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Service operation vessels for offshore wind farm maintenance: Optimal stock levels

Fábio Neves-Moreira *, Jasper Veldman, Ruud H. Teunter

University of Groningen, P.O. Box 800, 9700 AV Groningen, The Netherlands

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ABSTRACT

Service operation vessels are becoming the dominant mode for the maintenance of most offshore wind farms. To minimize turbine downtime, it is essential to bring the right components to the wind farm, while budget and volume constraints prohibit having excess inventories on board. This setting can be interpreted as a repair kit problem, which seeks to define a set of components that may be necessary for on-site maintenance operations in a given time period during which emergency resupply is costly. Current repair kit problem approaches however, do not cater sufficiently for some of the characteristics of offshore wind farm maintenance, including weather-dependent deterioration and the possibility to perform emergency resupplies. We propose mixed-integer programming models both to determine (tactical model) and validate (operational model) repair kits when maintenance operations are performed under different weather conditions. The models are flexible enough to be used with real world data considering multiple turbines composed of different deteriorating components, service operation vessels characteristics (speed and volumetric capacity), different weather conditions, and emergency resupplies. An important feature of this approach is its ability to consider detailed maintenance and vessel routing operations to test and validate repair kits in realistic wind farm environments. We provide valuable insights on the composition of repair kits and on relevant business indicators for a set of different scenarios. The practical implications are that repair kits should be adapted depending on weather forecasts and that considerable downtime reductions can be achieved by allowing emergency resupplies.

1. Introduction

Renewable energy generation is clearly on the rise. The European Commission (EC), for instance, has set the ambitious target for Europe that in 2030 at least 32% of total energy consumption should come from renewable energy [1]. The energy generated by offshore wind farms plays a crucial role in the energy transition. In 2019, Europe has reached 22.1 GW of offshore wind capacity [2], while recently the EC announced a 2050 offshore wind target of 300 GW [3]. Recent years have witnessed significant cost reduction of offshore wind energy production, while several offshore wind farms are currently planned based on zero subsidies. Yet lowering the offshore wind levelised cost of energy remains vital [4], especially as future costs may increase as offshore wind farms are built at larger distances from shore. It is well known that Operations and Maintenance (O&M) costs are a significant portion of total cost in a large number of industries, particularly in the offshore wind sector [5]. Although accurate estimates are hard to obtain, it is frequently mentioned that O&M costs are 20%–25% of an offshore wind farm's total life cycle cost [6,7]. Despite the growing body of knowledge and experience from offshore O&M, new methodologies are still needed to deal with the uncertain and disruptive events that occur on site, and that often result in considerable loss of availability [8]. Such methodologies are particularly critical for the maintenance of wind farms located far from shore. To avoid costly travel time and ensure quick response, many service providers make use of SOVs for the maintenance of small to medium sized turbine components. SOVs are capable of staying offshore during uninterrupted periods of typically 2 to 3 weeks, providing shelter and accommodation for crew and technicians. It is important to determine how many components should be taken on each trip, which relates to the selection of components that a repair (wo)man stores in the so-called repair kit, in practice also referred to as the car stock. Determining the optimal selection of components in such situations has been studied in the literature, termed the Repair Kit Problem (RKP).

Abbreviations: m.u., Monetary units; MIP, Mixed-integer programming; O&M, Operations and maintenance; PHM, Proportional hazards model; POD, Period-oriented decomposition; RKP, Repair kit problem; SOD, Scenario-oriented decomposition; SOV, Service operation vessel; TOD, Turbine-oriented decomposition

* Corresponding author.
E-mail addresses: f.neves.moreira@rug.nl (F. Neves-Moreira), j.veldman@rug.nl (J. Veldman), r.h.teunter@rug.nl (R.H. Teunter).

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List of abbreviations

m.u.	monetary units.
MIP	Mixed-Integer Programming.
O&M	Operations and Maintenance.
PHM	Proportional Hazards Model.
POD	Period-Oriented Decomposition.
RKP	Repair Kit Problem.
SOD	Scenario-Oriented Decomposition.
SOV	Service Operation Vessel.
TOD	Turbine-Oriented Decomposition.

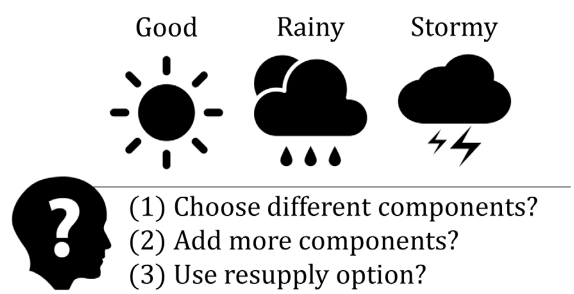


Fig. 1. The failure rate of each component is dependent on the weather conditions to which the equipment is exposed. Expected weather conditions therefore affect the efficient repair kit.

We adapt and extend existing methods to allow for such considerations. Fig. 1 provides a general visual overview of the challenges and trade-offs implicit in the RKPs we aim to solve.

The RKP literature is limited in terms of solution approaches and applications. Current approaches address unrealistic problems while disregarding important business constraints. Most publications dealing with the RKP propose knapsack heuristics to tackle the maintenance challenges of appliance and printer manufacturers [9–11]. In a recent publication, [12] propose a Mixed-Integer Programming (MIP) model to optimize inventory, ordering, and replenishment decisions in an office equipment manufacturer. However, studying the RKP in the offshore wind setting has not yet been done. In this paper, we propose a tactical model that is able to provide efficient repair kits for the case where a vessel needs to maintain a set of turbines in an offshore wind farm for a period of approximately two weeks (a 16-day planning horizon is considered). The repair kits provided by the tactical model are then validated using a more detailed operational model that is able to consider a larger set of business constraints. This validation is rarely considered in the RKP literature. Moreover, we apply a flexible failure generator that simulates turbines with several components that deteriorate differently according to their sensitivity to weather factors. This allows us to explore a large set of realistic scenarios when real data is absent.

The main contributions of this paper are threefold. First, we propose a novel approach to include new realistic features in the RKP. Second, we validate our approach with realistic data describing an offshore wind farm. Third, new managerial insights on the repair kit problem are provided to guide practitioners on how to define repair kits under the considered conditions.

2. Literature review

In order to develop an approach capable of capturing critical features present in offshore wind maintenance operations, we focus our review on the literature related to three main research fields: reliability engineering, spare part management, and maintenance routing and scheduling. The terms “component” and “part” are used interchangeably to refer to elements that are part of a more complex system.

2.1. Reliability engineering

Reliability is given as the probability that a component will perform its required function under certain conditions for a certain time interval [13]. It is common for reliability analysts to use several discrete or continuous probability distribution functions in reliability and safety studies. The most important discrete probability distributions are binomial, Poisson, hyper geometric, and geometric distributions. The continuous distributions that are used often include exponential, normal, lognormal, Weibull, and Gamma distributions [14].

Proper reliability analysis is critical. For instance, [15] show that availability of wind farms largely depends on failure distribution. In reality, reliability is influenced by several factors, such as the operational environment, geographical location and material design. Therefore, ignoring these factors often leads to incorrect reliability analysis [16]. However, despite their usefulness, models based on the aforementioned distributions still ignore most of the direct relationships between the environment, operating conditions and the reliability of each system.

Particularly within offshore wind farms, critical assets such as the wind turbines are constantly exposed to dynamic and demanding operational conditions. Indeed, factors such as varying wind speeds, wave heights, temperatures, lightning strike densities, may all affect a turbine’s condition, while at the same time the turbine is expected to function given some underlying requirements. This means that data is collected under non-similar conditions, so that the effect of most of these factors may be hidden.

One way to estimate the factors that influence the time to failure of a system is the Proportional Hazards Model (PHM) introduced by [17]. Although it started being used mainly in the medical field, it is now a widely spread method in the reliability engineering literature [18]. It has been used in many applications such as marine gas turbines [19], machine tools [20], diesel engines [21], and power transmission cables [22]. For a detailed review on PHMs, extensions, and other reliability models, the reader is referred to [18,23], and [24].

The dependence of the reliability of offshore wind turbines on weather conditions is well-known among the research community and practitioners. Nevertheless, only a few papers were published on this issue [25,26]. In [27], the authors model different failure mechanisms considering multiple wind turbine subsystems and structures, that are influenced by external factors. The approach is compared to a constant failure rate and to empirical wind turbine data to demonstrate its plausibility. In [28], a weather-centered operations and maintenance framework is proposed considering wind impacts on energy production and maintenance plans. The approach is able to improve revenue when facing high failure risks and energy production losses. For a more detailed review on degradation models for wind turbines, the reader is referred to [29] and [30]. Recently, [31] discuss the reliability, availability, and maintainability of offshore wind turbines to identify trends in offshore wind energy applications. Due to the scarcity of data from offshore wind industry, the analysis is complemented with onshore structures.

Reliability engineering approaches are also important for spare parts management. For instance, [16] apply the PHM to a real case study and explore the effect of time-dependent and time-independent covariates on components demand. An inadequate description and modeling approach to the behavior of each component can also lead to inefficient spare part management, which is covered next.

2.2. Spare part management

The aim of spare parts management is to provide components at the right time while keeping inventory cost low. For an overview on spare parts management, the reader is referred to the review papers of [32,33], and [34]. However, most of the spare parts management literature does not consider weather effects and restrictions, and many standard methods are therefore not applicable to wind energy. This also applies to the so-called repair kit problem, which will be described next as it is the most relevant spare parts management model for the offshore farm wind maintenance problem that we will consider.

The RKP is that of deciding what set of components a repair(wo)man should carry to repair jobs, with the objective to provide good service but at the same time limit inventory costs. As a first attempt to model the RKP, [35] assumed a single job with at most one failure of each component type. Since then, others have looked at more general settings with e.g. multiple jobs, multiple components of the same type needed per job, capital budget constraints and capacity restrictions. The most recent contributions are by [9,12] and [11], who also review the earlier literature. However, none of the studied models is directly applicable to stocking offshore wind service operation vessels, since neither weather influences nor the option of restocking during a tour of jobs have ever been considered. Our problem description in the next section will show both these elements to be of crucial importance for the SOV stocking problem that we consider.

Besides [36,37], and [38], little substantial work on spare part management for offshore wind farms has been reported.

2.3. Maintenance routing and scheduling

Routing and scheduling offshore wind farm maintenance services generally map into difficult decision optimization problems that require advanced solution methods for solving them. Several works on vessel routing and scheduling were recently published. In [39], a MIP model considering a crew of technicians is presented and solved with a commercial general-purpose solver. In [40], an exact decomposition approach is presented for a single period problem, and [41] discuss an extension to multiple wind farms and multiple depots and solve instances with up to 24 maintenance activities using a set partitioning formulation. An adaptive large neighborhood search procedure in [42] explores the benefits of sharing technicians between wind farms over multiple periods. Efficient vessel routes for delivering and picking up technicians to each wind farm are computed in each period, improving planning flexibility and reducing operational costs.

In a recent paper, [43] propose an optimization framework for daily route planning and scheduling of maintenance services in offshore wind farms. The proposed approach considers climate data, vessels specifications, failure information, wind farm attributes and cost-related specifics. The authors state that there is no optimization-based work reflecting a complete realistic scenario on the usage of SOVs for the daily route planning. A broad overview on the publications concerning offshore wind farm maintenance logistics optimization are presented in [44,45], and [8], but the literature focusing on the operations of SOVs is absent.

3. The service operations stocking problem

An SOV is a vessel of considerable size with work and storage facilities, capable of transporting around sixty workers (including crew). These vessels are specifically designed for performing offshore wind preventive and corrective maintenance, but can also be an auxiliary resource for other operations, such as vessel refueling, serving as an helicopter pad, fire fighting, among others. The SOV is designed to stay offshore for long periods that may span several weeks. The flexibility provided by an SOV is critical for the efficiency of offshore wind farm operations, as it allows for a large reduction in the number of offshore trips while providing a moving storage facility for technicians, components, and tools.

Restocking the SOV is costly and is preferably done when the vessel is in the harbor near storage locations. Furthermore, adverse weather conditions may yield unexpected maintenance tasks, which may have to be postponed to later periods. Thus, weather uncertainty may disturb the balance between the supply and demand for technicians, components, and tools available on board of an SOV. Therefore, restocking the SOV can be seen as an RKP (discussed in the previous section) where weather conditions play a crucial role.

3.1. Formal problem description

The RKP we aim to tackle is of utmost relevance to the offshore wind industry. In this setting, an SOV needs to maintain a set of wind turbines $\mathcal{N}$ located offshore. Each wind turbine $i \in \mathcal{N}$ is composed of a number of components of type p belonging to the set of component types $\mathcal{P}$. From time to time, these components may fail and have to be replaced or repaired by a team of technicians, using a component transported by the SOV. The crew of the SOV has enough supplies to stay offshore for a trip of $\mathcal{T}$ time periods, including a travel time of $2T$ time periods (i.e., for an SOV lead time T of 1 period, one time period to travel in each direction). To provide a sense of scale, consider that a time period is typically one day and that the entire trip lasts 16 days. During a trip, a stochastic number of jobs can occur according to some unknown probability distribution and at most J maintenance jobs demanding several components of each type are expected. In each maintenance job, the time taken to repair or substitute a component p is st_p. This number of jobs should be defined according to past experience regarding the number of jobs that the SOV is able to serve in each period. To serve these jobs, the SOV is able to transport a repair kit $\mathcal{S}$ comprising a number of components of each type $p \in \mathcal{P}$. This repair kit is defined by $\mathcal{S} = [n_1, n_2, \ldots, n_{|\mathcal{P}|}]$, where n_p denotes the number of components of type p included in the kit, $p \in \mathcal{P}$. There is also an option to resupply some components using an helicopter with capacity of R volumetric units for additional components. This helicopter is used for emergency purposes as it can reach the wind farm within a short period of time represented by L. The SOV has limited capacity of C volumetric units that needs to be respected at any time. The SOV is also assumed to travel at an average speed of s, taking a time of g for docking to a wind turbine. Note that the wind turbine failures are assumed to be dependent on the weather conditions to which they are exposed. Therefore, for each trip, a weather forecast $\hat{Z}_{ft}$ is available indicating the value of weather factor $f \in \mathcal{F}$ for each period $t \in \mathcal{T}$. This weather factor is to be incorporated in the methodology to define failure probabilities. In each trip, the weather forecast is assumed to be perfect. In this work, we consider that a scenario $\omega \in \Omega$ is a trip with a set of failures which demand $d_{pi}^{t\omega}$ components p to be substituted at wind turbine i in period t. Each scenario has a probability of occurrence represented by p^{ω}.

The unitary holding cost per period for component type p is denoted by h_p, the downtime cost per turbine and period is e, and a resupply event costs r. The objective is to minimize the sum of the expected holding, resupply, and downtime costs per trip. Throughout the paper, costs will be expressed in monetary units (m.u.). Fig. 2 depicts a schematic overview of the entities and parameters involved in this problem.

4. Tackling the repair kit problem in offshore wind farms

Our RKP solution approach is composed of three main phases, namely (1) scenario generation, (2) tactical model, and (3) operational model. These phases are presented in Fig. 3.

The first phase aims at generating realistic failure scenarios. Using data describing component reliability and different operating weather

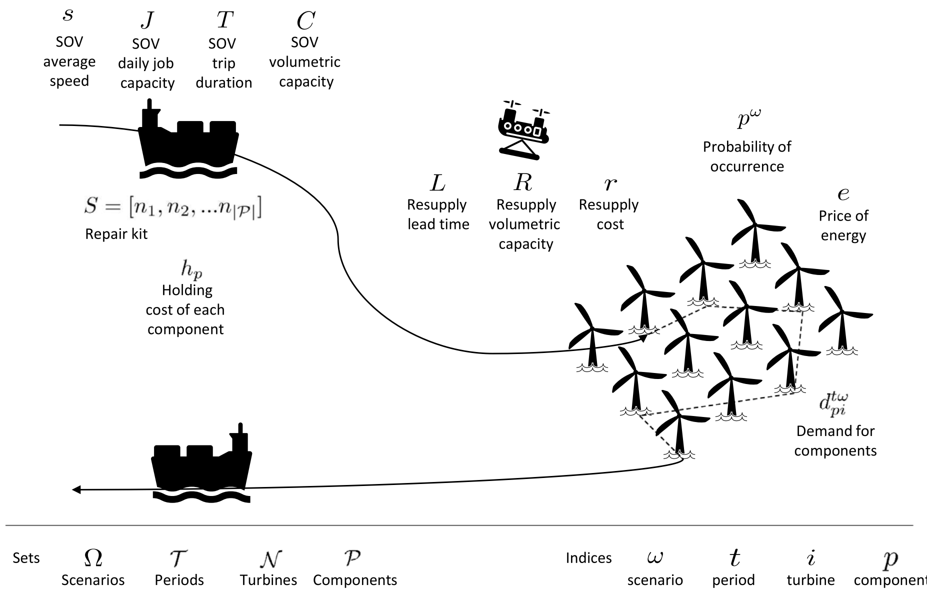


Fig. 2. An example of a trip performed by an SOV. The main parameters considered in this work are also presented.

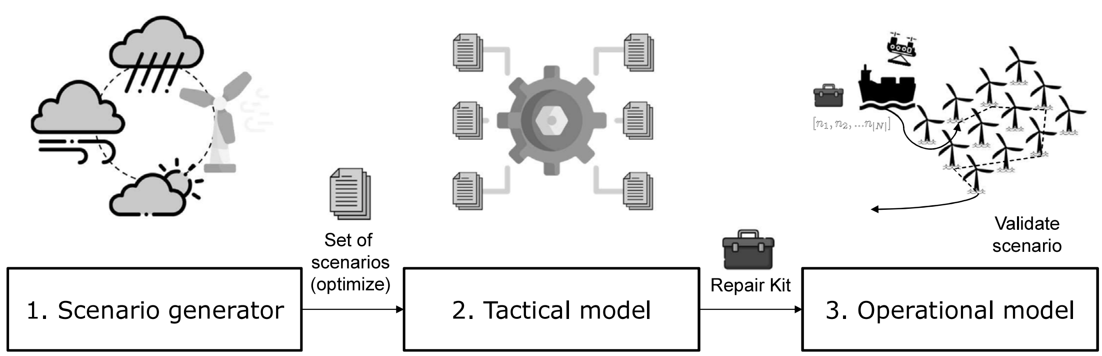


Fig. 3. Schematic overview of the three-phase approach.

conditions, we generate a set of failures to be used in the two subsequent phases.

In the second phase, a set of scenarios with controlled operating weather conditions serves as an input in a tactical model for the RKP associated with SOV activities. This model approximates several business constraints in order to consider relatively large sets of failure scenarios. For instance, explicit vessel routing is not considered but an estimation of the number of possible repairs per period is required. This allows the model to be treatable with current general-purpose solvers. The output of this model is a repair kit which serves as an input in the operational model. Note that to provide good decisions, the type of scenarios considered in this tactical model should be similar to the ones appearing later in the operational model.

The third and last phase of our approach deals with the operational level of SOV activities. The repair kit defined in the tactical model is tested considering additional business constraints along with explicit vessel routing and a costly resupply option which can be used to partially restock the repair kit. The operational model is, by definition, more complex and thus decomposition approaches are necessary to solve it in case the planning horizon is long. These decomposition approaches are introduced later in the paper.

The following subsections details the three phases of the proposed RKP solution approach.

4.1. Scenario generation

The baseline deterioration of each component is modeled as a stationary gamma process with shape parameter $\alpha > 0$, scale parameter $\beta > 0$, and density function f given by

$$f_{\alpha,\beta}(t) = \frac{1}{\Gamma(\alpha)\,\beta^{\alpha}}\, t^{\alpha-1}\, e^{-\frac{t}{\beta}}, \quad t > 0,$$

where $\Gamma(\alpha) = \int_0^\infty z^{\alpha-1}\, e^{-z}\, dz$ is the usual gamma function. The stationary gamma process has a shape function at with a shape parameter $a > 0$ and a scale parameter $b > 0$. It is a continuous-time process $\{X(t) : t \geq 0\}$ with $X(\tau) - X(t) \sim f_{a(\tau-t),b}$ for $\tau > t \geq 0$. As shown in the sample path presented in Fig. 4, the gamma process is a jump process and if we assume that a failure occurs when a certain deterioration threshold H is crossed, failure times follow a distribution function F_H given by

$$F_H(t; a, b) = P(X(t) > H) = \int_H^\infty f_{at,b}(x)dx = \frac{\Gamma(at, Hb^{-1})}{\Gamma(at)}, \quad t > 0$$

in which

$$\Gamma(\alpha, x) = \int_x^\infty z^{\alpha-1} e^{-z} dz, \quad x \geq 0, \quad \alpha > 0,$$

is the upper incomplete gamma function. For further details on the stationary gamma process on which our baseline deterioration is inspired, the readers are referred to the work of [46].

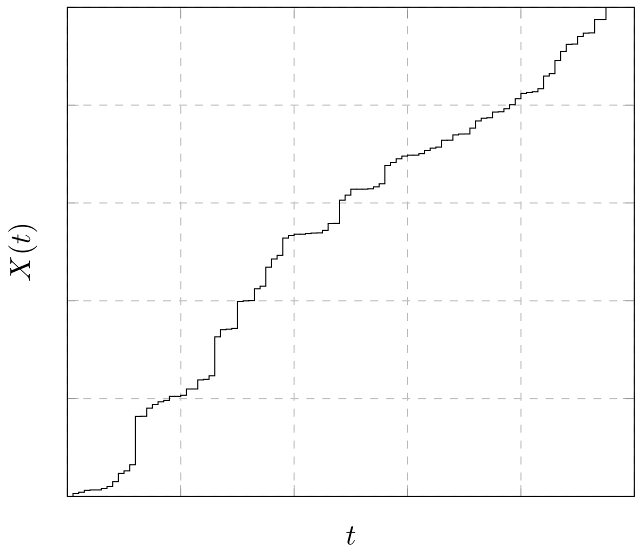


Fig. 4. Gamma sample path with small and large jumps in added deterioration.

To consider the effect of operating conditions, we further enhance this gamma process by hybridizing it with the Cox proportional hazards model [17]. In our model, the baseline deterioration δ_t (i.e., the deterioration increment of one gamma jump) is aggravated by a set of covariates representing the operating conditions. Each component is affected in a distinct manner, depending on its sensitivity to each of the covariates. In each period t, the operating conditions are described by a $1 \times f$ vector of covariate values given by $\mathbf{x}_t = (x_{t1}, \ldots, x_{tf})$. The sensitivity of each component to each covariate f is adjusted by a $f \times 1$ vector of values given by $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_f)$. Using these parameters in conjunction with the baseline gamma process, it is possible to compute the new incremental deterioration for each period t as follows

$$\hat{\delta}_t = \delta_t \, \exp(\mathbf{x}_t \, \boldsymbol{\beta}),$$

where $\hat{\delta}_t$ is the Cox proportional hazards deterioration in period t obtained by aggravating the baseline deterioration δ_t.

Using this method, we are able to consider incremental deterioration quantities caused by a number of factors that were present at a given moment in time. In the example presented in Fig. 5, we present the baseline (normal operating conditions) and the Cox proportional hazards-based (harsh operating conditions) gamma sample paths. The effect of harsh operating conditions cause the component to fail earlier.

After modeling the deterioration process of a component we are ready to also model the operation of a machine or a set of machines through a set of subsequent periods. To do so, we follow a gamma-increment sampling technique [47] to draw independent samples $\delta_t = x_t - x_{t-1}$, where $x_0 = 0$, from the gamma density function. This sampling technique iteratively simulates the increment on the deterioration level that occurs in each time period t. In each time period, the deterioration of the component will increase by a certain amount and when the deterioration level reaches the threshold H, the component fails. The deterioration level is re-set to 0 (assuming that repairs are immediate and the component becomes as good as new) and this continues until a certain number of periods t is achieved.

4.2. Tactical model

We propose a two-stage stochastic optimization programming model. We use decision variables n_p for the first stage decisions (i.e., tactical repair kit definition) and decision variables $x_p^{t\omega}$, $o_p^{t\omega}$, $y^{t\omega}$, $z_i^{t\omega}$, and $f_i^{t\omega}$ to model the second stage decisions (i.e., maintenance job scheduling, resupply events, and component inventories). Recall that integer variables n_p indicate the number of components p to be included in the repair kit. Let $x_p^{t\omega}$ be the integer variables that define the number of components p available at the end of period t of scenario ω. The integer variables $o_p^{t\omega}$ indicate the number of components p made available by a resupply event in period t of scenario ω. Binary variables $y^{t\omega}$ are positive if a resupply trip is performed in period t of scenario ω. Binary variables $z_i^{t\omega}$ model the state (i.e., active or inactive) of each turbine i in period t of scenario ω. Finally, let $f_i^{t\omega}$ be the binary variables defining whether a turbine i is maintained in period t of scenario ω. The proposed formulation reads as follows:

Sets

Ω	Set of scenarios
$\mathcal{T}$	Set of time periods
$\mathcal{N}$	Set of turbines
$\mathcal{P}$	Set of components

Cost parameters

e	Lost energy revenue per time period (m.u.)
h_p	Holding cost of component $p \in \mathcal{P}$ per time period (m.u.)
r	Cost of a resupply delivery (m.u.)

System parameters

p^ω	Probability of occurrence for scenario ω
J	Maximum number of jobs served per period
C	SOV volumetric capacity (m^3)
R	Resupply volumetric capacity (m^3)
L	Resupply lead time (periods)
$d_{pi}^{t\omega}$	Demand of turbine i for components p in period t of scenario ω

Decision variables

n_p	Number of components p assigned to the repair kit
$x_p^{t\omega}$	Stock of components p available at the end of period t of scenario ω
$q_{pi}^{t\omega}$	Components p used in period t of scenario ω
$o_p^{t\omega}$	Components p resupplied in period t of scenario ω
$y^{t\omega}$	Equal to 1 if a resupply trip is performed in period t of scenario ω; 0 otherwise
$z_i^{t\omega}$	Equal to 1 if wind turbine i is inactive in period t of scenario ω; 0 otherwise
$f_i^{t\omega}$	Equal to 1 if wind turbine i is repaired in period t of scenario ω; 0 otherwise

TPRKP:

$$\text{minimize} \sum_{\omega \in \Omega} p^\omega \left(\sum_{t \in \mathcal{T}} \sum_{p \in \mathcal{P}} h_p \, x_p^{t\omega} + r \sum_{t \in \mathcal{T}} y^{t\omega} + e \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}} z_i^{t\omega} \right) \tag{1}$$

s.t.

$$n_p + \sum_{t'=1}^{t} \left(o_p^{t'\omega} - \sum_{i \in \mathcal{N}} q_{pi}^{t'\omega} \right) = x_p^{t\omega} \qquad p \in \mathcal{P}, t \in \mathcal{T}, \omega \in \Omega \tag{2}$$

$$\sum_{i \in \mathcal{N}} q_{pi}^{t\omega} \le x_p^{t-1,\omega} \qquad p \in \mathcal{P}, t \in \mathcal{T}, \omega \in \Omega \tag{3}$$

$$\sum_{t'=1}^{t} (d_{pi}^{t'\omega} - q_{pi}^{t'\omega}) \le z_i^{t\omega} \sum_{t'=1}^{t} d_{pi}^{t'\omega} \qquad i \in \mathcal{N}, p \in \mathcal{P}, t \in \mathcal{T}, \omega \in \Omega \tag{4}$$

$$q_{pi}^{t\omega} \le f_i^{t\omega} \sum_{t'=1}^{t} d_{pi}^{t'\omega} \qquad i \in \mathcal{N}, p \in \mathcal{P}, t \in \mathcal{T}, \omega \in \Omega \tag{5}$$

$$\sum_{i \in \mathcal{N}} f_i^{t\omega} \le J \qquad t \in \mathcal{T}, \omega \in \Omega \tag{6}$$

$$\sum_{p \in \mathcal{P}} v_p \, x_p^{t\omega} \le C \qquad t \in \mathcal{T}, \omega \in \Omega \tag{7}$$

$$\sum_{p \in \mathcal{P}} v_p \, o_p^{t\omega} \le R \, y^{t-L,\omega} \qquad t \in \mathcal{T}, \omega \in \Omega, \, L < t \tag{8}$$

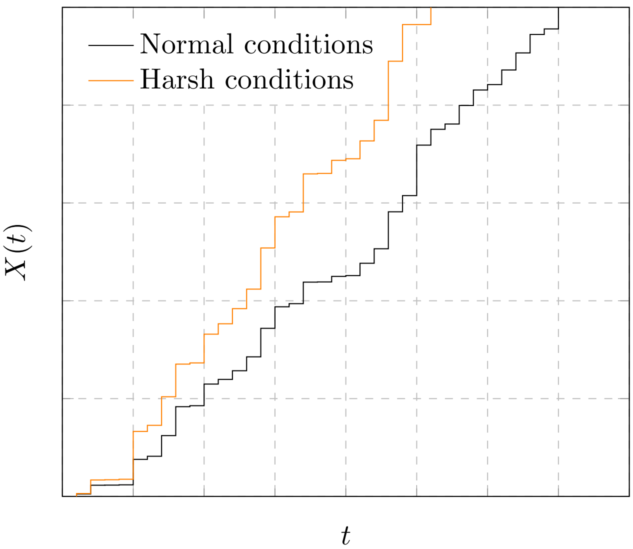


Fig. 5. Comparison between the gamma sample paths of a component operating in normal conditions and a component operating in harsh conditions.

$$n_p, x_p^{t\omega}, q_{pi}^{t\omega}, o_p^{t\omega} \in \mathbb{Z}_0^+, \quad y^{t\omega}, z_i^{t\omega}, f_i^{t\omega} \in \{0,1\}. \tag{9}$$

The objective function (1) minimizes the offshore wind farm expected holding cost, expected resupply cost, and expected downtime cost among all the scenarios. Constraints (2) define the inventory of components p available at the end of period t of scenario ω, based on the repair kit that is brought from shore, on the number of resupplied components, and on the number of components used in the maintenance jobs until period t. Constraints (3) ensure that components can only be used if they are available in the inventory (number of components remaining at the end of the previous day), excluding resupplies from the same day. Constraints (4) track the state of each turbine i in each period t based on the number of failures and repairs performed until period t. Constraints (5) ensure that components are used only if a maintenance job is performed. The right hand side of the constraint ensures that the number of parts used in one period is never larger than the total number of failures until period t. Constraints (6) to (8) are related to the capacities of the system. Constraints (6) impose a maximum number of maintenance jobs that can be performed by the SOV in each period. This constraint forbids the model to perform all maintenance jobs in a single period, capturing costs induced by the time dimension. Constraints (7) ensure that the total volume occupied by the stock of components in the SOV never surpasses its volumetric capacity. Constraints (8) impose a volumetric capacity on the vehicle that performs each resupply delivery. Finally, expressions (9) define the domains of all variables.

4.3. Operational model

In this section, we present an operational planning problem that, differently from the tactical model, considers vessel routing and can be implemented in a rolling horizon setting. As to the latter, we will explain in Section 5.3 how this is done.

This operational model considers one scenario at a time, meaning that one instance contains one scenario only. The repair kit is not a decision in this model, but rather an input parameter provided by a tactical model that is solved beforehand. The main purpose of the operational model is to come up with a route and schedule for maintenance services to test and validate the solutions (i.e., repair kits) provided by the tactical model. The detail of the operational model is higher due to the consideration of vessel routing decisions including service times, allowing the calculation of downtime, resupply, holding, and travel costs.

The operational model uses binary decision variables x_{ijt}, z_{it}, z_{it}^-, z_{it}^+, o_t^+, f_{ipt}, and u_{it}. Variables x_{ijt} are routing variables indicating that the SOV moves from turbine i to turbine j in period t. Variables z_{it} are visiting variables to indicate that the vessel visits turbine i in period t. Variables z_{it}^- and z_{it}^+ indicate the initial and final position of the vessel in each period t, respectively. Variables o_t^+ are used to model the requests for resupply deliveries in each period t. Maintenance operations to each component p of each turbine i in each period t are modeled with variables f_{ipt}. The state of each turbine i in each period t is indicated by variables u_{it}.

Integer decision variables n_{pt} and o_{pt} indicate the quantity of components of type p in stock and resupplied in period t, respectively. n_{p0} is used to set the initial repair kit in the formulation.

The formulation also uses continuous decision variables w_{it}, d_{ipt}, q_{ipt}. Variables w_{it} keep track of arriving times of the SOV at each turbine i in each period t. Variables d_{ipt} represent the deterioration level of each component p of each turbine i in each t, whereas q_{ipt} represent a decrease of deterioration provided by a maintenance operation.

The remaining parameters and decision variables are presented in the summary table preceding the model. The proposed formulation reads as follows:

Sets	
$\mathcal{T}$	Set of time periods
$\mathcal{N}$	Set of turbines
$\mathcal{P}$	Set of components
Cost parameters	
c_{ij}	Cost for moving from turbine i to turbine j (m.u.)
e	Energy revenue per time period (m.u.)
h_p	Holding cost of component $p \in \mathcal{P}$ per time period (m.u.)
r	Cost of a resupply delivery (m.u.)
System parameters	
v_p	Volume of component p (m^3)
C	SOV volumetric capacity (m^3)
R	Resupply volumetric capacity (m^3)
L	Resupply lead time (periods)
g	Docking time (periods)
st_p	Time to repair/substitute component p of turbine i (periods)
t_{ij}	Time to move from turbine i to j (periods)
$\hat{\delta}_{ipt}$	Deterioration of component p of turbine i in period t
M	Big number for modeling purposes
Decision variables	
x_{ijt}	Equal to 1 if the SOV moves from turbine i to turbine j in period t; 0 otherwise
z_{it}	Equal to 1 if the SOV visits turbine i in period t; 0 otherwise
z_{it}^-	Equal to 1 if initial position of the SOV is at turbine i in period t; 0 otherwise
z_{it}^+	Equal to 1 if final position of the SOV is at turbine i in period t; 0 otherwise
o_t^+	Equal to 1 if a resupply delivery is requested in period t; 0 otherwise
f_{ipt}	Equal to 1 if component p of turbine i is repaired in period t; 0 otherwise
u_{it}	Equal to 1 if turbine i is down in period t; 0 otherwise
n_{pt}	Number of components p available in the SOV at the end of period t
o_{pt}	Number of components p resupplied in period t

d_{ipt} Deterioration level of component p of turbine i in period t
q_{ipt} Deterioration level reduction of component p of turbine i in period t
w_{it} Arrival time at turbine i in period t

OPRKP:

$$\text{minimize} \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}\sum_{t\in\mathcal{T}} c_{ij}x_{ijt} + r\sum_{t\in\mathcal{T}} o_t^+ + \sum_{p\in\mathcal{P}}\sum_{t\in\mathcal{T}} h_p n_{pt} + e\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}} u_{it} + e\sum_{i\in\mathcal{N}}\sum_{t\in\mathcal{T}}\sum_{p\in\mathcal{P}} st_p f_{ipt} \tag{10}$$

s.t.

$$\sum_{j\in\mathcal{N}} x_{ijt} + z_{it}^+ = z_{it} \qquad i\in\mathcal{N}, t\in\mathcal{T} \tag{11}$$

$$\sum_{j\in\mathcal{N}} x_{jit} + z_{it}^- = z_{it} \qquad i\in\mathcal{N}, t\in\mathcal{T} \tag{12}$$

$$\sum_{i\in\mathcal{N}} z_{it}^- = 1 \qquad t\in\mathcal{T} \tag{13}$$

$$\sum_{i\in\mathcal{N}} z_{it}^+ = 1 \qquad t\in\mathcal{T} \tag{14}$$

$$z_{i,t-1}^+ = z_{it}^- \qquad i\in\mathcal{N}, t\in\mathcal{T} \tag{15}$$

$$w_{it} + \sum_{p\in\mathcal{P}} st_p f_{ipt} + (t_{ij}+g)\,x_{ijt} \le w_{jt} + (1 - x_{ijt}) \qquad i\in\mathcal{N}, j\in\mathcal{N}, t\in\mathcal{T} \tag{16}$$

$$d_{ipt} = d_{ipt-1} + \hat{\delta}_{ipt} - q_{ipt} \qquad i\in\mathcal{N}, p\in\mathcal{P}, t\in\mathcal{T} \tag{17}$$

$$d_{ipt} - 1 \le M\,u_{it} \qquad i\in\mathcal{N}, p\in\mathcal{P}, t\in\mathcal{T} \tag{18}$$

$$q_{ipt} \le f_{ipt} \qquad i\in\mathcal{N}, p\in\mathcal{P}, t\in\mathcal{T} \tag{19}$$

$$f_{ipt} \le z_{it} \qquad i\in\mathcal{N}, p\in\mathcal{P}, t\in\mathcal{T} \tag{20}$$

$$n_{pt} = n_{pt-1} + o_{pt} - \sum_{i\in\mathcal{N}} f_{ipt} \qquad p\in\mathcal{P}, t\in\mathcal{T} \tag{21}$$

$$\sum_{p\in\mathcal{P}} v_p\, n_{pt} \le C \qquad t\in\mathcal{T} \tag{22}$$

$$\sum_{p\in\mathcal{P}} v_p\, o_{pt+L} \le R\, o_t^+ \qquad t\in\mathcal{T}, t+L\le|\mathcal{T}| \tag{23}$$

$$o_{pt} = 0 \qquad t\in\mathcal{T}, t\le L \tag{24}$$

$$o_t^+ = 0 \qquad t\in\mathcal{T}, t+L>|\mathcal{T}| \tag{25}$$

$$d_{ipt}, q_{ipt} \in \mathbb{R}_0^+, \quad n_{pt}, o_{pt} \in \mathbb{Z}_0^+, \quad x_{ijt}, z_{it}, z_{it}^-, z_{it}^+, o_t^+, f_{ipt}, u_{it} \in \{0,1\}, \quad w_{it}\in[0,1] \tag{26}$$

Objective function (10) minimizes the transportation cost, the resupply deliveries cost, the components holding cost, and the downtime cost due to failures and service time. Constraints (11) and (12) ensure the vessel flow conservation through the transportation network. We assume that the can vessel start and finish the trip in any turbine position (starting point is not a parameter). The degree of starting (finishing) nodes is one, as the vessel only leaves (arrives at) that node. Constraints (13) and (14) ensure that there is a starting and a finishing location for the vessel, respectively, in each period. Constraints (15) ensure that the vessel remains in the same position between periods. Constraints (16) define the arrival times of the SOV at each location. When the vessel traverses an arc (i,j), its arrival time at location j needs to be greater than the arrival time at location i, plus the service time on substituting some components, plus the travel time t_{ij} and docking time g. These constraints also eliminate sub-tours and are responsible for most of the computational complexity of the model. The deterioration level of each turbine is modeled by constraints (17). When this level of deterioration surpasses 1 in any component of a turbine, the turbine is considered to be down. The turbine states are modeled by constraints (18). The variable representing a deterioration reduction can only be positive if a component is used, as ensured by constraints (19). Constraints (20) ensure that a repair operation is only performed if the turbine is visited by the SOV. The stock of components in the SOV is modeled by constraints (21). Note that the values of period 0, n_{p0}, are set to the values of the repair kit received by the tactical model. Constraints (22) ensure that the SOV capacity is not violated. Constraints (23) impose the capacity of the resupply vehicle and set the resupply delivery lead time. If a request is done in period t, the components are only received in period $t+L$. Constraints (24) and (25) ensure that no components are received before the lead time and that no resupply requests are done if there is no time to make the delivery, respectively. Finally, expressions (26) define the domains of each variable.

To illustrate the rationale of this model, we present Fig. 6. In this example, the SOV starts on Day 1 by performing maintenance interventions on turbines 6 and 5 (in this order). Since there was not enough time left on that day, turbine 0, which failed, stays inactive until the end of Day 1. On Day 2, the vessel first fixes turbine 0 and then performs maintenance operations on turbines 1 and 3. On Day 3, the SOV returns to turbine 5 to perform additional maintenance and thereafter also visits turbines 9 and 4 to perform maintenance operations. Note that components can be substituted before (preventive maintenance) or after a failure (corrective maintenance).

4.4. Decomposition approach

The tactical and operational models presented before are MIP formulations which can become intractable for larger problems. Therefore, to solve larger instances, we propose a matheuristic approach based on the fix-and-optimize approach proposed by [48]. In this matheuristic approach, predefined decomposition strategies are used to iteratively solve a series of tractable subproblems to find improvements in a large problem.

4.4.1. Decomposition strategies

We refer to a decomposition strategy as a subset of variables to find local improvements, maintaining the remaining variables fixed. Small sets of decisions are made iteratively using a MIP formulation. Consider the entire set of integer variables Υ in the formulation. Each decomposed subproblem is defined by selecting a subset of variables $\Upsilon^{Opt}\subseteq\Upsilon$ to be re-optimized. The remaining variables $\Upsilon^{Fix}=\Upsilon\setminus\Upsilon^{Opt}$ are fixed with the values obtained in the incumbent solution. Hence, as an example, a subproblem for the operational model $OPRKP-SUB$ can be stated as follows:

$(OPRKP-SUB)$: minimize objective function (10) subject to constraints (11)–(26) and the additional constraints:

$$x_{ijt} = \bar{x}_{ijt} \quad \forall(i,j,t)|(i,j,t)\in\Upsilon^{Fix} \tag{27}$$

$$z_{it} = \bar{z}_{it} \quad \forall(i,t)|(i,t)\in\Upsilon^{Fix} \tag{28}$$

$$f_{ipt} = \bar{f}_{ipt} \quad \forall(i,p,t)|(i,p,t)\in\Upsilon^{Fix} \tag{29}$$

$$u_{it} = \bar{u}_{it} \quad \forall(i,t)|(i,t)\in\Upsilon^{Fix}, \tag{30}$$

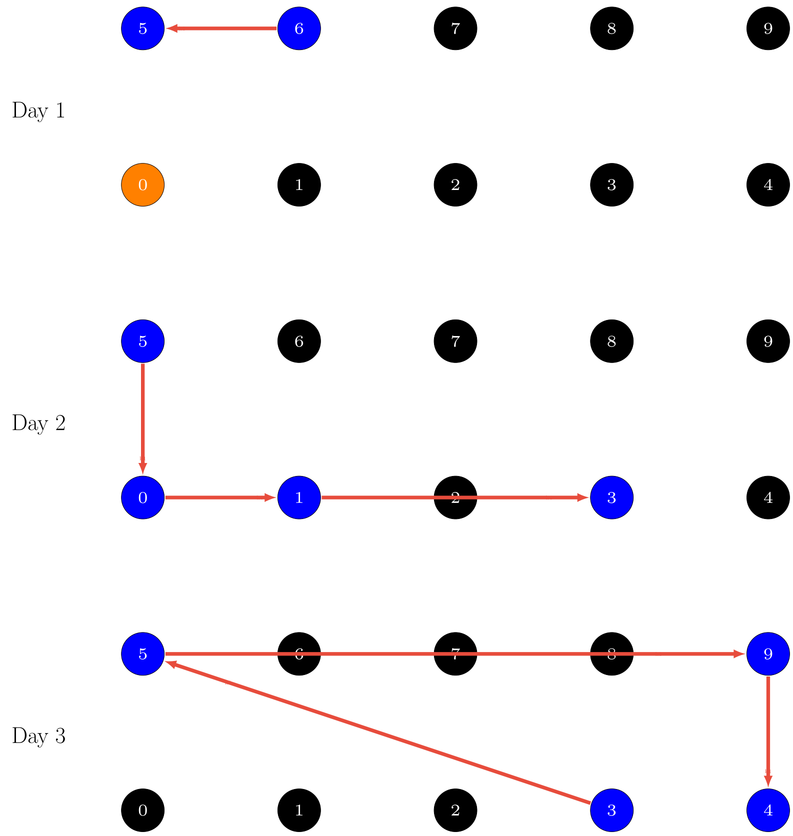


Fig. 6. Example of three periods of a solution to the operational model considering 10 wind turbines. Turbines represented in blue are repaired by the SOV whereas turbines represented in orange are down. Note that the routing model maintains the position of the vessel from one period to another.

where $\bar{x}_{ijt}$, $\bar{z}_{it}$, $\bar{f}_{ipt}$, and $\bar{u}_{it}$ are values coming from an incumbent solution.

The subset Υ^{Opt} is based on a combination of dimensions related to the problem we are tackling, which are identified by a decomposition strategy $\psi \in \Psi$. There is always a trade-off between computational complexity and the potential for finding improvements. To achieve tractable subproblems we propose three different decomposition strategies:

1. Period-Oriented Decomposition (POD): each subproblem considers the variables related to a subset of periods t (all turbines and components considered).
2. Turbine-Oriented Decomposition (TOD): each subproblem considers the variables related to a subset of turbines i (all periods and components considered).
3. Scenario-Oriented Decomposition (SOD): each subproblem considers the variables related to a subset of scenarios ω (all turbines and components considered). This strategy can only be used in the tactical model which is the only one that considers scenarios.

In Fig. 7, we provide a visual representation of the proposed decomposition strategies.

4.4.2. Matheuristic algorithm

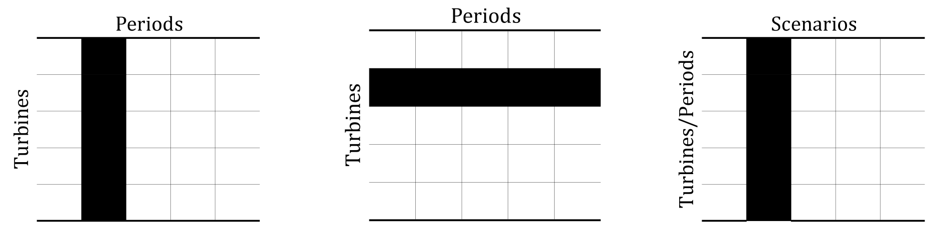
Our matheuristic algorithm iteratively solves a set of MIPs to explore the search space of the global problem. This kind of approach has been successful in several real world problems across several business sectors (see [49–51]) and it can improve the applicability and solution quality of optimization techniques that are currently applied to renewable energy problems [52]. The method requires a feasible integer solution to begin. In this problem, most variables can be set to zero meaning that there is no maintenance operation or SOV movement. Although this solution will have a low quality, it allows us to quickly start an iterative improvement phase. In the iterative improvement phase, the algorithm randomly selects one of our three decomposition strategies and solves the subproblem that is defined by using the set of variables to optimize Υ^{opt}. This is repeated until a maximum time limit $tlimit$ or a maximum number of solutions without improving the objective function $noimp_{max}$. Each subproblem iteration runs for a maximum time of sub_tlimit. We present the pseudo-code of the proposed matheuristic approach in Algorithm 1.

Algorithm 1 Matheuristic Approach

procedure MH($noimp_{max}, tlimit, sub\_tlimit$)
  $stop \leftarrow false, noimp \leftarrow 0, solution \leftarrow 0, solution_{best} \leftarrow 0$
  $solution_{best} \leftarrow$ Set integer variables to zero
  while not $stop$ **do**
    $\Upsilon^{Opt} \leftarrow$ Select variables using random strategy $\psi \in \Psi$
    $solution \leftarrow$ SolveSubproblem($solution_{best}, \Upsilon^{opt}, sub\_tlimit$)
    if $solution < solution_{best}$ **then**
      $solution_{best} \leftarrow solution,\ noimp \leftarrow 0$
    else
      $noimp \leftarrow noimp + 1$
    if $noimp > noimp_{max}$ **or** $time > tlimit$ **then**
      $stop \leftarrow true$
  return $solution_{best}$

5. Numerical experiments

The framework has been developed using Python 3.7 programming language and it is composed of methods to generate the necessary data and call external procedures to solve the tactical and operational models. For improved performance, the external procedures have been written in C++ and use the general-purpose solver CPLEX 12.9 to solve the mathematical formulations.



(a) $\psi = 1$ (b) $\psi = 2$ (c) $\psi = 3$

Fig. 7. Schematic representation of the proposed set of decomposition strategies Ψ.

Table 1
Factor intensification parameters used to build different operating conditions in the instances.

Conditions	Wind	Rain	Temperature
Normal	1	1	1
Windy	10	1	1
Rainy	1	10	1
Hot	1	1	10
Harsh	10	10	10

Table 2
Component scale, shape, and weather sensitivity parameters.

Component	Shape	Scale	Sensitivities (β)		
			Wind	Rain	Temperature
Pitch/Hydraulics	1	0.204	0.050	0.000	0.000
Generator	1	0.156	0.000	0.050	0.000
Gearbox	1	0.084	0.000	0.000	0.050
Electrical components	1	0.072	0.025	0.025	0.025
Converter	1	0.036	0.000	0.000	0.000

Table 3
Component parameters considered in the computational experiments.

Component	Volume (m^3)	Price (m.u.)	Yearly holding cost (m.u.)	Sensitivity factors
Pitch/Hydraulics	10	82.19	8.219	Wind
Generator	8	10.95	1.095	Rain
Gearbox	9	27.39	2.739	Temperature
Electrical components	2	8.22	0.822	All
Converter	5	10.96	1.096	None

Table 4
Parameters used in the tactical and operational models.

Description	Symbol	Value	Model usage
SOV job capacity	J	3 (jobs per period)	TP
SOV speed	s	7.716 (m/s)	OP
SOV capacity	C	250 (m^3)	TP and OP
SOV lead time	T	1 (periods)	TP and OP
Resupply capacity	R	20 (m^3)	TP and OP
Resupply lead time	L	2 periods	TP and OP
Resupply delivery cost	r	1 000 (m.u. per delivery)	TP and OP
Energy revenue	e	10 000 (m.u. per period)	TP and OP
Transportation unitary cost	c	0.027 (m.u./m)	OP
Docking time	g	5 min	OP
Service time per component	st_p	0.05 (periods)	OP

5.1. Instances generation

We start by using the failure generator to simulate the operation of a wind farm composed of a set of wind turbines through 3650 periods. Given that one period corresponds to one day, the output includes approximately ten years of operation. We considered a chessboard layout where the distance between turbines is 150 meters. This value is chosen for illustration purposes as wind turbines in the newest wind farms are further apart (i.e., 5 to 10 rotor diameters).

We consider three (weather) factors which will be simply called as **wind**, **rain**, and **temperature**. Each of these factors is described by a vector of random numbers Z_{ft} between zero and one. There is a value for each factor f and each period t. Based on these factors, we derive five types of operating conditions, namely **windy**, **rainy**, **hot**, **normal**, and **harsh**, by intensifying certain factors according to each case. In our experiments, to intensify a factor, we multiply its random vector by 10 to obtain the intensified vector Z'_{ft}. The harsh conditions correspond to the case where all factors are intensified. Table 1 shows the parameters used to obtain each operating condition. Through the intensification parameters different weather conditions are created according to the example depicted in Fig. 8. Although it would be straightforward for the proposed models to include turbine accessibility issues related to weather conditions (e.g., impose new constraints in inaccessible periods), the time-dependence of the weather conditions is kept simplistic in our illustrative examples.

Discussions with a large turbine manufacturer led to the identification of five main components, each with its associated failure rate. Although in reality these components consist of different sub-components and parts, we consider the component level to be appropriate for the sake of our study and illustration. Components deteriorate differently according to the operating conditions described by the three factors considered in the experiment. We consider one component that is not affected by any of the factors, one component that is affected by all factors, and three components that are affected by a single factor: wind, rain and temperature, respectively. To model these sensitivities we consider that the beta value figuring in our Cox proportional hazards deterioration model is different from zero. Table 2 summarizes the component shape, scale, and beta parameters. In Fig. 9 we present the average number of failures per turbine under the different conditions. Table 3 summarizes additional parameters related to the subassemblies considered in our experiments.

After setting the parameters related to each component and its relation to the operating conditions, the simulation outputs the deterioration of each component in each period, from where we can derive the instances for the tactical and operational models.

In our experiments one scenario is considered to be an SOV trip composed of 16 periods. The SOV stays offshore during this trip and is able to be resupplied by an helicopter. The parameters related to the SOV and the resupply events are described in Table 4. Additionally, we indicate in which models the parameters are needed.

The data or parameters used in our illustrative case are based on multiple sources. Apart from sensitivities, which have been constructed arbitrarily, the information in Tables 2 and 3 is mainly inspired by information provided by a large turbine manufacturer and by the parameters used in [38] and [6]. Table 4 was deducted using information from different SOV manufacturers and from [53].

To generate a tactical model instance we sample a set of scenarios of 16 consecutive periods ($|\mathcal{T}| - 2T = 14$ periods offshore where

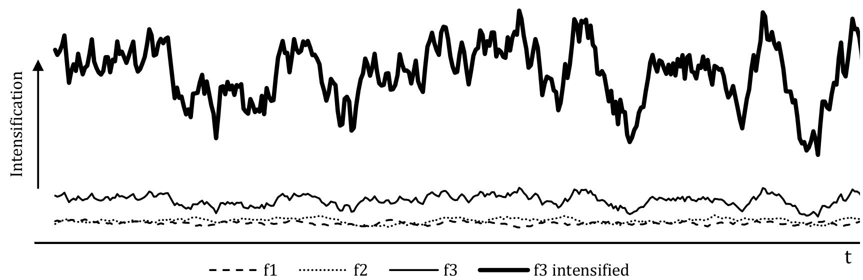


Fig. 8. An example with 3 weather factors. Factor $f3$ is intensified.

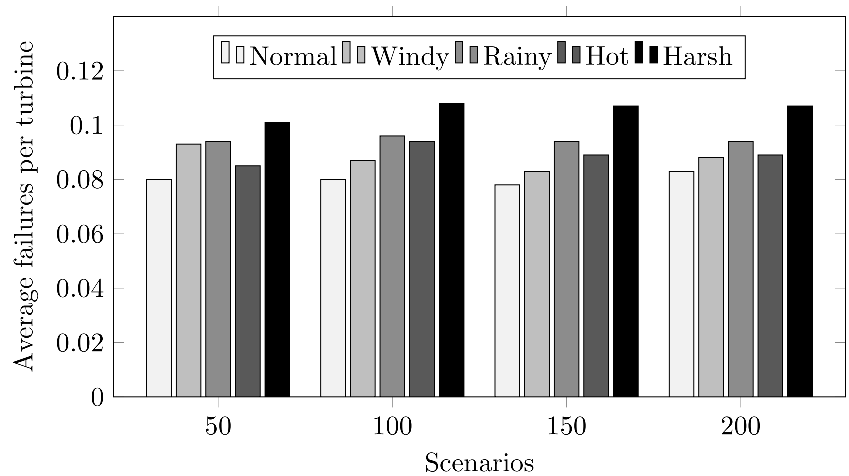


Fig. 9. Average number of failures per turbine for the generated instances, per combination of weather condition and number of scenarios.

Table 5
Parameters used in to build tactical and operational model instances.

Dimension	Values
#Operating conditions	{Normal, Windy, Rainy, Hot, Harsh}
#Scenarios	{50, 100, 150, 200}
#Turbines	{10, 20, 30, 40, 50, 60, 70, 80, 90, 100}
Total TP instances	200 ($5 \times 4 \times 10$)
Total OP instances	20000 (200×100)

Each repair kit coming from a TP instance is tested for 100 OP instances.

maintenance can be performed, $2T = 2$ periods for going back and forth). Each scenario includes a set of failures indicating the period in which the failure occurred and the corresponding turbine and the component.

To generate operational model instances, we continue the scenario sampling process but the instance files will now include a higher degree of detail. Each instance is composed of a single scenario with the initial deterioration of each component, and deterioration jumps of each component in each period. These deterioration jumps are based on a set of weather factors generated in each period. This is done for the five types of operating conditions considered.

Since the numbers of turbines and scenarios impact the computational complexity of our models, we tested our approach for certain combinations of the number turbines and scenarios. For each of these combinations, we test the repair kit on 100 operational instances with the same weather conditions and number of turbines that were used to compute the repair kit. Table 5 provides a summary of all the instances that were generated and solved.

5.2. Tactical model results

In this section we assess the computational efficiency and provide managerial insights regarding two versions of the tactical model. In the first version, **No Resupply**, the resupply option is deactivated by setting variables $o_p^{t\omega}$ to zero. In the second version, **With Resupply**, the resupply option is allowed.

5.2.1. Computational efficiency

The results obtained for the 200 tactical instances are presented in Table 6. Each row of the table corresponds to a set of 5 instances (weather conditions) with a certain number of turbines $|\mathcal{N}|$ and number of scenarios $|\Omega|$. For both versions of the tactical model (**No Resupply** and **With Resupply**), we indicate the number of instances that are solved to optimality (with an optimality gap of less than 0.1%) and provide averages for the objective function, relative gap, and runtime. These computational experiments were run with a time limit of 1 h.

As expected for both cases, larger instances, considering a larger number of turbines and scenarios, are more challenging, taking longer runtimes to be solved. The average optimality gap obtained is 0.01% when the resupply option is not allowed and 2.88% when the resupply option is allowed.

In terms of the objective function, which includes holding, resupply, and downtime costs, the results suggest a clear superiority of the model allowing resupplies, suggesting that extending the repair kit problem with the possibility to resupply additional components offers potential savings at the cost of more challenging problems to be solved. We will dive deeper into this in what follows, but first consider the effect of weather conditions on the tactical solutions.

Table 6
Results obtained using the general-purpose solver to solve the tactical model (**No Resupply** and **With Resupply** versions).

$\|\mathcal{N}\|$	$\|\Omega\|$	No Resupply				With Resupply			
		Objective function	Optimal	Relative gap (%)	runtime (s)	Objective function	Optimal	Relative gap (%)	runtime (s)
10	50	1.99	5/5	0.00	0.00	1.99	5/5	0.00	0.00
10	100	1.93	5/5	0.00	0.00	1.93	5/5	0.00	0.60
10	150	1.91	5/5	0.00	0.00	1.91	5/5	0.00	0.60
10	200	2.35	5/5	0.00	0.40	2.35	5/5	0.00	0.80
20	50	2.19	5/5	0.00	0.20	2.19	5/5	0.00	0.20
20	100	62.89	5/5	0.00	0.00	2.89	5/5	0.00	0.40
20	150	29.63	5/5	0.00	0.40	2.96	5/5	0.00	1.00
20	200	22.96	5/5	0.00	1.00	2.96	5/5	0.00	1.20
30	50	203.76	5/5	0.00	0.40	3.76	5/5	0.00	0.20
30	100	343.45	5/5	0.00	0.40	19.37	5/5	0.00	3.40
30	150	83.64	5/5	0.00	0.80	4.97	5/5	0.00	1.40
30	200	323.70	5/5	0.01	1.20	9.64	5/5	0.01	16.20
40	50	1963.62	5/5	0.00	0.20	39.60	5/5	0.01	2.20
40	100	1503.77	5/5	0.00	1.00	31.76	5/5	0.00	4.00
40	150	2630.15	5/5	0.00	1.00	52.89	5/5	0.05	32.20
40	200	2513.80	5/5	0.00	1.20	51.70	3/5	1.82	1021.80
50	50	7963.72	5/5	0.00	1.00	131.64	5/5	0.00	4.60
50	100	5583.83	5/5	0.00	1.00	99.67	5/5	0.04	28.80
50	150	7990.45	5/5	0.00	1.60	115.79	5/5	0.02	149.60
50	200	9323.90	5/5	0.00	2.60	148.83	0/5	7.99	3600.00
60	50	8483.68	5/5	0.00	0.20	123.69	5/5	0.00	4.00
60	100	11743.63	5/5	0.00	1.20	191.55	4/5	0.54	514.40
60	150	19430.40	5/5	0.00	2.20	272.99	1/5	5.22	1949.20
60	200	19193.66	5/5	0.01	3.60	267.69	0/5	7.90	3600.00
70	50	24563.68	5/5	0.00	0.20	315.68	4/5	0.34	514.60
70	100	32183.76	5/5	0.02	1.60	425.76	2/5	3.44	1736.60
70	150	38923.82	5/5	0.02	3.20	483.72	0/5	7.97	3600.00
70	200	35503.64	5/5	0.00	4.00	458.68	0/5	12.90	3600.00
80	50	37603.94	5/5	0.00	0.80	579.90	4/5	0.43	687.00
80	100	47083.86	5/5	0.03	2.20	589.79	1/5	5.17	1973.20
80	150	62523.78	5/5	0.01	3.20	757.22	0/5	8.08	3600.00
80	200	40713.88	5/5	0.00	3.80	551.08	0/5	11.73	3600.00
90	50	64603.90	5/5	0.00	0.80	767.87	1/5	1.41	1922.20
90	100	80824.06	5/5	0.02	1.80	1239.80	2/5	2.54	1533.20
90	150	71523.84	5/5	0.00	4.20	833.09	0/5	8.55	3600.00
90	200	80713.86	5/5	0.01	4.20	947.80	0/5	8.86	3600.00
100	50	87923.80	5/5	0.03	1.20	899.57	0/5	1.83	3600.00
100	100	111004.00	5/5	0.04	2.40	2079.80	0/5	2.19	3600.00
100	150	105430.46	5/5	0.01	4.40	1293.17	0/5	7.49	3600.00
100	200	100263.78	5/5	0.02	6.40	1131.77	0/5	8.67	3600.00
	Avg	28019.83	200/200	0.01	1.65	373.48	117/200	2.88	1382.60

Table 7
Average relative contribution of each component to the repair kit cost (allowing resupplies).

Conditions	Comp. 1 (Wind)	Comp. 2 (Rain)	Comp. 3 (Temp.)	Comp. 4 (All)	Comp. 5 (None)
Normal	0.649	0.101	0.151	0.053	0.047
Windy	**0.662**	0.098	0.135	0.059	0.047
Rainy	0.641	**0.112**	0.141	0.060	0.046
Hot	0.651	0.096	**0.151**	0.058	0.043
Harsh	0.646	0.107	0.150	0.055	0.043

5.2.2. Impact of weather conditions

Table 7 shows the ability of the tactical model to adapt the repair kit to the weather conditions. The first column indicates the weather conditions and the remaining columns give the relative contribution to the total holding cost for each component in the repair kit. An indication of the sensitivity to the weather factors is given in parentheses.

As shown in Table 7, a higher proportion of the repair kit cost is allocated to components that are sensitive to the type of weather conditions that are encountered in the considered scenarios. An additional take-away comes from the fact that, in the presented computational tests, the SOV capacity is generally completely used. This means that although we could not verify a large impact on the total number of components in the repair kit, the model is trading off different component failure rates, holding costs, and volumes to adapt the composition of the repair kit.

5.2.3. Impact of the resupply option

To assess the value of considering a resupply option in the tactical model we detail the values obtained for the repair kit and for the business indicators in Table 8.

The results suggest that the holding and downtime costs can be substantially reduced by allowing resupplies. This does of course lead to resupply costs, but there is still a sharp decrease in the total cost. Resupply avoids situations where several turbines are stopped for several periods until a new SOV trip is performed with a restocked repair kit.

5.2.4. Impact of the number of scenarios

Generally, with a larger number of scenarios it is expected that the repair kit cost increases, as it gets more difficult to perform well in all the scenarios. This trend should, however, stabilize with a sufficient number of scenarios. In Table 9, we present the distribution of the average costs per turbine for each combination of number of scenarios and operating conditions.

Table 8
Average repair kit and business indicators for each type of operating conditions and tactical model version.

Model	Conditions	Gap	Repair Kit Indicators		Business Indicators (per turbine)			
			# Components	Volume (m^3)	Holding (m.u.)	Resupply (m.u.)	Downtime (m.u.)	Total (m.u.)
No Resupply	Normal	0.00	32.95	226.08	0.086	0.00	298.69	298.78
	Windy	0.00	33.85	228.58	0.091	0.00	294.00	294.09
	Rainy	0.00	33.70	227.30	0.086	0.00	332.03	332.12
	Hot	0.00	33.10	225.50	0.089	0.00	358.74	358.83
	Harsh	0.00	33.53	228.55	0.085	0.00	394.66	394.75
	Avg	0.00	33.43	227.20	0.087	0.00	335.63	335.71
With Resupply	Normal	0.03	31.68	225.35	0.087	3.77	0.00	3.85
	Windy	0.03	32.80	228.08	0.091	3.57	0.00	3.66
	Rainy	0.03	32.50	226.63	0.085	4.25	1.56	5.90
	Hot	0.03	32.00	225.05	0.088	4.41	0.00	4.50
	Harsh	0.03	32.03	227.00	0.084	4.65	0.15	4.88
	Avg	0.03	32.20	226.42	0.087	4.13	0.34	4.56

Table 9
Average costs per turbine obtained using the general-purpose solver to solve the tactical model for each number of scenarios.

Model	Conditions	$\|\Omega\|$			
		50	100	150	200
No Resupply	Normal	255.71	301.83	312.98	324.60
	Windy	243.99	273.38	331.19	327.79
	Rainy	230.76	390.76	357.03	349.92
	Hot	362.88	315.82	396.10	360.51
	Harsh	294.09	426.31	472.94	385.65
	Avg	277.49	341.62	374.05	349.70
With Resupply	Normal	3.31	3.81	4.04	4.25
	Windy	3.02	3.49	4.03	4.11
	Rainy	3.29	10.88	4.78	4.65
	Hot	4.52	4.11	4.83	4.53
	Harsh	3.57	5.20	5.94	4.82
	Avg	3.54	5.50	4.73	4.47

We observe from Table 9 that there is generally quite an increase in average cost when using 100 instead of 50 scenarios, which indicates that 50 scenarios is not enough to determine a kit that performs well under all conditions. Going from 100 to 150 scenarios, and even more when going from 150 to 200 scenarios, the average costs do stabilize and indeed sometimes go down, indicating that the number of scenarios is sufficiently large to obtain a robust solution.

Of course, more scenarios does imply a higher computation time on average. So, for the settings that we considered, using 150 scenarios seems the best choice.

5.3. Operational model results

In this section we evaluate the repair kits provided by the tactical model using the operational model proposed in Section 4.3. To do so, we apply a realistic rolling horizon planning process where the operational model is solved for a reduced number of periods λ in each planning iteration. At the end of each planning iteration, the planned decisions are implemented (fixed) and the horizon rolls λ periods in order to continue the process. Fig. 10 provides a visual representation of two iterations of the devised rolling horizon planning process.

The model will decide upon the best moment to use a certain component and upon the best vessel route to be performed. Each planning iteration considers two days ($\lambda = 2$) and is solved using the general-purpose solver with a time limit of 30 seconds. After these 30 s, if the relative gap is larger than 10%, we use the matheuristic approach, Algorithm 1, to improve the solution for another 60 seconds.

Table 10 presents the results. These results confirm that significant cost savings can be achieved by allowing resupplies. The travel cost has a low impact on the total cost, but this will increase if we consider larger spacing between turbines. In the **With Resupply** version, we observe a slight reduction of the holding cost and, logically, the appearance of resupply costs. The downtime cost is drastically reduced when resupplies are allowed.

We observe that the repair kits obtained considering only 50 scenarios are the ones with the worst performances in the simulation, confirming that at least 100 scenarios are needed for the settings that we considered. Overall, considering a larger number of scenarios in the tactical model leads to better performance in the operational phase.

One last insight obtained from the operational model is that the repair kits proposed by the tactical model required resupplied components in 13.7% of the trips. The great majority of the trips that need at least one resupplied component required at least 5 repairs. This conclusion is illustrated in Fig. 11, which depicts the average number of repairs and the average number of resupplied components for several samples of trips. For each combination of weather condition and number of turbines, we consider 400 trips. These trips include 100 trips simulating the repair kit obtained with the four numbers of scenarios considered in the computational tests of the tactical model. These samples are divided into two samples. The first sample includes all the trips where no resupplies were performed and the second sample includes all the trips where at least one component was resupplied.

6. Conclusion

In this paper, we propose a novel MIP-based methodology to propose repair kits to be used during SOV trips where maintenance operations are to be performed in offshore wind farms. A two-stage stochastic optimization problem considers weather-dependent deterioration models for each component and the possibility to perform costly emergency resupplies. Furthermore, we propose an operational model which takes into account a detailed environment where vessel routing is integrated with the scheduling of maintenance operations using different components.

Using the proposed methodology, we analyze the impacts of weather conditions and resupply options on the repair kit composition and on holding, resupply, and downtime cost. We observe that the model adapts the repair kit with different components depending on the type of scenarios considered in the tactical problem. The results suggest that even under capacity constraints (commonly found in real applications), slight differences in the composition of the repair kits may result in turbine downtime (and cost) reductions. Therefore, in applications where the weather is accepted as an important factor influencing component reliability, considering weather-dependent deterioration is advisable. Moreover, considering resupplies allows for smaller repair kits, inducing smaller holding costs at a cost of some (not so frequent) resupply deliveries, while significantly lowering downtime cost. These

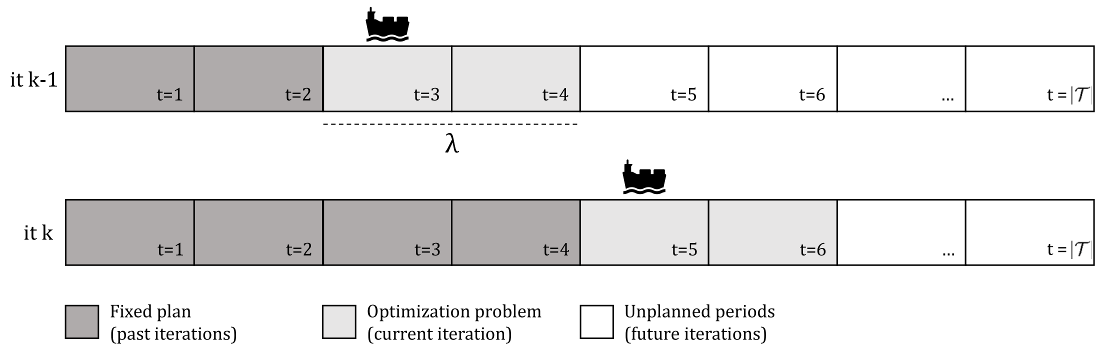


Fig. 10. Example of two successive iterations ($k-1$ and k) of the a rolling horizon planning process with $|\mathcal{T}|$ periods. In each iteration, a subproblem considering λ periods is solved. The decisions made in this iteration are fixed and the a new subproblem is defined, considering the following λ periods. The process ends when all the periods have been planned and fixed.

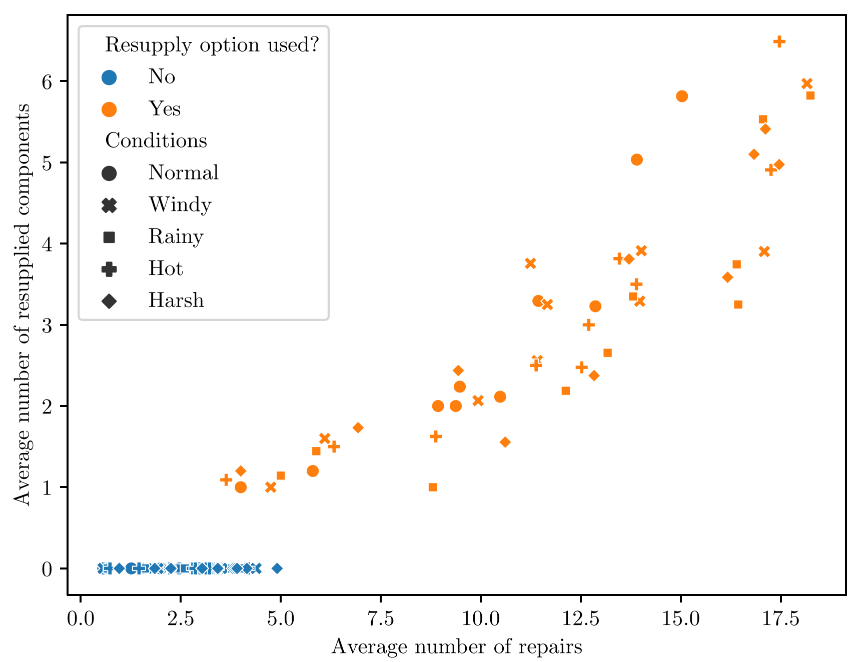


Fig. 11. Average number of repairs and the average number of resupplied components for several samples of trips.

findings stress the important role of service logistics in reducing the cost of renewable energy generation.

To test the repair kits provided by the tactical model, we evaluated them in a rolling horizon planning process for an offshore wind farm environment. This model is more detailed in the sense that it considers vessel routing and service times for each maintenance operation. The results suggest that the cost efficiency of the repair kits is improved when a larger number of scenarios is considered in the tactical model.

We consider that this approach can be extremely valuable to offshore wind energy generation. From a practical perspective, we expect to enable practitioners to improve SOV repair kits based on scientific methods, and reduce the cost of operations and maintenance.

Throughout this paper the resupply option has appeared to be important, which can largely be attributed to significant downtime reduction. In practice, service providers seem hesitant to incorporate resupply into their strategies, as resupply (particularly by means of helicopters) may expose workers to additional safety risks. Although we did not consider those risks, our results show that resupply should at least be seriously considered by wind farm service operators.

As future work, we encourage researchers to develop new extensions and rules to improve some aspects of the our approach. For example, we assumed that all emergency supplies were deterministic in terms of availability and lead time. However, it would be interesting to consider stochasticity in these two factors. Another interesting challenge would be to extend the model to consider several SOVs, serving several wind farms, using a central supplier of components. This would clearly open new opportunities to collaboration in the offshore wind industry. A preliminary analysis (available upon request) studied the effect of weather forecasting, showing that adapting the repair kit to specific forecasted weather conditions generally leads to reduced total costs. It is interesting to study the effect of forecast quality on the composition of repair kits and on wind turbine accessibility. The latter is particularly important for introducing periods where maintenance operations need to stop due to safety reasons. The models proposed in this paper can easily be extended to consider inaccessibility periods, enabling the exploration of the time-dependence of weather conditions. Alternatively, it is interesting to study long-term maintenance planning when a single SOV serves multiple wind farms, which is something that is considered in practice. Finally, data analytics approaches using

Table 10
Results obtained for the simulation of each repair kit (determined using the tactical model) in 100 operational instances. Each row corresponds to the average over 1000 instances (100 trips considering a number of turbines ranging from 10 to 100).

Conditions	$\|\Omega\|$	No Resupply					With Resupply				
		Holding	Resupply	Downtime	Travel	Total	Holding	Resupply	Downtime	Travel	Total
Normal	50	3.16	0.00	25183.50	34.72	25221.37	3.14	321.00	2191.50	42.74	2558.37
Normal	100	3.15	0.00	22390.00	34.91	22428.06	3.08	309.00	2161.50	42.01	2515.59
Normal	150	3.15	0.00	22667.50	34.54	22705.20	3.15	304.00	2131.50	41.94	2480.59
Normal	200	3.25	0.00	21318.00	35.28	21356.52	3.32	279.00	2141.50	42.63	2466.45
Windy	50	2.97	0.00	26187.50	39.75	26230.22	2.96	290.00	2588.00	47.67	2928.63
Windy	100	3.20	0.00	22645.00	41.04	22689.24	3.23	274.00	2479.50	47.49	2804.22
Windy	150	3.24	0.00	23417.00	40.50	23460.74	3.24	286.00	2549.50	48.05	2886.79
Windy	200	3.26	0.00	21214.50	40.78	21258.54	3.28	274.00	2649.50	47.39	2974.17
Rainy	50	3.25	0.00	25772.00	40.32	25815.58	3.19	303.00	2949.50	48.31	3304.00
Rainy	100	3.10	0.00	25591.50	39.81	25634.41	2.97	288.00	2889.50	48.46	3228.92
Rainy	150	3.11	0.00	21745.00	40.60	21788.71	3.11	287.00	2859.50	47.73	3197.34
Rainy	200	3.20	0.00	22397.50	40.93	22441.63	3.15	281.00	2869.50	48.59	3202.24
Hot	50	3.17	0.00	25920.50	37.10	25960.77	3.14	296.00	2494.00	45.61	2838.75
Hot	100	3.23	0.00	24067.50	37.42	24108.15	3.24	286.00	2435.00	44.94	2769.17
Hot	150	3.19	0.00	23873.50	37.79	23914.49	3.17	284.00	2394.50	44.75	2726.42
Hot	200	3.30	0.00	24152.50	37.30	24193.10	3.28	267.00	2424.50	44.66	2739.44
Harsh	50	2.93	0.00	26409.50	42.85	26455.29	2.90	304.00	3043.50	50.59	3400.99
Harsh	100	3.11	0.00	25951.50	42.82	25997.44	3.09	324.00	3013.00	50.79	3390.87
Harsh	150	3.02	0.00	25234.50	42.89	25280.41	3.02	287.00	3003.50	50.88	3344.39
Harsh	200	3.07	0.00	24940.50	43.23	24986.80	3.08	284.00	2993.00	51.05	3331.13
Avg		3.15	0.00	24053.95	39.23	24096.33	3.14	291.40	2613.08	46.81	2954.42

dynamic programming and machine learning could be explored in order to improve the performance of the optimization methods related to the offshore wind farm RKP.

CRediT authorship contribution statement

Fábio Neves-Moreira: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Jasper Veldman:** Conceptualization, Validation, Data curation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Ruud H. Teunter:** Conceptualization, Validation, Writing - original draft, Writing review & editing, Supervision, Project administration, Funding acquisition.

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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