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A Decision-making Model for Corrective Maintenance of Offshore Wind Turbines Considering Uncertainties

Sathishkumar Nachimuthu [1], Ming J. Zuo [1,*] and Yi Ding [2]

[1] Department of Mechanical Engineering, University of Alberta, Edmonton, AB T6G 1H9, Canada; nachimut@ualberta.ca
[2] College of Electrical Engineering, Zhejiang University, Hangzhou 310027, China; yiding@zju.edu.cn
* Correspondence: ming.zuo@ualberta.ca; Tel.: +1-(780)-492-4466

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Abstract: Maintenance optimization has received special attention among the wind energy research community over the past two decades. This is mainly because of the high degree of uncertainties involved in the execution of operation and maintenance (O&M) activities throughout the lifecycle of wind farms. The increasing complexity in offshore maintenance execution demands applied research and brings forth a need to develop problem-specific maintenance decision-making models. In this paper, a mathematical model is proposed to assist wind farm stakeholders in making critical resource-related decisions for corrective maintenance at offshore wind farms (OWFs), considering uncertainties in turbine failure information.

Keywords: offshore wind farm; offshore wind turbine; maintenance; failure classification; resource decision; uncertainty

1. Introduction

The widespread availability and high technological maturity make wind energy a reliable renewable option to satisfy the future energy demands of the global population [1]. The limited land area and the need to reduce noise pollution is forcing the wind energy sector to shift towards offshore technologies [2,3]. Offshore wind farms (OWFs) are energy assets that have experienced a considerable growth in terms of cumulative capacity, from 4 GW to more than 18 GW over the past five years [4]. OWFs are expensive assets not only to build, but also to operate and maintain. About 23% contribution of the operation and maintenance (O&M) to the life cycle cost (LCC) makes the O&M the second major contributor for the LCC of an OWF [5]. The increased O&M cost is mainly caused by the uncertainties encountered by OWFs, which include weather, sea-state conditions, component lifetimes, etc. The high O&M cost and the unproven economic feasibility remain a hindrance for the future growth and expansion of the OWFs.

The accessibility limitations of vessels and helicopters imposed by the weather and sea-state conditions combined with the unavailability of failure data makes maintenance decision-making at OWFs, a complex and challenging task for the O&M team. A significant portion of the annual budget is wasted on many large offshore projects because of improper maintenance decisions [6]. Numerous research studies have been carried out to assist the O&M team in making maintenance decisions at OWFs. Almost 80% of the total research articles (related to offshore wind farm maintenance) have been published in the last five years, which indicates the increasing importance of O&M-related research for offshore wind farms in operation and under construction [6]. The maintenance decision problems have been analyzed from Reliability, Availability, Maintainability and Serviceability (RAMS) perspectives and many maintenance models have been developed for optimal decision-making.

Almost 98% of the models in the literature address long-term (5–20 years) and/or lifetime (which is usually 20 years) maintenance decision problems. There exist arguments in the wind research community that optimizing short-term maintenance decisions may not greatly reduce the O&M cost. It is reported in [7] that the expected total cost of one corrective maintenance trip at an OWF is $70,000–$130,000 (approximately). From the model and results of [7], it is understood that one wrong resource decision (improper vessel selection or insufficient manpower) for a corrective maintenance execution could necessitate an additional trip and account for a wastage of no less than $70,000 in the annual maintenance budget. This study shows that the maintenance decisions for offshore wind farms are critical for all time horizons (an hour, a day, a month, a year and lifetime).

Existing long-term and lifetime models are not implemented at OWFs, because the OWF stakeholders treat the models as theoretical and incomprehensive [6]. The models are touted to be complex and the stakeholders believe that it will take considerable time and require technical force to solve the models. This viewpoint of OWF stakeholders about the existing models demands a shift from theoretical research to applied research. In addition, it creates a necessity to identify maintenance decision problems (either long term or short term) that have a significant effect on the life cycle O&M costs and to provide solutions to one decision problem at a time through simple maintenance models. The corrective maintenance and its associated resource decisions (both short-term and long-term) contributes more than 60% to the life cycle O&M costs and is the highest cost driver of OWF O&M [8]. The stakeholders view of the existing maintenance models and the high cost associated with the corrective maintenance resource decisions was the motivation to identify short-term resource decision problems for corrective maintenance of the OWFs.

Few models in the literature have addressed the short-term maintenance problems at OWFs. The work reported in [9] developed an opportunistic short-term maintenance model. Whenever there is a need for corrective maintenance, the model considers the corrective maintenance trip as an opportunity to perform preventive maintenance at other turbines in the wind farm. The model is developed for two different time horizons (a day and a week) and for wind farms that follows flexible maintenance schedules. The model requires the maintenance manager to optimize the maintenance schedule in the morning of every working day and the maintenance tasks to be performed are available only after the optimization. The results of the work showed that 43% of the total preventive maintenance cost could be saved if this opportunistic maintenance with flexible everyday schedule optimization is adopted at the OWFs. The work reported in [10] developed a short-term decision-making model for scheduling resources (vessels and maintenance personnel) at the OWFs. The time horizon considered in this model is a day and it helps the OWF maintenance managers and planners to make better resource scheduling decisions each day. The model studied the impact of the number of maintenance personnel on energy loss and pointed out the importance of scheduling optimal number of maintenance personnel for daily maintenance work.

Both the short-term models [9,10] reported in the literature assumed that the information about turbine failure is always available and known for offshore turbine maintenance. With this assumption, the kind of needed repair is known, the resource decisions are certain and the maintenance team easily picks the desired resources for maintenance. The short-term models [9,10] then focused on different objectives such as opportunistic preventive maintenance [9] and resource-scheduling [10] to minimize the total maintenance costs. When the turbine failure information becomes unavailable, the resource decision-making turns out to be uncertain and the short-term models [9,10] are inapplicable to address this maintenance problem situation.

In this paper, a short-term resource decision-making model is proposed for the corrective maintenance of offshore wind turbines, considering the uncertainty in turbine failure information. The proposed model will assist multiple OWF stakeholders in making critical resource decisions for a corrective maintenance trip. The proposed model addresses the maintenance problem situation for which the information on turbine failure is not available and so it cannot be compared with the short-term models [9,10] in the literature. The paper is organized as follows: the problem description is presented in Section 2. In Section 3, the mathematical model for the described problem is presented. In Section 4, a case study is presented to demonstrate the use of the maintenance decision-making model. Some concluding remarks and the possible future work suggestions are given in Section 5.

2. Problem Description

Each component failure of a wind turbine have different maintenance/repair severities, i.e., the effort needed from the maintenance personnel, the cost associated with the maintenance work and the time needed to perform the repair vary for each component failure. It is reported in [11] that the grouping of turbine component failures with similar maintenance severity is done to develop failure classifications and the reported methodology will be followed in our study. The offshore turbine component failures may be classified into a finite set of failure classifications and each failure classification have a maintenance rank and a probability of occurrence. The "maintenance rank" of a failure classification is defined as "the natural number assigned to each failure classification based on the severity of maintenance involved in solving component failures, with 1 assigned to the failure classification of lowest maintenance severity and N assigned to the failure classification of highest maintenance severity". As each failure classification is assigned a maintenance rank, the total number of ranks is same as the total number of failure classifications. The "probability of occurrence of a failure classification" is defined as "the sum of all the individual failure probabilities of turbine components under a specific failure classification".

Irrespective of the type of maintenance, certain resources are required to perform the intended maintenance task. Resources needed to complete a maintenance activity are an access vessel, maintenance personnel and spare parts. The right combination of maintenance personnel, access vessel and spare part to address the offshore turbine failure is termed as "resource combination". In the case of an offshore wind turbine, different resource combinations are required to solve component failures under different failure classifications. For example, to solve the failure of a gearbox under a given failure classification, more maintenance personnel, expensive vessel and spare gearbox parts (assembled or individual spare parts) are required, whereas to solve the failure of a brake shoe falls under another failure classification, and less number of maintenance personnel, inexpensive vessels and brake shoe spare parts are required. Hence, two failure classifications could potentially result in two resource combinations. The failure of both the brake shoe and gearbox could also be addressed using one resource combination.

This provides us an intuitive understanding that there may exist two types of resource combinations to address the offshore turbine failure. We assume that the first type are, resource combinations that are dedicated to address component failures under only one specific failure classification and are referred as "A-type Resource Combinations" or simply "A-type RC's" throughout the paper. A-type RC is defined as "the combination of maintenance personnel, spare parts and vessels which can identify and solve component failures under single failure classification". A-type RC's cannot solve the failures occurred in turbine components under other failure classifications. We assume that the second type are, the resource combinations that are capable of solving turbine component failures under multiple failure classifications within a specified maintenance rank and are referred as "B-type Resource Combinations" or simply "B-type RC's" throughout the paper. The B-type RC for the n^{th} ranked failure classification is defined as "the combination of maintenance personnel, spare parts and vessels which can solve component failures under the rank "1 to n" failure classifications". From the definition, it is understood that, if a B-type RC is sent to address the n^{th} ranked failure classification it cannot solve component failures under rank "n + 1 to N" failure classifications.

Though today's turbines are usually equipped with condition monitoring (CM) systems, we consider the scenario that such condition monitoring systems are unable to indicate the exact failure classification upon a turbine failure. That is, no information on the kind of needed repair/failure classification and spare parts requirements are obtained from the CM systems. Such scenarios arise when natural events, including but not limited to storms, icing, and waves occur and these natural events account for 60% of the offshore turbine failures [12]. The occurrence of these natural events is unpredictable and leads to failure of both the turbine components and the CM systems, respectively. The human-influenced events are generally reliability related issues of the CM systems. It is reported in [13] that the reliability of the CM system is not 100% and the CM systems sometimes fail to produce an alarm when the turbine component requires immediate attention for maintenance. The event of the CM systems not producing an alarm leads to the component failure and apparently turbine failure. During this CM system unreliability event, the information failed turbine component is not obtained from the CM systems. Hence, these random natural and human influenced events (of failure) leads to situation where the O&M team will have no direct information from the CM systems to make resource related maintenance decisions. In this paper, we focus on this scenario of corrective maintenance where the information on failed turbine component and its failure classification is not known.

A wind farm may have many turbines in operation, which may fail anytime in the future. If any wind turbine at an offshore wind farm failed suddenly and, no information on the failed turbine component and its failure classification could be obtained from the CM systems, the O&M team do not know the exact resource combination to address the failed turbine. In this situation, the O&M team is unsure about which type of vessel to use, how many maintenance personnel to send, whether to take spare parts or not and which spare parts to take. This creates uncertainty in making decision on the resource combination for maintenance execution. The hypothesized problem situation is "a corrective maintenance trip to an offshore wind turbine with unknown turbine failure information". The aim of our study is "to find the cost-effective resource combination for the hypothesized problem situation". In this problem, the failure classification is not known at the time of maintenance initiation and all the resource combinations that are available in the onshore port turn out to be decision choices for the O&M team. The resource combination to be selected by the O&M team might solve the unknown failure in one trip or might not solve the unknown failure in one trip and necessitate an additional trip to solve the identified failure known from the first trip. Therefore, the O&M team is put into a situation to select only one resource combination among all the available resource combinations considering the two possible results of their decision. In order to make a decision, the cost associated with each decision choice must be evaluated taking into account the probability of occurrences of different failure classifications. Then, the resource combination with least cost could be selected as the cost-effective resource combination to address the unknown turbine failure. The objectives are to propose a simple and useful mathematical model to aid decision-making and to demonstrate the use of the proposed model through a case study.

3. Mathematical Model

In this section, the mathematical model for the described problem is proposed. If the offshore wind turbine have a finite number of failure classifications and each classification has a probability of occurrence, then:

$$\sum_{i=1}^{N} P_i = 1 \tag{1}$$

where P_i denotes the probability of occurrence of the i^{th} failure classification. The probabilities of occurrences of all the failure classifications are assumed known.

To address the component failures under respective failure classifications of offshore wind turbine, two different types of resource combinations are described earlier in Section 2. In our model, both the types of resource combinations are considered as decision choices. Therefore, the selection of one resource combination among the available resource combinations (both A-type and B-type) is the only decision for the described problem. The decision is represented as a finite set of binary variables in our model:

$$S_{ij} = \begin{cases} 1, & use\ type\ j\ RC\ for\ failure\ classification\ i \\ 0, & don't\ use\ type\ j\ RC\ for\ failure\ classification\ i \end{cases} \tag{2}$$

$$\text{Constraint:} \sum_{i=1}^{N} \sum_{j=1}^{2} S_{ij} = 1 \tag{3}$$

where S_{ij} denotes the type j RC for the i^{th} ranked failure classification. The above constraint ensures that only one S_{ij} is selected among the available N number of $S'_{ij}s$, to solve the unknown failure. All the type j RC's that are dedicated to address their respective i^{th} ranked failure classifications are assumed known.

The uncertainty in turbine failure information brings in two possible situations namely trip success and trip failure. The "trip success" is defined as the situation where the unknown turbine failure is solved in a single maintenance trip using either an A-type RC or a B-type RC. The "trip failure" is defined as the situation where the unknown turbine failure cannot be solved in a single maintenance trip and necessitates an additional trip to solve the identified known failure using an appropriate A-type RC. Both the probability of trip success and trip failure depends on the decision and the probability of occurrences of the failure classifications. The trip success and failure situations along with their probabilities are considered in the model.

When an A-type RC which is dedicated for the i^{th} failure classification, is sent to address the unknown failure, the trip is successful when the failure classification is i and the trip is a failure when the failure classification is not i. For A-type RC, the probability of the maintenance trip to be a success is P_i and the probability of the maintenance trip to be a failure is $1-P_i$. If the failure classification is not i, we are able to identify that the failure is k and a single next trip with an A-type RC for k will solve the failure. When a B-type RC that is dedicated for the n^{th} failure classification is sent to address the unknown failure, the trip is successful when the failure classification is $1, 2, 3, \ldots, n$ and, trip is a failure when the failure classification is k ($k > n$). For B-type RC, the probability of the maintenance trip to be a success is $P_1 + P_2 + P_3 + \ldots + P_n$ and the probability of the maintenance trip to be a failure is $P_{n+1} + P_{n+2} + P_{n+3} + \ldots + P_N$. A single next trip with an A-type RC for k will solve the failure.

The objective is to find the expected total maintenance cost of the decision, to figure out the cost-effective decision and solve the unknown turbine failure. The total maintenance cost in our model includes the maintenance personnel cost, access vessel cost, special maintenance vessel cost (jack-up, crane, etc.), spare parts cost and, production losses due to downtime. The maintenance personnel and vessels are in use from the point of time they get ready to execute maintenance to the point of time they get back to shore after the maintenance activity. In addition, the turbine is unavailable until the maintenance crew get the turbine back to operation. Therefore, the mathematical model formulation involves various deterministic time elements of maintenance namely lead-time, logistic time, waiting time, travel time, failure identification time and repair time.

The time to get the vessel ready for maintenance is the lead-time and, the time to get the spare parts is the logistics time. It is assumed that all the resources (the vessels, the personnel and the spare parts) are always available in the onshore port for maintenance execution. This assumption eliminates the lead-time of vessels and the logistic time of spare parts in our model. The total delay in maintenance execution due to weather and sea-state conditions is the waiting time and is the sum of "the delay before travel starts" and "the delay at the turbine" [14]. It is dependent on weather and does not depend on the decision. Hence, the waiting time is a constant in our model. The time to identify the failure occurred at the turbine and figure out the component that requires maintenance is the failure identification time. The failure identification time does not depend on the decision and is a constant in our model. The time taken to travel back and forth the turbine using vessels is called the "travel time" and is the sum of the "travel time to the turbine" and "travel time from the turbine". The travel time is dependent on the decision, as the vessel speed may differ for different resource combinations. To calculate the travel time, the average distance of the turbines from the shore is considered in our model. The wind speed and wave height variations in the sea may affect the travel speed, which in turn affects the travel time. To simplify our analysis and exclude the hydrodynamics of the sea, the travel time is assumed to be independent of the wave height and wind speed in this paper.

The time it takes to perform the actual maintenance work is the repair time. In the case of trip success, the repair activity is completed successfully and the turbine failure is solved in one trip. In our model, the trip success situation includes the repair time. In the case of trip failure, the component failure is only identified and is not repaired in the first trip. The certain amount of time spent to identify the failure in the first trip (waiting time, failure identification time and travel time) along with the fixed cost for an additional trip to solve the known failure using an A-type RC is considered for trip failure. The fixed cost/purchase cost of spare parts are not considered in our model, instead the cargo handling costs of spare parts is considered as the spare parts cost in our model. The spare parts cost is the total tonnage of spare parts in a resource combination times the cargo handling cost per tonnage. To simplify our analysis, the weight of the spare parts is considered the only cargo weight in our model. Other weights such as the weight of the maintenance tools, technicians are not considered. The mathematical model for the described problem is given in Equation (4) as:

$$Z = \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times g_{ij} \times D + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times H_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times t_{ij} \times C_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times \alpha_{ij} \times r_{ij} \times C_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{2} S_{ij} \times \beta_{ij} \times A \quad (4)$$

$$C_{ij} = V_{ij} + (n_{ij} \times M) + R \quad (5)$$

$$\alpha_{ij} = P_i \text{ for } j = 1 \quad (6)$$

$$\alpha_{ij} = \sum_{k=1}^{i} P_k \text{ for } j = 2 \quad (7)$$

$$\beta_{ij} = 1 - P_i \text{ for } j = 1 \quad (8)$$

$$\beta_{ij} = \sum_{k=i+1}^{N} P_k \text{ for } j = 2 \quad (9)$$

Z Expected total maintenance cost for S_{ij}
g_{ij} Weight of spares for S_{ij} in tons
D Cost per tonnage of spares
H_{ij} Cost of special vessel for S_{ij}
t_{ij} Travel time for S_{ij} in hours
C_{ij} Cost of vessel, maintenance personnel, and revenue loss per hour for S_{ij}
V_{ij} Vessel cost per hour for S_{ij}
n_{ij} Number of maintenance personnel for S_{ij}
M Maintenance personnel cost per hour
R Revenue loss per hour
r_{ij} Repair time for S_{ij} in hours
α_{ij} Probability of trip success for S_{ij}
B_{ij} Probability of trip failure for S_{ij}
P_i Probability that the failure is of classification i
A Fixed additional trip cost of sending an A-type RC to solve known failure, which includes vessel cost, personnel cost, spare parts cost, and revenue loss due to downtime

The above mathematical model describes the expected total maintenance cost of sending S_{ij} to address the unknown failure. The first two terms in the model, is the sum of the spare parts cost and fixed special vessel cost of S_{ij}. The third term in the model is the total cost including vessel cost, personnel cost and revenue loss incurred because of the travel to and from the turbine using S_{ij}. The fourth term in the model is the trip success using S_{ij}. The trip success considers the total cost including the vessel cost, personnel cost ad revenue loss incurred because of the repair activity at the turbine using S_{ij} and, the probability that the turbine failure could be solved by S_{ij}. The fifth term in the model is the trip failure using S_{ij}. The trip failure considers the total cost including the vessel cost, personnel cost ad revenue loss to solve the known failure using an appropriate A-type RC and, the probability that the turbine failure could not be solved by S_{ij}. The waiting time and failure identification time are constants in our proposed model and both the time elements does not affect the decision and the results. Therefore, the waiting time and failure identification time are not included in the model. In the Equations (6)–(9), $j = 1$ represents the A-type RC and $j = 2$ represents the B-type RC.

With appropriate inputs, the proposed model is capable of calculating the expected cost of each decision choice. Utilizing the enumeration method, the expected total cost of all the resource combinations are evaluated and, the resource combination with minimum expected cost is selected as the cost effective option to address the unknown turbine failure. The mathematical model formulated above includes both types of resource combinations described earlier in Section 2, as decision choices and this allows the decision makers to consider all the available resource combinations for decision-making. In addition, the simplicity of the model ensures that it takes less time and less technical effort to solve the model. Hence, all the OWF stakeholders could use the model anytime. Given the failure classifications, their probabilities and resource combinations (decision choices) and, using the proposed model, the O&M team at any OWF would be able to figure out the cost-effective resource combination to address the unknown turbine failure.

4. Case Study

The objective of the case study is to demonstrate the use of the proposed model for offshore wind turbine maintenance. To simplify our analysis, a wind farm model with identical turbines is selected for our case study.

4.1. Wind Farm Models

The OWEZ wind farm model reported in [11] is selected for the study. The OWEZ wind farm has 36 identical VESTAS 3 MW wind turbines with a total capacity of 108 MW. The wind farm is in the North Sea at 10–18 km distance from the harbor and the turbines are installed to a maximum depth of 20 m. Four failure classifications for corrective maintenance reported in [11] for a 3 MW wind turbine is applicable for the selected OWEZ wind farm model and is given in Table 1.

Table 1. Failure classifications for a 3 MW offshore wind turbine [11].

Maintenance Rank	Failure Classification	Definition
1	Imperfect maintenance	An imperfect maintenance operation where there is no requirement for spare parts.
2	Minimal replacement	A minimal replacement of small sized sub-components with a maximum weight of 1 tonne.
3	Perfect replacement I	A perfect replacement of medium weight sub-components with a maximum weight of 50 tonnes.
4	Perfect replacement II	A perfect replacement of medium or large sized sub-components, with weight 50 tonnes to 100 tonnes.

In accordance with the vessel characteristics reported in [15] and the weight of spares under each failure classification reported in [11], the A-type RC's and B-type RC's for corrective maintenance is given in Table 2. From Table 2, it could be observed that S_{11} and $\boldsymbol{S_{12}}$ have identical resource elements, which means both A-type and B-type RC's are identical for imperfect maintenance in this study.

The probabilities of different failure classifications reported in [11] is applied to the OWEZ wind farm model. The reported probabilities are considered as the base case model in the study. It can be observed that majority of the corrective maintenance for the base case model is imperfect maintenance.

Thus, the base case model is interpreted as OWF in which the turbines are relative new and their age is less than 5 years, that is, the turbines are operating in its first 5-year service period.

As the base case model is interpreted as OWF with turbines that are less than 5 years old, three other models are established for OWFs with increasing age of turbines with appropriate assumptions to demonstrate the powerfulness of the proposed model for different OWFs. The model 1 represents the OWF in which the turbines in operation are 5 to 10 years old. For the wind farm model 1, it is assumed that the majority of corrective maintenance corresponds to minimal replacement and it has the highest probability of occurrence. The probability of other failure classifications are then descended in the order of imperfect maintenance, perfect replacement I and perfect replacement II.

The model 2 represents the OWF in which the turbines in operation are 10 to 20 years old. For the wind farm model 2, it is assumed that the majority of corrective maintenance corresponds to perfect replacement I and it has the highest probability of occurrence. The probability of other failure classifications are then descended in the order of perfect replacement II, minimal replacement and imperfect maintenance.

Table 2. Decision Choices [11,15].

Resource Combination	Resource Elements
S_{11}	No Spare part + Access Vessel (Crew Transfer Vessel -small) + 2 maintenance personnel
S_{21}	Required Spare part + Access Vessel (Crew Transfer Vessel -small) + 3 maintenance personnel. (Use of permanent internal crane for replacement).
S_{31}	Required Spare part + Crane Vessel + Access Vessel (Crew Transfer Vessel small) + 6 maintenance personnel.
S_{41}	Required Spare part + Access Vessel (Crew Transfer Vessel -small) + Access Vessel (Jack-Up Vessel) + 6 maintenance personnel.
S_{12}	No Spare part + Access Vessel (Crew Transfer Vessel - small) + 2 maintenance personnel
S_{22}	All Class B Spare parts + Access Vessel (Crew Transfer Vessel-Large) + 3 maintenance personnel (Use of permanent internal crane for replacement).
S_{32}	All Class B and C Spare parts + build-up crane with a vessel + Access Vessel (SUVs) + 6 maintenance personnel.
S_{42}	All Class B, C and D spare parts + Access Vessel (SUVs) + Access Vessel (Jack- Up barge) + 6 maintenance personnel

The model 3 represents the OWF in which the turbines are either more than 20 years old or affected by storms or other natural disasters. For the wind farm model 3, it is assumed that the majority of corrective maintenance corresponds to perfect replacement II and it has the highest probability of occurrence. The probability of other failure classifications are then descended in the order of perfect replacement I, minimal replacement and imperfect maintenance. The reported probabilities for the base case is changed for different failure classifications to represent the wind farm models 1, 2 and 3. The probabilities of failure classifications of the base case model and the three different wind farm models are given in Table 3. The probability numbers in Table 3 are absolute values and are not in percentages.

Table 3. Probabilities of failure classifications for different OWF models [11].

Failure Classification	Probability			
	Base Case Model	Wind Farm Model 1	Wind Farm Model 2	Wind Farm Model 3
Imperfect maintenance	0.995165258	0.002353569	0.000995862	0.000995862
Minimal replacement	0.002353569	0.995165258	0.001485311	0.001485311
Perfect replacement I	0.000995862	0.001485311	0.995165258	0.002353569
Perfect replacement II	0.001485311	0.000995862	0.002353569	0.995165258

4.2. Time and Cost Inputs

The values of time elements are essential inputs to find the expected total maintenance cost. Travel time is calculated using a 14 km average distance of the wind turbines from the shore and average speed of different access vessels. The repair time for rank 1 failure classification is assumed to be 4 hours in our study. It is reported in [14] that it will take 48 hours to switch out the component in question and replace a working unit for major maintenance. This time reported in [14] is the repair time for rank 2, 3 and 4 failure classifications in our study. The reported work in [11], which defined the failure classifications, did not provide any weight data for individual spare parts. Based on the turbine components listed under each failure classification reported in [11], the maximum cargo weight of spare parts for a failure classification is considered as the cargo weight of a resource combination. The fixed cost for corrective maintenance trip from [15] is the additional trip cost in this case study. All the time and cost inputs required to find the expected total maintenance cost are given in Tables 4 and 5.

Table 4. Inputs to calculate expected total maintenance cost [11,14–16].

Resource Combination	Travel Speed (km/h)	Travel Time (h)	Repair Time (h)	Access Vessel Cost/hour	Crane/Jack up Vessel Cost	Weight of Spare Parts (tonnes)
S_{11}	37.04	0.76	4	$62.5	N/A	0
S_{21}	37.04	0.76	48	$62.5	N/A	1
S_{31}	37.04	0.76	48	$62.5	$105,259.5	50
S_{41}	37.04	0.76	48	$62.5	$119,294.1	100
S_{12}	37.04	0.76	4	$62.5	N/A	0
S_{22}	46.3	0.6	48	$93.75	N/A	11
S_{32}	18.52	1.5	48	$93.75	$105,259.5	600
S_{42}	18.52	1.5	48	$93.75	$119,294.1	600

Table 5. Inputs to calculate expected total maintenance cost [17–19].

Parameter	Values
Maintenance Personnel cost/hour	70
Cost/tonnage of spares	29.72
Revenue Loss/hour	$18,684
Fixed cost for corrective maintenance trip for offshore wind turbine	$500,000

4.3. Results

The expected total maintenance cost of each decision choice for a specific wind farm model, is represented as a 4×2 matrix (there are eight decision choices in this study):

$$Z_n = \begin{bmatrix} z_{11} & z_{12} \\ z_{21} & z_{22} \\ z_{31} & z_{32} \\ z_{41} & z_{42} \end{bmatrix}$$

where Z_n is the cost matrix of the wind farm model n. The elements $z'_{ij}s$ of the matrix Z_n represent the expected total maintenance cost values (in $'s) of sending respective $S'_{ij}s$ for a specific wind farm model n. That is, the element z_{11} represent the expected total maintenance cost of sending S_{11}, the element z_{21} represent the expected total maintenance cost of sending S_{21}, and so on. It is earlier stated in Section 4.1 that both A-type and B-type RC's have identical resource elements for imperfect maintenance, which indicates, the elements z_{11} and z_{12} of the matrix Z_n will have identical values. The minimum of the $z'_{ij}s$ in the matrix Z_n is selected as the optimal solution and the corresponding resource combination is identified to be the cost-effective resource combination.

Using the model in Section 3, the model inputs in Sections 4.1 and 4.2, and using the explicit enumeration method the expected total maintenance cost is calculated for all the available resource combinations (decision choices) for the different wind farm models of Table 3 and the results are shown in matrix form.

The cost matrix for the base case model (Z_0) is:

$$Z_0 = \begin{bmatrix} 91951 & 91951 \\ 515401 & 922110 \\ 621730 & 1072754 \\ 637456 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 1 (Z_1) is:

$$Z_1 = \begin{bmatrix} 513354 & 513354 \\ 922366 & 922110 \\ 621935 & 1072960 \\ 637250 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 2 (Z_2) is,

$$Z_2 = \begin{bmatrix} 513931 & 513931 \\ 515045 & 512740 \\ 1039273 & 1072388 \\ 637821 & 1087414 \end{bmatrix}$$

The cost matrix for the wind farm model 3 (Z_3) is:

$$Z_3 = \begin{bmatrix} 513931 & 513931 \\ 515045 & 512740 \\ 622300 & 653925 \\ 1054794 & 1087414 \end{bmatrix}$$

The minimum value of the cost matrix Z_n for the wind farm model n represents the optimal solution, that is, the corresponding resource combination is identified to be the cost-effective resource combination.

To prove the effectiveness of the proposed model, it is appropriate to compare the results of the proposed model with the traditional practice of solving the described problem. When no information on the failed turbine is obtained from the CM systems, generally the offshore O&M team send technicians to inspect the failed turbine in a small Crew Transfer Vessel, identify the failure classification and then send the required resource combination to solve the turbine failure. In order to compare the results of the proposed model with the general practice, the cost of the general practice is assumed as the sum of the inspection activity cost using S_{11} and the fixed cost of corrective maintenance trip for offshore wind turbine. All the inputs presented in Sections 4.1 and 4.2 are used to calculate this cost of traditional practice and is found to be $514,353. The estimated cost of traditional practice is used to compare the results of the proposed model and to find the cost savings, if any.

The cost-effective resource combination for each wind farm model considered in this study with the total expected maintenance cost and, the cost savings in comparison with the traditional practice are given in Table 6.

Table 6. Cost-effective resource combination for different wind farm models given in Table 3.

Wind Farm Model	Cost-Effective Resource Combination	Expected Total Maintenance Cost (in $'s)	Cost Savings (in Comparison with Traditional Practice)
Base case	S_{11}	91591	82.12%
Model 1	S_{11}	513354	0.19%
Model 2	S_{22}	512740	0.31%
Model 3	S_{22}	512740	0.31%

The optimal resource combination can be directly selected from Table 6. From the results, it could be observed that, S_{11} (which is same as S_{12} in this study) is the cost-effective option to address the corrective maintenance for turbines that are in operation for less than 10 years (base case model and wind farm model 1). In addition, S_{22} is the cost-effective option to address the corrective maintenance for turbines that are in operation for more than 10 years (wind farm model 2 and 3). Comparing the results of the proposed model with the traditional practice, the proposed model produces very high cost savings of 82.12% for the base case model and a considerable cost savings for the other three different wind farm models. It has to be noted that the proposed model is for one corrective maintenance trip and when there are multiple corrective maintenance problem instances with no information from CM systems, the cost savings will be more for the wind farm models 1, 2 and 3.

The results that are generated from the model are not only dependent on the probability of failure classifications (given in Table 3) but also on the cost estimates (given in Tables 4 and 5). The value of the "fixed cost for corrective maintenance trip for an offshore wind turbine" in Table 5 is assumed to be the same for all types of corrective maintenance because of insufficient data and this affects both the estimated cost of the general practice and also the results generated from the models. This assumption on the fixed cost for corrective maintenance is a key reason that the base case has a huge amount of savings in comparison with the other three wind farm models. More accurate fixed costs for different types of corrective maintenance will result in better estimates for the general practice and, more accurate results for the wind farm models 1, 2 and 3. Accurate cost data in maintenance decision-making and sensitivity analysis of the proposed model to the cost estimates (in Tables 4 and 5) will be studied in our future work.

The case study provides a better understanding of the use of the proposed model to address a corrective maintenance situation when there is no information on turbine failure type. Three different wind farm models are considered in addition to the base case and the powerfulness of the model for different OWFs is demonstrated. The case study also gives us an understanding that when the number of failure classifications for an OWT/OWF increase, then the complexity in finding the cost-effective resource combination also increases.

5. Summary and Conclusions

In this paper, a short-term resource decision problem for corrective maintenance at offshore wind turbine is identified and described. A simple mathematical model is proposed to solve the decision problem. The model is proposed in such a way that the expected cost of the decision is mainly dependent on the probabilities of occurrences of failure classifications. The maintenance team at all offshore wind farm will have their own failure classifications, resource combinations and access to accurate failure data and, this model will assist the maintenance team in making resource decisions to address the corrective maintenance problem stated in this paper. Possible future work includes the lead-time and logistic time in the decision model and consider the uncertainty in weather and sea-state conditions and the hydrodynamics of the sea in the model.

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