Reliability Engineering and System Safety 238 (2023) 109475

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Impact of condition monitoring on the maintenance and economic viability of offshore wind turbines

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ARTICLE INFO

Keywords:
Wind turbine
Condition monitoring
Maintenance
Petri net
Offshore wind system

ABSTRACT

This study explores how condition monitoring (CM) can help operate offshore wind turbines (OWTs) effectively and economically. In this paper, the Petri Net (PN) simulation models are developed to quantitatively assess the OWT availability and operation and maintenance (O&M) costs. By investigating the impact of two CM approaches (i.e. purpose-designed CM and Supervisory Control and Data Acquisition (SCADA)-based CM) and their combinations with various maintenance strategies, the paper addresses two fundamental questions about OWT CM that have plagued the offshore wind sector for many years. They are 'is a wind farm SCADA system a viable alternative to purpose-designed condition monitoring system (CMS)' and 'what is the best way to integrate CMSs and maintenance strategies to maximise the financial benefit of OWTs'. The research suggests that although utilising both a wind farm SCADA system and a purpose-designed CMS can achieve the highest turbine availability, it is not the most cost-effective option in terms of maintenance expenses. Instead, combining purpose-designed CM with less frequent advanced service can achieve the desired availability at the lowest cost. Furthermore, the use of a purpose-designed CMS is essential for the economical operation of OWTs and cannot be replaced by the current wind farm SCADA system.

1. Introduction

Wind power has been widely recognised as a viable means of mitigating climate change [1]. Although most wind turbines today operate on land, there is a growing trend towards deploying larger wind turbines offshore, where there are better wind resources and less visual impact, noise pollution, and land use issues [2]. According to the Global Wind Report published by GWEC, offshore wind farms (OWFs) have expanded greatly over the past decade, and global offshore wind capacity additions are expected to exceed 70 GW in 2021–2025 [3]. According to the data published in the UK Wind Energy Database, as of mid-August 2022, the UK has 11,198 wind turbines with a total installed capacity of over 25.5 GW, of which 11.3 GW is offshore [4]. These wind turbines contributed about 28.8% of the UK's electricity generation in the first quarter of 2022, making wind power the UK's largest source of renewable electricity with a 63.3% share. The UK Government has pledged to further expand offshore wind capacity over the next few years to secure 50 GW of offshore wind capacity by 2030. However, the offshore wind industry is currently under intense pressure to reduce the Levelised cost of energy (LCOE) [3,5]. Today, this pressure is being exacerbated as wind farms are moved further offshore, where the operation and maintenance (O&M) costs and the unavailability of offshore wind turbines (OWTs) may increase exponentially due to the increased offshore distance [6–8]. Many studies have shown that maintenance costs pose a non-negligible financial risk to wind power projects [9–12]. In addition, harsh environments at remote OWFs and rising charter rate of wind farm maintenance vessels will further worsen the situation.

To address this issue, various wind turbine condition monitoring (CM) techniques have been studied over the past decade, as a successful condition monitoring system (CMS) is believed to be able to detect incipient faults, avoid catastrophic failure, assess fault severity, and even predict the remaining useful life of defective components. Thus, CM has been widely accepted by the wind industry as a common means of guiding O&M and reducing power generation costs [9]. A review of the literature highlights that, to date, the effort on wind turbine CM is mainly focused on the research of the following two types of CM approaches [13,14].

The purpose-designed CM approach is specifically designed for monitoring a particular wind turbine component or subassembly. For example, Frequency Response Transmissibility Analysis was proposed

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https://doi.org/10.1016/j.ress.2023.109475
Received 23 November 2022; Received in revised form 11 June 2023; Accepted 25 June 2023
Available online 26 June 2023

specifically for detecting and locating fractures that occur in wind turbine composite blades [15]; the oil debris counting technique was used specifically for monitoring the health condition of wind turbine gearbox [13,14]; Vibration analysis methods were developed for monitoring the health of wind turbine drive trains [16]; Variational mode decomposition was applied to assessing the health condition of wind turbine bearing and generator [17]; Load independent technique was developed dedicatedly for predicting the optimum maintenance time of wind turbine bearings [18]; etc. More details about recent advances in research of these kinds of techniques can be found in [19]. Such techniques enable early detection and location of faults in wind turbine components and subassemblies. However, their results are affected by time-varying wind loads, which can sometimes result in incorrect judgments. For this reason, their effectiveness in practice is sometimes unsatisfactory [13,20]. In addition, the application of such techniques requires multiple sensors and dedicated data acquisition systems. This is an additional hardware investment, and moreover the sensors and data acquisition systems are power electronics, which are less reliable in offshore environments and therefore also require regular calibration and maintenance. This results in additional maintenance costs.

Another type of CM approach is developed based on the wind farm Supervisory Control and Data Acquisition (SCADA) system. In contrast to purpose-designed CM techniques, the SCADA-based techniques are more cost-effective because the SCADA system is already installed in the wind farm and no additional hardware investment is needed [13,21]. Moreover, the SCADA system has collected operational and performance data for critical wind turbine components, which can be used for CM purposes. For example, Yang and his colleagues investigated the potential of SCADA data for wind turbine CM [21,22]; Xiang et al. developed a convolutional neural network to detect wind turbine fault from SCADA data [23]; McKinnon et al. investigated the accuracy of three different fault detection techniques based on SCADA data [24]; Pandit and Infield developed a SCADA-based wind turbine CM technique with the aid of Gaussian process models [25]; Castellani et al. analysed SCADA data for detecting faults occurring in wind turbine generators [26], etc. More details about the state-of-the-art of this kind of technique can be found in [27]. However, it is worth noting that wind farm SCADA systems were not designed for CM purpose. They collect data by using a very low sampling frequency (usually one data value every 10 min). Therefore, the collected SCADA data cannot provide all the information needed for CM. Coupled with improper threshold settings, wind farm SCADA systems often generate false alarms in practical use [13,28–30]. The frequent false alarms significantly increase unnecessary site visits and wind turbine downtime, resulting in huge financial and power generation losses.

As noted above, both wind turbine CM approaches have pros and cons and hence, operators often face a dilemma when deciding whether to invest in a purpose-designed CMS for their OWTs, particularly when cost reduction is a key concern. An alternative solution is to invest in building a stronger wind turbine O&M team to achieve the desired availability of wind turbines. This may work when operating easily accessible wind farms on land, but applying the same method to operating remote OWFs would be very risky for operators. Some of the risks, e.g. thrown ice pieces from wind turbines, cold stress to workers, tower collapse, etc., have been reported or predicted in [31–34]. In addition to these risks, two factors also need to be taken into account when selecting a CM approach. Firstly, the availability of an OWT is not only determined by how quickly the defective component can be repaired or replaced but is also dependant on the long waiting time for favourable weather for site visits. Such a fact cannot be changed by building a strong O&M team. Secondly, a purpose-designed CMS adds extra cost but can provide early fault alerts, giving people enough lead time to schedule cost-effective maintenance. By contrast, a SCADA-based CMS is almost free but lacks early fault warning capabilities. Sudden failures of wind turbines often result in prolonged downtime or even catastrophic damage to the entire wind turbine or adjacent facilities.

In addition to CMSs and maintenance strategies, many other factors can affect wind turbine availability and O&M costs, such as spare parts availability, the reliability of wind turbine components, weather conditions, etc. [35,36]. The impact of these factors may greatly dilute the contribution of CMSs. To date, the combined effects of these factors and their complementary management strategies on improving the effective management of wind farms remain unexplored. The unique contribution of this paper to the field is distinguished by answering the following two fundamental questions that have plagued the wind power industry for many years.

(1) Is a wind farm SCADA system a viable alternative to purpose-designed condition monitoring system (CMS).
(2) What is the best way to integrate CMSs and maintenance strategies to maximise the financial benefit of OWTs.

A mathematical modelling framework based on Petri nets (PNs) is developed in this paper to simulate the operation and impact of each type of CMS and different maintenance strategies. While developing the PN models, the false alarms triggered by CMSs and their impact on the O&M of OWTs and economics of wind power are carefully considered. As far as the authors are aware, no prior research has explored this area in existing literature.

The remaining part of the paper is organised as follows. In Section 2, a typical OWT structure and maintenance strategies are defined. In Section 3, the PN modelling technique is briefly reviewed. In Section 4, four PN models that consider multiple OWF factors are developed. In Section 5, simulation calculations are implemented using the PN models developed to investigate the impact of CM on the performance of the OWT. In Section 6, the paper concludes with key research findings and a description of future work.

2. Definition of offshore wind turbine structures and maintenance strategies

2.1. Offshore wind turbine structures

The six main subassemblies of the horizontal-axis OWTs, as depicted in Fig. 1, will be considered in the following research. They are the rotor system, yaw and pitch (YP) system, drivetrain system, braking system, power system, and turbine housing and support structures, respectively.

In the six subassemblies,

- the rotor system is composed of the blades and the hub;
- the YP system controls the yaw angle of the nacelle and the pitch angle of the blades to ensure that the OWT is always aligned with the wind direction and efficiently captures energy from the wind of various speed;
- the drivetrain system consists of the main bearing, main shaft, and gearbox;
- the braking system is responsible for slowing down the wind turbine and even locking it if needed. For example, the braking system will shut down the wind turbine whenever the wind speed is found to exceed the turbine's cut-off speed [6,37];
- the power system converts mechanical torque into electrical power and ensures that the frequency and voltage of the electricity generated meet grid requirements;
- the turbine structures include the nacelle, tower, and foundations of the wind turbine.

To facilitate the study, the health state of these subsystems is classified into four categories, i.e. normal, minor fault, critical fault, and failure [38]. The subsystem is still allowed to operate in the presence of a minor or critical fault. In comparison with minor faults, critical faults are more detectable by the CMSs due to excessive vibration or more heat

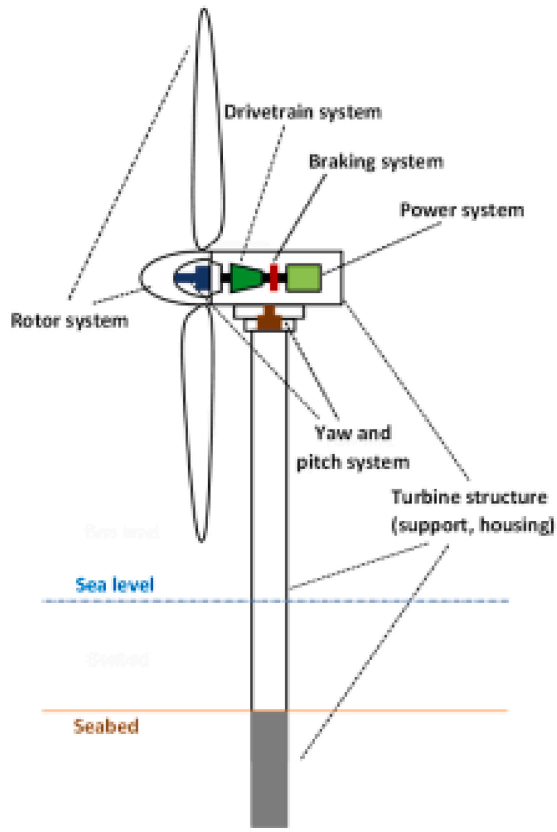


Fig. 1. Main subassemblies of horizontal-axis offshore wind turbines.

generation. Different wind turbine components have different critical characteristics (e.g. temperature, vibration and current), resulting in varying false alarm rates at different stages of fault development for different components. If the fault is not detected or repaired in time, it may cause the failure of the subsystem. It is assumed that the failure of any subsystem will trigger a turbine shutdown to prevent further damage to the entire machine.

In the study, the natural deterioration process of each subsystem is assumed to follow a Weibull distribution, of which the parameters are derived from the wind turbine failure rate data published in the open literature. As it is found that the failure rates reported in [39,40] differed considerably from those in [38], both sets of failure data were adopted in this paper. This also highlights the flexibility of the developed modelling framework, which can be easily adjusted for different OWTs. They are listed in Table 1. As in the work of Le and Andrews [38], the scale parameters (η) in the distributions are used to calculate the time that it takes for a normal subsystem to develop a minor fault, a critical fault, and finally the complete failure of the subsystem. In [38], a relatively crude estimation was used to obtain the scale paraments (η) of

Table 1
Failure rates of wind turbine subsystems.

Subsystem	Annual failure rate (/year)		Percentage share in MTTF		
	Dataset-A [38]	Dataset-B [39,40]	Normal	Minor fault	Critical fault
Rotor system	0.0868	0.1600	70%	20%	10%
Drivetrain system	0.0600	0.1600	70%	25%	5%
Power system	0.1430	0.1430	70%	25%	5%
YP system	0.1534	0.5100	70%	20%	10%
Braking system	0.0799	0.1000	70%	20%	10%
Structure	0.0790	0.1000	70%	20%	10%

subsystems residing in the normal, degraded and critical states covering a certain percentage of the Mean Time to Failure (MTTF) as shown in Table 1. The MTTF of each subsystem is the inverse of the failure rate which is also listed in Table 1. The shape parameters (β) of the distributions are assumed to be 1.2, which is larger than 1, to reflect the increasing deterioration rates of mechanical components as recommended in [38]. In practical application, the values of η and β can be updated once the corresponding failure rate data becomes available.

2.2. Maintenance strategies

Three kinds of maintenance strategies, i.e. corrective maintenance, periodic maintenance, and condition-based maintenance, are usually adopted to improve the availability of the OWT [41,42]. They are also employed in this study and are specifically defined as follows.

Corrective maintenance in this study is conducted only after a subsystem completely fails (i.e., a 'failure' occurs). Subsequently, the operators conduct a comprehensive turbine inspection, taking advantage of the readily available personnel and equipment. This should improve the safety and availability of the OWTs but results in extended downtime due to the prolonged corrective maintenance.

Periodic maintenance is performed at predefined intervals, but it causes many unnecessary site visits and huge financial losses in practice [43,44]. To overcome this issue, in this paper, it is classified into two types, namely 'basic service' (BS) and 'advanced service' (AS), as described in [33]. The BS aims only to find and fix those issues that frequently occur and are easy to fix but difficult to monitor, such as the looseness of bolts, loose connection of signal lead, leak of lubrication oil, etc. In contrast, all wind turbine subsystems will be inspected during the AS to find and fix any problems that have not been detected by CMSs. Consequently, the AS will take a longer time than the BS.

The condition-based maintenance involves continuously monitoring of OWTs, where maintenance decisions are based on the actual health conditions of the turbines. Hence, its effectiveness heavily relies on the fault detection capability of the CMSs (e.g. the purpose-designed wind turbine CMS or the SCADA-based CMS in the paper).

The overall logic of the O&M strategy adopted in this study is shown in Fig. 2. In the figure, three different maintenance processes, 'Maintenance 1′', 'Maintenance 2′', and 'Maintenance 3′' are performed for fixing 'minor faults', 'critical faults', and subsystem 'failures', respectively. They are different in terms of cost, time, and resources. 'Maintenance 3′' includes not only subsystem failure repairs, but also a full inspection of the entire OWT to find and fix all other problems present in the turbine. In the study, it is assumed that

- The OWT is operational initially.
- In the presence of a minor or critical fault,
  - if the CMS fails to detect the fault, the OWT will continue to operate with the fault, a check will be performed to see if the fault will be detected in the next AS in time. If 'Yes', the fault will be fixed by performing 'Maintenance 1′' or 'Maintenance 2′'. If 'No', the fault will further deteriorate and develop into a more serious one, e.g., from a 'minor fault' to a 'critical fault' or from a 'critical fault' to a subsystem 'failure'.
  - if the CMS successfully detects the fault, the model will judge whether an AS is scheduled or in progress. If 'Yes', 'Maintenance 1′' or 'Maintenance 2′' will be performed to fix the fault during the period of the AS. Otherwise, the OWT will continue its operation while necessary preparations are made for maintenance. Once everything is ready, 'Maintenance 1′' or 'Maintenance 2′' will be performed.
- In the presence of a subsystem failure, the OWT will be shut down and 'Maintenance 3′' will be performed to repair the fault.
- It is assumed that the health state of a subsystem after maintenance is 'as good as new'.

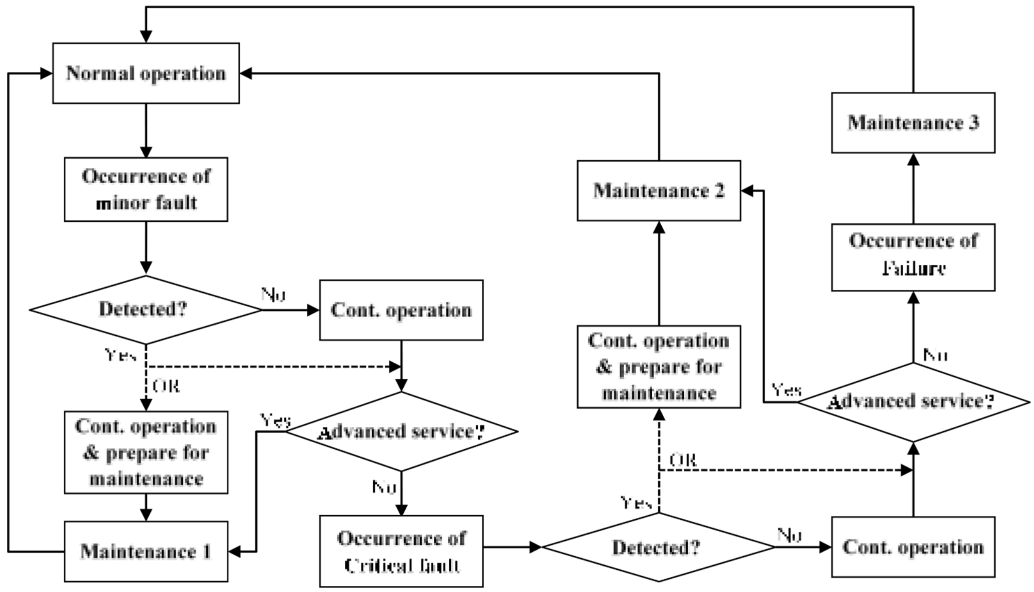


Fig. 2. The overall logic of the operation and maintenance strategy for the OWT.

3. A brief review of Petri net-based modelling technology

PNs have been increasingly adopted in reliability studies because they are not only able to provide an intuitive graphical representation of a system but also have great capabilities to model complex dynamic behaviours in a system [45–49]. For example, Yan et al. used PNs to assess the reliability and availability of automated guided vehicle systems [50]. Lee and Mitici adopted the PN method to assess the safety and efficiency of different aircraft maintenance strategies [51]. Rui et al. developed PN models to study the reliability of information networks [52]. Wang et al. proposed a method based on PNs to evaluate the reliability of manufacturing systems. In the field of offshore wind energy, PN methods have often been used to assess and optimise the maintenance strategies for OWTs. For example, Le and Andrews adopted the PN method to simulate the deterioration processes of wind turbine subsystems, maintenance processes and the function of the CMS [38]. Leigh and Dunnett developed a PN-based simulation model to optimise the maintenance process for an OWT [39]. Müller and Bertsche used PNs to assess and optimise the availability and maintainability of an OWF [53]. Elusakin et al. developed a PN model to simulate the O&M of floating OWTs [54]. However, how CMSs and O&M strategies can complement each other to improve the availability and reduce the O&M costs of OWTs has not, to the authors' knowledge, been studied before. Hence, this paper aims to fill this knowledge gap.

In this paper, four types of symbols are adopted to visualise PNs. They are illustrated in Fig. 3.

In Fig. 3, the circles in the first row represent the places, which are conditions or states of a system, such as working or failure. Coloured patterns inside the circles are used to represent special properties of these places as described in [33]. The condition place, marked with yellow-horizontal lines in the figure, can force the model to perform predefined actions if the conditions set for the place are met. The place filled with red-vertical lines can terminate the simulation if a token is placed in it. Rectangles represent the transitions, which are actions or events causing the change of condition or state. If the time of the transition is zero, the rectangle will be filled black, otherwise it is empty.

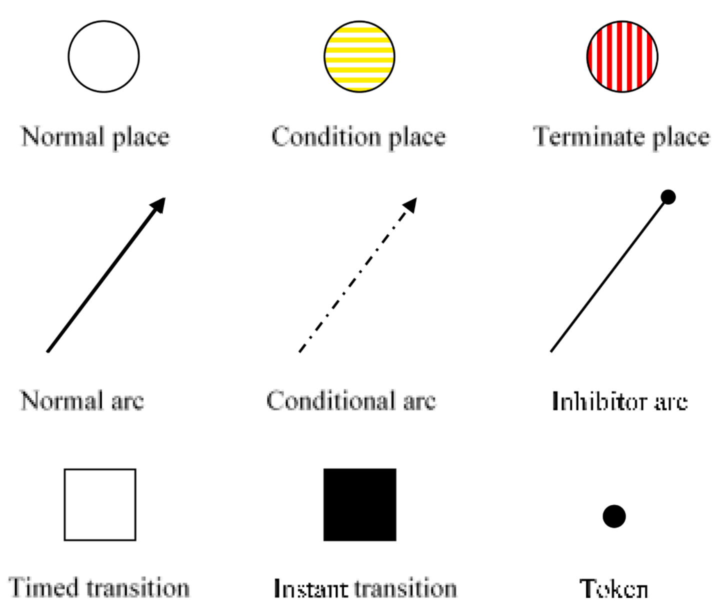


Fig. 3. Symbols used in the PN models [33].

Small solid black circles shown in the bottom row of Fig. 3 are used to represent tokens in the places. Arrows, known as arcs, are used to connect places and transitions. Arcs with a slash on and a number, *n*, next to the slash represent a combination of *n* single arcs and the arc is said to have a weight of *n*. The dashed arrow shown in the figure is a conditional arc. If the transition connected to a conditional arc is enabled, the probability of the expected tokens being produced in the output places is predefined. In addition, an arc with a small circle on one end is known as an inhibitor arc. This can prevent a transition from firing when enabled. A transition is enabled if the number of tokens in every input place is greater than or equal to the corresponding weights of the arcs to the transition. Once a transition is enabled, it will fire after the time associated with it has elapsed and the tokens will be removed from the input places and put into the output places according to the weight of the corresponding arcs. The movement of the tokens gives the dynamic property of the PNs. If there are two arcs with their arrows pointing in opposing directions between a place and a transition, then they can be combined into a single arc with arrows at both ends.

To ease understanding, Fig. 4 shows an example of the PN model. In this example, the net has two input places and one output place connected by a timed transition indicated by a blank rectangle with a time delay, *t*. There are two and three tokens in the top and bottom input places respectively. The two input places are connected by arcs of weight 1 and weight 2. It should be noted that the top arc is double-headed, which means it is not only an input arc but also an output arc. The output place is connected by an arc of weight 1. As shown in the net on the left of the figure, the transition is enabled, hence after the delay of time *t* associated with the transition, the number of tokens indicated by the arc weights will be removed from the input places and placed in the output place. By following the rules outlined above, one token will be removed from the top input place and two tokens will be removed from the bottom input place. Also, one token is placed in the output place and another one is placed back in the top input place.

4. Dynamic PN modelling of the O&M of an offshore wind turbine

In this section, four PN models are developed to simulate the O&M of an OWT. They are

(1) Operation Petri net (OPN) – for simulating the normal operation and periodic maintenance of an OWT. In the OPN, the lifetime of the OWT and the interval of the periodic maintenance will be defined.
(2) System Petri net (SPN) – for simulating the degradation, the health state of the OWT subsystems over time, and the shutdown of the turbine due to failure.
(3) Detection Petri net (DPN) – for simulating fault detection by the CMSs.
(4) Recovery and Maintenance Petri net (RMPN) – for simulating the process to prepare and conduct maintenance when a subsystem fails or a subsystem fault is detected.

These PNs work together and communicate with each other, as shown in Fig. 5. It should be noted that the OPN and SPN are two core models for the simulation, their structures will not change over the whole modelling process. The other two PN models, i.e. DPN and RMPN, are called upon in the simulation as needed. This can be achieved by importing new places, transitions, tokens, and connections (i.e. arcs) defined in the DPN and RMPN models into the existing PN structure. They will be removed from the simulation when the assigned PN simulation task is completed or cancelled. The details of the nets are explained in the following sections.

4.1. Operation Petri net (OPN)

The OPN adapted from [33] is designed to simulate the normal operation and periodic maintenance throughout the life cycle of an OWT. It is illustrated in Fig. 6.

In Fig. 6, the top part of the PN labelled ‘Operation of the wind turbine’ governs the normal operation of the OWT throughout its lifetime. Transition ‘S1’ represents the lifetime of the OWT, which is set to be 20 years in this paper, as in [39,55,56]. A token produced in the place ‘End of design life’ after the firing of Transition ‘S1’ means the end of the operation of the OWT, which also indicates the end of one iteration of the simulation.

The middle part, labelled as ‘Periodic maintenance’, is developed to simulate the periodic maintenance of the OWT. Both the AS and BS mentioned earlier are included in the model. Transitions ‘PM1’ and ‘PM3’ represent the time intervals between the maintenance for the two levels of service BS and AS, respectively. Transitions ‘PM2’ and ‘PM5’ represent the times that are required respectively for performing the BS and AS. They are assumed to be 6 h and 120 h, respectively. It is important to note that the turbine should be stopped while performing these services. The BS is performed regularly for checking non-major issues that frequently occur but difficult to monitor in practice, so that they will not cause extra failure beyond those considered in the simulation model. In the study, it is assumed that all faults can be detected and restores the components to an ‘as good as new’ state in an AS. Herein, it is worth noting that three types of wind farm maintenance vessels, i.e., crew transfer vessel (CT), jack-up vessel (JU), and crane vessel (CS), are considered in this study for repairing different types of faults. The details of this will be further explained later in this section. In the models, each AS requires one JU to conduct most of the maintenance tasks and the cost for charting the vessel has been included, but the cost of the CS will be calculated separately if needed.

The bottom part labelled ‘Time of year’ is developed to model the progression of time throughout a year. Different from the PN model developed in [33], this part simulates the time of year instead of directly simulating weather conditions. Considering wind speed can significantly affect the waiting time for favourable weather to conduct inspection and maintenance in the RMPNs and the average wind speed in summer is usually lower than the average wind speed in winter [57,58], this part of the model divides the annual time into two periods, i.e. April to the end of September and October to the end of the following March. This is one of the factors that most studies choose to ignore due to its complexity.

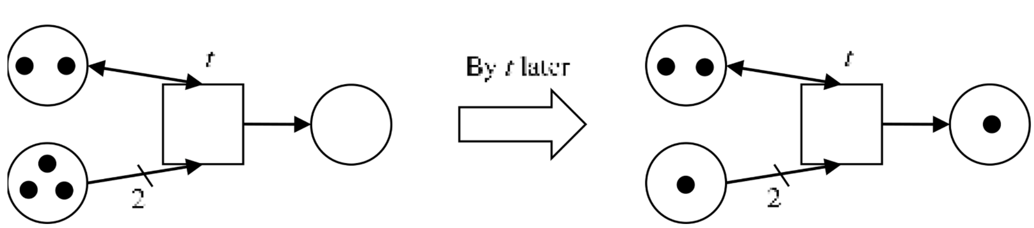


Fig. 4. Example of an enabled transition.

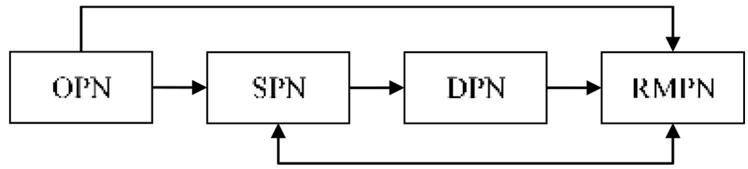


Fig. 5. Interactions between PNs [33].

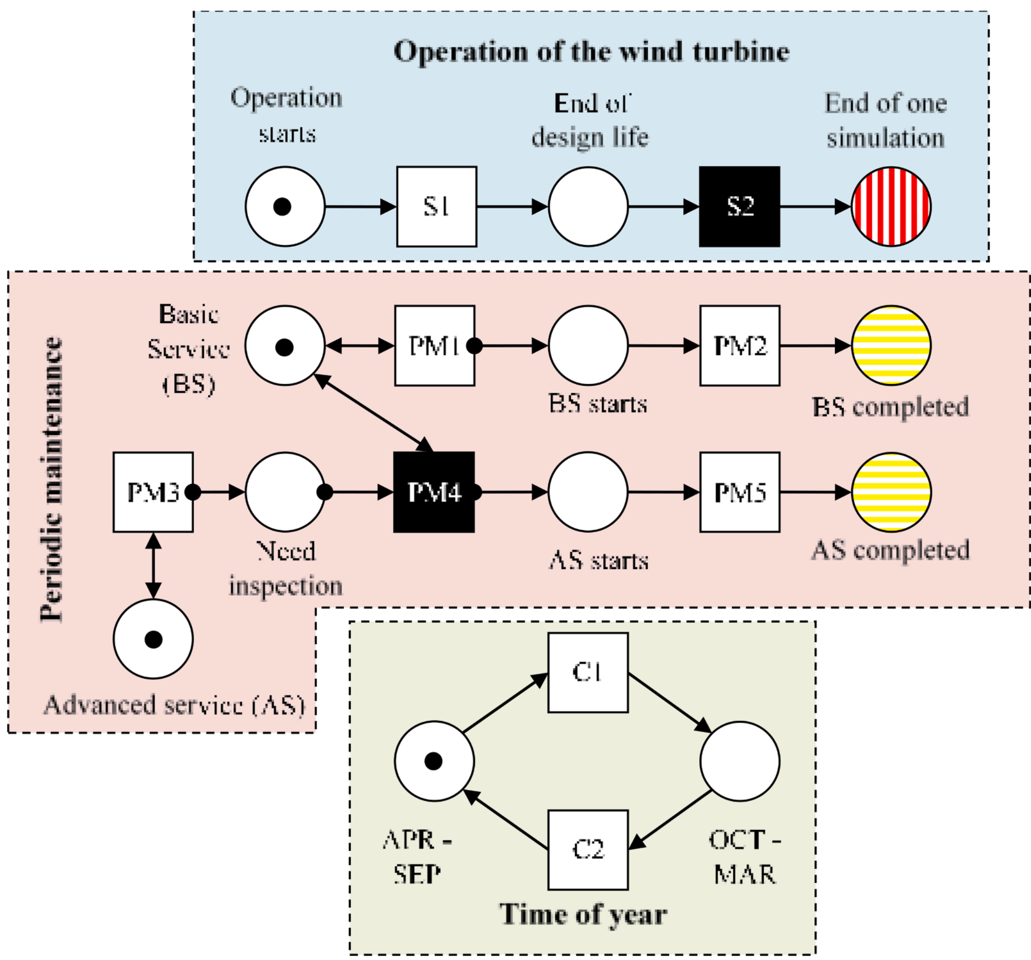


Fig. 6. Operation Petri net (OPN).

4.2. System Petri nets (SPNs)

The SPNs are developed to simulate the degradation process over time and the health states of the OWT subsystems. As mentioned in Section 2, the health states of the subsystems are categorised as 'Normal', 'Minor fault', 'Critical fault', and subsystem 'Failure'. As shown in Fig. 7, the degradation time from 'Normal' to 'Minor fault' is indicated by Transitions 'W1' to 'W6', and the degradation time from 'Minor fault' to 'Critical fault' is indicated by Transitions 'W7' to 'W12', respectively. Whenever a token is produced in any of the condition places representing fault conditions, the information is passed on to the DPNs to simulate the fault detection by the CMSs.

If the fault is not detected or repaired in time, the subsystem will fail eventually. The corresponding degradation time from 'Critical fault' to subsystem 'Failure' is indicated by Transitions 'W13' to 'W18'. Herein, it is assumed that time associated with Transitions 'W1' to 'W18' follow Weibull distributions that are characterised by the shape parameters (β) and scale parameters (η) defined in Table 2. The shape parameters in the distributions are assumed to be larger than 1 for all six subsystems in order to capture the gradual deterioration of the subsystems over time. As described in Section 2, two sets of failure rate data from different sources are considered in this paper to investigate the impact of the reliability of the OWTs on their availability and O&M costs.

In the model, the OWT will be shut down immediately upon the failure of any subsystem. This is modelled by Transitions 'W19' to 'W24'. Once a token is produced in the place, 'OWT shutdown', the OWT will be shut down and the information about the subsystem failure will be fed to the corresponding RMPNs.

After the failed subsystem is repaired, a token will be given to the place, 'Wind turbine recovered', and then Transition 'W25' will be activated for conducting a full inspection of the entire OWT. The time associated with the full inspection is assumed to be 5 days. As mentioned earlier, it is assumed that apart from the subsystem failure, all other problems present in the OWT can be found and fixed by performing a full inspection.

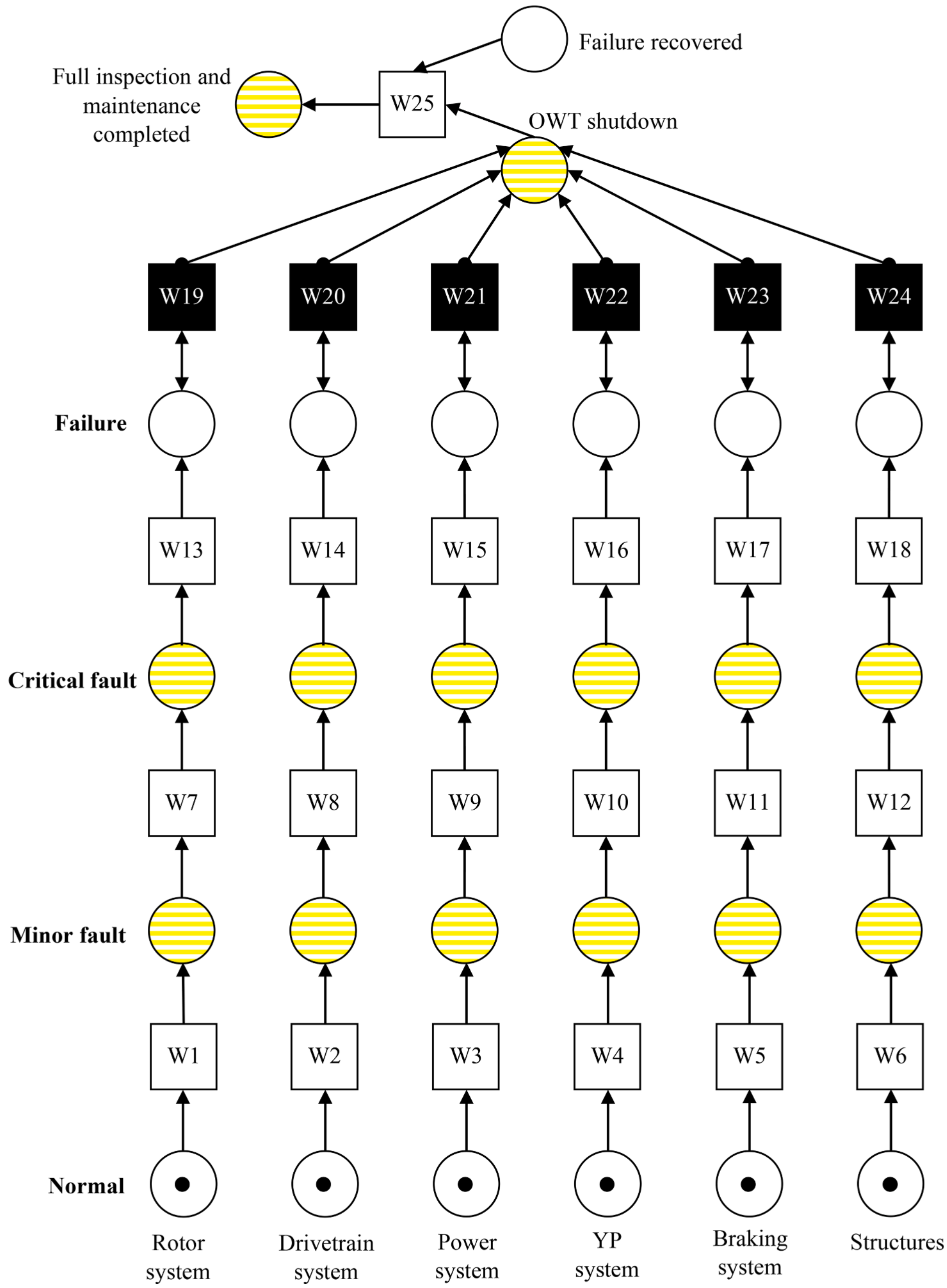


Fig. 7. System Petri Net (SPN).

Table 2
Weibull distribution parameters for Transitions 'W1' to 'W17'.

Transition	Parameters			Transition	Parameters		
	β	η (year)			β	η (year)	
		Dataset-A	Dataset-B			Dataset-A	Dataset-B
W1	1.2	8.06	4.38	W10	1.2	1.30	0.39
W2	1.2	11.67	4.38	W11	1.2	2.50	2.00
W3	1.2	4.90	4.90	W12	1.2	2.53	2.00
W4	1.2	4.56	1.37	W13	1.2	1.15	0.63
W5	1.2	8.76	7.00	W14	1.2	1.67	0.63
W6	1.2	8.86	7.00	W15	1.2	0.70	0.70
W7	1.2	2.30	1.25	W16	1.2	0.65	0.20
W8	1.2	3.33	1.25	W17	1.2	1.25	1.00
W9	1.2	1.40	1.40	W18	1.2	1.26	1.00

4.3. Detection Petri nets (DPNs)

Two DPNs are developed for respectively modelling the conditions and the monitoring process of the purpose-designed CMSs and the SCADA-based CMSs. Their net structures are the same. To facilitate understanding, the DPN for simulating the purpose-designed CMSs is illustrated in Fig. 8. Each DPN consist of two parts. As shown in Fig. 8, the first part of the DPNs is for simulating the health condition of the hardware in the purpose-designed CMSs, e.g., the health state of sensors and data acquisition (DAQ) system. It is assumed that the sensor groups for monitoring different subsystems can appear in three possible health states, i.e. working properly, failed, and working improperly (i.e., generating inaccurate signals due to the performance drift of the sensors). For example, a token in the place, 'CMS - rotor sensor group working', indicates that the sensor group for monitoring the rotor are normal and functioning properly. In the figure, Transition 'C1' represents the time duration before a false message about the rotor condition is generated, while Transition 'C2' represents simulates the time duration before the rotor sensor group fails. Once it fails, the health condition of the rotor will be unknown and the sensor group will be repaired during the next AS. These transitions are assumed to follow exponential distributions. The firing of Transition 'C1' means that the sensor will generate a false message about the health condition of the rotor, which could be 'normal', 'Minor fault', or 'Critical fault'. Their occurrence probabilities are assumed to be 0.4, 0.5, and 0.1, respectively. In the figure, this process is modelled by Transition 'C15'. Besides sensors, the DAQ system could also fail, which is modelled by Transition 'C13'. Once the DAQ system fails, the CMS will be completely unable to monitor any subsystem. The failure rates and false alarm rates of the CMS are listed in Table 3, sourced from [29,30,59]. In the study, it is assumed that false messages will be resolved during the BS and AS, and the failure of the CMSs can only be fixed during the AS. It is necessary to note that the CMS may indicate that a subsystem is functioning correctly even if there is a fault present. This could lead to a situation where no maintenance is carried out. Conversely, a false alarm may also be triggered by the CMS without any actual fault in the subsystem. Such false alarms could result in unnecessary site visits and the chartering of vessels. Assume that the OWF operators have complete trust in the CMS, they will schedule various vessels to rectify the false alarm's reported fault. Additionally, if either a CT, a JU, or a CS is chartered, the OWT must be halted for 2, 5, and 8 h, respectively, to investigate for any potential minor or critical faults in the OWT. These time periods are determined based on the inspection and docking times required.

The second part of the DPNs, as shown in Fig. 9, simulates the fault detection process by the purpose-designed CMS and wind farm SCADA

Table 3
Failure rate and false alarm rates of hardware systems [23,24,46].

Subsystem	Annual failure rate (/year)	Annual false alarm rate (/year)
SCADA sensor group for each subsystem	0.06	0.2
SCADA DAQ system	0.05	–
CMS sensor group for each subsystem	0.06	3
CMS DAQ system	0.05	–

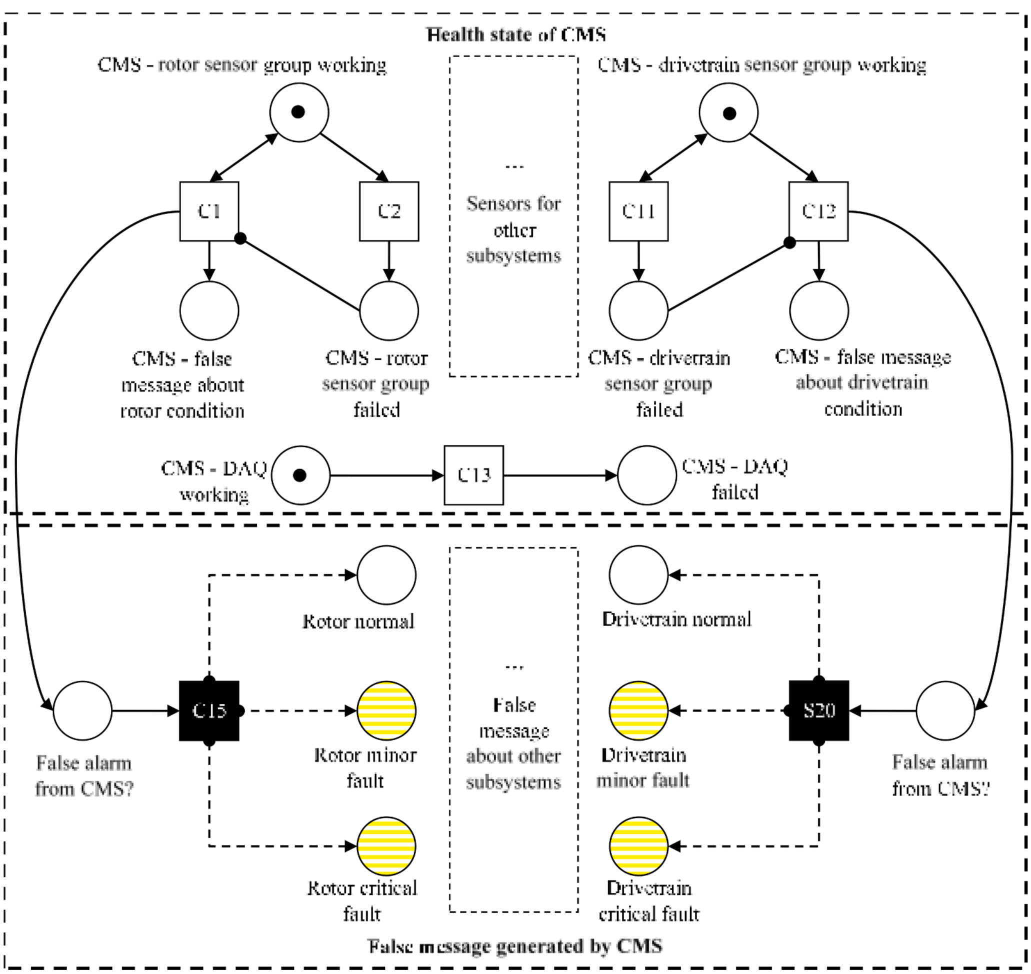


Fig. 8. PNs for simulating the health and operation of the CMSs.

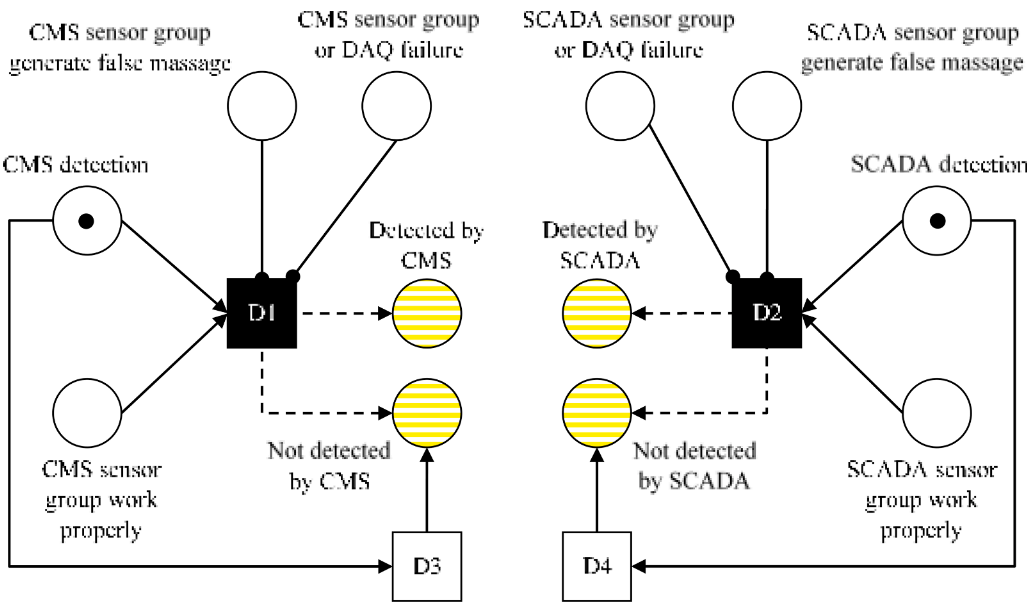


Fig. 9. Detection Petri Nets (DPNs).

system. In the presence of a fault, the information about the specific subsystem where the fault arises and the severity level of the fault will be given to the DPNs. As a result, the probability that the fault can be detected by each monitoring system will be given to the conditional arcs, represented by the dashed arrow lines in the figure. Both purpose-designed CMS and wind farm SCADA system are considered in the study. The subsystems that they can monitor and the corresponding probability that the fault can be detected by each monitoring system (i.e. Fault detection capability) are given in Table 4. They are assumed based on expert knowledge and the data given in [13].

Then, the health states of the corresponding sensor group and the DAQ systems of both monitoring systems will also be fed to this part of the DPN. This is achieved by reading the token markings in the first part of the DPNs depicted in Fig. 8 and then giving tokens to the corresponding places of the PNs in Fig. 9. The second part of the DPNs will be activated by placing a token in the places, ‘CMS detection’ and/or ‘SCADA detection’. Transitions ‘D1’ and ‘D2’ represent the fault detection process when the purpose-designed CMS and SCADA system work properly. If the purpose-designed CMS and/or SCADA system cannot work properly, Transitions ‘D3’ and/or ‘D4’ with a short time delay (0.000001 s) will fire. Once a token is produced in the places ‘Detected by CMS’ and/or ‘Detected by SCADA’, the corresponding information about the fault will be fed to the RMPNs to initiate access to essential maintenance resources, followed by a site visit to fix the identified fault. If the fault is not detected by the CMS, a token will be produced in the place, ‘Not detected by CMS’. Similarly, if the fault is not detected by the SCADA system, a token will be produced in the place, ‘Not detected by SCADA’. If neither the purpose-designed CMS nor the SCADA system detects the fault, no further action will be taken. In other words, whenever at least one of the monitoring systems detects the fault, appropriate maintenance procedures will be implemented.

Table 4
Fault detection capability for each subsystem of the OWT.

Subsystem	Detectability of SCADA system		Detectability of CMS	
	Minor fault	Critical fault	Minor fault	Critical fault
Rotor system	0.25	0.50	–	–
Drivetrain system	0.40	0.80	0.50	0.90
Power system	0.40	0.80	0.80	0.95
YP system	0.40	0.80	0.70	0.90
Braking system	0.30	0.80	0.70	0.95
Structures	–	–	0.50	0.90

4.4. Recovery and maintenance Petri nets (RMPNs)

The RMPNs are developed to simulate the preparation and implementation of corresponding maintenance when a subsystem fails or a subsystem fault is detected by the CMSs. As mentioned earlier, three types of vessels, i.e. CT, JU, and CS, are considered in this study for conducting the maintenance of different types of faults or subsystem failures, as in [38]. The CT is small in size and has limited lifting capacity (1 to 1.5 tonnes), primarily used to transport people and small tools or spare parts. The JU features a jack-up platform and increased lifting capacity, which enables it to perform more complex maintenance and part installation tasks. The CS is a kind of heavy lift vessel equipped with powerful cranes for carrying out the repair or installation of oversized and heavy OWT components. In the study, larger vessels can also conduct the maintenance tasks assigned to smaller vessels. For example, a minor fault will be assigned to the JU vessel already chartered for another maintenance task, rather than charter a new CT. An RMPN dedicated to each type of vessel is developed to differentiate these vessels in terms of charter rate and time required to operate. The structure of the RMPNs for different vessels will be the same, but the times for each stage will be different. To ease understanding, an example of RMPN is given in Fig. 10.

In Fig. 10, once a subsystem failure occurs or a subsystem fault is detected, a repair request will be made via instant transition, ‘M1’. Transition ’M2’ represents the time required to arrange a meeting to plan the maintenance. Transition ‘M3’ models the time required for approving the maintenance plan. After firing Transition ‘M3’, the tokens produced in the places ‘Charter vessel’ and ‘Organise crews, tools and spare parts’ will enable Transitions ‘M4’ and ‘M5’, respectively. Transitions ‘M4’ and ‘M5’ represent the time required for chartering the appropriate maintenance vessel and waiting for the vessel to arrive at the port, organising maintenance crews, collecting maintenance tools, and preparing spare parts. These times are assumed to follow a normal distribution with mean and standard deviation given by μ and σ. If there are spare parts stored onsite, Transition ‘M6’ will also be enabled. Its distribution time will be much shorter than the time of Transition ‘M5’. Once all the preparation works are completed, Transition ‘M7’ will fire, which indicates that the corresponding maintenance vessel is ready to go. After the maintenance vessel arrives at the port where the wind

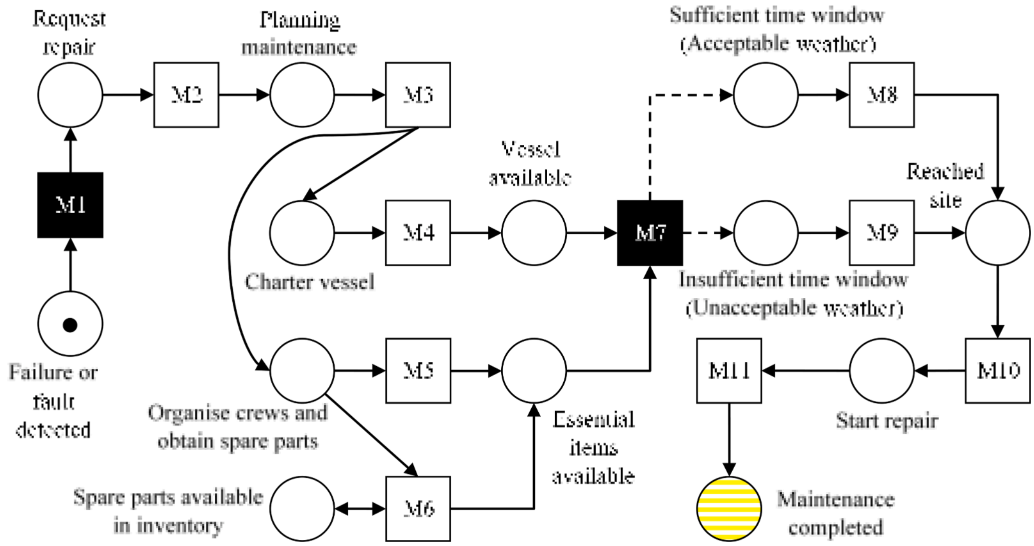


Fig. 10. Recovery and Maintenance Petri Nets (RMPNs).

turbine spare parts are stored, two scenarios may occur: one is where the maintenance time window is sufficient, and the other is where the time window is insufficient. The arcs, represented by the dashed arrow lines, connect Transition 'M7' with Places 'Sufficient time window' and 'Insufficient time window'. The probabilities that a token transfers to either of the two places are dependant on the seasons in a year. In the research, it is assumed that the probability of having a sufficiently long maintenance window is 0.8 from April to September and 0.6 from October to March. Of the two Transitions 'M8' and 'M9', the former indicates the time required to load spare parts and repair tools on board when the weather is favourable for wind farm maintenance. In contrast, the latter, which follows the Weibull distribution, represents the time to wait for favourable weather conditions to ensure a sufficient time window.

After the vessel arrives at the site, the maintenance crew will spend some time preparing for the maintenance to take place, which is indicated by Transition 'M10'. The time it takes for the maintenance crew to perform the maintenance is indicated by Transition 'M11'. The parameters for all transitions in RMPNs are listed in Table 5. Due to the lack of real data for these parameters, all data in Table 5 are hypothetical and based on expert knowledge. This has only been used to facilitate the model development and these parameters would need to be updated in future practical applications according to the actual situation of the OWTs of interest. Finally, a token will be produced in the place, 'Maintenance completed', indicating that the current maintenance has been completed and the new health status of the corresponding subsystem will be fed back to the SPNs. The vessel required and the average costs for different types of maintenance are listed in Table 6. They are cited from [38]. It is necessary to note that the monitoring systems are

Table 6
The vessel required and the average costs for different types of maintenance.

OWT Subsystems	Vessel required			Repair/replacement cost (£)		
	Minor fault	Critical fault	Failure	Minor fault	Critical fault	Failure
Rotor system	CT	JU	CS	3000	44,000	200,000
Drivetrain system	CT	JU	CS	5000	37,000	260,000
Power system	JU	JU	CS	12,000	30,000	150,000
YP system	CT	JU	CS	7000	9000	23,000
Braking system	JU	JU	CS	2000	2000	4000
Structures	CT	CS	CS	5000	40,000	264,000
SCADA/CMS sensor group	–	–	–	–	–	1000
SCADA/CMS DAQ system	–	–	–	–	–	10,000

Table 5
Timed transition parameters for RMPNs.

Transition	Type	Parameters (hour)		
		Crew transfer vessel	Jack-up vessel	Crane vessel
M1	constant	0	0	0
M2	constant	12	12	12
M3	constant	24	24	24
M4	Normal	$\mu = 24,\ \sigma = 9.6$	$\mu = 168,\ \sigma = 33.6$	$\mu = 480,\ \sigma = 96$
M5	Normal	$\mu = 120,\ \sigma = 24$	$\mu = 240,\ \sigma = 48$	$\mu = 360,\ \sigma = 72$
M6	Normal	$\mu = 24,\ \sigma = 4.8$	$\mu = 48,\ \sigma = 9.6$	$\mu = 72,\ \sigma = 14.4$
M7	constant	0	0	0
M8	constant	24	24	24
M9	Weibull	$\beta = 3.2,\ \eta = 1008$ (OCT-MAR) $\eta = 504$ (APR-SEP)	$\beta = 3.5,\ \eta = 504$ (OCT-MAR) $\eta = 252$ (APR-SEP)	$\beta = 3.1,\ \eta = 1008$ (OCT-MAR) $\eta = 504$ (APR-SEP)
M10	constant	1800	3600	10,800
M11	constant	2 (Clear false alarm) 3 (Minor fault) 10 (Critical fault) 50 (Failure)	5 (Clear false alarm) 10 (Minor fault) 50 (Critical fault) 70 (Failure)	8 (Clear false alarm) 10 (Minor fault) 50 (Critical fault) 70 (Failure)

only maintained during the AS.

5. Investigation of the impact of CM on the performance of offshore wind turbines

In the following, different wind farm O&M scenarios will be simulated by using the PN models developed in Section 4 to reveal the impact of CM on the performance of the OWT. The relevant calculations are performed on a personal computer with the Windows 10 operating system. The specification of the computer is Intel(R) Core(TM) i7–7500 U CPU @ 2.70 GHz, 16 GB RAM. The calculations are implemented by the following steps.

(1) Place tokens in the initialisation places of the PNs described in Section 4. Initialise the simulation time by setting $t = 0$ s.
(2) Randomly sample the values of transition times in the model based on the data listed in Tables 1 to 6.
(3) Determine the earliest timed transition to switch and fire it.
(4) Update the tokens in the PNs, and recompute the time of the transition fired.
(5) If a token is produced in a condition place or a terminate place, activate the predefined corresponding conditions.
(6) Find the next transition to switch and fire it. Repeat Steps 4 and 5.
(7) Repeat Step 6 until the lifetime of the OWT is reached.
(8) Iterate the above simulation until the defined number of iterations is reached.

First of all, a study was conducted to find the appropriate number of simulation iterations (n) that are needed to ensure the convergence of calculation results. In the calculation, the failure data from Dataset-A, in Tables 1 and 2, are considered. The conclusion obtained should be also applicable to the simulations based on the data from Dataset-B. This is because Dataset-A comprises smaller failure rate values, which means more simulation iterations will be required to achieve convergence. Fig. 11 shows the calculated average number of subsystem failures as a function of n. From the figure, It can be observed that the results for all six subsystems eventually converge to stable values after surpassing 30,000 iterations. To ensure the utmost reliability of the simulation results, 50,000 simulation iterations will be conducted in all subsequent calculations in this paper.

5.1. Impact of CM on turbine availability

This subsection investigates the impact of applying purpose-designed CMS and SCADA systems on turbine availability when using different wind farm maintenance strategies. In the investigation, the failure data from Dataset-A are considered and it is assumed that

- the lifetime of the OWT is 20 years
- both purpose-designed CMS and SCADA system are employed
- the time interval of the AS is 2 years
- spare parts stock is sufficient
- the time duration and cost of the BS are the same whether recalibration is carried out or not
- a 5-day full inspection is conducted following each failure recovery

Then, the average number of system failures recovered (F), the average number of minor and critical faults repaired (MF_D, CF_D) after being detected by the monitoring systems, and average the number of minor and critical faults repaired (MF_I, CF_I) after being found in the AS and full inspection following failure recovery are calculated. The calculation results are listed in Table 7.

From Table 7, it is found that the number of subsystem failures that cause shutdown within the lifetime of the OWT is only 0.164, although 15.080 minor subsystem faults (12.092 detected by monitoring systems and 2.988 found in full inspection) and 1.221 critical faults (0.961 detected by monitoring systems and 0.260 found in full inspection) are repaired before getting worse and causing failure. amongst the six subsystems, the YP system experiences the most failures, followed by the

Table 7
The average number of recovered failures and repaired faults within the lifetime.

Subsystem	Contribution from monitoring systems		Contribution from maintenance strategies		***F***
	MF_D	CF_D	MF_I	CF_I	
Rotor	1.524	0.095	0.590	0.075	0.041
Drivetrain	1.098	0.079	0.391	0.015	0.004
Power system	3.374	0.199	0.395	0.035	0.028
YP system	3.355	0.310	0.527	0.050	0.047
Braking system	1.755	0.087	0.329	0.016	0.006
Structure	0.986	0.191	0.755	0.069	0.038
Sum	12.092	0.961	2.988	0.260	**0.164**
	13.053		**3.248**		

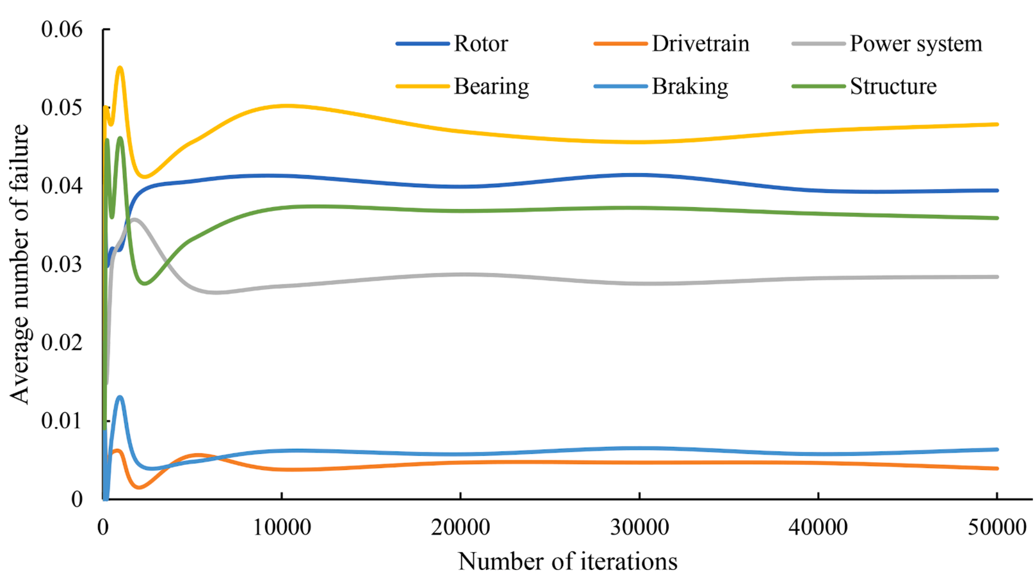


Fig. 11. Average number of subsystem failures as a function of number of simulation iterations.

rotor system and drivetrain system. The braking system has the minimum number of failures, which is 0.006. Notably, the number of faults fixed after being detected by monitoring systems is as high as 13.053 times, while the number of faults fixed after being found in the AS and full inspection following failure recovery is only 3.248 times. This demonstrates the important contribution of the monitoring systems to the O&M of OWFs.

In order to obtain the optimal mix of the monitoring systems and the O&M strategies and thus achieve the highest OWT availability, five different maintenance strategies are investigated. They are listed in Table 8. In the calculations, different input settings of the PN models are used in each strategy for revealing the different impacts of these settings on the availability of the OWT.

In each strategy, four different scenarios for using the monitoring systems are considered. They are (1) no monitoring system, (2) only the SCADA system, (3) only the purpose-designed CMS system, and (4) both the SCADA and purpose-designed CMS, respectively. By applying the above settings, the availability of the OWT in the 20-year lifetime is calculated, and the obtained simulation results are illustrated in Fig. 12.

From the calculation results shown in Fig. 12, it can be inferred that

- In the absence of monitoring systems, higher turbine availability can be achieved by performing frequent AS. However, the availability achieved by this method is still lower than that achieved with either monitoring system. This means that CM is indispensable, and it cannot be replaced by simply strengthening the maintenance of wind farms.
- Compared to scenarios without any monitoring system, the application of the SCADA-based CMS can significantly improve availability. However, the SCADA system should be calibrated regularly, otherwise, the increased false alarms will lead to more unnecessary site visits, ultimately reducing the availability of the OWT.
- The purpose-designed CMS outperforms the SCADA system in improving the availability of the OWT and mitigates the impact of 'no recalibration' and 'no stored spare'. Moreover, the use of the purpose-designed CMS enables the frequency of the AS to be reduced. Satisfactory OWT availability can still be obtained even without periodic calibration of the CMS.
- When the AS is infrequent, the combined use of the purpose-designed CMS and SCADA system can lead to the highest availability of the OWT. By contrast, when the AS is frequently executed, the combined use of the two types of monitoring systems will reduce the availability of the turbine due to the increase in downtime caused by the AS, full inspection following fault recovery, and false alarms.
- amongst all 20 cases shown in Fig. 12, the highest turbine availability can be achieved by using the two types of monitoring systems and eliminating full inspection following failure recovery. The full inspection following each failure recovery does increase downtime to a certain extent, which affects the availability.
- The small difference in the availability results obtained using Strategy 1 and Strategy 4 seems to indicate that insufficient spare parts stock does not have a large impact on availability. This is mainly because Dataset-A corresponds to a very reliable turbine, which rarely fails, so it does not require many spare parts.

To further investigate the impact of turbine reliability on availability, the above simulation calculations are repeated using the data from Dataset-B. The obtained availability results are shown in Fig. 13.

By comparing Fig. 12 and Fig. 13, it is found that

- The availability results in Fig. 13 are lower than the corresponding values in Fig. 12. This suggests that the reliability of the OWT does have a significant influence on its availability. The lower the reliability, the lower the turbine availability.
- With any monitoring system, the availability is increased more in Fig. 13 than in Fig. 12. This suggests that the monitoring systems are more important to improve the availability of unreliable OWT.
- The difference in the availability obtained using Strategy 1 and Strategy 4 is only 0.01% in Fig. 12, while the difference increases up to 0.06% in Fig. 13. This suggests that insufficient spare parts stock will have a greater impact on the availability of unreliable OWTs.

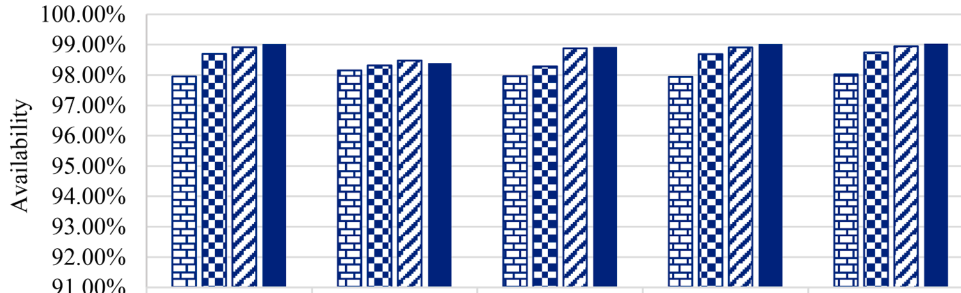
5.2. Impact of CM on the cost on availability

Since the average maintenance cost on availability (COA), i.e. the ratio of maintenance cost to availability, is closely related to the cost of energy (COE), this subsection focuses on exploring the impact of applying purpose-designed CMS and SCADA systems on the COA when using different wind farm maintenance strategies. In the investigation, it is assumed that the average costs of the BS and AS are £10,000 and £50,000 per occurrence, respectively. The values of other model parameters are the same as those used in Section 5.1. In order to calculate the COA, the maintenance costs for those cases in Section 5.1 are initially estimated based on the cost information given in Section 4. The cost estimation results are presented in Figs. 14a and 14b, which represent the costs based on Dataset-A and Dataset-B respectively.

From Fig. 14, it is noticed that compared to the cases without monitoring systems, the application of the SCADA system increases the cost when using any maintenance strategy to look after a reliable OWT. This is mainly due to the false alarms generated by the SCADA system causing many unnecessary site visits and therefore additional costs. A similar observation can also be found when using the first four maintenance strategies to look after an unreliable OWT. However, one exception is when using Strategy 5 to maintain the unreliable OWT, where the application of the SCADA system reduces the cost. This highlights the important complementary role of the SCADA system to the AS in securing the OWT and ensuring its availability, especially when no purpose-designed CMS is used. In contrast to the application of the SCADA system, using the purpose-designed CMS always results in significant cost savings regardless of the reliability of the OWT and the maintenance strategy employed. However, Figs. 12 and 13 have shown that using the purpose-designed CMS alone cannot result in the highest availability of the OWT. The highest turbine availability can only be achieved when the purpose-designed CMS and the SCADA system are jointly used for monitoring, but the corresponding costs of the combined

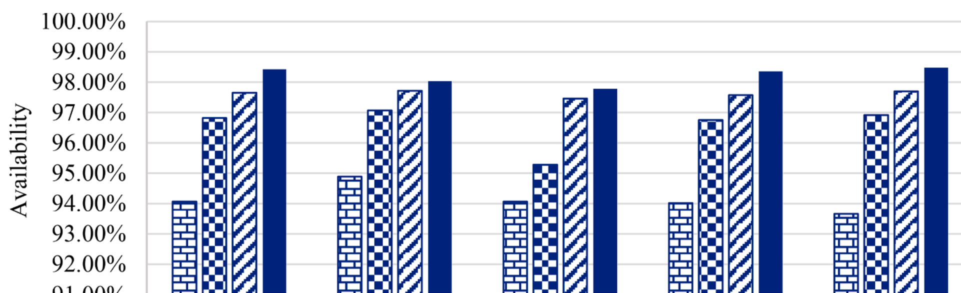
Table 8
Five maintenance strategies considered.

Maintenance strategy		Input settings				
		Time interval of the BS	Time interval of the AS	Recalibrate monitoring systems during the BS and clear false alarms	Sufficient spare parts stock	Conduct full inspection after each failure recovery
1	2-year periodic AS	6 months	24 months	Yes	Yes	Yes
2	1-year periodic AS	6 months	12 months	Yes	Yes	Yes
3	No recalibration	6 months	24 months	No	Yes	Yes
4	No stored spare	6 months	24 months	Yes	No	Yes
5	No inspection after failure recovery	6 months	24 months	Yes	Yes	No



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	97.95%	98.15%	97.96%	97.94%	98.02%
SCADA	98.70%	98.32%	98.29%	98.69%	98.74%
CMS	98.92%	98.47%	98.88%	98.91%	98.95%
CMS & SCADA	99.03%	98.39%	98.92%	99.02%	99.04%

Fig. 12. The availability of the OWT obtained when using different maintenance strategies and dataset-A.



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	94.07%	94.88%	94.07%	94.02%	93.66%
SCADA	96.82%	97.07%	95.28%	96.75%	96.91%
CMS	97.65%	97.72%	97.46%	97.58%	97.70%
CMS & SCADA	98.42%	98.04%	97.78%	98.36%	98.48%

Fig. 13. The availability of the OWT obtained when using different maintenance strategies and dataset-B.

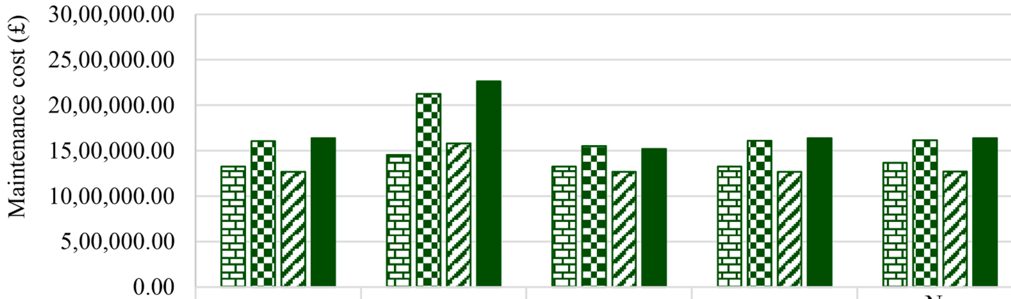
use of the two types of monitoring systems will be higher as shown in Fig. 14. This highlights the problem, should we use the purpose-designed CMS alone or should we use it in conjunction with the SCADA system in future wind farms? To answer this question, the COA is calculated. It is believed that the COA can help wind farm operators make appropriate judgments when faced with a choice. The COA results obtained in the cases outlined in Table 8 are shown in Fig. 15. In the figure, Fig. 15a and Fig. 15b show the results obtained based on Dataset-A and Dataset-B, respectively.

From Fig. 15, it is found that regardless of the reliability of the OWT, using a purpose-designed CMS alone in conjunction with maintenance Strategy 1 can always result in the lowest COA. This suggests that the combined use of a CMS and less frequent AS is currently the best option in terms of the COA. This rule is applicable to the maintenance of any OWT with varying reliability due to differences in age or product quality. In addition, from Fig. 15 it is also found that regardless of the reliability of the OWT and the maintenance strategy employed, neither the use of the SCADA system alone nor the joint use of a purpose-designed CMS and SCADA system is the best choice. This proves once again that the purpose-designed CMS is indispensable to ensure the economical operation of OWFs and it cannot simply be replaced by current wind farm SCADA systems.

6. Conclusion

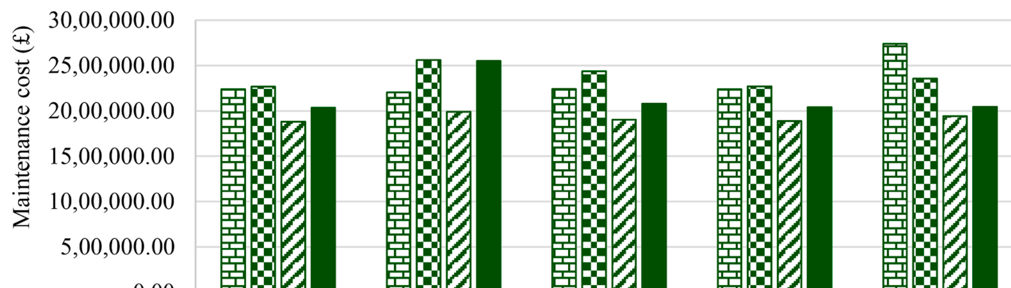
In light of the debate over the use of various CMSs in the operation of OWFs, a mathematical modelling framework is developed in this paper using PNs to investigate whether the wind farm SCADA system is a viable alternative to purpose-designed CMS and how to integrate CMSs and maintenance strategies to maximise the financial benefit of OWTs. From the work reported above, the following conclusions can be drawn:

- The combined use of a purpose-designed CMS and wind farm SCADA system yields the highest OWT availability. However, neither the use of the SCADA system alone nor the joint use of a purpose-designed CMS and SCADA system for monitoring is the best choice in terms of COA.
- Regardless of the reliability of the OWT, using purpose-designed CMS alone in conjunction with maintenance Strategy 1 can



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	13,26,432.35	14,51,611.01	13,23,597.44	13,24,470.70	13,67,739.92
SCADA	16,07,099.65	21,24,425.73	15,50,557.10	16,08,589.73	16,14,517.53
CMS	12,68,103.42	15,80,081.97	12,68,503.86	12,68,907.48	12,70,959.56
CMS & SCADA	16,37,827.00	22,61,902.58	15,20,786.53	16,37,211.49	16,37,396.39

(a) Maintenance costs obtained based on Dataset-A



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	22,39,149.32	22,01,485.96	22,41,667.20	22,36,147.47	27,37,015.27
SCADA	22,65,918.40	25,60,633.60	24,34,345.82	22,70,033.50	23,54,431.15
CMS	18,81,063.13	19,89,372.94	19,03,613.42	18,87,401.18	19,41,177.83
CMS & SCADA	20,33,606.55	25,51,685.15	20,76,981.00	20,41,022.58	20,42,311.84

(b) Maintenance costs obtained based on Dataset-B

Fig. 14. Maintenance costs for different cases.

always result in the lowest COA. This suggests that the combined use of a purpose-designed CMS and less frequent AS is the best option in terms of the COA.

- The purpose-designed CMS is indispensable to ensure the economical operation of offshore wind farms and its function currently cannot simply be replaced by a wind farm SCADA system.
- Insufficient spare parts stock has a greater impact on the availability of unreliable OWTs.
- A comparison of maintenance cost and COA results obtained when using Strategy 1 and Strategy 5 shows that a full inspection following each failure recovery helps reduce maintenance cost and the value of COA, although it may slightly affect turbine availability.

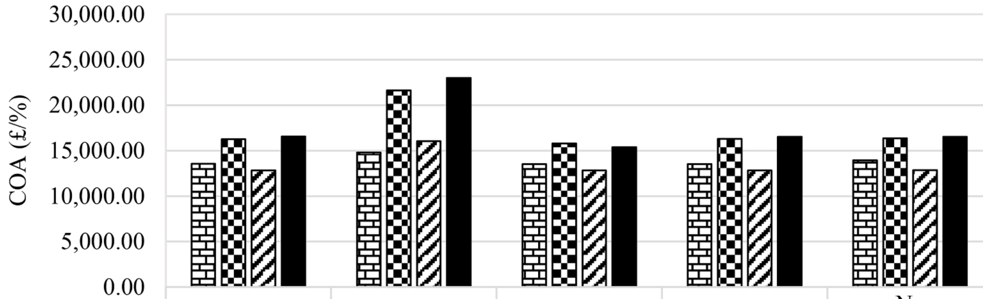
In the future, the accuracy of the PN models will be further improved by considering factors, such as the costs of different types of purpose-designed CMSs, the reliability of different types of OWTs, the influence of extreme weather, etc. These factors are not taken into account in this paper, but they can also have a significant impact on the economic operation of OWTs and can be incorporated into the framework developed.

CRediT authorship contribution statement

Rundong Yan: Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Sarah Dunnett:** Writing – review & editing, Supervision. **Lisa Jackson:** Writing – review & editing, Supervision.

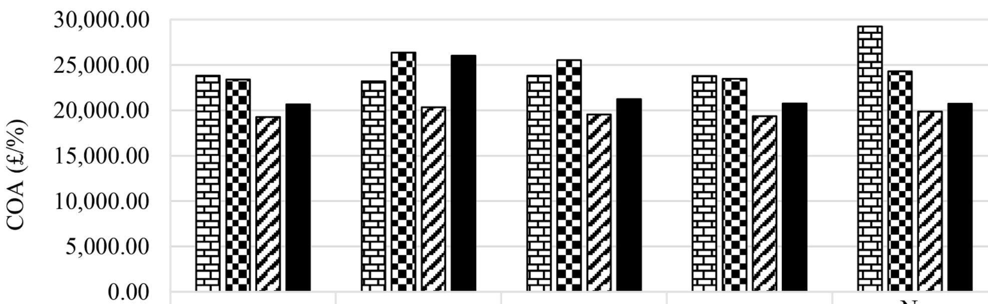
Declaration of Competing Interest

The authors declare that they have no known competing financial



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	13,541.93	14,789.72	13,511.61	13,523.29	13,953.68
SCADA	16,282.67	21,627.06	15,775.33	16,299.42	16,351.20
CMS	12,819.48	16,046.33	12,828.72	12,828.91	12,844.46
CMS & SCADA	16,538.70	22,989.15	15,373.90	16,534.15	16,532.68

(a) The COA obtained based on Dataset-A



	2-year periodic AS	1-year periodic AS	No recalibration	No stored spare	No inspection after failure recovery
No monitoring	23,803.01	23,202.85	23,829.78	23,783.74	29,222.88
SCADA	23,403.41	26,379.25	25,549.39	23,462.88	24,295.03
CMS	19,263.32	20,357.89	19,532.25	19,342.09	19,868.76
CMS & SCADA	20,662.53	26,026.98	21,241.37	20,750.53	20,738.34

(b) The COA obtained based on Dataset-B

Fig. 15. Average maintenance cost of availability for different cases.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

This work is supported by the Doctoral Prize Fellowship Scheme funded by Loughborough University and the Postdoctoral Fellowship Scheme of the Centre for Postdoctoral Development in Infrastructure Cities and Energy.

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