance costs, which are the biggest concerns of the wind energy sector [9, 10], which requires a comprehensive understanding of wind turbine failures and maintenance resource scheduling [11, 12]. However, this depends on the effective failure data collection and analysis to clarify the following features [13-15]: (i) Failures that may happen to wind turbines, including failure modes, frequencies, and criticalities; (ii) Reliability features, especially failure rate, serving as the basis for inferring reliability and failure probability; (iii) Maintenance features like maintenance actions and resources scheduling properties related to inspection, maintenance, and logistics. Manual-based and machine-based methods are available for failure data analysis. Manual-based tools appeared earlier and have been widely applied, but rely on professional knowledge. In contrast, machine-based methods, utilising Natural Language Processing methods, can deal with large datasets and extract the relevant information to feed the appropriate databases.

Failure Mode and Effect Analysis (FMEA) and its enhanced version, Failure Mode, Effect, and Criticality Analysis (FMECA), are conventional manual-based concepts for managing failure data [9, 16]. These methods present system failure information through a designed hierarchy listing of failure items, including, but not limited to, failure modes, causes, and effects. For instance, Scheu et al. [17] collected failure data from multiple operating offshore wind farms across Europe. By driving the FMEA process, 337 failure modes associated with 10 key components and systems are identified. The analysis enhances the understanding of diverse failures of offshore wind turbines and guides condition-based maintenance of offshore wind farms. Additionally, Li et al. [18], following a similar procedure, reported 42 failure modes with 104 failure causes, supporting failure identification and prevention of offshore wind turbines. Rather than collecting and analysing failure data from real operating wind farms, Kang et al. [19] turned to analysing datasets recording failure information of wind turbines and characterised failure properties of offshore wind turbine components, which was then extended to the failure rate prediction of floating offshore wind turbines. More recently, for better managing and transferring the existing failure data/features accumulated from onshore or bottom-

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fixed offshore wind turbines to the recently emerged floating platforms, Li et al. [7, 14] provided failure feature transformation models, localised and globalised, to determine potential floating turbines' failures (lacking data, knowledge, and experience) according to maturely installed equipment (onshore and bottom fixed). The data management schedule, however, is still based on FMEA. It is pointed out that the above failure transfer concept applies to potential failure reasoning and supports the predictive failure data analysis of wind turbines [20].

The rapid accumulation of failure and maintenance data challenges manual-based data management tools. The growing dataset, fuelled by continuous wind farm operations and new installations, renders manual methods impractical due to the substantial labour required. Accordingly, the creation and implementation of machine-based methods contribute to the effective utilisation of fast accumulated failure and maintenance data with reduced labour efforts, knowing that several wind farms and wind turbine manufacturers have already terminated data analysis due to the boom of data amount and limitation of labour resources.

The widespread adoption of deep learning has led to the extensive use of Natural Language Processing methods in textual data management [21]. These methods can autonomously learn target elements, such as failure modes, from maintenance records [22]. Natural Language Processing methods have been applied across various sectors, addressing diverse needs in data analysis. Specifically, Ji et al. [23] combined the Long Short-Term Memory and Conditional Random Field model (LSTM-CRF) for labelling textual data. Sun et al. [24] explored a Bidirectional Encoder Representation from Transformers (BERT) model for recognising pharmacological substances, compounds, and proteins recorded in biomedical texts, which provides a foundation for knowledge graph construction. Zhong et al. [25] adopted a BERT-Span model to enable the automated extraction of rehabilitation entities and support the construction of decision-making systems. Zheng et al. [26] applied a BERT-CRF model to identify entities, including events, equipment, and operations. More relevantly, Ding et al., [22] proposed a semi-supervised knowledge graph construction framework to analyse onshore wind turbines' failure and maintenance data. The model can accurately ascertain failure items according to maintenance records in diverse languages.

However, the failure and maintenance data collected by the wind energy sector possess unique characteristics, introducing new challenges to machine-based methods, including (i) the sector has sufficient knowledge (labels such as components and corresponding failure modes) for onshore wind turbines, but it is inadequate for offshore systems; (ii) failures (labels) are unevenly distributed due to imbalanced numbers of failures associated to electrical or mechanical components (e.g., generators reported majority failures) and very-few-reported structural failures such as towers. The former means analysts cannot provide machine-based methods with necessary inputs (failures/labels), while the latter makes it difficult to identify minority failures.

Hence, this paper proposes an intelligent failure feature learning framework to support the failure and maintenance data analysis. The novel contributions are as follows:

(1) Develop a transfer-based failure identification module to extract failure information of offshore wind turbines based on the onshore failure knowledge.

(2) Develop an adaptive resampling mechanism to enhance item recognition of minority failures.

(3) Apply these methods to two datasets in terms of failure and maintenance for onshore (LGS-Onshore) and offshore (LGS-Offshore) wind turbines and determine differences and similarities in terms of failure and maintenance to support the design and lifelong management of wind turbines.

The outcomes of this paper contribute to both academia and industry. It introduces a novel data management concept to minimise labour efforts, applicable across various textual data management scenarios. Simultaneously, the released dataset and their comparisons enhance and broaden the data foundation of the wind energy sector.

This paper is organised as follows. The proposed intelligent failure feature learning framework is displayed in section 2. The released datasets are provided in Section 3. Section 4 displays the results of the framework. Comparative analysis of onshore and offshore wind turbines in terms of failure, maintenance, and discussions are provided in Section 5. Conclusions are in Section 6.

2. The Intelligent Failure Feature Learning Framework

The intelligent failure feature learning framework is designed as illustrated in Figure 1. In Step #1, the Failure Identification Module is constructed using a BERT-CRF model to identify failure modes. Step #2 constructs a Failure Identification for offshore wind turbines based on onshore labels (failures) classified in [7]. Step #3: Create an adaptive resampling model to emphasise minority failures.

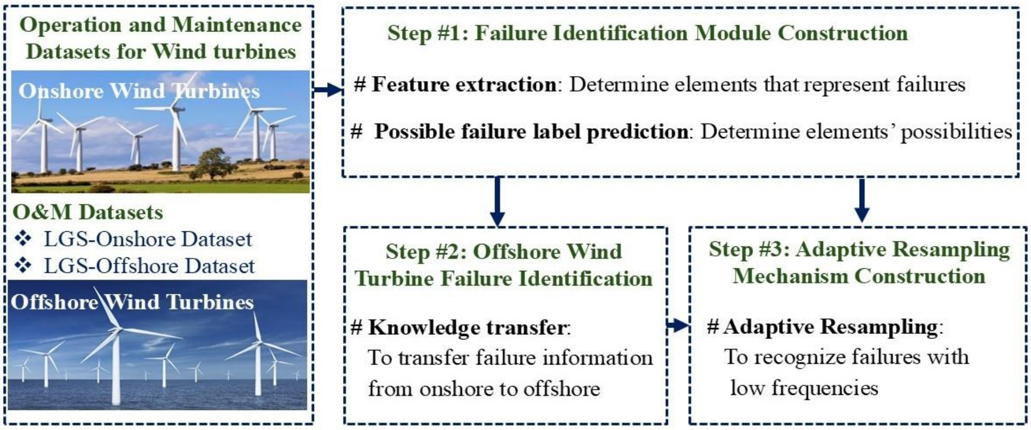

Figure 1. The designed intelligent failure feature learning framework

Step #1: Failure Identification Module Construction

The failure identification model is based on the BERT-CRF concept. The BERT-CRF model determines whether a token (word) belongs to a specific failure symptom (such as damage, crack, or showdown) in records (descriptions of failure and maintenance scripted by the maintenance crew). It assigns a label sequence $Y = \{y_l\}_{l=1}^{|L|}$ to the record $r = \{x_l\}_{l=1}^{|L|}$, where $|L|$ is the number of words in the record r.

BERT captures contextual information and embeds records to extract semantic features, which is formulated as:

$$h^{[CLS]}, h = BERT\left(r\right) \tag{1}$$

where, $h^{[CLS]}$ indicates the semantic features of records and h reflects token embeddings.

Based on the extracted token embedding h, CRF is adopted to decide tokens' labels by considering the neighbouring tags and specific constraint rules. The score of predictions ($s_\theta\left(r,Y\right)$) for a sequence Y is defined as:

$$s_\theta\left(r,Y\right) = \sum_{l=0}^{|L|} A_{y_l,y_{l+1}} + \sum_{l=1}^{|L|} S_{y_l,y_{l+1}} = \sum_{l=0}^{|L|} A_{y_l,y_{l+1}} + \sum_{l=1}^{|L|} (Wh+b)_{l,y_{l+1}} \tag{2}$$

where, A is the transition matrix such that $A_{y_l,y_{l+1}}$ scores the transition from y_l to y_{l+1}, S_{l,y_l} scores the *l*th tag of the token *l* in a record, which is obtained by introducing extracted token embedding h into a linear layer, W and b are weight and bias of the linear layer, θ represents the learned parameters of the BERT-CRF model, including the parameters of BERT model, linear layer, and the transition matrix.

Additionally, a softmax for all possible predictions yields a probability for the label sequence Y, which is computed by:

$$p\left(Y \mid r\right) = \frac{e^{s_\theta\left(r,Y\right)}}{\sum_{Y\in Y_r} e^{s_\theta\left(r,Y\right)}} \tag{3}$$

where, Y_r represents possible sequences.

Step #2: Offshore Wind Turbine Failure Identification

The failure features of onshore wind turbines are recorded as $R^{on} = \left\{r_i^{on}\right\}_{i=1}^{|R^{on}|}$. To be specific $|R^{on}|$ is the number of records (onshore). Given failure modes in records r_i^{on}, the first token describing a failure mode is labelled as B-failure, while the remaining are I-failure. The label Y_i^{on} is then gained from records r_i^{on}. Accordingly, the label dataset $\left\{r_i^{on}, Y_i^{on}\right\}_{i=1}^{|R^{on}|}$ for the BERT-CRF model training maximises the log probability of the correct sequence by maximising the loss function as:

$$\max_{\theta} \sum_{i=1}^{\left|R^{on}\right|} \left(s_{\theta}\left(r_i^{on}, Y_i^{on} \right) - \log\left(\sum_{Y \in Y_r} e^{s_{\theta}(r,Y)} \right) \right) \tag{4}$$

where, Y_i^{on} denotes possible sequences predicted for the record r_i^{on}.

The learned model is then implemented for failure modes identification of records offshore $r_j^{off} \in R^{off}$, where the maintenance record of offshore wind turbines R^{off} is defined by:

$$R^{off} = \left\{ r_j^{off} \right\}_{j-1}^{\left|R^{off}\right|} \tag{5}$$

where, $\left|R^{off}\right|$ is the number of records offshore. Specifically, for the record r_j^{off}, the label sequence for failure modes inferring Y_j^{off} is calculated by:

$$Y_j^{off} = \arg \max_{\dot{Y}_j^{off} \in Y_{r_j}^{off}} s_{\theta}\left(r_j^{off}, \dot{Y}_j^{off} \right) \tag{6}$$

Step #3: Adaptive Resampling Mechanism Construction

This step decomposes (separates failure records into several sections) and then randomly resamples records reflecting most failures with high frequency, such as generators, electrical elements, and cooling systems. For the contexts set, assess the number of high-frequency contexts in records N_m and the number of low-frequency contexts in records N_i, respectively. Determine the sampling ratio N_{ratio} and the number of samples of high-frequency contexts by:

$$N_{sample} = N_{ratio} \times N_i \tag{7}$$

Accordingly, gain N_{sample} random samples from records with high-frequency contexts in the constructed dataset.

The records with low-frequency contexts are put into the new dataset directly. The offshore wind failure dataset is then reconstructed, in which labels in terms of the majority contexts and major failures are reasonably reduced to make a balance with those of minor failures like failures of towers, pitch systems, etc. With the resampled dataset, the BERT-CRF model can identify failure modes of offshore wind turbine components.

3. LGS-Onshore and LGS-Offshore Datasets

Numerous datasets, see Table 1, have been released, but they are more than 7 years old and primarily focus on failure features of small-scale wind turbines (power and structure) designed and manufactured using traditional concepts. The advancements in wind energy techniques, particularly in materials, manufacturing, and design optimisation [20-23], have significantly enhanced the performance of modern wind turbines. Consequently, analysing failure and maintenance features based on previous datasets may fail to accurately reflect the properties of failure and maintenance of today's wind turbines. In response, this paper uses the latest maintenance records collected from both onshore and offshore wind farms [7, 14] (refer to Figure 2), categorises failures and events, characterises failure and maintenance properties, identifies differences and similarities between the two types of wind turbines, and offers guidance for the operation and maintenance of wind farms.

<u>LGS-Onshore Dataset</u> comprises 76 wind turbines in four distinct wind farms, exhibiting noticeable geographic and climatic variations. The dataset encompasses 1.44 million operational hours. Notably, it records 423 wind turbine failures across five models. The dataset provides insights into failure features, including failure mode, criticality, frequency, failure rate, and mean time to failure for components and the entire wind turbine. Maintenance features encompass details about maintenance measures and corresponding maintenance times.

<u>LGS-Offshore Dataset</u> encompasses 313 bottom-fixed wind turbines operating across six wind farms. The dataset comprises 1742 failures. The observation period spans 8.05 million operational hours. Key insights provided by the dataset include failure features, covering failure mode, criticality, frequency, failure rate, and mean time to failure for components and systems; Maintenance features, including details on maintenance measures, maintenance times, vessel scheduling, and personnel arrangement. Overall, 305 wind turbines in LGS-Offshore are less than three years old. The six offshore wind farms exhibit varying distances to the coast, ranging from 20 to 60 kilometres. Detailed information regarding the four onshore wind farms is given in [7]. The failures happened to 22 components of onshore and 26 elements of offshore wind turbines.

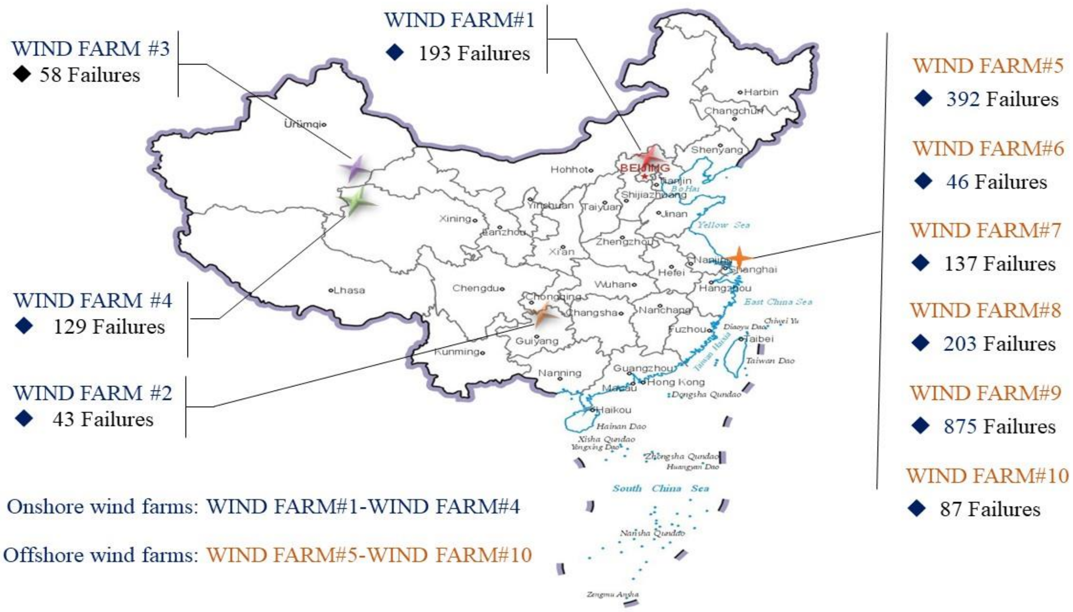

Figure 2. Released datasets and their wind farms

Table 1. Typical databases of wind turbines [6]

Country	Name of Databases	Number of WTs	Years	Primary features of WTs
Germany	Windstats-Germany, LWK, WMEP	6428	1989-2006	Failure rate, downtime
Denmark	Windstats-Denmark	2345	1994-2004	Failure rate
Finland	VTT	72	1996-2008	Downtime, productivity,
Sweden	Sweden	723	1997-2005	Failure rate, downtime
Spain	CIRCE	4300	~2013	Number of failures
USA	CREW	800-900	2011-2015	Stop rate
India	India	15	2000-2004	Failure rate
China	Huadian, East China, SE China	1555	2009-2013	Number of failures, stop rate
UK	Round 1 UK*, SPARTA*, Strathclyde	1516	2004-2016	Number and classification of repair
Netherlands	NoordzeeWind	36	2007-2009	Stop rate
——	LGS-Onshore	76	2018-2020	Failure classification, failure rate, maintenance times
——	LGS-Offshore*	313	2017-2022	Failure classification, failure rate, maintenance, and logistic times

*: Offshore wind; LWK: Landwirtschaftskammer Schleswig-Holstein; WMEP: Wissenschaftliches Mess- und Evaluierungsprogramm; VTT: Technical Research Centre of Finland; CIRCE: Universidad de Zaragoza; CREW: Continuous Reliability Enhancement for Wind; SPARTA: System Performance, Availability, and Reliability Trend Analysis.

A representative configuration of wind turbines, see Figure 3, includes Rotor (Blades, Hub, Main Bearing, Main Shaft), Generator, Gearbox, Electrical Facilities (Converter, Transformer, Monitoring and SCADA, Weather Unit, Power and Controller, and Others), Pitch & Yaw (Pitch System, Yaw System), Cooling & Hydraulic (Cooling System, Dehumidification system, Hydraulic), and Auxiliary system (Crane, Climbing Aid, Brake, Nacelle, and Automatic Firefighting System). The Automatic Firefighting System, Dehumidification system, cable, and tower failures are observed in offshore wind turbines but no failure has been reported in onshore devices.

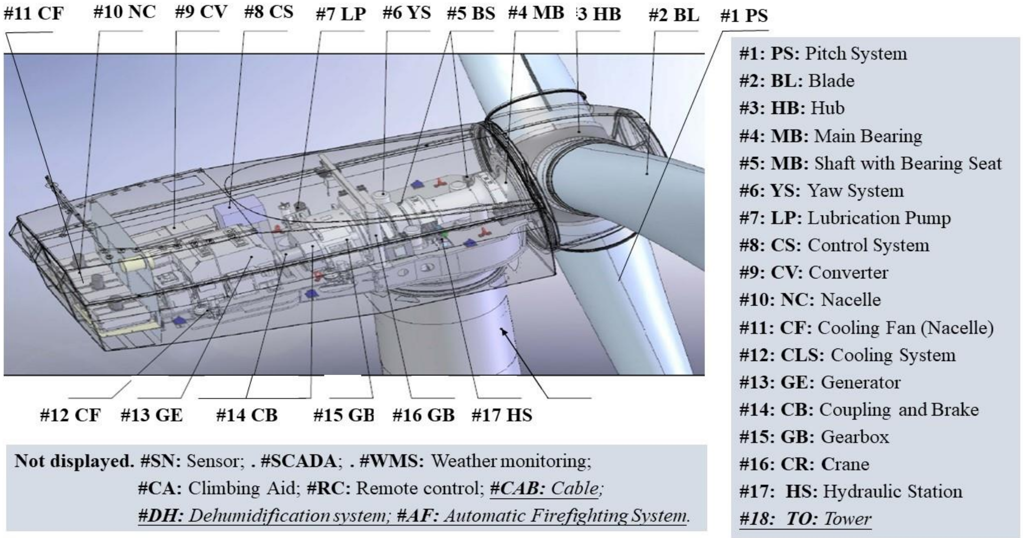

Figure 3. A representative configuration of wind turbine/Elements with italics and underlined represent failures observed in offshore but not onshore wind turbines

4. Results of the Proposed Framework

4.1 Failure mode identification

Failure mode, failure cause, and failure criticality are key factors of failure classification. Failure modes represent the observable states of wind turbines, the root reasons of which are failure causes [27-29]. Root causes are the ultimate reason for a failure and cannot be decomposed further. Failure criticality reflects the internal and external impact of failures on entire wind turbines [30-32]. The proposed model learned 175 failure modes from 1742 failures of 313 offshore wind turbines, which can be compared with 112 failure modes of 76 onshore wind turbines (423 failures in total), see Appendix A. It is noted that the proposed framework can identify failure modes and components, but further failure causes identification that requires human interactions. Figure 4 and Table 2 show a comparison of wind turbine failure modes.

The comparison confirms that (i) harsh sea conditions and untimely inspections introduce diverse failures to offshore wind turbines, especially the rotor and electrical facilities. Auxiliary system failures commonly happen to offshore wind turbines due to the complex systems designed. For instance, the Automatic Firefighting System is specially designed for offshore devices; (ii) large-scale and recent offshore wind turbines (5.6-6.2 MW) are more robust than smaller onshore equipment (2 MW); (iii) more than 20% onshore equipment failures resulted in stoppage of wind turbines, which is more than three times of offshore systems (6%) due to their younger (two years old) age than onshore ones (three to five years old).

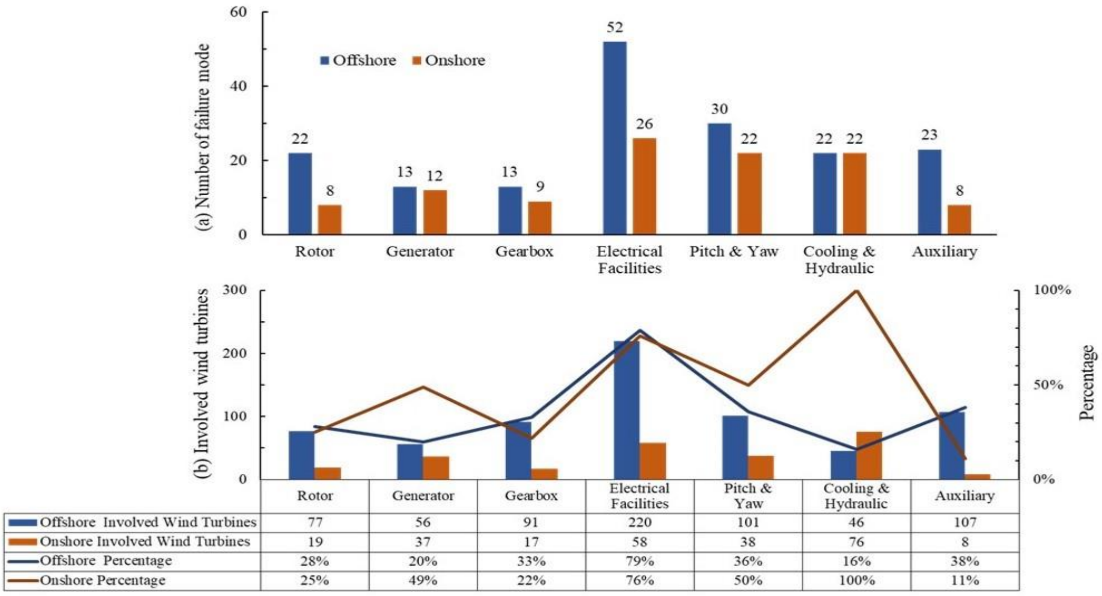

Figure 4. Comparison of failure modes of onshore and offshore wind turbines/ (a) Number of failure modes; (b) Failures involved in wind turbines

Table 2. Comparison of the number of failure modes

Components	Onshore wind turbines			Offshore wind turbines		
	Normal Failures	Shutdown Failures	Share of Shutdown Failures*	Normal Failures	Shutdown Failures	Share of Shutdown Failures*
Rotor	13	8	39%	92	12	12%
Generator	68	10	13%	84	7	8%
Gearbox	16	5	24%	116	4	3%
Electrical Facilities	72	31	30%	970	58	6%
Pitch & Yaw	39	7	15%	188	17	8%
Cooling & Hydraulic	113	28	20%	69	3	4%
Auxiliary	12	0	0%	217	5	2%
Average/per turbine**	4.4	1.17	--	5.54	0.34	--

*: Share of shutdown failures to the total; **: 76 onshore wind turbines and 313 offshore wind turbines.

The performance of the proposed approach is compared with five existing methods to verify its superiority in failure feature learning and failure data analysis, including the LSTM-CRF Model [23], BERT-Softmax Model [24], BERT-Span Model [25], and BERT-CRF Model [26]. Three metrics are implemented to qualify the performance of the models: precision (*P*, see Equation (8)), recall (*R*, see Equation (9)), and F1-score (*F1*, see Equation (10)).

$$P=\frac{|predition \cap true|}{|predition|} \tag{8}$$

$$R=\frac{|predition \cap true|}{|true|} \tag{9}$$

$$F1=\frac{2\times P\times R}{P+R} \tag{10}$$

where $prediction$ and $true$ reflect the predicted and true failure modes, $|predition \cap true|$ refer to the number of words that overlap in the predicted and actual failure modes, $|predition|$ and $|true|$ indicate the number of words of the predicted and true failure modes.

The comparative results in Table 3 indicate that the proposed method identifies the majority failure modes of offshore wind turbines and outperforms the other models as the adaptive resampling mechanism module highlighted rare failures and thus improved the accuracy for information extraction. The proposed method reduces the labour efforts of analysts engaged in textual data identification and classification. Specifically, out of 24,327 original records, 3,919 words with failure information are extracted, indicating 84% of non-failure-related appendant information is filtered.

Table 3. The comparison of model performance

Models	Metrics		
	P	*R*	*F1*
BERT-SPAN	0.71	0.81	0.76
BERT-SOFTMAX	0.80	0.76	0.78
LSTM-CRF	0.75	0.71	0.73
BERT-CRF	0.78	0.75	0.76
The Proposed Method	**0.75**	**0.83**	**0.79**

4.2 Failure criticality

Normal failures, critical failures, and extremely critical failures are categorised according to [6]: (i) normal failures have limited impact on productivity; (ii) critical failures reduce availability, resulting in wind turbines operating at low-rated power; (ii) Extremely critical failures refer to the event giving rise to the shutdown of wind turbines and the restart of which require additional materials and professional maintenance crew.

Table 4 and Figure 5 compare the failure criticalities of onshore and offshore wind turbines. It indicates that normal failures are the ones that a restart or minor repair can fix, while extreme critical shutdown failures are a minority (onshore (6%) and offshore (4%)). Younger offshore wind turbines perform better and benefit from advances in manufacturing, materials, and increased reliability of key components. Function failures of electrical, hydraulic, and electromechanical devices like electrical devices, cooling systems, hydraulics in pitch and yaw systems, and generators contribute more malfunctions than structural failures of rotors and gearboxes. Electrical components, including converter, transformer, monitoring/sensors and SCADA, weather unit, power, and controller, fail frequently and give rise to severe consequences, which call for special attention of practitioners to implement failure identification, monitoring, prevention, and control. The conclusion applies to both onshore and offshore wind turbines.

Table 4. Failure criticalities of components

Component	Normal failure		Critical failure		Extremely critical failure	
	Offshore	Onshore	Offshore	Onshore	Offshore	Onshore
Rotor	1%	5%	15%	4%	19%	4%
Generator	3%	15%	9%	31%	11%	27%
Gearbox	28%	4%	15%	7%	6%	8%
Electrical Facilities	66%	27%	28%	11%	40%	27%
Pitch & Yaw	13%	11%	11%	14%	11%	0%
Cooling & Hydraulic	4%	34%	5%	32%	2%	35%
Auxiliary	11%	3%	17%	1%	11%	0%

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From the component's point of view, the rotor, generator, gearbox, cooling & hydraulic, and auxiliary system of offshore wind turbines are prone to encounter critical/extremely critical failures. Failures of the mentioned components may result in unbearable and costly consequences due to low accessibility of offshore wind farms, low availability of weather windows, and high requirements for maintenance crews. Preventive actions for releasing impacts of the mentioned failures include (i) robust design and qualified supplier selection (ii) failure warning and prognosis based on SCADA or condition monitoring system data (CMS) (if any). The failure criticality comparison by wind farms, see Table 5, confirms that weather or geographical factors of wind farms have a significant impact on wind turbine failures. However, the characterisation of the mentioned impacts and the identification and modelling of weather and geographical factors are not in the scope of this paper.

Table 5. Failure criticalities by wind farm

Wind farms		Normal failure	Critical failure	Extremely critical failure
Offshore	Wind farm #1	298	81	15
	Wind farm #2	10	30	6
	Wind farm #3	58	75	4
	Wind farm #4	98	97	8
	Wind farm #5	641	221	13
	Wind farm #6	28	42	17
Onshore	Wind farm #1	167	23	3
	Wind farm #2	17	21	5
	Wind farm #3	32	11	15
	Wind farm #4	104	22	3

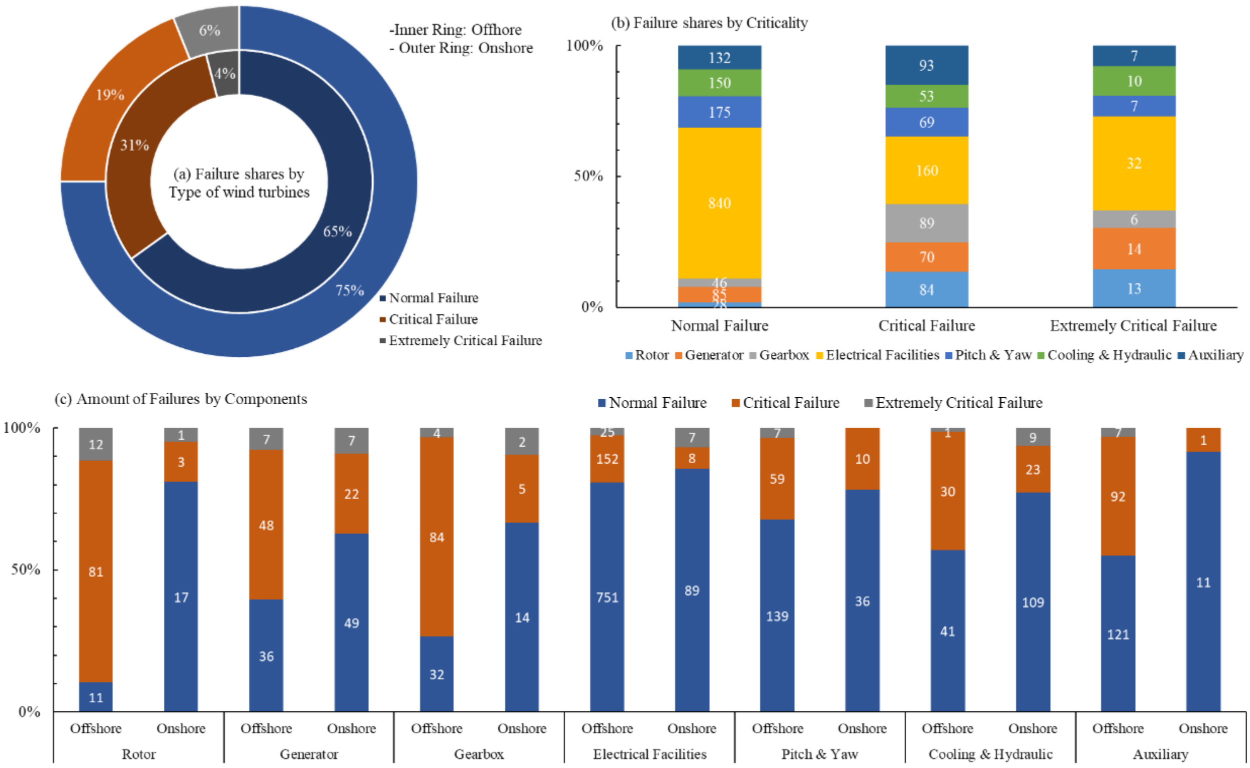

Figure 5. Comparison of failure criticality of wind turbines/(a) Failure shares by wind turbines; (b) Failure shares by criticalities; (c) Amount of failures by components

4.3 Failure frequencies and failure rate

Failure frequency, the number of failures within the observation period, helps to understand the number of failures of wind turbines or wind farms during a given period, according to which maintenance resources can be ordered and delivered before the preventive or corrective action. Figure 6 lists the failure frequencies of onshore and offshore wind turbines. According to Figure 6(c), offshore wind turbines are more robust in withstanding failures. It is noted that failure frequencies provide rough evidence for failure counting, which is impacted considerably by the observation period and amount of wind turbines involved.

Critical/extremely critical failure prevention supports productivity improvement of wind turbines and reduces shutdowns [6, 30], representing the primary tasks of wind farms' operation and maintenance. Table 6 lists critical failure statistics by wind farms, which confirms that offshore wind turbines are prone to encounter failures with severe consequences but the differences between onshore and offshore wind turbines in terms of such failures are less than 15%.

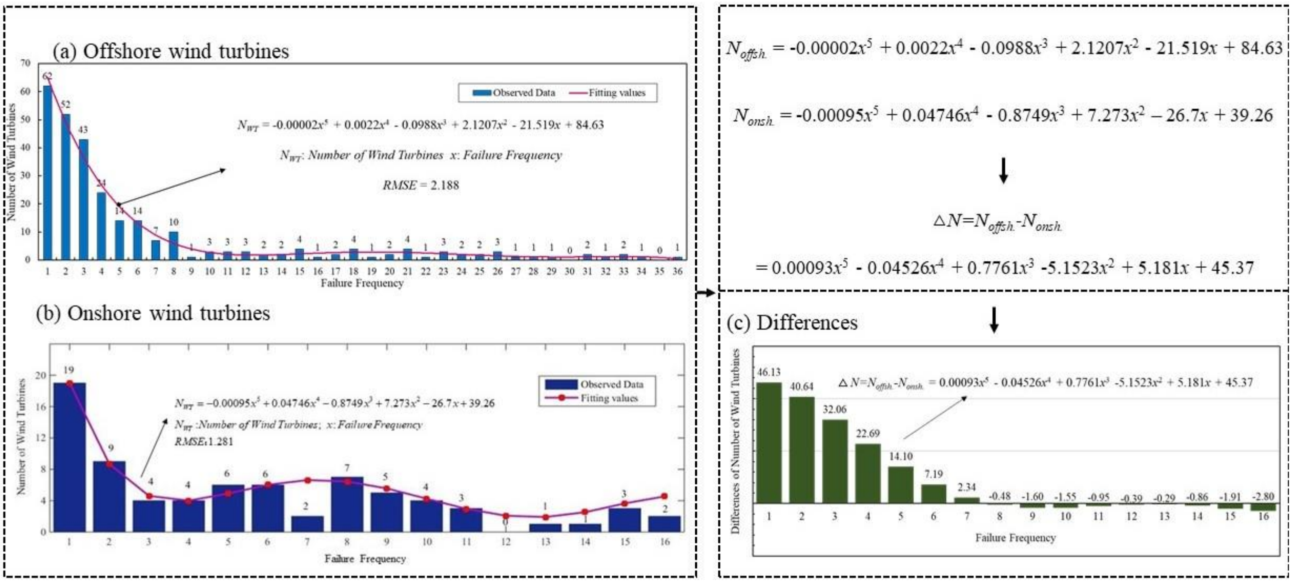

Figure 6. Failure frequency of wind turbines/(a) Offshore wind turbines; (b) Onshore wind turbines; (c) Differences between the two types of wind turbines; RMSE: Root Mean Square Error; Failure frequency: The number of failures monthly

It is noted that wind farm locations (onshore and offshore), weather conditions, and wind turbine models (manufacture) significantly impact the failures of wind turbines. Specifically, sea conditions, particularly air humidity and salt content, bring additional vulnerability to electrical switches and tiny structural elements like sealing rings. The specifically designed dehumidification system of offshore wind turbines should be strengthened. The evidence is insufficient to judge the degree of impact of weather conditions on failures as the offshore wind farms are close to each other, but geographical differences of onshore wind turbines illustrate obvious influences of weather conditions (or geographical factors) on failures. Modelling the abovementioned factors and mapping influential factors to failure properties of wind turbines are promising and practically needed, which is not in the scope of this paper and is still an open question of the wind energy sector.

Failure rate represents the likelihood of a failure in a unit of time [33, 34]. It is an inherent capability of wind turbines to withstand failures that give rise to coupling internal and external excitations [35-37]. Failure rates of components and the entire wind turbines are the foundation of failure, risk, reliability, availability, and maintainability investigation of wind turbines and other social and engineering systems, which links to fundamental characteristics of systems, for instance, failure probability (the foundation of the reliability and risk analysis), MTTF (the key factor of maintenance resources management), and so forth [38-41].

Table 6. Failure frequencies by criticality

Wind farm	Critical Failure		Extremely Critical Failure		In total	
	Percentage	Failure frequency	Percentage	Failure frequency	Percentage	Failure frequency
Offshore #1	2.21%	34.7	0.41%	6.4	2.62%	41.1
Offshore #2	0.82%	12.9	0.16%	2.6	0.98%	15.5
Offshore #3	2.05%	32.1	0.11%	1.7	2.16%	33.8
Offshore #4	2.65%	41.5	0.22%	3.5	2.87%	45.0
Offshore #5	6.04%	94.8	0.36%	5.5	6.4%	100.3
Offshore #6	1.15%	18	0.46%	7.3	1.61%	25.3
Average	**2.49%**	**39**	**0.29%**	**4.5**	**2.78%**	**33.8**
Onshore #1	2.59%	10.7	0.34%	1.4	2.93%	12.1
Onshore #2	2.36%	9.8	0.56%	2.3	2.92%	12.1
Onshore #3	1.24%	5.1	1.69%	7.0	2.93%	12.1
Onshore #4	2.48%	10.2	0.34%	1.4	2.82%	11.6
Average	**2.17%**	**9**	**0.73%**	**3**	**2.9%**	**12**

Percentage: The share of (extremely) critical failures in the total; Failure frequency: The amount of (extremely) critical failures per year.

Overall, the failure rate of the 313 offshore wind turbines is 2.38 failures/turbine/year with an MTTF of 3672 hours, which is at a comparable level to the 76 onshore wind turbines, which are 2.57 failures/turbine/year and 3409 hours, see Figure 7 and Table 7.

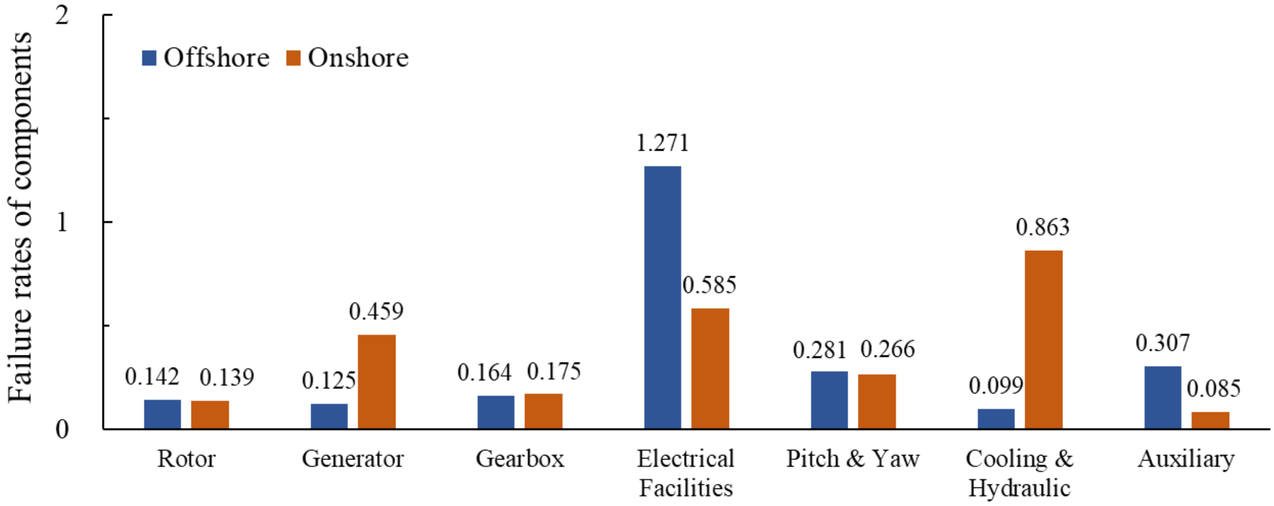

Figure 7. Failure rates of wind turbines by components/ Failrue rate denotes failure/turbine/year

Table 7. Failure rates and MTTFs of subcomponents

Components	Subcomponents	MTTF/h		Failure Rate /Year/Turbine		Differences in failure Rate /Offshore to Onshore	
		Onshore	Offshore	Onshore	Offshore	De/Increase	Amount
Rotor	Blades	50563	101775	0.0905	0.0849	↘	0.0056
	Hub	126407	6310080	0.0362	0.0014	↘	0.0348
	Main Bearing	758441	701120	0.0061	0.0123	↗	0.0062
	Main Shift	758441	573644	0.0061	0.0151	↗	0.009
	Others	--	6310080	--	0.0164	--	--
Generator	Generator	9979	87640	0.4585	0.0986	↘	0.3599
	Others	--	332109	--	0.0260	--	--
Gearbox	Gearbox	26153	76025	0.1750	0.1136	↘	0.0614
	Others	--	170543	--	0.0507	--	--
Electrical Facilities	Convener	12641	36901	0.3620	0.2341	↘	0.1279
	Monitoring and SCADA	29171	57891	0.1568	0.1492	↘	0.0076
	Weather Unit	68949	901440	0.0664	0.0096	↘	0.0568
	Others	--	9844	--	0.8777	--	--
Pitch & Yaw	Pitch System	21068	35056	0.2172	0.2465	↗	0.0293
	Yaw System	94805	252403	0.0483	0.0342	--	0.0141
Cooling & Hydraulic	Cooling System	10835	161797	0.4223	0.0534	↘	0.3689
	Hydraulic	10390	191215	0.4404	0.0452	--	0.3952
Auxiliary	Crane	758441	788760	0.0061	0.0110	↗	0.0049
	Climbing Aid	758441	252403	0.0061	0.0342	↗	0.0281
	Brake	252814	2103360	0.0181	0.0041	↘	0.014
	Nacelle	84271	126202	0.0543	0.0685	↗	0.0142
	Others	--	45725	--	0.1890	--	--

The comparison indicates that:

- Failure rates and MTTFs of the two types of wind turbines are comparable. The evidence, however, is insufficient to confirm that large-scale offshore facilities are more robust to withstand the damages than onshore devices as offshore wind turbines are younger. To this end, it is unfair to identify differences in failure rate and MTTF of wind turbines in unequal operational periods.
- Generator and cooling & hydraulic equipped in offshore devices are more robust, indicating that larger generators (5.6 MW-6.2 MW) and novel cooling and hydraulic system configurations designed (such as the

designed dehumidification system) process superior reliability than smaller 2 MW onshore wind turbines. Electrical facilities of offshore wind turbines are failure-prone components, but the failure rates of onshore facilities are lower. The conclusion explains the latecomer advantages of recent offshore wind turbines as a consequence of novel design concepts, advances in materials, manufacturing, and so forth.

- The elements of offshore devices hold higher failure rates, for instance, the main bearing, main shaft, nacelle, etc., reflecting that salty and humidity sea conditions introduce damages to structures when the dehumidification system cannot cover, but failure rates are low.

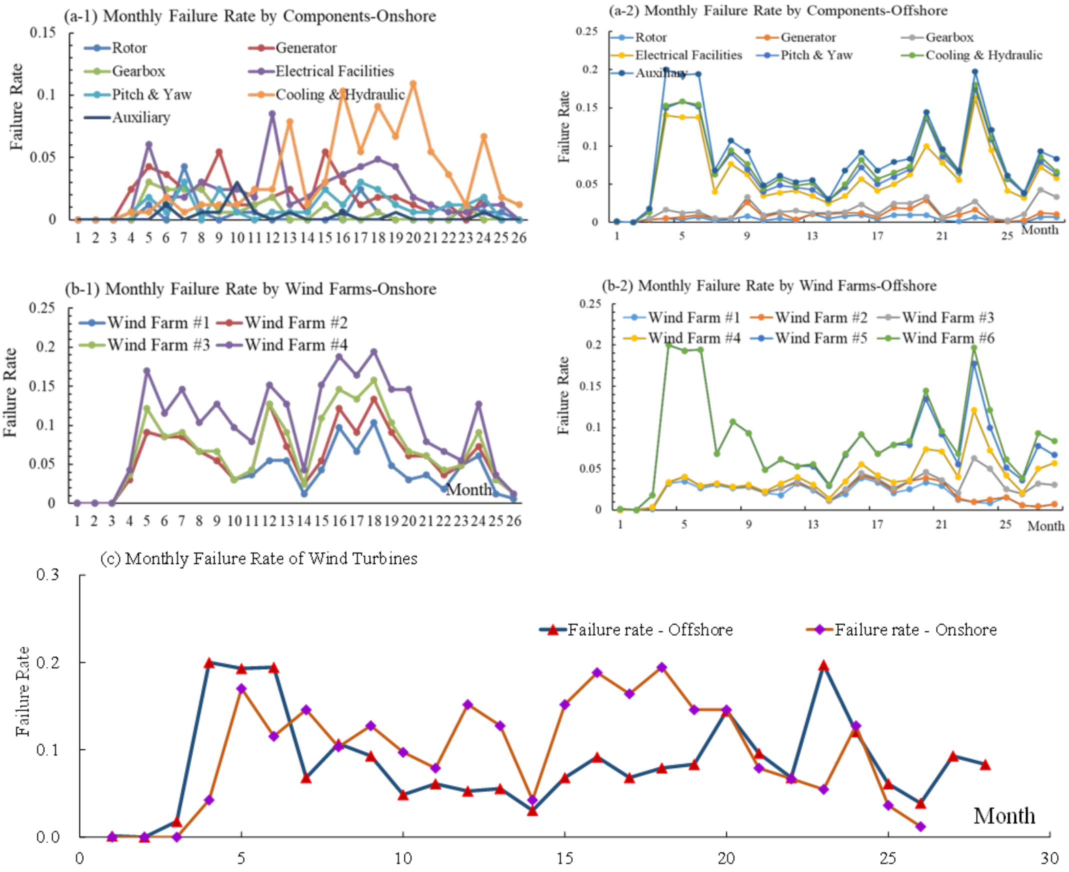

Figure 8. Failure rates of wind turbines/(a) by components; (b) by wind farms; (c) overall

Figure 8 lists the monthly failure rate of wind turbines. No obvious change regulations, such as periodicity and monotonicity, were found, but the results give the wind sector a basic understanding of system dynamics. On the other hand, several components in specific wind farms are weak links of wind turbines, such as electrical facilities in wind farm #4 (onshore) and cooling & hydraulic elements and auxiliaries in wind farm #6 (offshore). The reason can be traced back to the model of wind turbines selected by wind farms.

4.4. Maintenance properties of wind turbines and logistics of wind farms

Maintenance actions are corrective responses to failures [42, 43]. According to LGS-Onshore and LGS-Offshore, maintenance actions have been implemented, as seen in Table 8, including (i) Restart. Restart with no materials consumption; (ii) Replace. Repairing with replacement; (iii) Repair. Repair without replacement; (iv) Failure checking. Checked and waiting for materials; the wind turbines can be in operation or in a stoppage state; (v) Waiting for the supplier. Waiting for the maintenance crew or suppliers, the wind turbines can be in operation or at a stoppage state. (vi) Waiting for instructions: Unrepaired due to unknown failure causes; a lack of experience; minor failures with limited impact; beyond the authority of the maintenance crew; huge and expensive structures.

The statistics concluded that replacement and failure checking for minor events fix most failures. Specifically, the on-site maintenance crew handled more than 87% (failure checking 42.9% and replacement 44.8%) of offshore wind turbine failures in one or two visits. The same conclusion is also applicable to onshore wind turbines, knowing that the difficulty of maintaining onshore devices is less than 17%.

Compared with onshore wind turbines, the maintenance of offshore facilities is more complicated, and spare parts management is crucial. For instance, 16% of unfixed failures of onshore wind turbines resulted from a lack of spare parts, and the same proportion of offshore systems is more than 34%. Additionally, some 45% of offshore wind turbine failures are fixed in one visit, which is lower than that of onshore systems (more than 68%). It indicates that the management of maintenance resources, especially spare parts, should be optimally scheduled especially for offshore facilities as visits and port rent are costly.

Unknown failures of offshore wind turbines take fewer proportions of the entire maintenance activities than those of onshore owing to the well-accumulated onshore wind sector maintenance experiences. However, training the maintenance crew is still recommended to reduce the impact of unknown failures, which require additional visits and add costs to the operation and maintenance of wind farms, especially offshore ones.

Maintenance consequences represent the results after the maintenance actions had been implemented, including the state of wind turbines and the supply chain in case of additional materials are needed, see Figure 9. Unfixed failures (which cannot be handled in one visit) call for the special attention of wind farm operators, despite these events taking only 8% (offshore) and 9% (onshore) of wind turbine failures. These events, however, result in the shutdown of wind turbines and are the main reasons for the capacity factor and availability reduction of wind turbines and wind farms.

Table 8. Maintenance actions of wind turbines

Maintenance Actions	Offshore		Onshore		Differences in failure Rate /Offshore to Onshore	
	Amount	Share	Amount	Share	De/Increase	Amount
Restart	4	0.2%	0	0%	↗	0.2%
Failure checking	747	42.9%	63	14.9%	↗	28%
Replace	781	44.8%	235	55.6%	↘	10.8%
Waiting for the supplier	127	7.3%	26	6.1%	↗	0.8%
Waiting for instructions	76	4.4%	45	10.6%	↘	6.2%
Repair	7	0.4%	54	12.8%	↘	12.4%

Electrical facilities fail frequently but more than 80% of these can be fixed once, which is the same as the cooling & hydraulic system. However, the rotor of offshore wind turbines and the generator of onshore wind turbines are difficult to repair and require additional maintenance and even the intervention of suppliers or manufacturers. To this end, maintenance crew training and redundancy design for the mentioned components are suggested.

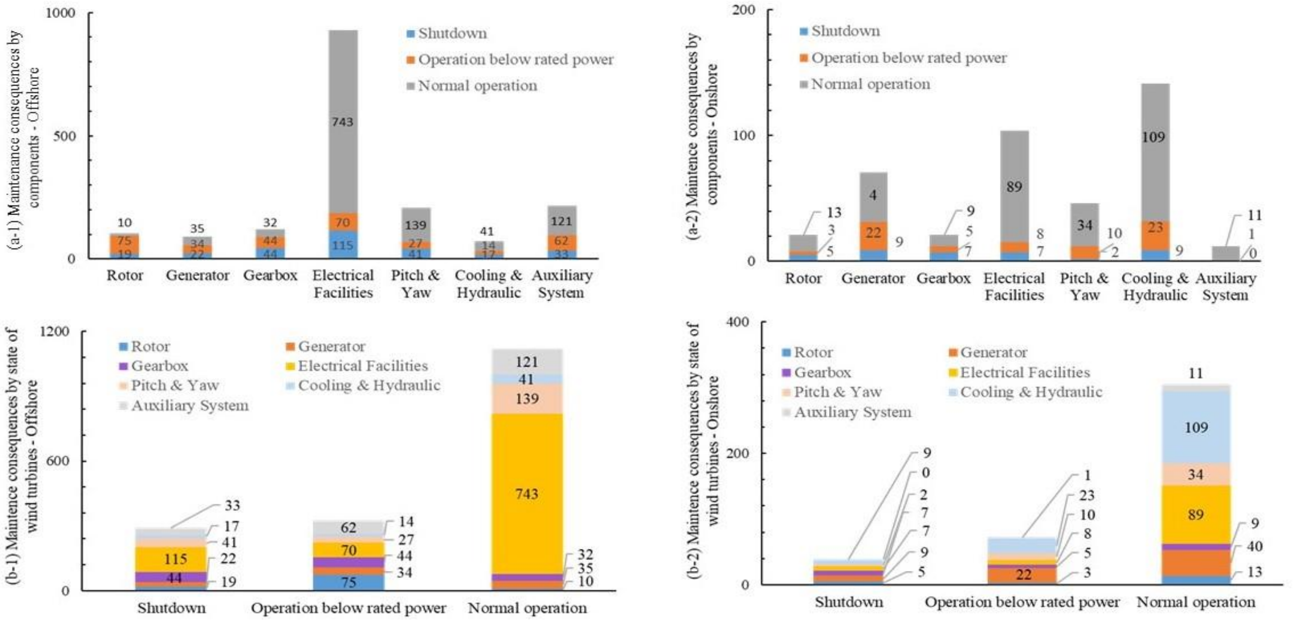

Figure 9. Failure consequences/ (a) by components; (b) by the state of wind turbines

Logistics of wind farms characterise the arrangement of maintenance resources, including vessels, personnel, and time and frequency of travelling to wind farms [44-46]. Overall, 1168 visits to offshore wind farms and 338 visits to onshore wind farms are recorded together with an additional 26 visits (with an average of 244 hours) for the offshore wind turbine installation. The statistic reveals key factors of wind farm management, for instance:

- **Offshore wind**. The average visit is 1.7 times/turbine/year and 199 visits/farm; the average duration of maintenance crew is 137 hours/turbine/year and 8572 hours/farm; the average duration is 87 hours per visit. Most failures of offshore wind turbines can be fixed within 24 hours (90 visits, 5% of the total), 48 hours (198 visits, 11%), and 72 hours (292 visits, 17%), see Figure 10. Visit time comprises vessels' travelling time to wind farms (round trip) and time to repair of each failure. According to Table 8, the travelling time is impacted slightly by distance to the coast, which confirms that the time to repair and the time to visit are primary factors.

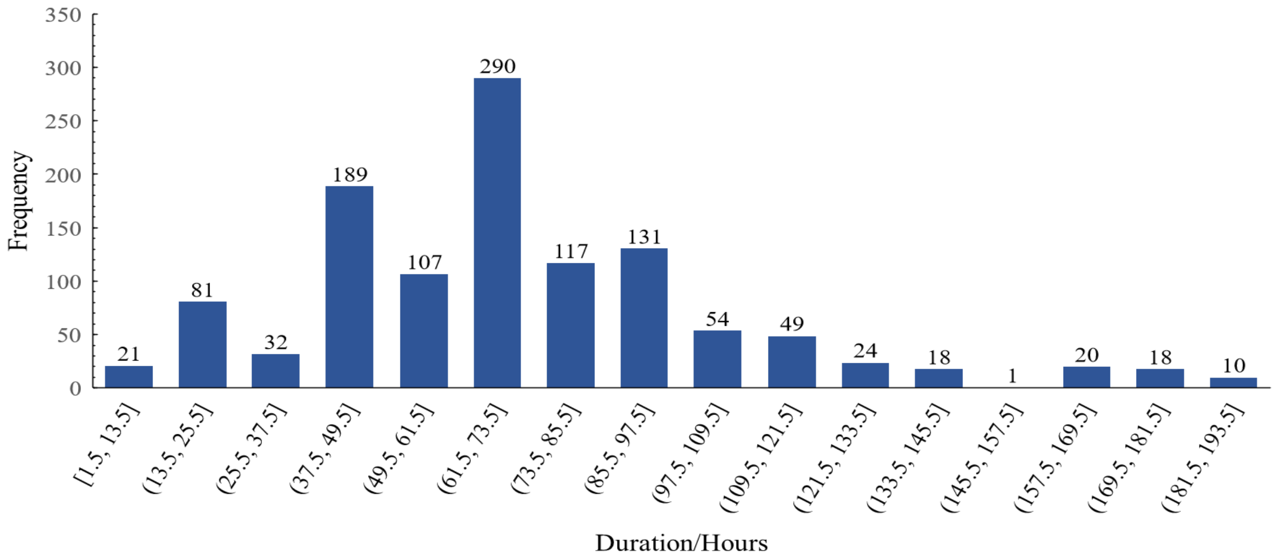

Figure 10. Visit times of wind turbine

Table 8. Visit times of wind farms (offshore)

Wind farms	Visits	Total Duration / hours	Average Duration / hours
Wind farm #1	356	26993.8	75.83
Wind farm #2	--	--	--
Wind farm #3	6	382.5	63.75
Wind farm #4	73	7240.35	99.18
Wind farm #5	754	63387.6	84.07
Wind farm #6	5	578.2	115.64
Average	199	19716	87.69

- **Onshore wind**. The maintenance record of onshore wind turbines decomposes a maintenance procedure into Reaction Time (RT), Traveling Time (TT), and Time to Repair (TR). To be specific, RT is a period between failure and maintenance instructions being made, and TT is a period between maintenance instructions being formed and maintenance starting. RT and TT reflect the quality of monitoring and management of wind farms. TR is a period between the maintenance start and completion, representing the capability of the maintenance crew. RT, TT, and TR of onshore wind turbines are listed in Table 9. The visit time of onshore wind turbines (40 hours) is significantly less than that of offshore ones (87 hours). The shorter visit time of onshore wind turbines is the consequence of multiple aspects, for instance, the onshore maintenance crew completes the maintenance schedule as soon as the wind turbines restart, while maintenance of offshore wind turbines will be complete after maintenance vessels return to port and which, sometimes, make maintenance crew staying at the mother vessels (hotel vessels) hours or even days without tasks to carry out.

Table 9. Visit times of wind farms (onshore)

Wind Farms	Reaction Time /hours	Travelling Time /hours	Time to Repair /hours	Average Visit time /hours
Wind Farm #1	1	5	2.5	8.5
Wind Farm #2	4	7	3.4	14.4
Wind Farm #3	50	6	6.2	62.2
Wind Farm #4	67	5	4.4	76.4
Average	30.5	5.75	4.13	40.38

Another primary aspect of offshore wind farm management is the vessel and crew scheduling, see Table 10. The statistics confirm that almost all maintenance of offshore wind turbines can be completed by one vessel, except for major events (less than 3%), with an average number of 6.5 crew members, more than that of onshore wind turbines requesting less than four crew members. The limited maintenance windows and requirements of security personnel are the reasons for more crew demand for offshore wind.

Table 10. Maintenance vessels and crew scheduling

Vessel demand in one visit			Crew demand in one visit		
Amount	Visits	Percentage	Amount	Visits	Percentage
1	1322	97.78%	0-5	508	37.57%
2	12	0.89%	6-10	665	49.19%
3	16	1.18%	11-15	142	10.50%
4	2	0.15%	>15	37	2.74%
In Total	1352	100%	In Total	1352	100%

5. Discussions

With the surging demand for wind energy and the continuously increased installation of onshore and offshore wind turbines, failure and maintenance issues become crucial for cost-saving oriented operation and maintenance. This paper proposes an intelligent failure feature learning framework to support the wind energy sector's failure and maintenance data management. Additionally, with the assistance of the two most recent datasets, failure and maintenance features of both types of wind turbines are characterised, and their differences are highlighted as a basis to provide the sector with a deep understanding of the design and operation of wind turbines and wind farms, onshore and offshore, bottom-fixed and floating. One should realise that:

(i) In total, 3919 entries (contexts with failure information) have been extracted from the original set of 24327 entries in the maintenance record. This highlights an impressive 84% reduction in extraneous information not directly related to failures. The proposed failure data analysis framework can significantly diminish labour efforts by over 80%, especially in identifying components and their corresponding failure modes. However, analyst interactions are still required for projects or analyses that demand more in-depth and detailed failure classification, such as specific root failure causes and maintenance activities, although the workload has been substantially reduced. To provide the sector with a deep understanding of root failure causes for the identified failure modes, seven maintenance crew members (three from onshore wind farms and four from offshore wind farms) have been consulted to analyse and identify the root failure causes of the wind turbines, see Appendix B.

(ii) The most recent datasets present features of recent wind turbines (20% 2 MW and 80% 5.6-6.2 MW) rather than the previous small-scale devices. The statistical results can be applied to wind projects with similar wind turbines. The failure and maintenance features of smaller and older wind turbines can be accessed in [15] and [47].

(iii) The failure features of onshore and offshore wind turbines are similar, as all wind turbines are in their early stage (less than five years old, and most of them are younger than three years old). It indicates that the identified failure features can be applied directly at the early stage of wind projects. However, for the decision-making of wind farms over five years old or those stepping into the degradation phase, failure information transformation to old [7] and varied turbine types, such as floating offshore wind turbines [14] is needed.

(iv) The 2165 failures in this paper, 423 onshore and 1742 offshore, are mostly equipment failures. No structural failures happened to the transition piece and foundation as those failures will experience a long degradation process before occurrence. However, structural failures will become critical with age extending, which has been determined in [17], [18], [20], and [28].

(v) One should have a dialectical view toward failure rate that is a time-varying index affected by, at least, age, sea/weather conditions, and operation measures. This paper reveals a lower failure rate of offshore wind turbines, specifically 2.57 failures/turbine/year, which disagrees with the published results of almost 5-8 failures/turbine/year [3, 7, 14, 15]. The reason is that advances in material, manufacturing, and design concepts and younger age offset the additional damages introduced by sea conditions. With age increases, failure rates of both wind turbines will be subject to increscent, and the failure rate of offshore wind turbines is expected to increase faster.

(vi) The maintenance features released can be directly applied to the design and understanding of onshore and offshore wind farms, especially maintenance times and the arrangement of vessels and personnel, as the onshore wind farms are similar (refer to wind farms and operation centre). The distance from shore of offshore wind turbines varies but which have limited impact on maintenance arrangement according to the results concluded in this paper.

6. Conclusions

This paper introduces an intelligent failure feature learning framework designed for efficient failure and maintenance data management of the wind energy sector. The framework demonstrates its capability to accurately identify wind turbine failures from extensive failure and maintenance data. Additionally, the paper presents the LGS-Onshore and LGS-Offshore datasets, representing the latest and most comprehensive records of wind turbine failure and maintenance information. Leveraging the proposed framework, the analysis reveals distinctions and similarities between onshore and offshore wind turbines. The findings contribute valuable insights to enhance wind turbine design, optimise operation and maintenance strategies, improve lifelong performance, and achieve overall cost savings.

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Appendix A. Failures of main components

Components	Subcomponents	Failure Descriptions
Rotor	Hub	Hub broken; *Hub disordering*; *Size of nose mounting hole mismatch*; *Rainproof ring failure*; *Nose interference*; *Rainproof brush failure*; *Nose cracked*
	Main Bearing	Bearing over-heat; Bearing seat failure; *Abnormal noise*; *Abnormal wear*
	Blade	Cracked; Comes off; Delamination; Wear with Hub; Replace for a new standard; *Rust on blade bolts*; *Blade bolt tensioner failure*
	Main Shaft	*Main shaft bolt detachment*; *Abnormal noise*; *Bolt failure*; *Main shaft overtemperature*
Generator	Generator	Carbon brush failure*; Slip ring failure*; Cooling water pump failure*; Generator elastic support failure; Lubrication pump motor failure; Cooling water tank failure; Cooling fan failure; Generator encoder failure; Bearing failure; Insufficient bearing grease; Cable failure; generator converter short circuit; *Generator lightning arrester failure*
Gearbox	Components	Temperature control valve failure; Abnormal gear wear; *Pressure sensor failure*; *Elastic support failure*; *Gear root peeling*; *Gearbox desiccant failure*; *Gearbox paint peeling*
	Lubrication	Fe content exceeded; Leak; Lubrication pump filter failure*; Lubrication pump motor failure*; Seal damage; Cooling water pump failure
Electrical Facilities	Converter	Cooling failure; Cable failure; Contactor damage; Fuse blown; Breaker failure; Power failure*; Circuit failure*; Reactor damage*; Crowbar board failure*; Current transformer failure*; Communication module failure; *overt-heat*
	Transformer	*Cooling water pump leakage*; *Cooling water pump overload*; *winding insulation layer broken*; *over-heat*; *Oil pump motor failure*; *Power module failure*; *Temperature controller failure*; *Water pump pressure sensor failure*
	SCADA	SCADA reports unknown data; *Abnormal power*
	Control System	Yaw fuse failure; Yaw contactor failure*; Communication module failure; Fiber damage*; Yaw starter failure; Unknown failure*; Cooling Fan failure; Cable failure; Shutdown; *Yaw brake resistor box failure*; *Ring network switch failure*; *Tower base switch failure*; *Loose control cabinet plug*; *Grid measurement module*; *Safety relay failure*; *Programmable Logic Controller Module failure*; *Screen failure*; *Lightning protection module failure*; *Ring network cabinet failure*; *Arc light protection device failure*
	Weather Units & Sensors	The wrong temperature reported*; Pressure sensor damage; Brake sensors failure; Anemometer damage*; Anemometer failure; *Acceleration sensor failure*; *Smoke sensor failure*; *Grounding resistance failure*
Pitch & Yaw	Gearbox & Motor	Wrong pitch angle*; Fe exceeding standard; Leak, Encoder damage*, Malfunction; *Oil collection bottle detachment*; *Lubrication pump failure*; *Bolt of pitch bearing broken*
	Electric & Controller	Fuse blown*; Motor damage*; Cable failure; Power failure; Blockage; Pump damaged; Pitch Reducer Leak; Capacitor damage*; Contactor damage; Power overload*; Cable failure; Fuse blown; Limit switch triggered by mistake*; Slip Rings*; *Pitch control cabinet overtemperature*
	Yaw	Leak; structural damage; Yaw reducer broken tooth; *Yaw electromagnetic brake failure*; *Yaw motor failure*; *Yaw brake pad wear*; *Oil collection tray failure*
Cooling & Hydraulic	Internal Cooling	Water Cooling pump failure*; Lubrication pump motor failure*; Cooling water tank failure; Seal damage*; Water Cooling switch*; Water pump seal failure; Air cooler failure; Lubrication pump filter failure
	External Cooling	Motor failure*; Blade failure*; Cover failure; Fan failure
	Hydraulic Units	Storage tank damage; Storage tank leak gas and oil*; Improper maintenance; Electromagnetic valve damage*; Storage tank low pressure (unknown reasons); Periodical replacement of filter (half a year)**; Hydraulic tubing leaks; Brake pressure switch failure; Hydraulic motor failure; Filter failure
Auxiliary	Auxiliary Components	Lightning protection belt broke; Water leak; sunroof support rod damage; Guardrail damage; Shroud broken; Beam failure; Brake failure; *Electric hoist failure*
	Lifting equipment	Climbing Aid Control elements failure; *Climbing Aid battery failure*; *elevator pulley failure*; *Power supply phase loss*; *Fuse failure*; *Limit switch failure*; *Water penetration*
	Dehumidification System	*Power module failure*; *Motor failure*; *Salt mist filter failure*; *Contactor failure*
	Auto-Firefighting System	*Firefighting element failure*; *Firefighting mistake*; *Low automatic fire protection pressure*; *Firefighting bottle failure*

*: failures resulted in wind turbines shutdown; **: Replacement without failure; Elements with *italics and underline* represent failures are observed in offshore but not onshore wind turbines; Several failure similar failure modes are integrated.

Appendix B. Failure causes of wind turbines

Component	Failure Mode	Failure Causes
Rotor		
Hub	Hub broken	Manufacturing error
	Hub disordering	Manufacturing error; Fitting error
	Unmatched mounting hole	Manufacturing error; Fitting error
	Rainproof ring failure	Locking pin defect
	Noise interference	Impeller speed exceeds limit; Cam wear
	Rainproof brush failure	~~
	Nose cracked	Hit by objects; Material failure; Manufacturing error
Main Bearing	Bearing over-heat	Lubrication failure; Manufacturing error; Fitting error
	Bearing seat failure	Fatigue; Material failure
	Abnormal noise	Substandard lubrication; Wear
	Abnormal wear	Substandard lubrication
Blade	Crack	Manufacturing error
	Comes off	Connectors failure; bolt crack
	Delamination	Insufficient lighting protection
	Wear with Hub	Manufacturing error; Fitting error
	Replace for a new standard	~~
	Rust on blade bolts	Anti-corrosion failures; Painting failure
	Blade bolt tensioner failure	Device failure
Main Shaft	Main shaft bolt detachment	Fatigue; bolt tensioner failure
	Abnormal noise	Lubrication failure
	Bolt failure	Tensioner failure; Fitting error
	Main shaft overtemperature	Lubrication failure; Wear; lubrication pump failure
Generator		
Generator	Carbon brush failure	Wear; Over tighten
	Slip ring failure	Wear
	Cooling water pump failure	Cooling internal circulation inverter failure
	Generator elastic support failure	Degradation; fatigue-temperature cycle
	Lubrication pump motor failure	Overheat; Abnormal winding temperature
	Cooling water tank failure	Crack
	Cooling fan failure	Overheat
	Generator encoder failure	Electrical logic elements failure
	Bearing failure	Rollaway electric corrosion; Wear; Improper grease
	Insufficient bearing grease	Lubrication failure - pump, tank, human error
	Cable failure	Cable insulation failure
	Generator converter short circuit	Overheat; Lightning protection failure
	Generator lightning arrester failure	Devices Failure
Gearbox		
Components	Temperature control valve failure	PLC failure; Sensor failure; Actuator failure
	Abnormal gear wear	Wear; Fatigue; Dirty or lacking lubrication
	Pressure sensor failure	Devices Failure
	Elastic support failure	Vibration; Aging
	Gear root peeling	Dirty or lacking lubrication; Shock exceed limitation
	Gearbox desiccant failure	~~
	Gearbox paint peeling	Paint peeling; Vibration; Corrosion
Lubrication	Fe content exceeded	Wear
	Leak	Seal damage
	Lubrication pump filter failure	Crack
	Lubrication pump motor failure	Power Failure; Short circuit
	Seal damage	Corrosion
	Cooling water pump failure	Fatigue; Crack
Electrical Facilities		
Converter	Cooling failure	Cooling system failure
	Cable failure	Overheat; Load mutation; Invert power input fault
	Contactor damage	Ware; Spark erosion
	Fuse blown	Overheat; Corrosion
	Breaker failure	Corrosion: Converter safety chain disconnected
	Power failure	Abnormal current; Vibration
	Circuit failure	Preheat inverter; Abnormal current; Welding failure
	Reactor damage	Device failure
	Crowbar board failure	~~
	Current transformer failure	Electromagnetic compatibility equipment failure
	Communication module failure	Cable failure; Network failure

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	Overheat	Cooling system failure
Transformer	Cooling water pump leakage	Overheat; Corrosion
	Cooling water pump overload	Cooling water block; Dirty water; Pump failure
	Winding insulation layer broken	Overheat; Corrosion; Aging
	Over-heat	Cooling system failure; Abnormal impedance
	Oil pump motor failure	Power Failure; Short circuit
	Power module failure	Open circuit
	Temperature controller failure	Bus failure; PLC failure; Actuator failure
	Water pump pressure sensor failure	Device failure
SCADA	SCADA reports unknown data	Sensor failure; Motherboard failure; Communication failure
	Abnormal power	Connector failure; Cable failure
Control System	Yaw fuse failure	Corrosion
	Yaw contactor failure	Device failure
	Communication module failure	Software failure; Sensor failure
	Fiber damage	Aging
	Yaw starter failure	Device failure
	Cooling Fan failure	Overheat; Devices failure
	Cable failure	Cable insulation failure; Aging
	Shutdown	~~
	Yaw brake resistor box failure	Open circuit; Aging; Corrosion
	Ring network switch failure	Switch failure
	Tower base switch failure	Switch failure
	Control cabinet plug lose	Human error; Vibration
	Grid measurement module failure	Sensor failure; Devices failure
	Safety relay failure	Device failure
	Logic Controller Module failure	~~
	Screen failure	Broken; cable connection failure
	Lightning protection module failure	Open circuit
	Ring network cabinet failure	Circuit failure; Aging; Corrosion; Devices failure
	Arc light protection device failure	~~
Weather Units & Sensors	The wrong temperature reported	Sensor failure
	Pressure sensor damage	Devices failure
	Brake sensors failure	Devices failure
	Anemometer damage	Broken; Hit by objectives
	Anemometer failure	Low quality
	Acceleration sensor failure	Device failure
	Smoke sensor failure	Device failure
	Grounding resistance failure	~~
Pitch & Yaw		
Gearbox & Motor	Wrong pitch angle	Poor calibration
	Fe exceeding standard	Wear
	Leak	Joint corrosion
	Encoder damage	Device failure
	Malfunction	Manufacturing error; Measurement failure; Position failure
	Oil collection bottle failure	Detachment failure; Overtight
	Lubrication pump failure	Fatigue; Crack
	Bolt of pitch bearing broken	Overload
Electric & Controller	Fuse blown	Overheat; Corrosion
	Motor damage	Overload
	Cable failure	Wear; Corrosion
	Power failure	Power Cable failure; Abnormal current; Vibration
	Blockage	Software failure; PLC failure
	Pump damaged	Fatigue; Crack; Control failure
	Pitch Reducer Leak	Joint corrosion; Welding failure
	Capacitor damage	Overload
	Contactor damage	Devices failure
	Power overload	Grid failure
	Limit switch triggered by mistake	Switch failure
	Slip Rings	Wear
	Pitch control cabinet overtemperature	Cooling system failure; Overload; Short circuit
Yaw	Leak	Joint corrosion; Lubrication oil over limit
	structural damage	Overload; strong wind
	Yaw reducer broken tooth	Overload; Fatigue; Ware
	Yaw electromagnetic brake failure	Aging; Electromagnetic disturbance
	Yaw motor failure	Connector failure; Cable failure
	Yaw brake pad wear	Devices failure
	Oil collection tray failure	Devices failure

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Cooling & Hydraulic		
Internal Cooling	Water Cooling pump failure	Cooling radiator fan failure; Three-way valve failure
	Lubrication pump motor failure	Variable flow water cooling low pressure; Power failure
	Cooling water tank failure	high pressure cooling water; Crack
	Seal damage	Aging; Corrosion
	Water Cooling switch failure	Devices failure
	Water pump seal failure	Fitting error; high pressure cooling water; Corrosion
	Air cooler failure	Device failure
	Lubrication pump filter failure	Device failure
External Cooling	Motor failure	Overheat; Power failure
	Blade failure	Device failure
	Cover failure	Crack; Hit by objectives
	Fan failure	Device failure
Hydraulic Units	Storage tank damage	Sensor failure; Crack; Corrosion; Pump failure
	Storage tank leak gas and oil	Crack; Corrosion; Pump failure; Improper maintenance
	Electromagnetic valve damage	Aging; Electromagnetic disturbance
	Storage tank low pressure	~~
	Hydraulic tubing leaks	Aging; Corrosion
	Brake pressure switch failure	Device failure
	Hydraulic motor failure	Power Cable failure; Motor damage; Control failure
	Filter failure	Device failure
Auxiliary		
Auxiliary Components	Lightning protection belt broke	Open circuit; Aging; Corrosion
	Water leak	Aging; Corrosion
	Sunroof support rod damage	Device failure
	Guardrail damage	Aging; Corrosion; Fatigue
	Shroud broken	Hit by objectives
	Beam failure	Crack
	Brake failure	Wear
	Lightning protection belt broke	Open circuit; Aging; Corrosion
Lifting equipment	Climbing Aid Control elements failure	PLC failure; Actuator failure
	Climbing Aid battery failure	Power Failure; Human errors
	Elevator pulley failure	Device failure
	Power supply phase loss	Human errors; Grid error
	Fuse failure	Device failure
	Limit switch failure	Device failure
	Water penetration	Seal failure
Dehumidification System	Power module failure	Aging; Corrosion; Control failure
	Motor failure	Overload
	Salt mist filter failure	Device failure
	Contactor failure	Device failure
Auto-Firefighting System	Firefighting elements failure	Overheat; Pump failure
	Firefighting control failure	PLC failure; Sensor failure
	Low automatic fire protection pressure	Sensor failure
	Firefighting bottle failure	Device failure

Devices failure: The failure will not be analysed further by maintenance crew; ~~: Unknown failure causes