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Availability Assessment of Offshore Wind Turbines with Condition-based Opportunistic Maintenance Using GSPN

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Abstract: This paper assesses the availability of an offshore wind turbine under condition-based opportunistic maintenance strategies. Generalized stochastic Petri nets (GSPN) are adopted to analyze the impact of implementing the maintenance strategy, with the consideration of factors such as vessel hiring and weather windows. A 25-year operational period is simulated using a Monte-Carlo simulation to evaluate availability and total cost of the wind turbine. By examining the availability and total cost under various opportunistic maintenance efficiencies, it is concluded that an opportunistic maintenance efficiency in a certain range offers a cost-availability trade-off. Overall, the method and the results of this paper contribute to the effective operation and maintenance of offshore wind turbines.

Keywords: offshore wind turbine, availability, condition-based opportunistic maintenance, GSPN

1. INTRODUCTION

Offshore wind has witnessed widespread impacts on the global energy consumption structure (Edwards et al., 2023). However, the harmful and harsh operating conditions at sea generate difficulties in failure avoidance as well as lifelong cost saving of offshore wind turbines (OWTs). Accordingly, availability assessment, quantifying the impact of components' failure and maintenance strategies on electricity production, becomes a special need for overall performance improvements of such devices (Abeynayake et al., 2021).

Availability guides the operation and maintenance (O&M) activities of wind farms, serving as the basic evidence to examine the effectiveness of the designed O&M strategies at the design and operation stages (Huang et al., 2017). The assessment of the availability of wind turbines/farms relies on a thorough understanding of the failure, reliability, and maintenance resource scheduling of wind farms and their entire supportive supply chain (Koukoura et al., 2021).

Petri nets (PNs) combine graphical representation with mathematical rigor, enabling the description, simulation, and analysis of dynamic discrete-event systems, as well as the evaluation of their availability (Lotovskyi et al., 2022). To be specific, Ramos et al. (2017) established a stochastic Petri net (SPN) model to analyze the availability of simplified gas treatment systems, which illustrated the effectiveness of SPN in handling the system dynamics. To capture the complexity of the evolution process, a hybrid method combining PN and Monte-Carlo simulation (MCS) is proposed to model and analyze the complex behavior of industrial multi-unit systems in terms of reliability, availability, and production efficiency. The method is able to assess the uncertainty generated in the simulation process. Similar applications of the PN-MCS methods were also used to assess the availability and maintenance strategies of OWT in the North Sea off the coast of Germany (Santo et al., 2018), taking into account both corrective and preventive maintenance of wind turbines. Additionally, Jalal et al. (2023) evaluated the availability of dock cranes by PN-MCS, examining the performance of the method in modeling various weather conditions. It is concluded that PNs provide an intuitive approach to system availability evaluation by leveraging their strengths in formal, dynamic, and concurrent modeling.

The availability of wind turbines is determined by multiple critical factors, including offshore wind farm accessibility, prevailing weather conditions, implemented maintenance strategies, and spare parts supply chain efficiency (Fallahi et al., 2022). The key to the availability assessment of wind turbines is the determination and modeling of availability-influencing factors. For instance, Zhang et al. (2019) proposed an opportunistic maintenance (OM) strategy, combining dynamic maintenance thresholds and inventory management methods, which provides a close-to-practice maintenance solution for OWT availability estimation. Lotovskyi et al. (2022) applied a PN to evaluate OWT availability combined with corrective maintenance (CM) and preventive maintenance (PM) strategies. By considering the usage of vessels, mobilization time, cost, and weather windows, the model is able to optimize maintenance decisions, improve operation efficiency, and reduce the overall O&M cost of wind turbines. However, the reliability of the above modeling concepts is limited by taking the CM/PM of wind turbines as the basic unit in availability assessment, and they are not able

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to model dynamic maintenance processes generated by dynamic failure features of wind turbines.

To this end, this paper proposes a PN-based availability evaluation framework that integrates condition-based maintenance (CBM) and OM to reduce O&M costs while improving the availability of wind turbines. The framework employs the generalized stochastic Petri net (GSPN) to model the availability of OWTs, incorporating the mean time to failure (MTTF) of their critical components. The model dynamically simulates turbine operational behaviour under seasonal variations while systematically accounting for key operational constraints, including vessel logistics and weather-dependent accessibility windows. The key contributions of this paper are as follows:

(1) Construction of a maintenance model based on GSPN to evaluate the availability of OWTs and the total cost of O&M.

(2) Propose an O&M parameter updating mechanism (with time and season) of OWTs to improve the accuracy and reliability of the GSPN model.

The paper proceeds as follows. Section 2 outlines the GSPN and provides the key factors for OWT availability assessment. The proposed GSPN models are described in Section 3. Section 4 presents the results and discussions, and the conclusions come in the last section.

2. METHODOLOGY

2.1 GSPN

PNs integrate graphics and mathematics and consist of: Places, Transitions, Tokens, and Arcs (Marsan et al., 1998). To be specific, a Place reflects a state of the system to be modelled; a Transition controls, fire or not, the transformation of tokens among states, which denotes the current state of the system if the token is located in a certain place; Arcs are the one-way path that a token transfers through. A graphical representation of basic elements is shown in Fig. 1. In GSPN, the transition enhances the expressiveness and flexibility of models through Guard and Assignment. A guard is a logic condition that controls whether a transition can be fired, while an Assignment is used to modify variables or information after a transition is fired.

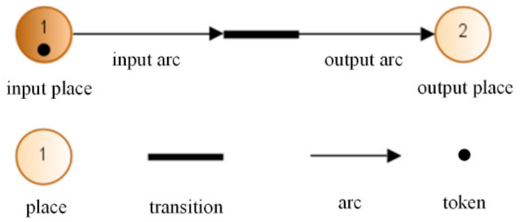

Fig. 1. Basic elements of PNs

Pitch system (PS), gearbox (GB), generator (GT), and blade (BL) are critical components of OWTs (Li et al., 2021). Table 1 lists the parameters for modelling that are generated from LGS datasets (Li et al., 2022; Li et al., 2025).

Table 1. Failure data/lifetime distribution of components

Component	Distribution	Shape parameter	$MTTF_0$ (h)
PS	Weibull	3	35056
GB	Weibull	3	76025
GT	Weibull	2	87640
BL	Weibull	3	101775

2.2 Maintenance

Wind turbine failures can be categorized into normal failures (NFs), critical failures (CFs), and extremely critical failures (ECFs). NFs have a limited impact on production; CFs reduce availability and result in wind turbine operating at below-rated power; ECFs cause the wind turbine to shut down and require additional materials to repair and restart (Li et al., 2022).

Aiming at reflecting the above failures characteristics of wind turbine, this paper adopts the condition-based opportunistic maintenance (CBOM) strategy to support the availability assessment of OWT, which is defined as: (i) generating a random number of the component when a failure warning is issued by the SCADA system; (ii) assigning the component to be a normal failure if the random number is less than threshold I, and the OWT is in the Degraded state I; (iii) assigning the component to be a critical failure if random number is between threshold I and II, and the OWT is in the Degraded state II; (iv) assigning the component to be an extremely critical failure if random number is larger than threshold II or $MTTF(t)$ (see Eq. (1) is lower than 3% of $MTTF_0$, and the OWT is shutdown. The mentioned thresholds are designed in Table 2 according to the records of the LGS datasets.

Table 2. Thresholds for the degree of component failure

Component	Threshold I	Threshold II
PS	0.696	0.967
GB	0.267	0.967
GT	0.396	0.923
BL	0.105	0.881

Commonly used vessels for O&M of wind turbines are supply vessels (SV) and Jack-Up vessels (JU). The maintenance duration of each failure follows a log-normal distribution with a transition coefficient of 20%. The nature of failures, maintenance strategies, O&M vessels, and maintenance durations are displayed in Table 3, where the SD denotes the standard deviation. CM requires new equipment and materials. New equipment and materials need to be transported from the supplier to the port, and the logistics time follows a log-normal distribution as well, with a transition coefficient of 20%, see Table 4. CM for large components (including GB, GT, and BL) is performed only during the summer due to the requirement for favourable operating conditions. Details in terms of the maintenance actions of wind turbines can be accessed at the LGS datasets.

Table 3. Failures, vessels, maintenance strategies and durations

	Failure	Vessel		Duration (h)	
		SV	JU	Mean	SD
PS	NF	CBM		15	3
	CF	CBM&OM		55	11
	ECF	CM&OM		60	12
GB	NF	CBM		40	8
	CF	CBM&OM		80	16
	ECF		CM&OM	90	18
GT	NF	CBM		40	8
	CF	CBM&OM		80	16
	ECF		CM&OM	90	18

BL	NF	CBM		50	10
	CF	CBM&OM		85	17
	ECF		CM&OM	95	19

Table 4. Components logistics time for CM

	PS	GB	GT	BL
Logistic Time (h)	72	288	288	360
SD (h)	14.4	57.6	57.6	72

2.3 Weather window and failure updating

The probabilities of occurrence of the accessible state H and the inaccessible state $\widetilde{H}$ and the waiting time due to adverse weather conditions in this paper is in line with Kang et al. (2020), see Table 5. The geographic information of the wind farm is generated from a wind farm in the East China Sea, according to which the LGS datasets were created, so as to ensure the integration of the data used in this study.

Table 5. Accessibility of the weather window, and waiting time

Season	H	$\widetilde{H}$	Waiting Time (h)
Spring	0.624	0.376	26.2
Summer	0.786	0.214	14.9
Autumn	0.570	0.430	29.9
Winter	0.455	0.545	37.9

In this paper, the failure rate of each component shows cyclical seasonal characteristics of being high in summer and autumn and low in spring and winter. At the same time, the failure rates tend to increase as operational time progresses, resulting in a decreased MTTF. To express the cyclical dynamics of the failure characteristics of OWTs, this paper describes the MTTF of the components in real wind farms by:

$$MTTF(t) = \mathrm{MTTF}_0 \cdot e^{-\alpha t} \cdot \left(\beta + \gamma \cos\left(\frac{2\pi}{T_y}(t - t_{offset}\right)\right) \quad (1)$$

where, MTTF_0 is the initial MTTF; α denotes the attenuation coefficient; β reflects the seasonal fluctuation benchmark; γ represent the seasonal fluctuation amplitude; T_y is the seasonal period; t displays operating time; t_{offset} is the offset value.

Component MTTF degrades to 20% of its baseline value (MTTF_0) following continuous operation spanning MTTF_0 duration under invariant seasonal conditions. The attenuation coefficient α quantifies this degradation, with β and γ regulating dynamic *MTTF* variability, see Table 6.

Table 6. Dynamic model parameter values

Component	α	β	γ	t_{offset}
PS	4.59E-5	0.8	0.3	8030
GB	2.12E-5	0.9	0.2	
GT	1.84E-5	0.95	0.1	
BL	1.58E-5	0.8	0.3	

2.4 Costs

The total cost (TC) of OWTs' O&M is expressed by:

$$TC = \sum_{i=1}^{n} t_i^{CBM} \cdot p_i^{CBM} + \sum_{i=1}^{n} t_i^{CM} \cdot p_i^{CM} + \sum_{i=1}^{n} t_i^{OM} \cdot e^2 \cdot p_i^{CM} + C_m + C_t + C_O \quad (2)$$

where, t_i^{CBM}, t_i^{CM} and t_i^{OM} are the number of times component i is subjected to CBM, CM, and OM; p_i^{CBM} and p_i^{CM} are the cost of subjecting to CBM and CM, see Table 7; C_m is the cost of manpower; C_t is the transportation cost incurred by the voyage of vessels; C_O is the opportunity cost of loss of potential power; e is the OM efficiency, which reflects the equivalent life time of a component compare to a new one after each maintenance. For instance, the equivalent lifetime of component i, reaches 80% as good as new after implementing a maintenance by e=20%.

Table 7. Cost for CBM and CM

Component	Cost of CBM (RMB)		Cost of CM (RMB)
	NF	CF	
PS	8,000	16,000	140,000
GB	30,000	60,000	1,900,000
GT	20,000	40,000	600,000
BL	24,000	480,000	800,000

3. THE GSPN MODEL

The proposed framework models OWT components by three failure scenarios: NFs, CFs, and ECFs. Operational factors, including maintenance source logistics, weather windows, and seasonal variations, are incorporated to represent the various operational states of the OWT.

3.1 Maintenance strategy modelling by GSPN

Each component is described using the same maintenance strategy. In this research, the maintenance strategy of the generator (see Fig. 2) is described rather than all components, so as to reduce the repeated information and shorten the length of the paper. To understand the model, one should note that:

(i) The generator stays working normally if the place *GT_Work* is marked. A failure warning is issued in case the transition *GT_Failure_EW* is fired, and the token moves to the place *GT_Failure_EW*, and variable *GT_Random* is generated.

(ii) The generator is assigned an NF state if *GT_Random* < *GT_Threshold I*, and the transition *GT_JudgeNF* will fire. The token moves to the place *GT_NF*, requiring a CBM. The token stays at the place *GT_NF* until the transition *GT_CBM* is enabled, which calls for the interaction of the maintenance crew and the order of an SV. The token then moves to *GT_WaitingRepair1* and waits for the start of the maintenance activity. The maintenance activity will start when SV arrives. After maintenance, the OWT returns to its normal working state, and SV is ready for the next maintenance.

(iii) The generator is assigned an EC failure if *GT_Random* > *GT_Threshold II* or *GT_MTTF* < *GT_Dead* (3% of GT MTTF_0). The token movement process is similar to the NF state. After CM, OM can be carried out on the components apart from the generator. After OM, *OM_AF_GT* becomes false, and the variables *PS_AM*, *GB_AM*, and *BL_AM* are assigned values for calculating the equivalent lifetime PS, GB, and BL.

(iv) The generator is assigned to be a critical failure if *GT_Threshold I* < *GT_Random* < *GT_Threshold II*. The token movement process is similar to the normal failure state, and

CBM and OM are required. The situation of OM is in line with ECF.

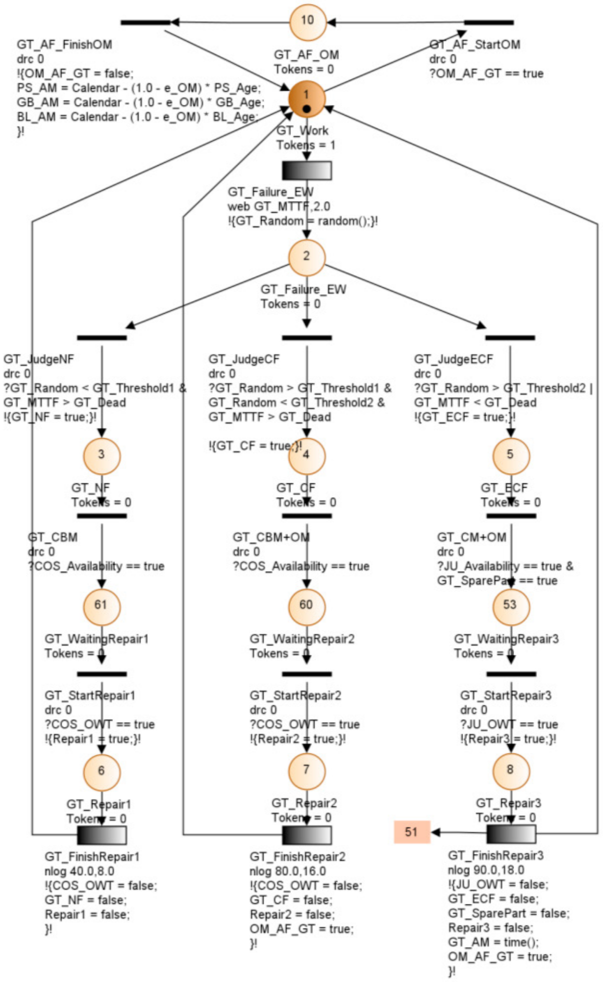

Fig. 2. The GSPN model for the maintenance of the generator

Fig. 3 displays the GSPN model of the OWT system. It calculates the duration of the OWT in each operational phase.

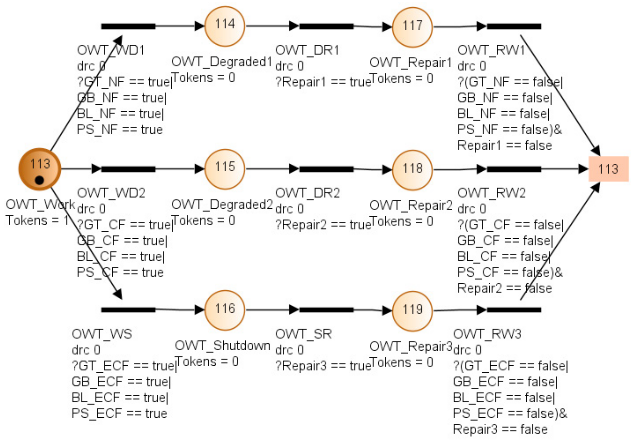

Fig. 3. The GSPN model of OWT

3.2 Vessel and weather window modelling

As mentioned, SV and JU are considered to perform the maintenance, see Fig. 4. The vessels are scheduled as:

(i) CM of the generator can be performed only in summer. The transition *GT_Deliver* fires with *GT_ECF* and *JU_Availability* become true, and the token moves from place *GT_Manufacturer* to *GT_SparePart*. If both the place *Vessel_Port* and *GT_SparePart* are marked, the transition *GT_JU_CM+OM* fires after the mobilization time has elapsed, and the maintenance starts.

(ii) Then, *JU_Availability* becomes false, and the variable *RandomWW* is assigned as 0 to 1. The token will only move from the place *GT_JU_StartSail* to *GT_JU_SailOWT* if the variable *WW* is available or the waiting time runs out.

(iii) After a delay for shipping, *JU_OWT* becomes true, and the token moves to *OWT_GT_CM+OM*. The completion maintenance enables *JU_OWT* to become false, transition *GT_JU_LeaveOWT* becomes fired, which indicates that the JU is returning to port.

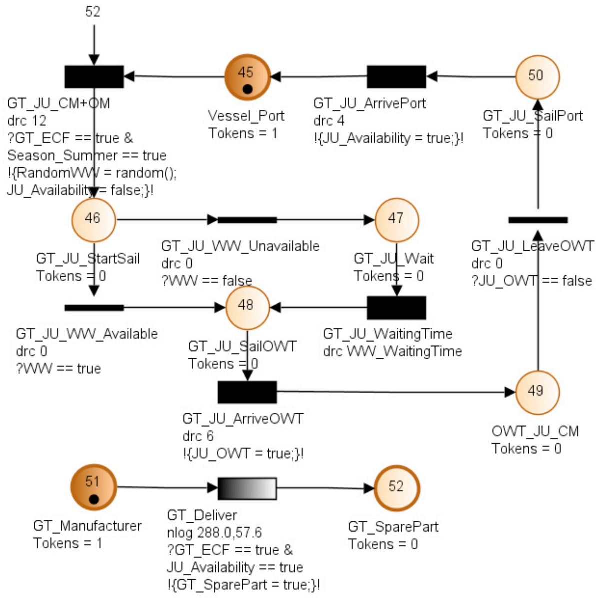

Fig. 4. The GSPN model for JU scheduling

It is noted that the scheduling of SVs follows similar processes, which, however, will not be extended here to avoid repeated information. Seasons are modelled to describe the failure characteristics and maintenance activities, see Fig. 5.

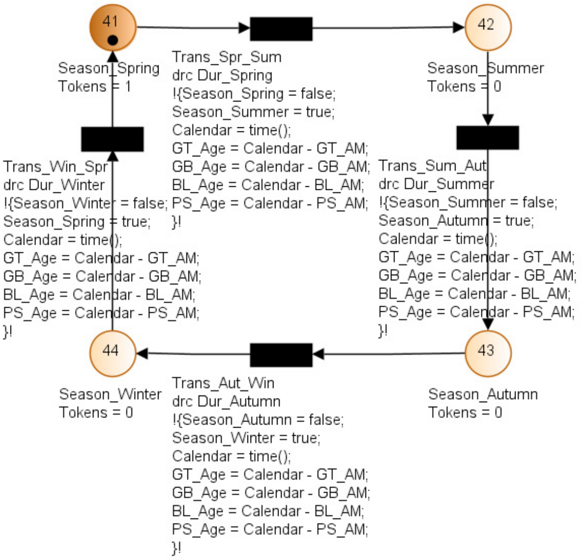

Fig. 5. The season alternation GSPN model

4. RESULTS AND DISCUSSIONS

The availability assessment of the OWT is carried out using the PN analysis module of the GRIF (Graphical Interface for Reliability Forecasting) software. The proposed GSPN model simulates O&M over a 25-year lifecycle, totalling 219,144 hours.

Fig. 6 displays the availability and total cost of OWT maintenance changing with OM efficiency *e* (see Eq. (2)). It is concluded that the higher the OM efficiency, the greater the availability of OWT. As *e* grows, the total cost shows a decreasing and then increasing trend. When *e* is below 40%, the total cost decreases; when above 40%, it increases. As *e* increases, OM effectiveness approaches saturation. The consequent rise in OM cost elevates the total cost, indicating an over-maintenance state. The lowest overall total cost appears at *e*=40%, as a worse maintenance (lower *e*) generates more failures, but a better maintenance (greater *e*) requires additional maintenance resources. It is noted that the OM efficiency *e* is a critical control factor for the entire maintenance process, which guides the determination of the level of maintenance to be carried out on wind farms. For structure degradation components like carbon brushes of generators, even though replacement with a new element refreshes the performance of the generator, as most wind farms conduct, they require a long time waiting for the shipping of new elements from the operation centres onshore. This study pointed out that the used elements are acceptable under the required conditions. It provides the maintenance crew with an idea that keeping the wind turbines operating by using used components instead of replacing them with new ones in the next visit will keep the wind turbines operating continuously before the completion of the next maintenance.

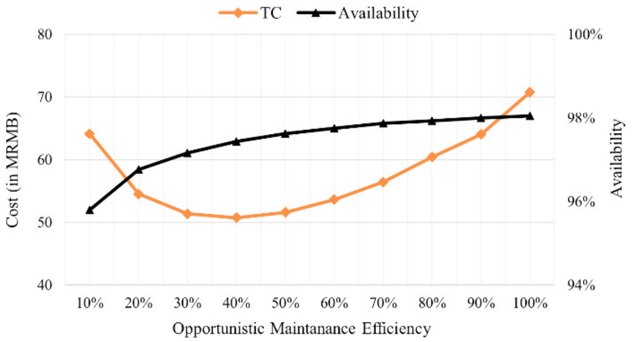

Fig. 6. Availability and cost of OWT maintenance

Fig. 7 illustrates the maintenance cost and its shares. CM cost, CBM cost, manpower cost, and transportation cost decrease with the growth of *e*. The reason is that the higher the OM efficiency, the higher the reduction of the equivalent lifetime of the components in the OM. Hence, the MTTF of the components is maintained at a relatively high state. Consequently, the OWT operates in a relatively healthy state, leading to fewer maintenance interventions and reduced associated costs. In contrast, the OM cost increases with the growth of *e*. Due to the increase in maintenance difficulty, the higher the efficiency of the OM, the more materials and resources need to be invested, and the greater the growth rate of the OM cost.

Opportunity cost is negatively correlated with availability, decreasing rapidly in the interval of 10%-30% and slowing down after reaching 30%, see Fig. 8.

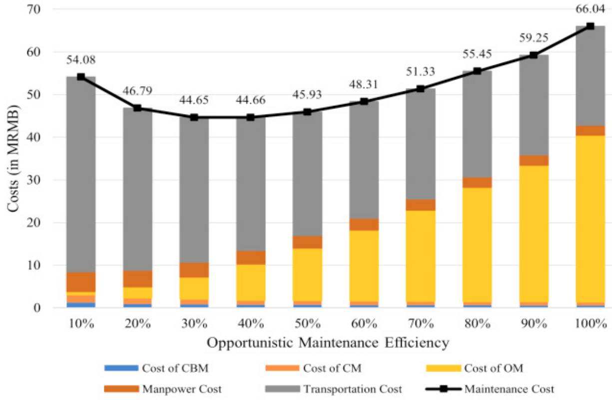

Fig. 7. Maintenance costs and their decompositions

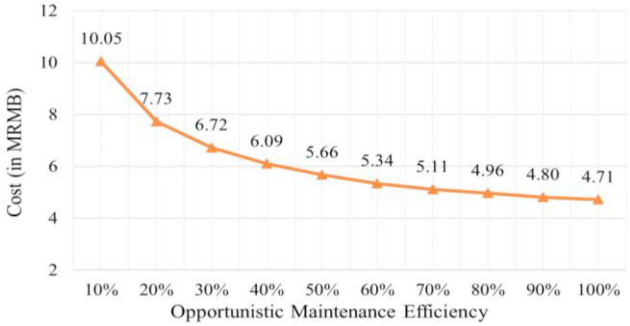

Fig. 8. Opportunity Costs of the wind turbine

As shown in Figure 9, at *e*=30%, the factors affecting OWT availability are ranked in descending order of significance. This sensitivity analysis is conducted through individual parametric variations, where each input parameter is increased by 10% from its baseline value while holding others constant. Notably, component MTTF exhibits the strongest correlation with OWT availability, underscoring that operational reliability is the primary determinant of system availability.

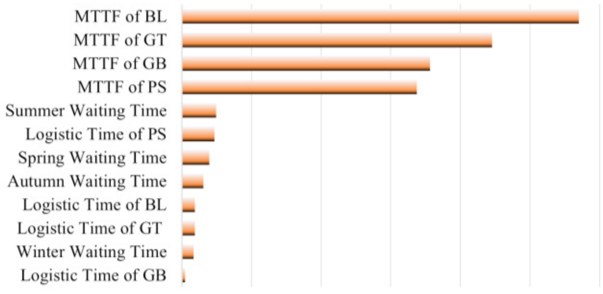

Fig. 9. Availability sensitivity analysis factors

Table 8 summarizes maintenance cost, opportunity cost, total cost, and availability for OWT under CBOM (10%-50% efficiency) versus CBM. At *e*=10%, CBOM incurs lower maintenance and opportunity costs than CBM. It indicates that OM effectively lowers maintenance and opportunity costs. The total cost reaches its minimum at *e* = 40%, beyond which it increases progressively with rising efficiency. Therefore, over the long term, CBOM at 50%≥*e*≥30% effectively reduces costs by renewing critical components earlier and lowering the frequency of critical failures.

Table 8. Costs and availability for two maintenance strategies

Maintenance		Costs ($\times 10^6$ RMB)			Availability
		C_M	C_O	TC	
CBM		74.14	24.07	98.21	90.50%
CBOM	e=10%	54.08	10.05	64.13	95.80%
	e=20%	46.79	7.73	54.52	96.76%
	e=30%	44.65	6.72	51.37	97.16%
	e=40%	44.66	6.09	50.75	97.43%
	e=50%	45.93	5.66	51.59	97.62%

5. CONCLUSIONS

This paper evaluates the availability of OWTs under the CBOM strategy, incorporating weather windows and vessel transit logistics. A GSPN with predicates is employed for modelling, enabling the dynamic representation of the component failure behaviour by allowing failure parameters to vary over time and seasons. The simulation spanning a 25-year lifecycle is conducted. By examining the availability and total maintenance cost across varying levels of opportunistic maintenance efficiency and comparing it with condition-based maintenance, it is concluded that an opportunistic maintenance efficiency range of 30%-50% represents an optimal solution.

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