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Operation and maintenance management for offshore wind farms integrating inventory control and health information

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ABSTRACT

Effective operation and maintenance (O&M) management is significant for enhancing the economic performance of offshore wind farms. Despite recent research progress in O&M, there remains a gap in integrating health prognostics and spare parts inventory into decision-making processes at the scale of offshore wind farms. To bridge this gap, this paper develops an optimisation framework integrating these aspects to establish cost-effective joint maintenance and inventory policies. In the framework, a maintenance policy is firstly developed to plan maintenance actions based on component health and maintenance opportunities. Meanwhile, in order to support maintenance implementation, a multi-echelon inventory network using (s, S) policies is proposed to store diverse units across distinct warehouses. A genetic algorithm (GA) is then employed to identify the optimal policy, aiming to minimise overall costs. Upon developing the optimisation framework, in order to illustrate the application of the proposed approach in practice, a numerical simulation of a generic offshore wind farm in the North Sea is performed. Results demonstrate that comprehensive O&M management considering interrelationship between maintenance and inventory policies reduces overall costs, showcasing its capacity in strengthening the economic performance. Finally, sensitivity analysis is performed to investigate the most influential O&M factors, providing actionable insights for O&M management.

1. Introduction

1.1. Background

The 2021 United Nations Climate Change Conference has highlighted the significance and urgency of curbing greenhouse gases through enhancing climate action [1]. The target is to reach net-zero CO_2 emissions around 2050 for the purpose of limiting global warming to 1.5 °C [2,3]. As a sustainable and reliable alternative to conventional energy sources, renewable energy, including offshore wind energy, is experiencing a notable increase in recent years [4–6]. In Europe, the Netherlands is one of the leading countries in new installation of offshore wind energy. The Dutch Government has raised the offshore wind energy target to about 21 GW around 2030. By then, offshore wind energy is expected to supply 16% of the Netherlands energy needs and 75% of the current electricity requirements [7].

With the significant increase in annual new installation and operational capacity of offshore wind power [8], maintaining the operation of offshore wind farms and ensuring the availability of spare parts has become more vital and challenging [9,10]. Up to 30% of the total cost of wind energy is attributed to operation and maintenance (O&M) [11,12], and maintenance activities and spare parts account for the largest portion (43%) of O&M for wind turbines [13]. The improvement of O&M represents a significant cost reduction opportunity and will continue to be a primary factor in shaping the future development of the wind sector [14–16].

In order to enhance the economic performance of the wind sector, Prognostics and Health Management (PHM) has been developed to enable informed maintenance decisions based on health prognostics information [17,18]. This proactive approach effectively monitor the health of wind turbines and predict potential failures in advance, thereby improving wind turbine reliability, enhancing operational efficiency, and reducing O&M costs [19,20].

Maintenance decisions and inventory management are interrelated processes. On one hand, the successful implementation of maintenance decisions for offshore wind turbines depends on the availability of spare parts [21,22]. On the other hand, the procurement and storage of

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spare parts need to consider the demand for spare parts generated by maintenance actions. This mutual interdependence underscores the relationship between maintenance and inventory. Moreover, in practical O&M for offshore wind farms, it is common for the original equipment manufacturer (OEM) or maintenance service provider to assume dual roles as decision-makers responsible for both maintenance planning and spare parts provision. In this context, ensuring the interests of decision makers is essential, underscoring the need to recognise the mutual dependencies between maintenance and inventory. Therefore, developing an optimal joint policy is significant to guide decisions concerning maintenance and spare parts procurement effectively.

1.2. Literature review

Although maintenance and inventory are better to be considered simultaneously as discusses in Section 1.1, the existing studies commonly study these two problems separately. In the studies on maintenance optimisation, a common assumption is that the required spare parts are always available while maintenance decisions are made [23–25]. This assumption may be applicable in the situations where the components are homogeneous and the stock on site is always sufficient [26,27]. However, the components of offshore wind turbines, including their subcomponents, vary significantly in size, weight, and shape, posing challenges for inventory management. In addition, the high holding costs associated with large wind turbine components necessitate keeping spare parts inventory levels low to avoid unnecessary expenses. Hence, this assumption violates the real situation in the wind industry. Compared to the research on maintenance optimisation, there is relatively little research on spare parts inventory. The limited number of studies rarely consider optimising inventory policies with regard to maintenance demand [28].

The past studies focusing on joint optimisation of maintenance and spare parts is reviewed and concluded in Table 1. In the Table 1, the literature is concluded based on the following indicators: (1) system level, ranging from onshore to offshore and component to farm; (2) maintenance characteristics, including maintenance policies, maintenance degree; (3) level of hierarchy of offshore wind turbines systems; (4) inventory characteristics, which encompass inventory policies, unit characteristics, transport delays, diversity of units, inventory echelons. These indicators in maintenance and inventory models are selected according to [29–31] and further extended.

(1) System level: The system level represents the level of the system which the model is concerned about, from component level (*e.g.*, bearings) to turbine level and finally farm level. Most of the models concern onshore wind energy while offshore wind energy receives less attention. The only paper on offshore wind energy investigates the model of an offshore wind turbine system where only two types of component-level units, *i.e.*, blades and generators, are considered [36]. A 'unit' typically refers to an individual piece of a product or part that can be used for maintenance and managed within the inventory system. A model tailored for an offshore wind farm consisting of a number of wind turbines with diverse components and subcomponents is still missing.

(2) Maintenance characteristics: Owing to the development of industry 4.0 in the wind industry, novel maintenance policies have been proposed to use health states of wind turbines components to make maintenance decisions. The majority of the papers on joint optimisation of maintenance and inventory for wind energy employ condition-based maintenance (CBM), predictive maintenance (PdM), opportunistic maintenance (OM), or a combination of these novel maintenance policies.

In accordance with maintenance degree, maintenance actions can be categorised into perfect maintenance and imperfect maintenance. Perfect maintenance is to replace the component with a new one and to recover the component state to 'as good as new'. Imperfect maintenance is to improve the component state back to a state between 'as good as new' and 'as bad as old', done by replacement of major constituent parts that have deteriorated, which can be recognised as 'major repair'. The concept of maintenance effect corresponds to the units in the inventory characteristics which are categorised into consumable and repairable [40]. A consumable unit can only be repaired by replacing it. If a consumable unit breaks down, it is removed and replaced by a new unit [29]. In comparison, a repairable unit is capable of being repaired and returned to service without the necessity to replace the entire unit [41]. Most of the studies consider that units in the wind turbines are consumable and can only be replaced (perfect maintenance). A few papers use the concept of hybrid (consumable and repairable) units which can be performed perfect and imperfect maintenance on.

(3) Level of hierarchy: An offshore wind turbine, as a typical complex system, can be decomposed into multiple hierarchical levels [42]. The first level is the wind turbine, which can be comprised of components (*e.g.*, gearboxes) at the second level. These components are further composed of subcomponents (*e.g.*, gears) at the third level. It is noted that all the past studies are limited to two-level hierarchy, namely wind turbines and components, ignoring the fact that a component can be decomposed into subcomponents at lower-level and the subcomponents also require maintenance actions. This research gap does not only exist in the past research on joint optimisation of maintenance and inventory within the wind power sector but also prevails across a wide range of industries, *e.g.*, traffic systems and electromechanical systems [43,44]. These studies commonly adopt a two-level hierarchy where the level of subcomponents is not considered.

(4) Inventory characteristics: The most common inventory policies adopted in the inventory management include (s, S) policy and (s, Q) policy. In (s, S) policies, orders are placed when the stock level drops to or below the minimum limit s, and the level is recovered to maximum limit S [34]. In (s, Q) policies, orders with a fixed quantity Q are placed as soon as the inventory drops to or below the reorder point s [35]. The (0,1) policy means ordering a new unit once the current unit is consumed, which is simplified from the (s, S) policy and (s, Q) policy [33]. The adoption of (0,1) policy is because the object is a single wind turbine and there is no need to store a large number of spare parts. Safety inventory level and economic order quantity policies are also simplified from (s, S) and (s, Q) policies, but are not commonly used in existing inventory models. Economic order quantity is a given quantity ordered at a constant periodicity [37]. In safety inventory level policies, an order is placed when the quantity of spare parts cannot satisfy the maintenance requirements or the remaining spare parts after maintenance are lower in number than the safety inventory level [32]. New units are ordered to ensure that the inventory level is safe before the next inspection. Regular orders are the orders placed to transfer the units from warehouses to the maintenance site [45]. Emergency orders occur when the current stock level is insufficient to satisfy maintenance demands [46]. The delay in the inventory characteristics represents that there are lead times for regular and emergency orders to be prepared and delivered, which is common in practical situations. Hence, most of the studies consider the potential delays in regular and emergency orders.

Inventory networks can store either single or multiple types of units [29]. Even though some papers have claimed that a wind turbine system is composed of multiple components [34], the models actually adopt a single-unit inventory. The reason is that the diversity of components/subcomponents is not considered in the models and the number of diverse units is aggregated without allocating an individual storage level. In this case, the

Table 1
Literature on joint optimisation of maintenance and inventory for wind energy.

Literature	System level					Maintenance characteristics					Level of hierarchy	
						Policy			Degree			
	Onshore	Offshore	Component	Turbine	Farm	CBM/PdM	OM	Other	Perfect	Imperfect	Two	Three
[32]	✓		✓			✓	✓		✓		✓	
[33]	✓			✓		✓	✓		✓		✓	
[34]	✓				✓		✓		✓		✓	
[35]	✓				✓	✓			✓	✓	✓	
[36]		✓		✓		✓		✓	✓		✓	
[21]	✓			✓		✓	✓		✓		✓	
[37]	✓				✓			✓	✓	✓	✓	
[38]	✓				✓	✓	✓		✓		✓	
[39]	✓				✓	✓	✓		✓		✓	
This paper		✓			✓	✓	✓			✓		✓

Literature	Inventory characteristics								
	Policy	Unit		Delay		Type		Echelon	
		Consumable	Repairable	Regular	Emergency	Single	Multiple	Single	Multiple
[32]	Safety inventory level	✓		✓		✓		✓	
[33]	(0, 1)	✓			✓		✓	✓	
[34]	(s, S)	✓			✓	✓		✓	
[35]	(s, Q)	✓	✓	✓		✓		✓	
[36]	(0, 1) and (s, S)	✓		✓	✓		✓	✓	
[21]	(0, 1)	✓		✓	✓		✓	✓	
[37]	Economic order quantity	✓	✓			✓		✓	
[38]	–	✓				✓		✓	
[39]	(s, S)	✓				✓		✓	
This paper	(s, S)	✓	✓	✓	✓		✓		✓

inventory policy is optimised in a single-unit pattern which neglects the diversity of units.

Moreover, all the papers adopt a single-echelon inventory network. A multi-echelon inventory network for offshore wind farms still lacks. The network structure entails the structure of the logistics system structure, which can be grouped into two categories: single-echelon and multi-echelon [47]. A single-echelon network structure is comprised of a single warehouse location that serves the system. Comparatively, a multi-echelon network structure contains a multitude of warehouses. For example, in the offshore industry, a multi-echelon system can comprise a main warehouse which is possibly associated with the OEM, which consecutively serves smaller onshore warehouses which in turn finally serve offshore warehouses close to the wind farm location [42]. The distinction between a single- or multi-echelon logistics system has a significant influence on the problem of joint maintenance and inventory optimisation.

1.3. Research gaps and contributions of this paper

After reviewing the literature above, the research gaps existing in joint optimisation of maintenance and inventory for offshore wind energy can be concluded. First, the past papers only consider a two-level hierarchy of offshore wind turbine systems, encompassing wind turbines and components. However, this hierarchy overlooks the fact that components can be further decomposed into subcomponents, each necessitating maintenance actions. Therefore, it is imperative to develop a model that considers subcomponent-level units to effectively manage the O&M of offshore wind turbines, given the complexity and multi-level nature of such systems, thereby bridging this identified gap.

Second, prior studies concerning spare parts management have predominantly focused on the replacement of aged or failed units within wind turbines, while overlooking other practical maintenance approaches, such as major repairs. A study investigating and modelling the connection between maintenance and inventory models that account for the diversity of component-level and subcomponent-level units has not been undertaken previously. Fulfilling this gap is important for establishing an O&M model containing diverse maintenance actions for wind turbines, aiming to narrow the disparity between O&M models and real practices.

Third, the past papers used a single-echelon inventory network where all different types of units are stored in the same warehouse, which does not align with the logistics system in the offshore wind energy industry in practice. Existing research still lacks multi-echelon inventory networks capable of storing diverse units to satisfy the maintenance demands of offshore wind farms.

Considering the above research gaps, in this paper, a joint optimisation model is proposed to optimise the maintenance policy and inventory policy for the offshore wind farm. Firstly, the construction hierarchy of the offshore wind turbine system is decomposed into turbines, components, and subcomponents based on the results obtained through Fault Tree Analysis (FTA) and Failure Modes and Effects Criticality Analysis (FMECA) methods. Subsequently, a predictive opportunistic maintenance model is proposed considering the health prognostics information and economic dependence. The model is capable of translating the failure prediction of wind turbine components into the basis for maintenance decision-making. Within the maintenance model, diverse maintenance actions for components and corresponding relationships between different hierarchical spare parts are established. Furthermore, an inventory network model following a multi-echelon structure is established. Units are transported in the network and are stored in local warehouses and central warehouses at different geographical locations, based on the varying sizes, weights, and maintenance requirements. The stock level of units in the warehouses is controlled following the (s, S) policy. Then, the mutual connections between the maintenance model and the inventory model are established and the two models are integrated into a joint model. A metaheuristic algorithm is employed to find the optimal joint policy with the objective of minimising the total cost incurred by maintenance implementation and spare parts management. Finally, a numerical example of a generic wind farm in the North Sea is provided for illustration. A comparative study is performed to reveal the economic benefit of the proposed policy. Sensitivity analysis is conducted to investigate the most significant factors influencing decision-making and the overall costs.

In summary, the contributions of this paper are:

(1) Integrating health information and spare parts inventory control into modelling O&M for offshore wind farms.
(2) Establishing the correspondence between the diversity of spare parts hierarchies and maintenance degrees according to construction hierarchy of offshore wind turbine systems.
(3) Modelling the mutual connection between the predictive maintenance model and the multi-echelon inventory model, and proposing a joint optimisation framework which captures the comprehensive effect of maintenance costs and production losses.
(4) Identifying the optimal joint maintenance and inventory policy to enhance performance of offshore wind farms, and investigating the influences of O&M factors on total costs and policy formulation.

1.4. Outline

The remainder of the paper is listed as follows. In Section 2, the construction hierarchy of the offshore wind farm system, the maintenance policy, and the inventory policy are introduced. This section also introduces the joint maintenance and inventory model and the optimisation method. In Section 3, a generic offshore wind farm is used as a representative case study. A comparison of two policies with different optimisation methods is performed to highlight the superiority of the proposed method. Sensitivity analysis is conducted to investigate the most significant O&M factors influencing costs and joint policies. Conclusions are presented and insights for the practical implications and limitations of this study are provided in Section 4.

2. Methodology

This section outlines the characteristics of offshore wind farm systems, detailing a construction hierarchy decomposed into three levels. The necessary assumptions are given to simplify the analysis while ensuring the realism of the model. Subsequently, the models formalising the predictive opportunistic maintenance policy and the (s, S) inventory policy are developed separately, providing provide basis for the subsequent development of the joint optimisation model. Then, the two models are integrated to form the joint model, which explicitly models the interconnections between the maintenance and inventory models. This joint model is used to assess the economic performance of the joint policy and guide the search for the optimal solutions minimising total O&M costs. Finally, the search for the most cost-effective policy utilises a genetic algorithm (GA), a widely employed technique for addressing non-linear, single-objective optimisation problems that involve mixed variables and constraints.

2.1. Construction hierarchy of offshore wind turbine systems

An offshore wind farm is a system composed of a number of offshore wind turbines. The construction hierarchy of wind turbines describes the system composition and the functionalities and positions of its elements, encompassing multiple levels, ranging from system level to component level and subcomponent level [48]. At the system level, the wind turbine is considered as an integrated unit. Dividing downwards from the system level, the system involves the integration of a series of critical component-level units, such as gearboxes. Component-level units are further divided into more refined subcomponent-level units (such as gears). These levels are interdependent, forming the complete structure of a wind turbine, ensuring its proper operation and efficient power generation. In this study, we mainly focus on the units in the nacelle. Tower and support structure are not considered due to the extremely low failure rates and different storage methods compared to the units in the nacelle.

FTA is a systematic engineering and risk assessment method that breaks down system failures or accidents into a logical tree structure of contributing factors, allowing for the quantification of their probabilities. FMECA is a structured methodology used to assess potential failure modes of a system, their impacts on system performance, and the criticality of these failure modes. A significant amount of research has been conducted to utilise these methods including FTA and FMECA methods on construction hierarchy of wind turbines and criticality ranking of components and subcomponents. Based on the results in the past research [49–52], we mainly consider 4 components and 15 subcomponents with high criticality in the construction hierarchy of wind turbines, as illustrated in Fig. 1.

The offshore wind turbine system is a series system. In the system, the failure of the critical components including gearboxes, rotor blades, generators, and speed trains, causes the failure events in wind turbines. These critical components are subject to degradation, which leads to degradation failures. Considering that these critical components are mechanical or electromechanical, it is appropriate to model the lifetimes of components as two-parameter Weibull distributions [23].

The components are assumed to be repairable, indicating that they can be repaired or replaced according to the health condition. When replacing the component that has already failed or is about to fail, a corresponding new component-level unit is required. A component is composed of multiple subcomponent as shown in Fig. 1, and the subcomponents are assumed to be consumable. When conducting major repairs on the defective component, it is necessary to replace one of the subcomponents to recover the health of the component. For example, when performing the major repair on a gearbox, one type of the five subcomponents, *i.e.*, gears, gear bearings, auxiliary systems, housings, shafts, needs to be replaced and corresponding new subcomponent-level units are required. The subcomponents with a higher failure rate are considered to have a greater impact on the component condition and are more likely to lead to component defects. Therefore, the probability of replacing this particular type of subcomponent is higher in major repairs.

2.2. Assumptions

In order to better understand this problem and ensure that it is representative of the reality, the necessary assumptions are given as following:

- Maintenance-related assumptions:
  (1) All the components in the offshore wind farm are brand new at the beginning of operation.
  (2) The inspection and RUL prediction are performed at a regular interval, regardless of the time elapsed since the last maintenance of the individual components.
  (3) Inspections are nondestructive and RUL prediction is accurate. Compared to the repair times and logistics times, the inspection time can be ignored.
  (4) The maintenance action of components has a priority than the order action of spare parts.
  (5) Lead times for service vessels are random values following Weibull distributions. Maintenance cycles start after the service vessels and spare parts are well prepared.
  (6) Replacing a component requires corresponding component-level units of the same type. Performing a major repair for a defected component requires the replacement of one type of its subcomponents. The quantity of subcomponents within the same type is disregarded during the maintenance process.
  (7) A preventive replacement is cheaper than replacing the component after the failure occurs, which is half that of failure replacement.

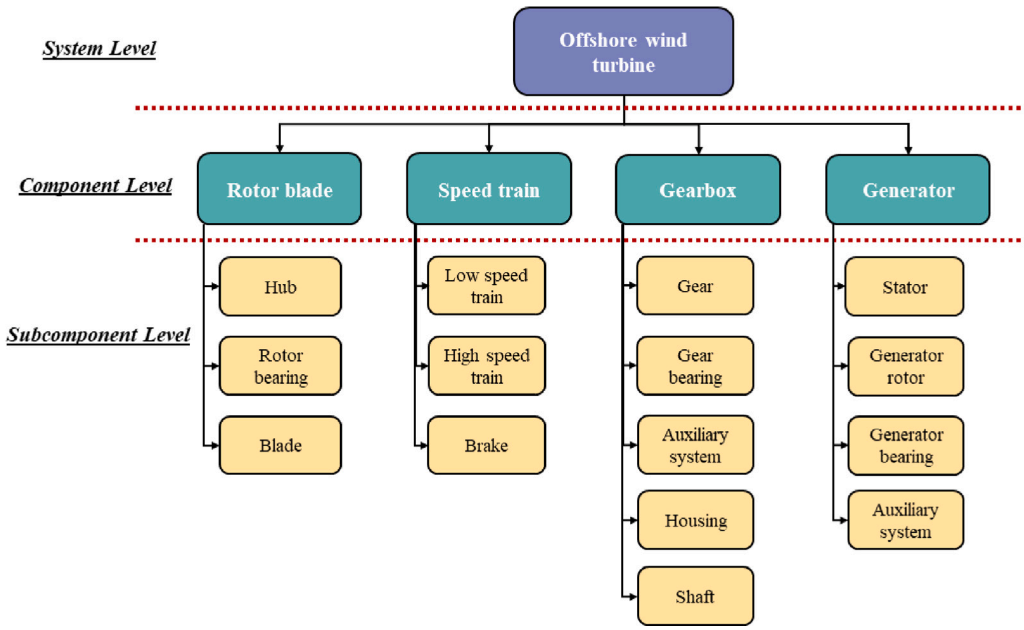

Fig. 1. Three-level construction hierarchy of offshore wind turbine systems.

Assumption (1) is a common situation in practice where the turbines ave never operated before commissioning. Assumptions (2) and (3) stipulate regular inspections of the offshore wind farm and full observability of component conditions. Assumption (4) prioritises maintenance actions over ordering actions, underscoring the need for adequate spare parts inventory to support maintenance needs. If spare parts are insufficient, maintenance activities are delayed to accommodate emergency orders instead of cancellation. Assumption (5) states maintenance cycles begin upon availability of required spare parts and vessel mobilisation. The lead time for vessels includes the time for organisation, check, and awaiting appropriate metocean conditions, which is assumed to be random, following Weibull distributions. In assumption (6), it is assumed that a replacement for a component requires a new component-level unit, while a major repair is performed by replacing a type of subcomponent-level units. In practice, a component may contain multiple subcomponents within the same type, such as gears in a gearbox where the number of gears may vary depending on the type of gearbox. It is assumed that the quantity of subcomponents within the same type is disregarded during the maintenance process. This means that when performing major repair on this component, the approach is to treat all subcomponents of the same type equally by replacing them to ensure that all these subcomponents are brand new, with the aim of achieving optimal performance of the component. Assumption (7) suggests cost-effective preventive replacements before ultimate failure, enabling overhauling or recasting of failed components to offset costs.

- Inventory-related assumptions:

(8) The inventory level is checked after the offshore wind farm inspection is completed.
(9) The inventory flow is in one way, from the top to the bottom of the inventory network.
(10) Component-level units are stored in the central warehouse, while the subcomponent-level units are in the local warehouse. The local and central warehouse both adopt the (s, S) inventory policy.
(11) The lead times for orders are constant values. Emergency orders are more expensive and time-consuming than regular orders.
(12) The situation where multiple maintenance service suppliers and multiple OEM component against or collaborate with each other to maintain the wind farm and manage the inventory is ignored.

Assumption (8) states the demand for spare parts is determined according to the maintenance requirement after the wind farm inspection. Assumption (9) outlines a unidirectional flow of inventory from OEM to central warehouses, to local warehouses, finally to offshore wind farm site. The inventory flow for the returned units is not considered. Assumption (10) states 4 types of component-level units and 15 types of subcomponent-level units are stored in different warehouses considering their diversity in size, weight, and shape. Both warehouses employ (s, S) policies to manage inventory levels. Assumption (11) highlights that emergency orders incur higher costs and time due to preparation, scheduling, and delivery considerations. Assumption (12) states the scenario where multiple OEM and service providers may be involved simultaneously, bringing potential conflicts or collaboration with each other. This scenario happens in practice considering the size and capacity of an offshore wind farm tend to increase, but is not specifically addressed in this study.

2.3. Predictive opportunistic maintenance policy

Owing to the development in the condition monitoring and remaining useful life (RUL) prediction technology in recent years, the health state of the critical components can be monitored [53]. The operational data (*e.g.*, vibration signals) is acquired and pre-processed, in order to be prepared for the following prediction models [54]. The RUL prediction approaches, including data-driven approaches, mode-based approaches, and hybrid approaches, are adopted to evaluate potential remaining time before the component failure [55]. The remaining life is utilised to construct a heatmap for assessing the component health, which in turn is transformed into a basis for making decisions regarding the implementation of maintenance actions. This process is illustrated in Fig. 2.

In this paper, our main focus is on establishing a joint policy where the maintenance policy is developed based on the component health information. The process of analysing condition monitoring data to predict RUL illustrated in Fig. 2, represents a significant topic. However, it

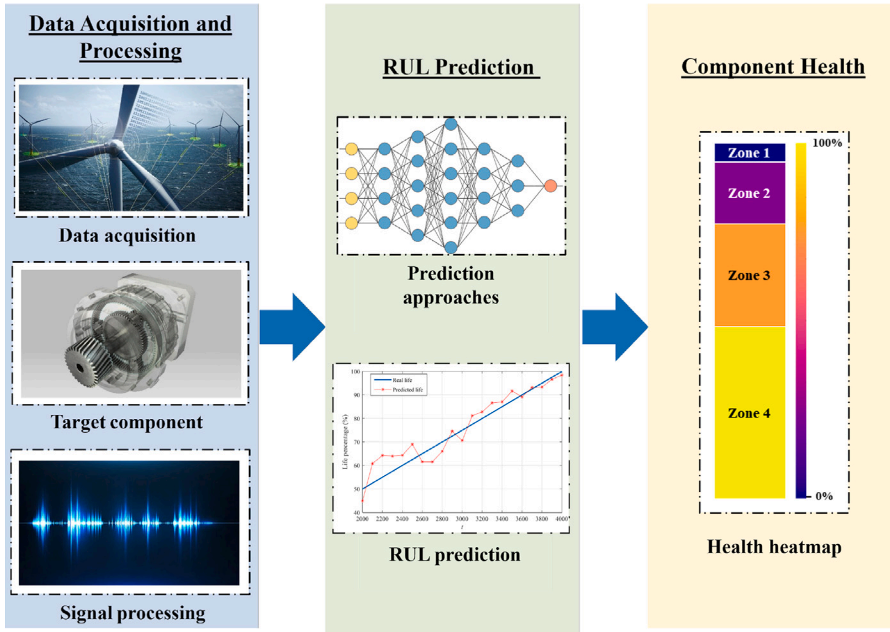

Fig. 2. The general process from data acquisition to the construction of health heatmaps.

will not be the focus of this study. In our model, maintenance decisions are directly guided by RUL predictions that have been previously completed, bypassing the step-by-step conversion of condition monitoring data into RUL predictions for decision-making. This approach is justified by two reasons. Firstly, our O&M model covers the entire life cycle of offshore wind farms and involves policy optimisation across numerous wind turbines and their hierarchical units. The existing condition monitoring data comprising high-frequency signals and SCADA data are challenging to consistently convert into a basis for maintenance decisions within our model due to disparities in the time scale and the scale of model objects. Secondly, multiple maintenance cycles are triggered throughout the life cycle in our model. This entails multiple maintenance actions for individual turbines or components to enhance their condition. Both the component state and the monitoring data naturally undergo changes correspondingly. However, the current monitoring dataset cannot capture these changes induced by maintenance actions, posing obstacles to leveraging monitoring data for developing predictive maintenance models.

The maintenance policy in this study is extended based on the past work [56], where more details can be found. Suppose that the offshore wind farm contains K turbines, and each wind turbine consists of I components in series. The overall offshore wind farm is inspected at a regular interval T_{P}. The designed lifetime of the wind farm is Z, and the total number of inspection is denoted by L during the wind farm lifetime. In the inspection, the wind turbine component states are observable and the RUL of components can be predicted. Denote l as the number of inspection since the offshore wind farm begins to operate, and a degradation indicator ψ_{ik}^{l} is used to represent the degradation state of component i ($i = 1, 2, \ldots, I$) at turbine k ($k = 1, 2, \ldots, K$) at lth ($l = 1, 2, \ldots, L$) inspection.

The lifetime of component i at turbine k is assumed to follow a Weibull distribution with scale parameter σ_{ik} and shape parameter ε_{ik}. By sampling the Weibull distribution, the lifetime of component is randomly generated. At the lth inspection, the predicted lifetime of component i at turbine k is v_{ik}^{l}. Knowing that the elapsed time since the component began to operate, the current age of component i at turbine k is represented by ι_{ik}^{l}. The real lifetime is predicted after inspecting the wind turbine and performing RUL prediction. Hence the degradation indicator is calculated to determine which type of maintenance action is suitable for the component, as

$$\psi_{ik}^{l} = \frac{\iota_{ik}^{l}}{v_{ik}^{l}} \cdot 100\%. \tag{1}$$

The influence of maintenance actions is to restore or recover the component condition, indicating that the component age is reduced. The Kijima type II virtual age model is exploited to model the age reduction of components as [57]

$$\iota_{ik}^{l} = \vartheta_{\mathrm{m}} \left[\iota_{ik}^{l^-} + (l - l^-) T_{\mathrm{P}} \right], \tag{2}$$

where l^- is the sequence number of the latest inspection which triggers a maintenance cycle; ϑ_{m} is the age reduction of major repair.

The range of ϑ_{m} is $[0, 1]$. When a replacement is conducted, the component is recovered to 'as good as new' state, so ϑ_{m} equals 0. On the contrary, a basic repair cannot improve the component condition, keeping the state to be 'as bad as old'. In this case, ϑ_{m} is equal to 1. Major repair is an intermediate repair, thus the value of ϑ_{m} is between 0 and 1.

According to Fig. 1, component i is decomposed into J_i types of subcomponents. The probability of requiring replacing subcomponent j_i to complete the major repair on component i is denoted as P_{j_i}. In each major repair, the probability that which type of the subcomponent is required follows a categorical distribution as $X_i \sim \mathrm{Cat}(P_{1_i}, P_{2_i}, \ldots, P_{J_i})$, where $\sum_{j=1}^{J} P_{j_i} = 1$. By randomly sampling the categorical distribution, the required type of the subcomponent can be determined.

In order to judge the health condition of components, the preventive replacement threshold Ω and the major repair threshold Θ are introduced to classify the component condition into different zones as depicted as heat map of component condition in Fig. 3. The classification of component condition and corresponding maintenance actions are as follows:

(1) Zone 1: if ψ_{ik}^{l} reaches 100%, it means this component has failed because it reaches the end of the lifetime. In this case, this component requires a failure replacement. The component condition is restored to a perfect state.

(2) Zone 2: if $\Omega \leq \psi_{ik}^{l} < 100\%$, the component is determined as an aged component, requiring a preventive replacement with a new unit.

(3) Zone 3: if $\Theta \leq \psi_{ik}^{l} < \Omega$, the defective component requires a major repair to improve its condition. The major repair, also called imperfect

maintenance, will not recover the component back to a state "as good as new", but younger.

(4) Zone 4: if $0\% < \psi_{ik}^{l} < \Theta$, the component is young and there is no need for costly repairs. Basic repair is conducted to maintain its current state.

As stated in [58], positive economic dependence applies when combining maintenance on multiple components is less expensive than maintaining each component separately. A type of opportunistic maintenance is naturally developed based on this dependence. In maintenance cycles, the maintenance action which is performed on a component generates opportunities to repair other components in this turbine and remaining turbines. The key point of the problem is how to determine which components need to be repaired and which ones do not, and what type of repair is required for these components. This can be accomplished based on the aforementioned categorisation of component conditions.

After identifying the health state of the offshore wind turbine components, the decision-maker will decide whether to initial a maintenance cycle. Maintenance cycles refer to the sequence of events from the definition to the completion of maintenance tasks. More specifically, a maintenance cycle is to conduct the following steps include mobilising vessels to prepare for repairs, transporting necessary spare parts to the nearby port, dispatching the maintenance teams and vessels to the site, and repairing the components requiring maintenance. The maintenance cycles are triggered in the following scenarios:

(1) Occurrence of a failure event: In order to assure the efficient operation of the wind farm, a maintenance cycle starts once a turbine stops working.

(2) Presence of a certain percentage of aged components: when the portion of aged components in the wind farm exceeds a specific threshold ζ, a maintenance cycle is initiated.

The setting of ζ is to flexibly adjust the frequency of the maintenance cycles. If the value of ζ is low, the scenario where multiple components aged are aged simultaneously is more likely to arise, and the maintenance cycle is easier to be triggered. On the contrary, a high ζ represents that such a scenario is difficult to occur, so that the trigger of the maintenance cycles remains dominated by wind turbine failures.

In maintenance cycles, the process of judging component conditions and implementing maintenance actions is depicted in Fig. 3 to enhance the comprehension of the maintenance model. The component gradually degrades with operation. A maintenance cycle is triggered at t_1, and the component condition is determined to be lower than major repair thresholds, so it is at Zone 4 and a basic repair is performed on it. The basic repair does not improve the component condition. The maintenance action is completed at time t_2, and the wind turbine recover to operational state. In the maintenance cycle started at time t_3, the component condition is between the preventive replacement threshold and the major repair threshold. Hence a major repair is conducted to improve the condition a certain degree. The component begins to operate from time t_4 until reaching the end of the lifetime at t_5 when the component fails. In this maintenance cycle, the component is completely replaced with a new unit, so the condition is restored to completely new. Compared to basic repair and major repair, the time for failure replacement is longer, lasting until t_6. At time t_7, the component requires another major repair which ends at t_8. In the maintenance cycle at t_9, the component is higher than preventive replacement threshold. The component in Zone 2 requires a preventive replacement which restores the condition.

In the maintenance model, the decision vector $\boldsymbol{\alpha}$ is

$$\boldsymbol{\alpha} = (\Theta, \Omega, \zeta). \tag{3}$$

The decision vector $\boldsymbol{\alpha}$ controls the frequency of maintenance cycles and the range of components qualified for various types of maintenance. Once the decision of a maintenance cycle is initiated, the service vessels and technicians are mobilised to carry out maintenance. Additionally, considering the weather constriction of different types of vessels, the vessels have to wait for appropriate metocean conditions including wave and wind before departing to the offshore wind farm location. The above time constitutes the lead time assumed to be random values in this model. It is assumed that the lead time of heavy lift vessels (HLVs), field support vessels (FLVs), crew transfer vessels (CTVs) in maintenance cycle n ($n = 1, 2, \dots, N$) follows Weibull distribution, which is $m_n^{\mathrm{H}} \sim \mathrm{Weibull}(\varepsilon^{\mathrm{H}}, \sigma^{\mathrm{H}})$, $m_n^{\mathrm{F}} \sim \mathrm{Weibull}(\varepsilon^{\mathrm{F}}, \sigma^{\mathrm{F}})$, and $m_n^{\mathrm{C}} \sim \mathrm{Weibull}(\varepsilon^{\mathrm{C}}, \sigma^{\mathrm{C}})$, respectively.

In the maintenance cycle n, decisions are made on whether or not to replace or repair a component. The binary variables x_{ikn}^{f}, x_{ikn}^{p}, and x_{ikn}^{b} represent the decision of failure replacement, preventive replacement, and basic repair on component i at turbine k, respectively. The binary variable $x_{kj_in}^{\mathrm{m}}$ means, in maintenance cycle n, the component i at turbine k requires a major repair by replacing subcomponent j_i. If the maintenance decision is made, the binary variable equals 1. Otherwise, it is equal to 0. Hence the total unit costs for maintenance C^{R} is

$$C^{\mathrm{R}} = \sum_{n\in N}\sum_{k\in K}\sum_{i\in I}\left(x_{ikn}^{\mathrm{f}}\delta_i + x_{ikn}^{\mathrm{p}}\delta_i^{\mathrm{p}} + x_{ikn}^{\mathrm{b}}\delta_i^{\mathrm{b}} + \sum_{j_i\in J_i} x_{kj_in}^{\mathrm{m}}\delta_{j_i}\right), \tag{4}$$

where δ_i, δ_i^{p}, δ_i^{b}; δ_{j_i} are the cost for failure replacement, preventive replacement, basic repair, and major repair.

In the total maintenance cycle N over the lifetime of offshore wind farm Z, the total vessel costs C^{V} is

$$C^{\mathrm{V}} = \sum_{n\in N}\sum_{k\in K}\sum_{i\in I}\left(x_{ikn}^{\mathrm{f}}\chi_{ikn}^{\mathrm{f}}q^{\mathrm{H}} + x_{ikn}^{\mathrm{p}}\chi_{ikn}^{\mathrm{p}}q^{\mathrm{H}} + x_{ikn}^{\mathrm{b}}\chi_{ikn}^{\mathrm{b}}q^{\mathrm{C}} + \sum_{j_i\in J_i} x_{kj_in}^{\mathrm{m}}\chi_{kj_in}^{\mathrm{m}}q^{\mathrm{F}}\right), \tag{5}$$

where χ_{ikn}^{f}, χ_{ikn}^{p}, χ_{ikn}^{b}, $\chi_{kj_in}^{\mathrm{m}}$ are the repair times for different types of maintenance; q^{H}, q^{C}, q^{F} are the respective vessel cost per day.

The total technician cost C^{T} is

$$C^{\mathrm{T}} = \sum_{n\in N}\sum_{k\in K}\sum_{i\in I}\left(x_{ikn}^{\mathrm{f}}\chi_{ikn}^{\mathrm{f}}h^{\mathrm{H}} + x_{ikn}^{\mathrm{p}}\chi_{ikn}^{\mathrm{p}}h^{\mathrm{H}} + x_{ikn}^{\mathrm{b}}\chi_{ikn}^{\mathrm{b}}h^{\mathrm{C}} + \sum_{j\in J_i} x_{kj_in}^{\mathrm{m}}\chi_{kj_in}^{\mathrm{m}}h^{\mathrm{F}}\right)\rho, \tag{6}$$

where h^{H}, h^{C}, h^{F} are the required number of technician working at three types of vessels; ρ is the daily cost per technician .

The total mobilisation costs C^{L} is

$$C^{\mathrm{L}} = \sum_{n\in N} C_n^{\mathrm{l}}. \tag{7}$$

where C_n^{l} is the mobilisation cost of maintenance cycle n.

In summary, the total costs for maintenance-related activities C^{M} is

$$C^{\mathrm{M}} = C^{\mathrm{R}} + C^{\mathrm{V}} + C^{\mathrm{T}} + C^{\mathrm{L}}. \tag{8}$$

2.4. (s, S) Inventory policy

With the maintenance policy described in Section 2.3, the objective of the inventory policy is to fulfil the requirements for spare parts to the greatest extent feasible, while simultaneously minimising the costs associated with managing the spare parts inventory. With the reference to the hierarchical levels in Fig. 1, an offshore wind turbine system is decomposed into component-level units and subcomponent-level units. A facility, termed as a warehouse, is where the spare parts are stored. In reality, it is inappropriate to store all the spare parts in a single warehouse considering the differences in size, weight, and criticality.

A inventory network in the wind industry is shown in Fig. 4. The OEM is located at the top of the hierarchy, manufacturing all the units necessary for maintenance implementation. Central warehouses are beneath the OEM in the hierarchy, storing the units delivered from the OEM. Local warehouses are closer to offshore wind farms than central warehouses, and are usually located in the harbour used for

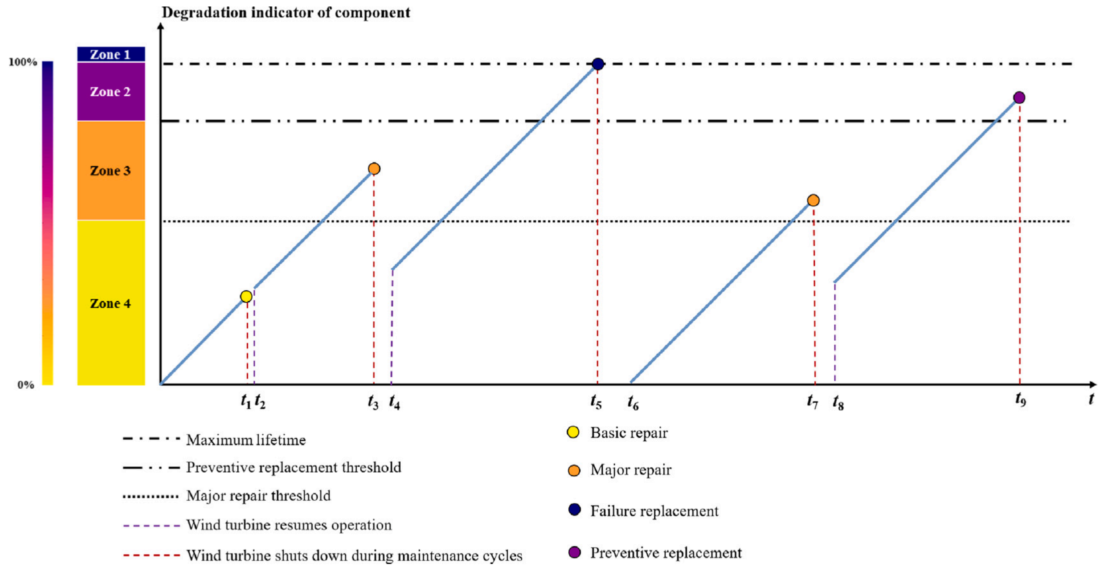

Fig. 3. Schematic representation of component degradation and maintenance implementation.

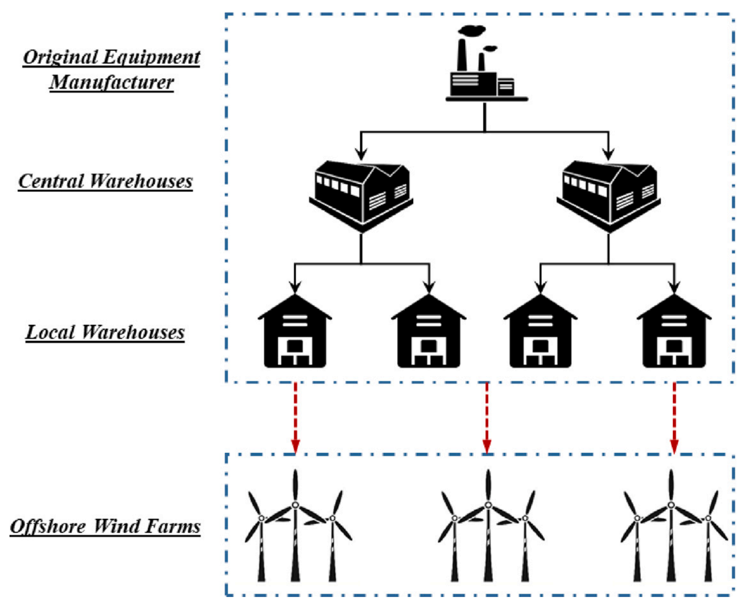

Fig. 4. Hierarchy of a multi-echelon inventory network.

the maintenance service work. Such an inventory network supports the supply of spare parts for offshore wind farm maintenance.

In this study, a multi-echelon inventory network containing a central warehouse and a local warehouse is established.As introduced in Section 1.2, the inventory policy (s, S) is one of the common inventory polices applied in the industry. The inventory policy (s, S) signifies the reorder point s and order-up-to level S, where orders are placed when stock reaches the reorder point s to maintain the stock level back to S. The advantage of this inventory policy lies in its ease of implementation and management. The policy involves continuous monitoring and replenishment based on inventory levels, triggering reorders when inventory drops to a fixed minimum level. Furthermore, this policy entails low risk because replenishment promptly occurs when inventory levels reach the minimum threshold, thereby minimising the risk of stockouts and ensuring relatively stable inventory levels.

The control of stock levels under an (s, S) inventory policy is illustrated in Fig. 5 and we depict the changes in the inventory level to facilitate understanding of the model. At the beginning, the stock level Q starts at S and does not change until t_1, at which point a number of units are dispatched from the warehouse for maintenance. After that, the stock level is maintained until new maintenance requirement arrives at t_2. The level Q is reduced to reach the reorder point s. According to the(s, S) inventory policy, the stock level is replenished to order-up-to level S at t_3. The lead time between t_2 and t_3 is the amount of time between when a purchase order is placed to replenish units and when the order is received in the warehouse. The length of the lead time is influenced by the factors including geographical location, local weather, and transportation modes. Similarly, the level Q decreases to be lower than s after dispatching units at t_4 and t_5, and consequently, a replenishment order is placed to recover the stock at t_6.

The central warehouse employs the inventory policy $\left(s^{\mathrm{C}}, S^{\mathrm{C}}\right)$ while the inventory policy used in the local warehouse is $\left(s^{\mathrm{L}}, S^{\mathrm{L}}\right)$, thus the decision vector of the inventory model $\boldsymbol{\beta}$ is

$$\boldsymbol{\beta} = (s^{\mathrm{C}}, S^{\mathrm{C}}, s^{\mathrm{L}}, S^{\mathrm{L}}). \tag{9}$$

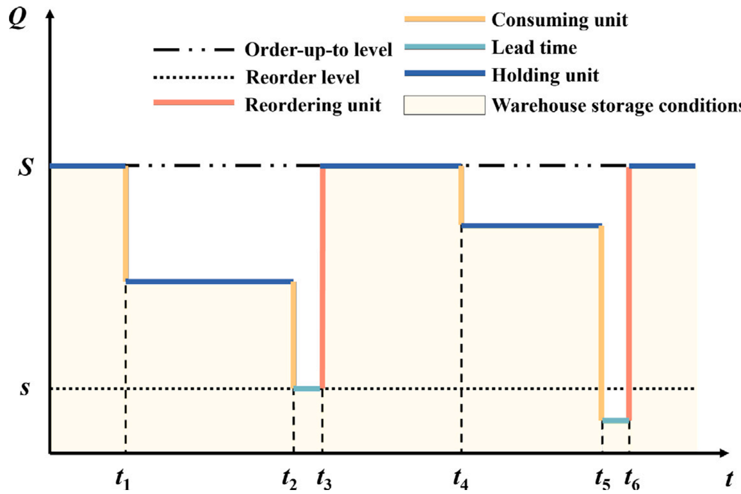

Fig. 5. Change of stock levels under an $(s,\ S)$ inventory policy.

At the beginning, the warehouses are fully stocked with the quantity of component-level units S^{C} and the quantity of subcomponent-level units S^{L}. In the maintenance cycle n, while the vessels and technicians are mobilised after triggering a maintenance cycle, the requirement of diverse spare parts is determined according to the comparison between maintenance thresholds and component conditions.

Suppose that the required number of component-level unit i in maintenance cycle n is γ_{in}, calculated as

$$\gamma_{in} = \sum_{k\in K} \left(x^{\mathrm{f}}_{ikn} + x^{\mathrm{p}}_{ikn}\right). \tag{10}$$

The required number of subcomponent-level unit j_i in maintenance cycle n, $\kappa_{j_i n}$, is obtained as

$$\kappa_{j_i n} = \sum_{k\in K} x^{\mathrm{m}}_{kj_i n}. \tag{11}$$

The inventory level of spare parts in the warehouse is inspected to check whether the current quantity is sufficient to support maintenance requirements. At the beginning of maintenance cycle n, the quantity of component-level and subcomponent-level units are ${}^{-}\lambda^{\mathrm{C}}_{in}$ and ${}^{-}\lambda^{\mathrm{L}}_{j_i n}$. If the current stock level is sufficient enough to support the maintenance implementation, regular orders are placed to deliver the needed spare parts to ports near the offshore wind farm site. The lead time for regular orders for component-level and subcomponent-level units are $\varphi^{\mathrm{c}}_{in}$ and $\varphi^{\mathrm{l}}_{j_i n}$ respectively.

The remaining quantity of spare parts in the central and local warehouse is $\left({}^{-}\lambda^{\mathrm{C}}_{in} - \gamma_{in}\right)$ and $\left({}^{-}\lambda^{\mathrm{L}}_{j_i n} - \kappa_{j_i n}\right)$, respectively. If the spare parts are insufficient, all the components in stock will be delivered out of the warehouse. In addition, an emergency order is placed to replenish the missing quantity of spare parts. The emergency order means that there are no available spare parts in the current warehouse and an emergency shipment of available parts from elsewhere is required. The emergency order requires more time and cost to organise the shipment. For subcomponent-level units, the spare parts will be transshipped from the central warehouse to the site. While the component-level units are insufficient, the OEM will urgently provide the spare parts.

Binary variables y^{C}_{in} and $y^{\mathrm{L}}_{j_i n}$ represent whether an emergency order is placed for component-level units and subcomponent-level units. The lead time for emergency orders for component-level and subcomponent-level units are η^{o}_{in} and $\eta^{\mathrm{c}}_{j_i n}$ respectively. The total emergency cost is

$$C^{\mathrm{E}} = \sum_{n\in N} \left\{ \sum_{i\in I} y^{\mathrm{C}}_{in} E_{\mathrm{c}} \delta_i \left(\gamma_{in} - {}^{-}\lambda^{\mathrm{C}}_{in}\right) + \sum_{i\in I}\sum_{j\in J} y^{\mathrm{L}}_{j_i n} \delta_{j_i} E_{\mathrm{c}} \left(\kappa_{j_i n} - {}^{-}\lambda^{\mathrm{L}}_{j_i n}\right) \right\}, \tag{12}$$

where E_{c} is the emergency cost rate.

After delivering the spare parts to the offshore wind farm, the stock level in the central warehouses $\lambda^{\mathrm{C}}_{in}$ is updated as

$$\lambda^{\mathrm{C}}_{in} = \begin{cases} {}^{-}\lambda^{\mathrm{C}}_{in} - \gamma_{in}, & {}^{-}\lambda^{\mathrm{C}}_{in} > \gamma_{in}, \\ 0, & {}^{-}\lambda^{\mathrm{C}}_{in} \le \gamma_{in}. \end{cases} \tag{13}$$

The stock level in the local warehouses $\lambda^{\mathrm{L}}_{j_i n}$ is updated as

$$\lambda^{\mathrm{L}}_{j_i n} = \begin{cases} {}^{-}\lambda^{\mathrm{L}}_{j_i n} - \kappa_{j_i n}, & {}^{-}\lambda^{\mathrm{S}}_{j_i n} > \kappa_{j_i n}, \\ 0, & {}^{-}\lambda^{\mathrm{S}}_{j_i n} \le \kappa_{j_i n}. \end{cases} \tag{14}$$

Afterwards, the stock levels are compared with the minimum storage limit s^{C} and s^{L}. In the central warehouse, if $\lambda^{\mathrm{C}}_{in} \le s^{\mathrm{C}}$, it is necessary to restore the quantity of units back to S^{C}, and the binary variable z^{c}_{in} is equal to 1. In a similar way, the quantity of spare parts in the local warehouse $\lambda^{\mathrm{L}}_{j_i n}$ is compared with s^{C}. If $\lambda^{\mathrm{L}}_{j_i n} \le s^{\mathrm{L}}$, the binary variable $z^{\mathrm{l}}_{j_i n}$ equals 1.

Orders will be placed separately for to replenish all the respective units in both warehouses. The binary variables z^{C}_{n} and z^{L}_{n} represent whether it is required to place an order to replenish units in the central warehouse and local warehouse respectively, as

$$z^{\mathrm{C}}_{n} = \max\left(z^{\mathrm{c}}_{in}\right) \quad i = 1, \ldots, I. \tag{15}$$

$$z^{\mathrm{L}}_{n} = \max\left(z^{\mathrm{l}}_{j_i n}\right) \quad i = 1, \ldots, I, j = 1, \ldots, J. \tag{16}$$

After replenishing the units to the warehouses, the stock level of the central warehouse is updated as

$${}^{+}\lambda^{\mathrm{C}}_{in} = \begin{cases} \lambda^{\mathrm{C}}_{in}, & \lambda^{\mathrm{C}}_{in} > s^{\mathrm{C}}, \\ S^{\mathrm{C}}, & \lambda^{\mathrm{C}}_{in} \le s^{\mathrm{C}}. \end{cases} \tag{17}$$

The stock level of the local warehouse is

$${}^{+}\lambda^{\mathrm{L}}_{j_i n} = \begin{cases} \lambda^{\mathrm{L}}_{j_i n}, & \lambda^{\mathrm{L}}_{j_i n} > s^{\mathrm{L}}, \\ S^{\mathrm{L}}, & \lambda^{\mathrm{L}}_{j_i n} \le s^{\mathrm{L}}. \end{cases} \tag{18}$$

Ordering costs are the expenses associated with placing, processing, and receiving orders. The total ordering cost C^{O} is

$$C^{\mathrm{O}} = \sum_{n\in N} \left(z^{\mathrm{C}}_{n} C^{\mathrm{c}}_{\mathrm{o}} + z^{\mathrm{L}}_{n} C^{\mathrm{l}}_{\mathrm{o}}\right). \tag{19}$$

where $C^{\mathrm{l}}_{\mathrm{o}}$ is the cost of replenishing subcomponent-level units and $C^{\mathrm{c}}_{\mathrm{o}}$ is the cost of replenishing component-level units.

Managing spare parts in the warehouse also incurs costs, known as holding costs. The holding cost is relevant to the unit costs, the quantity of spare parts stored, and the duration the spare remain stored in the warehouse. Suppose that t_n represents the time of maintenance cycle n. After delivering the units required for maintenance to maintenance sites

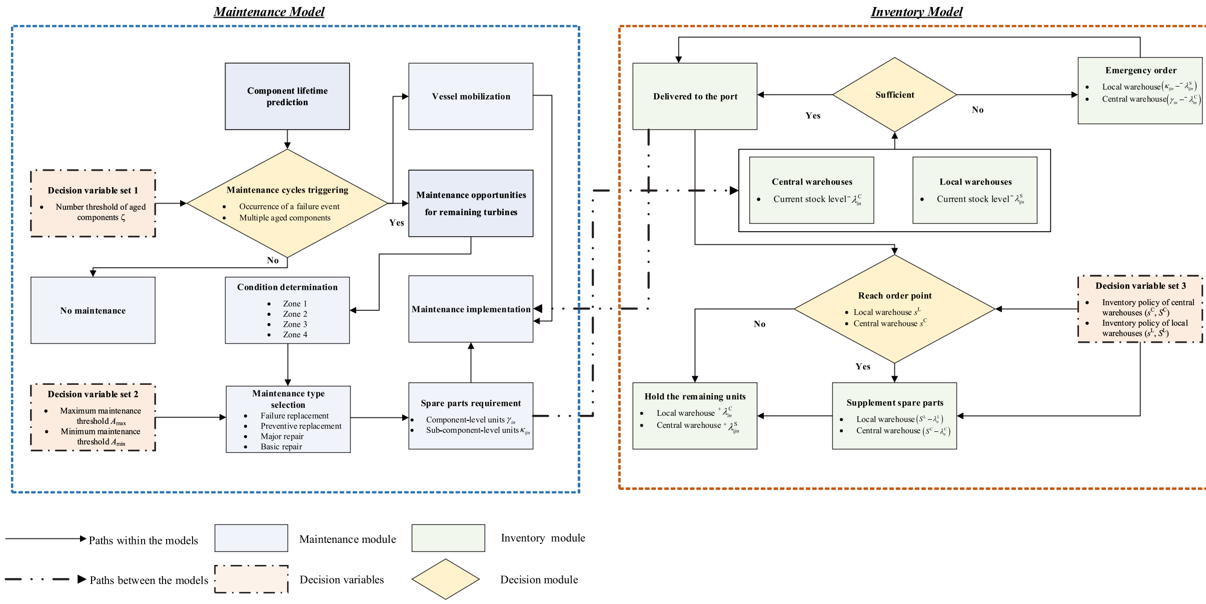

Fig. 6. Illustration of the joint model.

and replenishing units in the warehouses, the quantity of spare parts in the central and local warehouses are $^{+}\lambda^{\mathrm{C}}_{in}$ and $^{+}\lambda^{\mathrm{S}}_{j_i n}$, respectively. The total holding cost C^{H} is calculated as

$$C^{\mathrm{H}} = \Xi \left\{ \begin{array}{l} \sum_{n=2}^{N} \left[\sum_{i\in I} {^{+}\lambda^{\mathrm{C}}_{i(n-1)}} \delta_i \left(t_n - t_{n-1}\right) + \sum_{i\in I} \sum_{j_i\in J_i} {^{+}\lambda^{\mathrm{L}}_{j_i(n-1)}} \delta_{j_i} \left(t_n - t_{n-1}\right) \right] \\ + \sum_{i\in I} {^{+}\lambda^{\mathrm{C}}_{iN}} \delta_i \left(Z - t_N\right) + \sum_{i\in I} \sum_{j_i\in J_i} {^{+}\lambda^{\mathrm{L}}_{j_i N}} \delta_{j_i} \left(Z - t_N\right) \\ + \sum_{i\in I} S^{\mathrm{C}} \delta_i t_1 + \sum_{i\in I} \sum_{j_i\in J_i} S^{\mathrm{L}} \delta_{j_i} t_1 \end{array} \right\} \tag{20}$$

where Ξ is the holding cost rate.

The total cost for inventory C^{I} is the sum of holding cost C^{H}, emergency cost C^{E}, and ordering cost C^{O}, as

$$C^{\mathrm{I}} = C^{\mathrm{O}} + C^{\mathrm{H}} + C^{\mathrm{E}}. \tag{21}$$

2.5. Joint optimisation model

The developed maintenance model in Section 2.3 and the inventory model in Section 2.4 can be integrated as a joint model as illustrated in Fig. 6. The flowchart explanation is as follows to provide a clearer description of the interrelation within the joint maintenance and inventory model.

At the beginning, periodic inspections of the offshore wind farm and RUL predictions are conducted for critical components. Considering comprehensively the health conditions of all the components within the wind farm, decision variable set 1, *i.e.*, $\boldsymbol{\alpha}$, is employed to determine whether to initiate a maintenance cycle. If the triggering conditions are not met, there is no need for maintenance. Otherwise, potential maintenance opportunities are identified and service vessels are mobilised. Simultaneously, based on the component conditions, decisions are made regarding the appropriate maintenance actions for each component, leading to the determination of maintenance requirements for diverse spare parts.

Maintenance requirements are delivered to both central and local warehouses, where the requirements are compared with the current stock levels. If the quantity of spare parts is sufficient, the required spare parts are transferred to nearby ports. If the quantity is insufficient, all available spare parts in the current warehouse will be transported away, and emergency orders are placed to replenish the remaining spare parts. Subsequently, the remaining quantity of spare parts in the warehouse is compared with the order point specified in decision variable set 2, *i.e.*, $\boldsymbol{\beta}$, and a decision is made on whether to order the new parts. Following that, the spare parts in the warehouse are stored until next maintenance cycles.

In addition to the maintenance and inventory cost, the production loss during the downtime which is caused by turbine failure and maintenance implementation will also generate revenue losses. The production loss C^{P} is calculated by

$$C^{\mathrm{P}} = r \sum_{n\in N} \left\{ \begin{array}{l} \sum_{k\in K} \sum_{i\in I} \left(x^{\mathrm{f}}_{ikn} \chi^{\mathrm{f}}_{ikn} + x^{\mathrm{p}}_{ikn} \chi^{\mathrm{p}}_{ikn} + x^{\mathrm{b}}_{ikn} \chi^{\mathrm{b}}_{ikn} + \sum_{j_i\in J_i} x^{\mathrm{m}}_{kj_i n} \chi^{\mathrm{m}}_{kj_i n} \right) \\ + \max\left(\max\left(m^{\mathrm{H}}_n, m^{\mathrm{F}}_n, m^{\mathrm{C}}_n\right), \max\left(\varphi^{\mathrm{l}}_{j_i n}, \varphi^{\mathrm{c}}_{in}, \eta^{\mathrm{o}}_{in}, \eta^{\mathrm{c}}_{j_i n}\right)\right) \\ + \sum_{k\in K} \left(t_n - T^{\mathrm{F}}_{kn^-}\right) \end{array} \right\}, \tag{22}$$

where r is the expected cost of the lost production per turbine per day; $T^{\mathrm{F}}_{kn^-}$ is the failure time of the turbine k before maintenance cycle n.

The aim of this paper is to minimise the O&M costs by optimising the maintenance policy $\boldsymbol{\alpha}$ and the inventory policy $\boldsymbol{\beta}$, which can be described as

$$\min_{\boldsymbol{\alpha},\boldsymbol{\beta}} \quad d_{\mathrm{c}} = \frac{C^{\mathrm{I}} + C^{\mathrm{M}} + C^{\mathrm{P}}}{Z} \tag{23}$$

$$\text{s.t.} \quad 0\% < \Theta < \Omega < 100\% \tag{24}$$

$$0\% < \zeta \leq 100\% \tag{25}$$

$$KI\zeta \in \mathbb{Z}^{+} \tag{26}$$

$$0 \leq s^{\mathrm{L}} < S^{\mathrm{L}} \tag{27}$$

$$0 \leq s^{\mathrm{C}} < S^{\mathrm{C}} \tag{28}$$

$$s^{\mathrm{L}}, S^{\mathrm{L}}, s^{\mathrm{C}}, S^{\mathrm{C}} \in \mathbb{Z} \tag{29}$$

The objective function (23) minimises the total O&M costs per year by explicitly accounting for maintenance costs, inventory costs, and production losses. This optimisation problem includes constraints (24)–(29). Constraints (24) and (25) indicate the upper and lower bounds as well as the magnitude relationship of the maintenance thresholds. Constraint (26) means the quantity of aged components which trigger maintenance is an integer. Constraints (27)–(29) denote the lower bounds and magnitude relationships of the inventory levels, which must be integer values.

This problem is a non-linear single-objective optimisation problem with mixed variables and constraints. There are millions of potential policies in terms of combining maintenance and inventory. It is difficult to search this large solution space to find the best policy through an exhaustive search. A metaheuristic algorithm is necessary to solve this optimisation problem where the solution space is too vast to search exhaustively in a reasonable amount of time.

In this paper, GA is employed due to the strengths of dealing with a multivariate and non-linear problem and has been applied in various engineering optimisation problems [59–61]. GA is the optimisation technique inspired by natural selection and genetics, operating by simulating the process of evolution within a population of potential solutions. Initially, a population of candidate solutions is generated randomly. Through successive generations, solutions evolve using operators such as selection, crossover, and mutation. These operations mimic natural selection processes, where better solutions are more likely to be selected for reproduction.

The more detailed procedure of employing GA to solve this optimisation problem is depicted in Fig. 7, and the main steps are as follows. It should be clarified that while enhancing the performance of the GA algorithm by adjusting configuration parameters and comparing its performance with other heuristic algorithms are interesting issues, they are out of the scope of this paper.

Step 1: Initialisation. The algorithm parameters in GA and the ranges of variables are set. An initial population of potential solutions is created to the optimisation problem. These solutions are typically represented as individuals that embody a range of joint maintenance and inventory policies $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ meeting constraints.

Step 2: Evaluation. The fitness of each individual in the population is evaluated by running a large number of Monte Carlo simulation to estimate the expected value of the objective function d_c, which quantifies how well each individual solves the problem. It guides the search towards better solutions. Individuals possessing better fitness values are deemed superior.

Step 3: Determination of termination criteria. If the genetic generation meets the termination criteria, the optimisation process is over, and the optimal solution is obtained. Otherwise, the optimisation process continues.

Step 4: Selection. The selection process determines which individuals are retained to produce the next generation. This process is based on the fitness of individuals, with those having higher fitness given a higher probability of being chosen.

Step 5: Crossover. New individuals are then produced through the crossover of genetic material from parents in the mating pool, facilitating genetic information exchange. The crossover operation allows offspring to inherit traits from their parents and possibly generate new individuals with higher fitness.

Step 6: Mutation. Mutation introduces small random changes to some individuals' genetic information, increasing diversity and aiding in the exploration of new search space regions. Then, the subsequent population is generated and the procedure switches to Step 2. The above process repeats until reaching termination conditions.

3. Results and discussion

In this section, a numerical example is presented to demonstrate the developed joint optimisation model. A generic 400-MW offshore wind farm with a designed lifetime of 20 years is located in the North Sea, as shown in Fig. 8. The offshore wind farm consists of 100 4-MW wind turbines. The offshore site is 15 km away from the main port for the O&M of this wind farm. Both the maintenance base and the local warehouse are located at this port. The production facility for this operational offshore wind farm is located in the central region of Denmark, where also the central warehouse is situated.

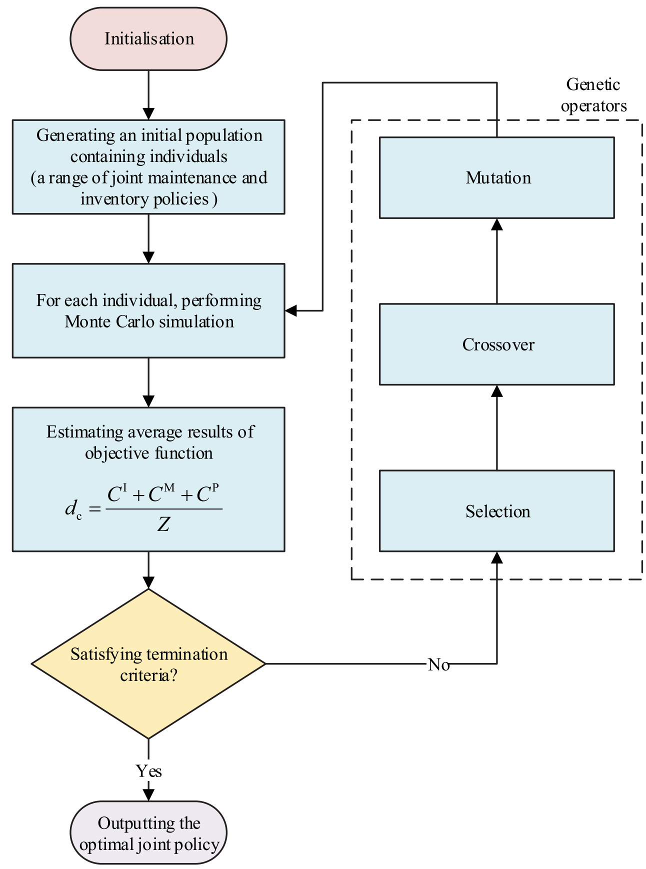

Fig. 7. Flowchart of GA developed for solving the joint maintenance and inventory problem.

The degradation failure times of components are modelled using two-parameter Weibull distributions, and the Weibull parameters are given in Table 2. The maintenance-related parameters are also given in Table 2, including maintenance costs, age reduction of major repairs, and inspection and RUL prediction intervals. The above parameters are specified based on the data given in the literature [56].

The service vessel-related parameters are shown in Table 3, including Weibull distribution parameters for lead time, which consists of mobilisation and waiting for suitable metocean conditions, vessel charter costs, maintenance personnel-related parameters, and working shifts. The parameters are derived and estimated from [56,62,63].

The parameters on replacement probability for subcomponents in Table 4 are derived according to the studies [49–52], where the failure relationships between components and subcomponents are analysed. The replacement costs for subcomponents are estimated from the literature [64].

The inventory management-related parameters include lead times for regular and emergency orders, order placement costs, holding cost rate, and emergency order cost rate, as listed in Table 5. The values of these parameters are specified based on the data provided in [34,64].

To address the inherent uncertainty associated with certain numerical values in these parameters, a sensitivity analysis performed to quantify the impact of fluctuations in the key parameters on model outputs in Section 3.2. This approach not only strengthens the verification of our findings but also demonstrates the robustness of our proposed framework in diverse real-world scenarios.

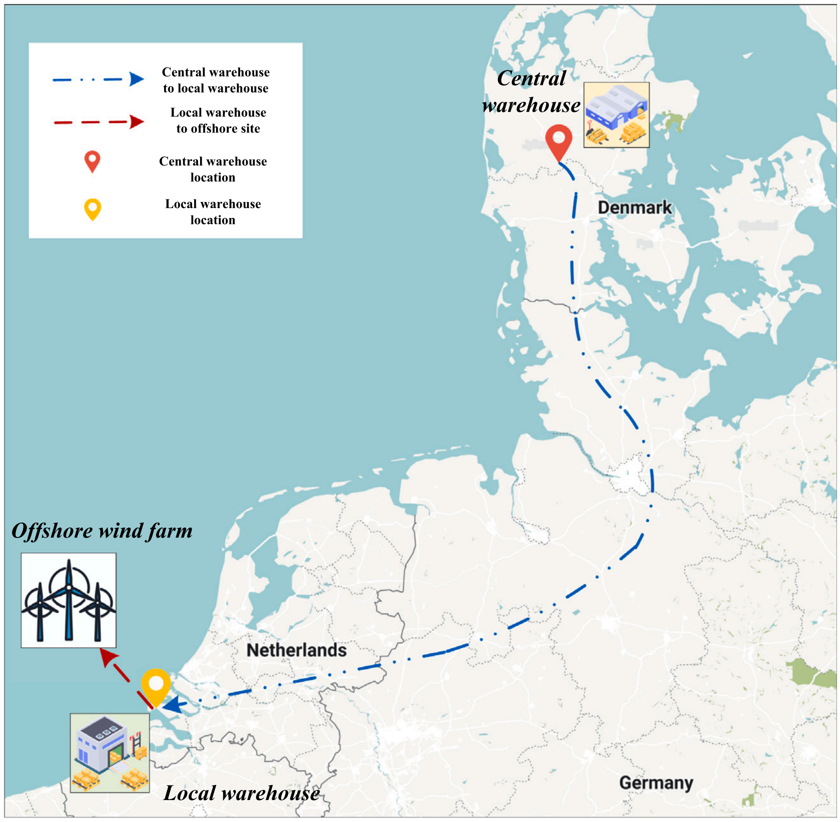

Fig. 8. Geographical location of the offshore wind farm and warehouses.

Table 2
Failure and maintenance parameters for components [56].

Component	Failure distribution		Cost (k€)		Age reduction of major repair	Inspection and RUL prediction interval (days)
	Scale parameter (days)	Shape parameter	Failure replacement	Basic repair		
Rotor blade	3000	3	185	4	0.4	60
Speed train	3750	2	45	1		
Gearbox	2400	3	230	5		
Generator	3300	2	60	1.5		

Table 3
Service vessel-related parameters [56,62,63].

Vessel	Mobilisation and awaiting favourable metocean conditions		Cost (k€)		Technician		Working shift (hours)
	Scale parameter (weeks)	Shape parameter	Mobilisation	Day rate	Number	Day rate (k€)	
HLV	4	3.1	80	50	8	0.6	24
FSV	2	3.4	–	18	4		12
CTV	1	3.3	–	8	2		12

3.1. Computational results and comparative performance

The simulation of the joint model considers a number of stochastic parameters, so the output of the simulation is also stochastic. In order to evaluate the performance of the joint policy, a 1000-repetition Monte Carlo simulation is run to estimate the expected value of the objective function which is used to guide the search for the optimal solutions. The optimisation procedure takes around 19 h to find the optimal solution on a computer with the configuration of 4-CPU E5-1620 V3 3.5 GHz and 32 GB RAM. The configuration parameters of GA are: (1) a population size of 40 individuals; (2) a maximum number of generations of 50; (3) mutation probability of 0.2; (4) crossover probability of 0.8.

The convergence of the optimisation results is represented in Fig. 9. The performance of the best individual gradually converges with the increase of the generation, reaching a stable value after about 20th generation. Therefore, the convergent result can be considered as the optimal result.

The optimisation results and the corresponding decision variables are shown in Table 6. Compared to the inventory policy of the local warehouse, the values of s^C and S^C of the central warehouse are both less. The reason is, on the one hand, the holding costs of the component-level units are higher considering the component-level units are more costly than subcomponent-level units. Hence, it is more economical to keep a low level of component-level units in the warehouse.

Table 4
Replacement probability and cost parameters for subcomponents [49–52,64].

Component	Subcomponent	Replacement probability (%)	Cost (k€)
Rotor blade	Hub	60.6	35
	Rotor bearing	11.6	10
	Blade	27.8	140
Speed train	Low speed train	45.6	26
	High speed train	30.4	13
	Brake	24	6
Gearbox	Gear	1.1	74
	Gear bearing	69.2	70
	Auxiliary system	12.6	15
	Housing	3.1	7
	Shaft	14	64
Generator	Stator	12.7	28
	Generator rotor	8.5	18
	Generator bearing	36.4	7
	Auxiliary system	42.4	7

Table 5
Parameters relevant to spare parts inventory management [34,64].

Unit	Lead time (days)		Order placement cost (k€)	Holding cost rate (per day)	Emergency order cost rate
	Regular	Emergency			
Component	3	28	50	0.001	1
Subcomponent	1	7	25		

Table 6
The optimal joint policy minimising the annual O&M costs.

	Θ (%)	Ω (%)	ζ (%)	S^{L}	s^{L}	S^{C}	s^{C}	d_c (k€/year)
Value	72.40	88.20	3.25	9	3	4	2	21 220.40

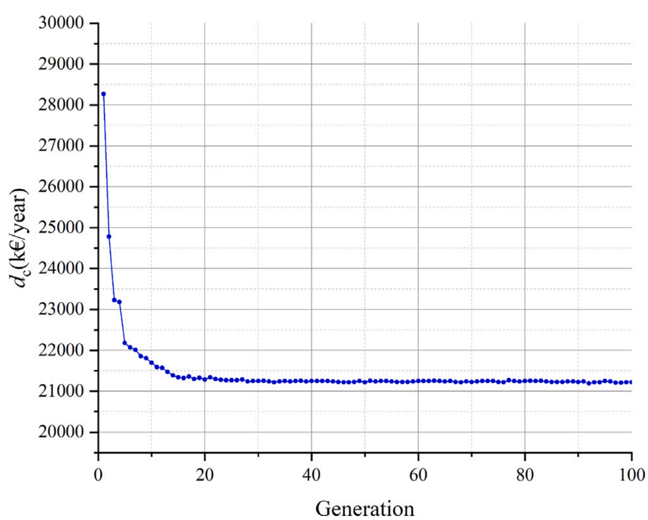

Fig. 9. Convergence of the optimisation results with the increase of the generation.

On the other hand, the gap between Θ and Ω is larger than the gap between Ω and 1, indicating that the quantity of replacement is lower than major repair in the maintenance cycles. Consequently, the requirement of component-level units is less than subcomponent-level units. Therefore, the inventory policy of the central warehouse (4, 2) is lower than the inventory policy of the local warehouse (9, 3).

A comparative study is performed to compare the performance of two different joint maintenance and inventory policies in which different optimisation methods are employed.

- Joint policy 1 (the proposed policy): This joint policy presented herein is derived from the joint optimisation method outlined in Section 2.5. Maintenance and inventory models are integrated, whereby the output of the maintenance model, *i.e.*, the demand of spare parts, influences decision-making processes in the inventory model. Within this joint optimisation framework, the obtained joint policy ($\boldsymbol{\alpha}^*$, $\boldsymbol{\beta}^*$) represents an optimal solution aimed at minimising the overall costs associated with maintenance and spare parts management.
- Joint policy 2: Previous studies have predominantly focused on optimising maintenance and inventory policies separately, as exemplified by the studies [11,65]. The policy proposed herein follows a similar approach, entailing a two-stage optimisation process. In the first stage, the maintenance model is optimised to identify the optimal solution $\boldsymbol{\alpha}^*$ that minimises the costs associated with maintenance (C^{M}) and production losses (C^{P}). In this stage, the impact of maintenance on spare parts storage and the influence of stock levels of spare parts on maintenance implementation are not considered. Following the completion of the first stage optimisation, the optimal policy $\boldsymbol{\alpha}^*$ obtained is then utilised as input for decision-making in the inventory model. In the second stage, the inventory model is optimised with the objective of minimising the inventory-related costs (C^{I}), leading to the optimal inventory policy $\boldsymbol{\beta}^*$. The optimal joint policy obtained is (66.6%, 89.9%, 2.5%, 11, 4, 2, 1). The total O&M cost is the sum of the costs obtained from the first and second stage optimisation, which is 21799.7 k€/year.

The Monte Carlo simulation with 1000 iterations which evaluates the performance of two policies is shown in Fig. 10. The simulation is run independently in each iteration. After running 600 iterations of the Monte Carlo simulation, the average values gradually stabilise without significant variations. This suggests that the 1000 iterations have provided a sufficiently accurate statistical analysis of the results. The final results at 1000 iterations are utilised to estimate and compare the economic performance of the joint policies. The comparison suggests

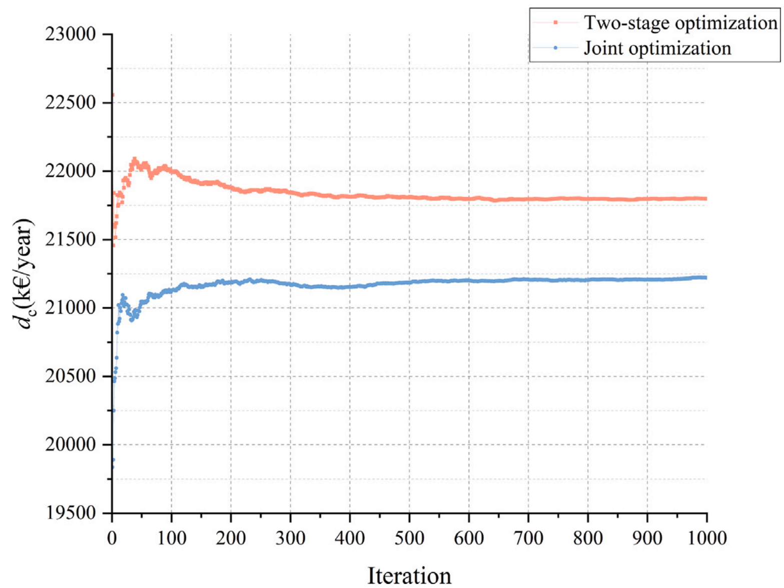

Fig. 10. 1000-iteration Monte Carlo simulation of the joint policy 1 and 2.

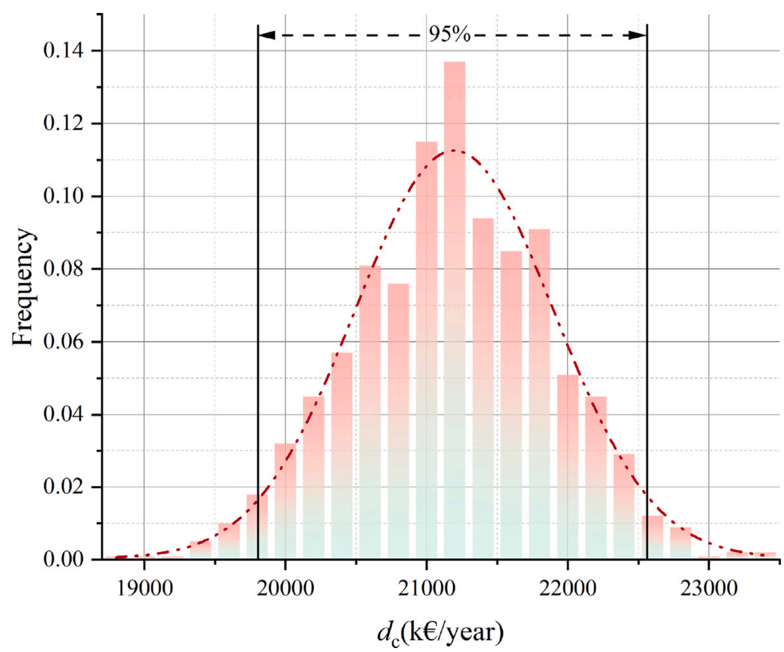

Fig. 11. Variation of the Monte Carlo simulation results.

that the joint policy 1 using the joint optimisation method shows the economic advantage compared with the joint policy 2 using the two-stage optimisation method. The variation of the 1000 simulations of the optimal joint policy 1 and the confidence interval with a 95% confidence level are demonstrated in Fig. 11. The results vary within the range [18800,23400] and the highest concentration of results centred around 21200 k€/year.

The cost breakdown of the annual O&M costs of the optimal joint policy 1 is presented in Fig. 12. The biggest portion of the costs is related to service vessels. Offshore wind farms are located far from shores. The service vessel fleet is essential for the loading and transportation of wind turbine components, accessing offshore wind farm sites, supporting maintenance operations, and accommodating both crew and technical personnel. In practice, the costs associated with vessels typically represent the largest proportion, aligning with this research finding. Unit costs hold the second position in the overall cost structure. Production loss costs denote the expenses associated with the loss of production during wind turbine downtime, ranking third in the total cost breakdown. Holding costs refers to the expenses incurred in storing spare parts in warehouses. Emergency costs is the expenses incurred when emergency orders are placed because the quantity of inventory is insufficient to meet repair maintenance demands. Holding costs and emergency costs are interrelated, and their equilibrium is essential. Excessive inventory results in high holding costs, while insufficient inventory leads to a shortage of available stock, resulting in high emergency costs. Following optimisation, the optimal solution attains a balanced distribution with holding costs and emergency costs exhibiting similar proportions. Ordering costs are determined solely by

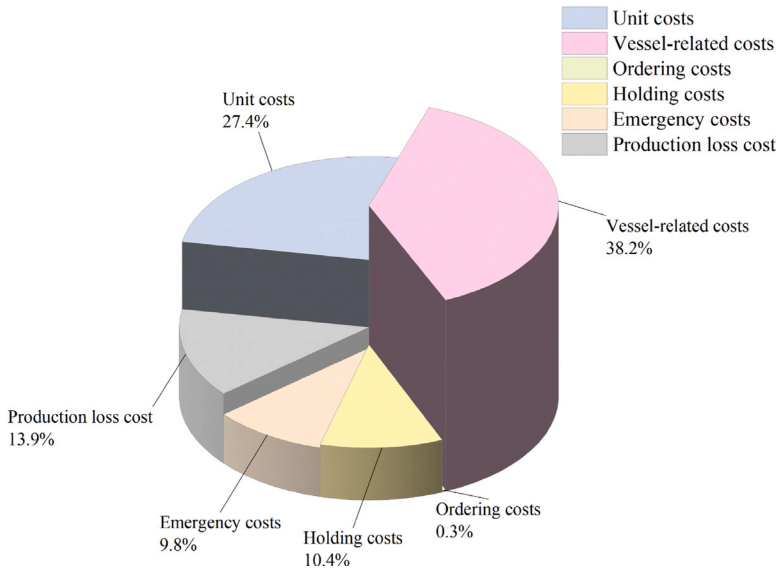

Fig. 12. Breakdown of the annual O&M costs.

the order quantity, regardless of the unit cost. Given that the cost of placing a order is much lower compared to other expenses, the ordering cost occupies the lowest portion.

A more detailed comparison between the joint policies 1 and 2 is shown in Fig. 13. Although joint policy 1 appears to be more cost-effective than joint policy 2, it does not exhibit superior performance in all cost categories. The first stage optimisation in joint policy 2 is aimed at minimising the total costs in the maintenance model, encompassing unit costs, vessel-related costs, and production loss costs. Consequently, in comparison to joint policy 1, joint policy 2 achieves lower vessel-related costs and production loss costs by 5.20% and 6.45%, respectively. Despite the higher costs in unit costs, joint policy 2 lowers the costs due to its optimisation objective and considered factors while considering the overall costs of these three categories. However, in the inventory costs category, joint policy 1 demonstrates a significant cost advantage compared to joint policy 2. Joint policy 2 results in an additional 18.8% in inventory costs. Consequently, from an overall perspective, joint policy 1 exhibits superior economic performance because it considers the interrelationship between the maintenance and inventory models. While incurring marginal additional maintenance costs, joint policy 1 substantially reduces inventory costs. In summary, a joint optimisation of maintenance and spare parts policies can reduce overall O&M costs by approximately 2.66% compared to individual optimisation of two policies.

3.2. *Influence of policy parameters on o&m costs and joint policies*

In practical scenarios, the O&M of offshore wind farms is confronted with uncertainties. These uncertainties affect inputs, such as fluctuating maintenance costs over time and among operators, or unstable maintenance quality due to marine environments, subsequently influencing decision-making and outcomes. In such situations, it is necessary to investigate which O&M factors significantly impact joint policies and how their changes affect costs. Therefore, we analyse the influence of the parameters relevant to the maintenance and inventory model on the O&M costs under the optimal policy. This highlights the importance of maintaining accuracy and stability of parameters related to key factors. Furthermore, understanding how changes in O&M factors affect joint policies helps enhance the resilience of the policy.

Five key parameters in the maintenance and inventory models, including age reduction of major repair, emergency order cost rate, holding cost rate, unit costs, vessel-related costs, are selected considering their impact on the respective cost categories and the significance of their influence on decision-making.

Table 7 shows the results for sensitivity analysis. In Scenario 1, the benchmark represents the joint optimisation results in Section 3.1. For each of the five key parameters, two scenarios are configured. In even-numbered scenarios (*i.e.*, Scenarios 2, 4, 6, 8, 10), the parameter values are reduced to 0.5 times their original values. Conversely, in odd-numbered scenarios (*i.e.*, Scenarios 3, 5, 7, 9, 11), the parameter values are increased to 1.5 times the original values. All other parameters were held constant. Subsequently, with the new parameter settings, a re-optimisation process is conducted, resulting in new maintenance policies (Θ, Ω, ζ) and inventory policies (S^{L}, s^{L}, S^{C}, s^{C}), along with the optimised cost d_c. Using the value of d_c in the benchmark as a reference, the proportion of d_c in the new scenarios to d_c in the benchmark is calculated.

The comparison of the annual cost d_c and proportion is depicted in Fig. 14. The influence of the parameters on the maintenance policy and the inventory policy is illustrated in Fig. 15(a) and Fig. 15(b), respectively. The detailed comparison and results are discussed as follows.

(1) Sensitivity to the age reduction of major repairs ϑ_m

The age reduction reflects the impact of maintenance actions on component health. The execution of maintenance actions is influenced by various factors, such as the marine environments in which maintenance operations take place and the expertise of technicians. These factors result in variations in the effectiveness of maintenance, which may either exceed or fall short of expectations.

The comparative results in Table 7 and Fig. 14 indicate age reduction of major repairs ϑ_m has a positive impact on O&M costs, and the value of ϑ_m significantly influences the joint policy. In Scenario 3, a higher ϑ_m implies that, at an equivalent cost, major repairs have a more significant effect on component condition, leading to a reduction in O&M costs by 15.97%. In contrast, as ϑ_m decreases, O&M costs rise notably by 20.32%. Upon modifying parameters and performing re-optimisation, it is observed that a higher ϑ_m leads to a lower Θ and a higher Ω as shown in Fig. 15(a). This result suggests that the applicability of major repairs expands while the range for preventive replacements diminishes, which is reasonable logically, because major repairs are generally preferred over preventive replacements if they prove to be effective with the increase of ϑ_m.

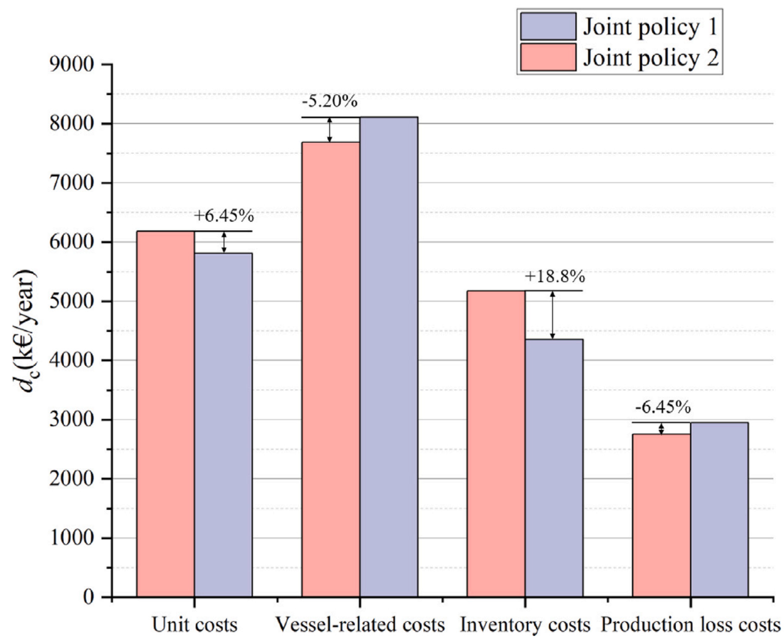

Fig. 13. Comparison of different cost categories under the joint policy 1 and 2.

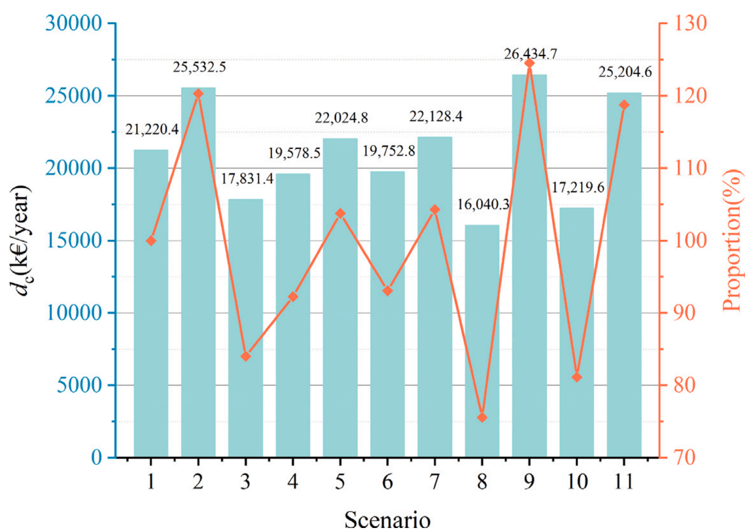

Fig. 14. Comparison of annual O&M costs in various scenarios.

Table 7
Influence of the parameters relevant to the maintenance and inventory model on the O&M costs and the optimal policy.

	Scenario	Θ (%)	Ω(%)	ζ (%)	S^L	s^L	S^C	s^C	d_c	Proportion(%)
Benchmark	1	72.40	88.20	3.25	9	3	4	2	21 220.40	100.00
Age reduction of major repair	2	81.10	83.00	7.50	2	1	12	8	25 532.50	120.32
	3	64.30	88.50	2.00	9	2	2	1	17 831.40	84.03
Emergency order cost rate	4	68.60	88.10	7.25	1	0	1	0	19 578.50	92.26
	5	72.90	88.30	3.00	12	6	6	3	22 024.80	103.79
Holding cost rate	6	71.80	87.60	3.75	18	8	7	4	19 752.80	93.08
	7	72.30	89.10	3.75	6	0	2	0	22 128.40	104.28
Unit costs	8	69.10	88.40	4.50	11	4	4	2	16 040.30	75.59
	9	73.70	88.60	3.50	9	2	5	2	26 434.70	124.57
Vessel-related costs	10	72.70	87.20	3.50	8	2	5	3	17 219.60	81.15
	11	71.70	88.70	3.50	10	3	4	2	25 204.60	118.78

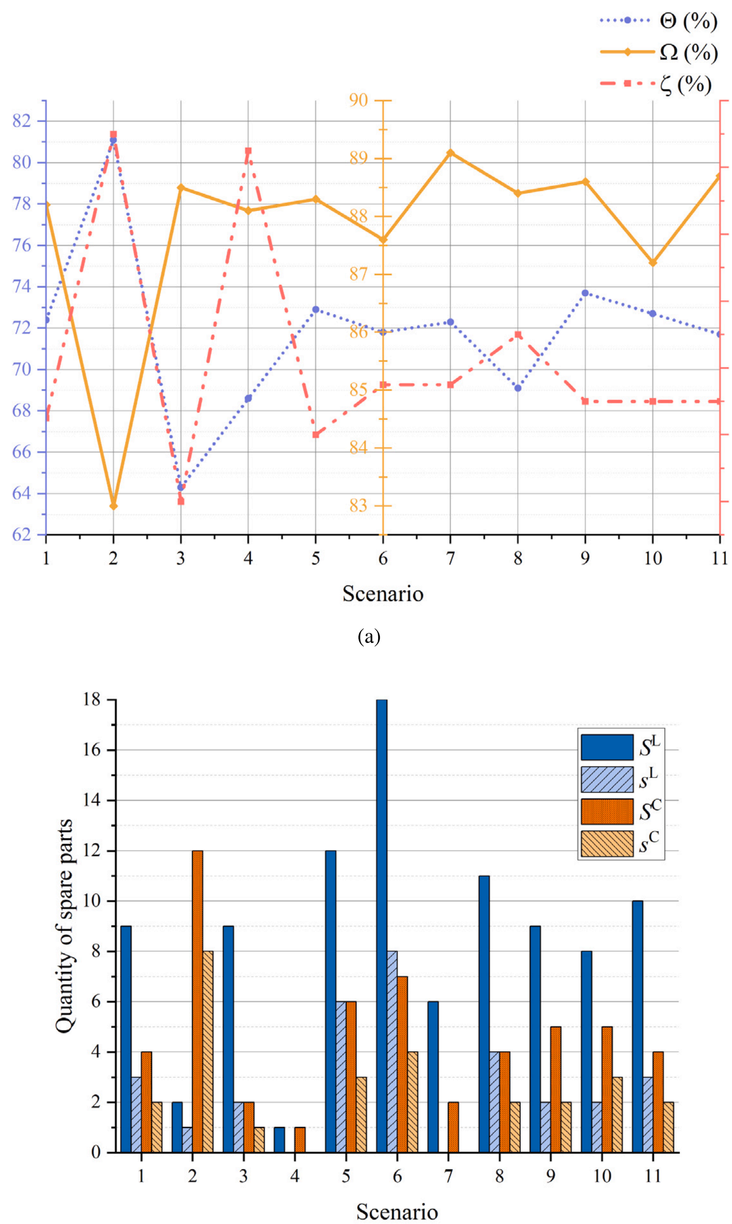

Fig. 15. Influence of the parameters on the joint policy: (a) Maintenance policy. (b) Inventory policy.

The decrease in ζ indicates that maintenance cycles are more frequent to be triggered, resulting in a significant increase in the frequency of major repairs. As the frequency of replacement drops, the storage requirements for the central warehouse decrease corresponding (Fig. 15(b)). The inventory policy for the local warehouse shows no significant change, probably because the inventory policy for the central warehouse in the benchmark is already sufficient to satisfy the additional demand of subcomponent-level units arising due to the increase in ϑ_m. Even in cases of unit shortages, emergency orders are sufficient to meet the maintenance need.

In comparison, in Scenario 2, when ϑ_m decreases, the impact on inventory policy becomes remarkable. Both upper and lower limits in the inventory policy of the local warehouse decrease, implying a substantial reduction in demand for subcomponent-level units. Meanwhile, the increase of the storage requirements for the central warehouse indicate that the joint policy predominantly relies on replacements as the primary maintenance approach.

(2) Sensitivity to the emergency order cost rate E_c

The fluctuation in the emergency order cost rate E_c reflects changes in maintaining an efficient supply chain. The cost of emergency orders due to spare parts shortages can vary over time and under different circumstances. As shown in Table 7 and Fig. 14, the impact of the emergency order cost rate on O&M costs (−7.74% ~ +3.79%) is relatively small compared to age reduction of major repair. It mainly affects spare parts inventory polices, resulting in a less impact on decision variables Θ and Ω in the maintenance policy, as depicted in Fig. 15(a).

In Scenario 4, a decrease in the emergency order cost rate leads to an increase in the parameter ζ, indicating that maintenance cycles are less likely to be triggered. As a result, the number of maintenance cycles drops, but the demand for units within each maintenance cycle rises. As shown in Fig. 15(b), the stock levels in both the local and central warehouses remain exceptionally low. This implies that, with the decrease in the emergency order cost rate, almost all maintenance demands are supplied through emergency orders to minimise holding costs associated with storing spare parts in the warehouse.

In Scenario 5, an increase in the emergency order cost rate results in a corresponding rise in the cost of emergency orders. Consequently, the stock levels in both local and central warehouses are determined to be maintained at a higher level compared to Scenario 1 in order to avoid emergency orders.

(3) Sensitivity to the holding cost rate Ξ

The holding cost rate Ξ may vary due to changes in the factors,*e.g.*, warehouse rent, warehouse depreciation, warehouse management. Similar to the emergency order cost rate E_c, the holding cost rate Ξ exhibits minor impact (−6.92% ~ +4.28%) on the maintenance policy. In Scenarios 6 and 7, the changes in maintenance polices do not change significantly when compared to Scenario 1. The change in O&M costs is also close to the change caused by the emergency order cost rate E_c.

The main impact of changes in the holding cost rate Ξ lies in the inventory policy. In Scenario 6, the reduction in Ξ implies that the cost of holding units becomes less costly, so the spare parts policy tends to store more units. Conversely, in Scenario 7, the spare parts policy tends to reduce the quantity of units in the warehouse to reduce holding costs. In this case, the lower limit in the inventory policy is optimised to be 0, indicating that new units will only be ordered to replenish the stock level once all units in the warehouse are consumed.

(4) Sensitivity to the unit costs

The unit costs may fluctuate due to changes in materials, manpower, manufacturing, and other factors. Among the five key parameters, the unit costs are the most influential (−24.41% ~ +24.57%), although the proportion of unit costs ranks second according to Fig. 12. The reasons is emergency costs and holding costs are directly associated with unit costs. With the increase of unit costs, these two costs also increase proportionally. Comprehensively, unit costs are identified as the most significant factor in the O&M costs.

Through a comparison between Scenarios 8, 9 and 1, it is found that the changes in unit costs have a relatively minor impact on the joint policy. There is a slight variation in the maintenance policy, with an increased scope for major repairs (Fig. 15(a)). The change in the inventory policy indicates a preference for storing slightly more units when unit costs decrease (Fig. 15(b)). Conversely, when unit costs increase, there is almost no change in the inventory policy.

This can be explained by the fact that an increase in unit costs signifies an increase in various maintenance costs, such as failure replacement, preventive replacement, and major repair. In this context, the changes in the costs of different types of maintenance offset each other, resulting in less obvious variations in maintenance policies. In the spare parts inventory policy, the changes in unit costs lead to corresponding changes in emergency costs and holding costs, which conflicts with each other. Overall, while the impact of unit costs on the joint policy is not significant, it noticeably influences O&M costs.

(5) Sensitivity to the vessel-related costs

Maintenance service vessels can be owned by operators or leased in the market. The cost fluctuates depending on the availability of vessels in the market. According to Fig. 12, vessel-related costs constitute the largest proportion of O&M costs. The change in vessel-related costs significantly impact the economic performance (−18.85% ~ +18.78%) as shown in Table 7 and Fig. 14, following unit costs. As observed in Fig. 15(a) and Fig. 15(b), Scenarios 10 and 11 exhibit slight impact of vessel and technician costs on the joint policy when compared to Scenario 1. This phenomenon is similar to the unit costs, where an increase in vessel-related costs implies a corresponding rise in the prices of HLVs, FSVs, and CTVs. In this case, the effects of different types of maintenance tend to counterbalance each other, resulting in subtle changes in maintenance policies. Additionally, vessel-related costs have slight impact on spare parts management decisions, leading to only marginal changes in inventory policies.

In summary, based on the results of sensitivity analysis, several key findings can be summarised. Firstly, among all key parameters, unit costs, vessel-related costs, and age reduction of major repair have the most significant impact on O&M costs, whereas the impact of emergency order cost rate and holding cost rate is less. Secondly, concerning the influence on maintenance policies, age reduction of major repair has the most substantial impact, with less effects observed for the other parameters. Thirdly, regarding the impact on spare parts policies, age reduction of major repair, emergency order cost rate, and holding cost rate all exhibit significant effects, while unit costs and vessel-related costs have a relatively smaller impact.

4. Conclusions, limitation of the research, and future directions

Improving O&M for offshore wind sector represents a promising cost-reduction opportunity and will continue to be an important factor in shaping the future development of the offshore renewable energy. In this paper, health information and inventory control are integrated into O&M management for offshore wind farms. The offshore wind turbines system is modelled as a three-level construction hierarchy including wind turbines, components, and subcomponents. The units in different levels are stored in a multi-echelon inventory network. The joint optimisation framework is proposed where the mutual connection between the predictive maintenance model and the multi-echelon (s, S) inventory model is considered. The comprehensive effect of maintenance costs and production losses is captured and the GA method is employed to find the most cost-effective joint policy.

The proposed method is applied to a generic offshore wind farm at North Sear with the warehouses in the Netherlands and Denmark for illustration. Results reveal that the joint optimisation of maintenance and inventory policies can decrease overall O&M costs by about 2.66% in comparison to two stage optimisation, indicating that the comprehensive O&M management considering the interrelationship between the maintenance and inventory models is a more cost-effective manner for offshore wind farms. Moreover, sensitivity analysis is performed to investigate the influences of critical parameters on O&M costs and optimal joint policies. Unit costs (−24.41% ~ +24.57%), vessel-related costs (−18.85% ~ +18.78%), and age reduction of major repair (−15.97% ~ +20.32%) exert the greater impact on O&M costs, with emergency order cost rate (−7.74% ~ +3.79%) and holding cost rate (−6.92% ~ +4.28%) having a less significant effect. From the perspective of policy formulation, age reduction of major repairs significantly influences maintenance policies, and inventory policies are notably affected by age reduction of major repairs, emergency order cost rate, and holding cost rate.

In practice, the maintenance of wind farms and the storage of spare parts may be managed by the same decision-maker, highlighting the necessity of integrating these two policies. The framework proposed in this paper aims to effectively connect these two parts and perform optimisation jointly to reduce overall costs. This approach is able to avoid situations where decisions made independently in one aspect adversely affect another, thereby enhancing the economic of offshore wind energy. Sensitivity analysis highlights the factors in O&M processes that significantly impact costs and decisions, providing guidance to mitigate adverse effects of uncertainties on offshore wind farm maintenance.

However, there are still limitations resulting in gaps between O&M simulations and reality in this paper due to the assumptions made for simplification, which deserves more research in the future. The limitations and future directions are concluded as below:

(1) Predicting RUL of wind turbine components remains a challenging task in reality, due to factors such as the lack of condition monitoring data in practice and the varying conditions in wind turbine systems. The inaccuracy of RUL prediction is ignored in this paper. However, inaccurate RUL predictions in practice can

lead to deviations in spare parts demand, subsequently affecting the implementation of maintenance and inventory control . Therefore, considering this factor will be an important research direction in the future.
(2) In this model, it is assumed that all units within the same-level warehouse are managed under the same inventory policy. While this assumption may not be entirely realistic, considering the complexity and computational challenges associated with introducing individual policies for each type of unit, this assumption is made in the model. In future research, involving the consideration of individual policies for each type of unit can enhance the realism of the model.
(3) The model does not consider the presence of multiple subcomponents of the same type within their respective components, assuming that the replacement of specific subcomponents is independent of their quantity. Future research can address this issue by building a more detailed construction hierarchy of offshore wind turbine systems tailored to specific turbine configurations. For instance, considering distinctions between direct-drive and geared wind turbines, or between single-stage and multi-stage gearboxes, will contribute to a better understanding of the system.
(4) In real-world scenarios, the O&M of an offshore wind farm are typically carried out by multiple maintenance providers and spare parts suppliers. Conflicting interests and decisions may arise among these stakeholders. Considering the game and collaboration among multiple stakeholders would be an interesting subject. Furthermore, future research could also explore multiple offshore wind farms and multiple warehouses to address the complexities of spare parts supply networks in the real world.
(5) In this study, it is assumed that maintenance implementation takes priority over spare parts preparation to avoid potential conflicts between maintenance decisions and inventory management decisions. However, in reality, situations may arise where maintenance is postponed or cancelled due to the unavailability of spare parts. This aspect will be incorporated into the model in future work.
(6) In this study, specific modelling of metocean conditions is not conducted. An alternative approach is used to include the time waiting for suitable weather conditions in mobilisation time. Future research could consider modelling wind speed and wave height to trigger more dynamic maintenance decisions.

CRediT authorship contribution statement

Mingxin Li: Writing – original draft, Visualization, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Xiaoli Jiang:** Writing – review & editing, Supervision. **James Carroll:** Writing – review & editing. **Rudy R. Negenborn:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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