A Hybrid Heuristic Optimization of Maintenance Routing and Scheduling for Offshore Wind Farms

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***Abstract*—As the operation and maintenance (O&M) costs constitute a substantial portion of the overall life-cycle cost of offshore wind farms, routing, and scheduling of maintenance are very important for cost reduction. With the multi-type of vessels, multi-period, multi-base of O&M, multi-wind farm and uncertain weather conditions, the optimization of O&M cost is more challenging. In this article, a hybrid heuristic optimization of maintenance routing and scheduling for offshore wind farms is proposed. First, with the maintenance service protocol, mixed particle swarm optimization (MPSO) is applied to seek a desired mapping relation between vessels and wind farms. Utilizing the formalized rules, an optimal vessel allocation scheme is explored in the large solution space by individual crossover, swarm crossover and mutation. Then, with the scheme of vessel allocation, a discrete wolf pack search (DWPS) is introduced to optimize the maintenance route under all constraints. As the evaluation standard of MPSO, the purpose of DWPS is to search the solution space with depth and breadth balanced and find the optimal and open maintenance route with multiple round trips to bases that minimize O&M costs, including travel, technician and penalty costs. Finally, computational experiments and analysis are carried out. The results provide both the optimized cost and detailed arrangements, which can be directly used in the maintenance schedule.**

***Index Terms*—Maintenance scheduling and routing problem; Offshore wind farm; Particle swarm optimization; Wolf pack search.**

1 Introduction

The wind power industry has continued to grow rapidly over the past twenty years (Chaviaropoulos et al., 2006). Due to higher wind speeds and lower turbulence levels in the offshore environment, the industry has been encouraged to invest in offshore wind farms, and the amount of electricity produced has thus increased exponentially. However, because of the complicated foundations, long electrical networks (Cai et al, 2019), and exorbitant cost of installation and maintenance (Dalgic et al., 2015) the power production from offshore wind is still significantly more expensive than power generation from onshore wind farms. The Renewables Advisory Board (2010) reported that the operation and maintenance (O&M) costs constitute a substantial portion (20%-35%) in the overall life cycle of offshore wind farms (Snyder and Kaiser, 2009)Brain, and thus, the organization and optimization on logistics, routing, and scheduling of maintenance have been studied, especially in recent years (Emary et al., 2018; Akbari et al., 2017). One of the effective methods for reducing costs is to optimize the schedules and maintenance routing of vessels (Feng et al., 2017a, 2017b).

The purpose of maintenance routing and scheduling for offshore wind farms is to obtain the detailed schedule and route (Zhang et al., 2018) for each vessel to minimize the total cost of O&M. Due to the harsher climate conditions offshore (Huang et al., 2017), some factors should be considered when scheduling maintenance activities (Dalgic et al., 2015a), including the following. 1) The weather conditions. Considering the performance of vessels and safety, maintenance can only be performed in the periods when some conditions, e.g., wind speed and wave height, meet the requirements. As good weather periods are limited and discrete in most locations where wind farms are currently located, maintenance schedules must be optimized to exploit the resulting discrete weather windows. 2) The availability of various resources, e.g., service vessels, technicians, and spare parts. The resources are generally based on the O&M bases (Feng et al., 2019). If the resources are available, they can be delivered to the turbine that needs to be maintained. Otherwise, the turbine has to wait for maintaining. 3) The capacity of vessels for equipment and technicians. Equipment and technicians are not allowed to exceed the maximum limitation of the vessel at any point in the route of delivering. 4) The disruption to electricity generation. Penalty costs should be considered in such a context.

As a complex optimization problem, the maintenance routing and scheduling for offshore wind farms have increasingly attracted researcher attention.

1) Routing optimization problems

Typically, the routing and scheduling problem can be categorized as a vehicle routing problem (VRP), and comparable studies for the VRP, including its extensions and variations, can be found from recent years. Aiming at the dynamic vehicle routing problem (DVRP), Sabar et al., (2019) utilized evolutionary algorithms (EM) to find a set of routes to serve multiple customers at minimal total travelling cost while the travelling time between points may vary during the process due to traffic congestion. Wilck

IV and Cavalier, (2012) addressed the split-delivery vehicle routing problem (SDVRP) in which delivery to a demand point can be served by any number of vehicles. Liu and Tao, (2019) addressed a special VRP, which extends the classic problem by considering the time window and synchronized service constraints. Utilizing the mixed-integer programming model, an efficient adaptive large neighbourhood search heuristic was proposed to minimize the computation time and cost (Moura, 2019). Integrating the multiple neighbourhood search (MNS) and tabu search (TS), the multi-depot open vehicle routing problem was optimized by Soto et al., (2017), where the vehicles start from different depots, visit customers, deliver goods and are not required to return to the depot at the end of their routes.

Although most researchers focus on routing optimization, discrete time window and transportation restrictions (vessel number and type, technicians, etc.) for offshore maintenance are often ignored.

2) Maintenance routing and scheduling for offshore wind farms

According to the specific VRP for offshore wind farms, the length of a shift and the width of the weather window for a given route limits the maximum route duration, while the requirement of a minimum elapsed time between when the technicians are delivered to a turbine and picked up again are the opposite of customer ride time considerations where a maximum time between pickup and delivery is enforced. Hence, it is insufficient to find the optimal route for each vessel, and the optimal schedule for the route should also be proposed and optimized simultaneously. Dai et al., (2015) introduced the routing and scheduling problem of a maintenance fleet for offshore wind farms, which determined the optimal assignments of turbines and routes to the vessels in terms of cost. Furthermore, the authors developed a mixed-integer linear program (MILP) to generate all feasible routes and maintenance schedules for the vessels for each period. Based on the Duo Ant Colony Optimization (duo-ACO), the utilization of the maintenance resources was improved by Zhang (2014), especially on the scheduling and routing of the maintenance fleet, to reduce the O&M cost. Similarly, Stålhane et al., (2015) proposed two alternative models to solve the optimization problem. Utilizing the arc-flow and path-flow formulation, the models are solved heuristically by generating a subset of the possible routes and schedules and produce close to optimal solutions using considerably less computing time.

The studies above usually consider one O&M base and one wind farm, but the multi-service model of offshore wind farms is rarely established. In addition, the present maintenance routing problems generally hypothesise that the starting and returning bases are the same, the open maintenance route for offshore wind farms and multiple round trips to the bases are, to the authors' knowledge, not mentioned in the previous studies.

Aiming at the problem above, a hybrid heuristic optimization of maintenance routing and scheduling for offshore wind farms is proposed. Considering the discrete weather window and limited resources (spare parts and technicians), the article aims to find the optimal open and multi-depot maintenance route to minimize the cost of O&M with the scheduling of vessel allocation and multiple round trips. First, with the maintenance service protocol, mixed particle swarm optimization (MPSO) is applied to seek a desired mapping relation between vessels and wind farms. Utilizing the formalized rules, an optimal vessel allocation scheme is explored in the large solution space by individual crossover, swarm crossover and mutation. Then, with the scheme of vessel allocation, a discrete wolf pack search (DWPS) is introduced to optimize the maintenance route under all constraints. As the evaluation standard of MPSO, the purpose of DWPS is to search the solution space with depth and breadth balanced and find the optimal and open (Xia and Fu, 2018; Brandão, 2018) maintenance route with multiple round trips to bases that minimize O&M costs, including travel, technician and penalty costs. Finally, computational experiments and analysis are carried out. The results provide both the optimized cost and detailed arrangements, which can be directly used in the maintenance schedule. The main contributions of this paper are as follows: 1) to extend the routing and scheduling problem with discrete window time and consider several logistics bases and the possibility of servicing more than one wind farm with the same fleet; 2) to introduce the open and multi-depot maintenance routing and scheduling problem with pickup/delivery; 3) to propose a new hybrid heuristic optimization technique integrated with MPSO and DWPS to support multiple round trips to the bases during maintenance.

2 Maintenance Modelling for Offshore Wind Farms

2.1 System description of offshore wind farms

The offshore wind farm is a cluster of wind turbines connected to the power grid that acts as a power station (Liu et al., 2011). With the gradual maturity of wind power technology, more than one cluster of wind turbines are located in ultra-deepwater at long distances from the shore and surrounded by a harsh marine environment (Dai et al., 2015). In this article, we assume that there are 64 turbines in one cluster and 16 of them need to be maintained in the next 7 days planning horizon based on the recommended period in which the turbines need to be serviced. Three O&M logistics bases (Wang et al., 2019; Sazonov et al., 2018) owning resources such as vessels, technicians and warehouses are located around the wind farms with different distances.

Within the given planning periods, the vessels can make multiple round trips and service more than one wind farm, as shown in Fig. 1. In addition, the maintenance routing of vessels can be an open loop, which means that the vessels can start from an arbitrary base and return to another base after delivering the spare parts and technicians to the turbines. Meanwhile, each maintenance task is required to be performed on each turbine during the maintenance window, and each task has an associated deadline by the end of the maintenance window and is a specified number of hours in duration.

The following notations are used to describe the sets of the proposed maintenance routing and scheduling optimization problem, as shown in Table I.

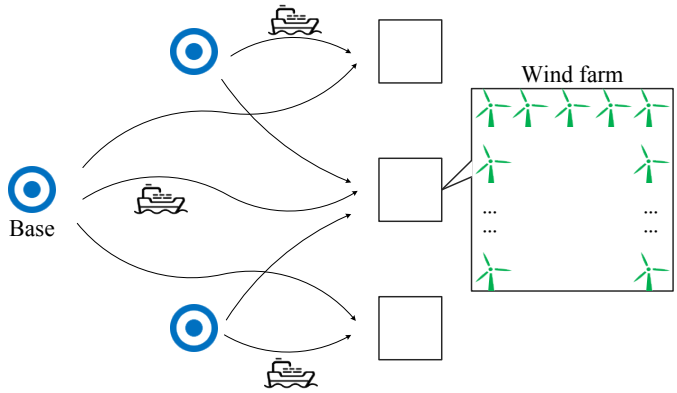


Fig. 1. An organization of maintenance bases for offshore wind farms

TABLE I
SETS OF NOTATIONS IN MAINTENANCE ROUTING AND SCHEDULING OPTIMIZATION PROBLEM

No.	Notation	Description
1	W	Set of offshore wind farms with w as index
2	U	Set of turbines that need to be maintained with u as index
3	U^w	Set of turbines at offshore wind farm w
4	$\hat{U}^w$	Set of turbines that require the vessel to be present during maintenance $\left(\hat{U}^w \subseteq U^w\right)$
5	J	Set of weather window with j as index
6	B	Set of O&M bases with b as index
7	V	Set of vessels with v as index
8	V_b^φ	Set of vessels of type φ at O&M base b
9	P	Set of technician with p as index
10	P_b^γ	Set of technicians of type γ at O&M base b
11	T	Set of periods with t as index

2.2 Parameters of turbines

One of the main inputs required for the routing and scheduling of maintenance of offshore wind farms is the set of turbines that need to be maintained during the planning horizon. The specific parameters are shown in Table II. Parameters 1 to 4 are related to the condition and the required maintenance tasks, and the necessary maintenance time and technicians that are needed. In addition, based on the maintenance pattern, the vessel delivers the technicians and picks them up on the same day after the maintenance ends if the maintenance operation does not need a vessel. Parameters 5 and 6 are set based on the system operation and the outage impact. Typically, maintenance should be accomplished within a few days. However, due to the hashed weather or the unavailable spare parts or technicians, the maintenance tasks may have to be postponed. If the last period of maintenance is exceeded, the penalty fee will incur. Parameter 7 is the real time in which the vessel arrives at turbine u and begins maintenance.

TABLE II
PARAMETERS OF TURBINES

No.	Notation	Description	Unit
1	m_u	Calendar hours to complete specified maintenance task of turbine u	hour
2	n_u^γ	Number of technicians required to maintain turbine u classified as type γ	person
3	a_v^u	$=1$ if vessel v is required to be present when service for the turbine u $=0$ otherwise	N/A
4	ϖ_u	The required weight of spare parts that delivered from the bases to turbine u	tons
5	θ_u^t	$=1$ if the turbine u is scheduled to be maintained in period t $=0$ otherwise	N/A
6	$\hat{t}_u$	The latest period to maintain turbine u without penalty	day
7	t'_u	The real time to get to the maintained turbine u	day
8	n_{vu}^γ	Number of technicians (type γ) on vessel v after leaving turbine u	person

2.3 Parameters of bases and vessels

The specific parameters of based and vessels are proposed in Table III. Parameters 1 to 4 display the generic features of the bases. Owing to the limitations of space and technology requirements, we assume that $\sum_\varphi \widetilde{nv}_\varphi^1 = 3, \sum_\varphi \widetilde{nv}_\varphi^2 = 2$, $\sum_\varphi \widetilde{nv}_\varphi^3 = 2$, and $\widetilde{np}_\gamma^b = 4$. Parameters 5 and 6 present the availability of vessels and technicians at the O&M base. Parameters 7 to 11 show the characteristics of vessels. Parameters 7 and 8 limit the maximum number of technicians and load capacity due to the safety constraints, and parameters 10 and 11 provide the speed and fuel consumption of vessels of type φ. Parameter 12 is the transfer

time that includes the unloading of the spare parts and technicians and the related preparation time for maintenance when the vessel arrives at the turbine. Parameter 13 is the travel time from node i to i', and node i and i' involve the turbines and bases. Parameters 14 to 17 are related to time, and they are mainly used to determine the operating state of the system in period t.

TABLE III
PARAMETERS OF BASES AND VESSELS

No.	Notation	Description	Unit
1	$\widetilde{nv}_{\varphi}^{b}$	The maximum number of vessels at O&M base b	vessel
2	φ	Various types of vessel with different maximum load capacity and speed	N/A
3	$\widetilde{np}_{\gamma}^{b}$	The maximum number of technicians of type γ at O&M base b	person
4	γ	Total technicians for each type, $\gamma=\{1,2,3\}$ corresponding to electrical, mechanical, and electromechanical respectively	N/A
5	$a_{v}^{b\varphi}$	$=1$ if vessel v of type φ at O&M base b is able to deliver the maintenance spare and technicians $=0$ otherwise	N/A
6	$a_{p}^{b\gamma}$	$=1$ if technician p of type γ at O&M base b is able to provide the maintenance $=0$ otherwise	N/A
7	$\tilde{n}_{v}$	The maximum number of technicians on board vessel v (technician capacity)	person
8	$\tilde{\varpi}_{v}$	The maximum load capacity that can be delivered by vessel v	tons
9	ϖ_{v}	The total weight of spare parts or equipment that are delivered by vessel v	tons
10	sp_{φ}	Speed at maximum continuous power	knot
11	fc_{φ}	Fuel consumption at operational speed	mt/h
12	m_{v}^{φ}	The transfer time of type φ for technicians and equipment from vessel v to a turbine	hour
13	$m_{vii'}^{\varphi}$	The travel time of vessel v of type φ to travel from node i to i'	hour
14	n_{v}^{wt}	The number of vessels that provide service for wind farm w in period t	vessel
15	n_{v}^{bt}	The number of vessels at O&M base b in period t	vessel
16	n_{v}^{t}	The number of technicians of vessel v in period t	person
17	θ_{v}^{wt}	$=1$ if the vessel v provides service for wind farm w in period t $=0$ otherwise	N/A

2.4 Cost and climate

The costs considered in this article include 1) travel costs, 2) technician costs, and 3) penalty costs. Based on the maintenance routing and scheduling, the vessels deliver the spare parts and technicians to the turbines. Parameter 1 is the fuel cost for transportation of vessels between turbines and bases. Additionally, the salary denoted by parameter 2 should be paid to the technicians who are on board. We assume that the salary is 300€, 325€ and 350€ per day for the electrical, mechanical, and electromechanical technicians, respectively. For condition-based maintenance, the recommended period of maintenance and the penalty cost could be set to reflect the estimated condition of the turbine. The determination of parameter 3 depends on the preferences and perspective of the user and whether he or she represents a wind farm owner/operator or an O&M service provider. And the parameter 3 also reflects the loss of electrical energy production, revenue loss and other unpredictable effects due to the maintenance delay in actual situation. Parameters 4 to 6 display the weather conditions in the period time. Due to the uncertainty of the ultra-deep water environment, the weather window for each period is different for each vessel depending on its specification or accessibility level. The duration for a vessel leaving from the bases until its return must be less than its weather window. Parameter 7 defines the mapping relationship between the O&M base and the offshore wind farm. If $\sigma_1^1=\sigma_1^2=1$, then the O&M base b_1 will service wind farm w_1 and w_2.

TABLE IV
PARAMETERS OF COST AND CLIMATE

No.	Notation	Description	Unit
1	$c_{vii'}^{\varphi}$	The travel cost of vessel v of type φ to travel from node i to i'	€/hour
2	c_{γ}	The technician cost of type γ per period.	€/day
3	c_{u}	The loss of profit and electricity without accomplishing the maintenance per period if turbine u is maintained after period $\hat{t}_{u}$	€/day
4	$\overleftarrow{m}_{vwj}^{t}$	The ending time of jth weather window at time period for vessel v to the wind farm w in period t	hour
5	$\overrightarrow{m}_{vwj}^{t}$	The starting time of jth weather window at time period for vessel v to the wind farm w in period t	hour
6	ζ_{vwj}^{t}	Either discontinuous window or continuous window to perform the repair of specified maintenance task for vessel v to the wind farm w in period t	hour
7	σ_{b}^{w}	$=1$ if O&M base b services wind farm w $=0$ otherwise	N/A

2.5 Objective and constraints

Typically, with vessel scheduling and maintenance routing, optimization problems can be developed that must share the maintenance resources of the organization. Regarding the discrete weather windows, maintenance technicians and resources as constraints, the maintenance routing and scheduling for offshore wind farms is a typical non-deterministic polynomial (NP) problem. The following objective function is used for the routing problem:

$$\min C = C_{tec} + C_{pen} + C_{tra} \tag{1}$$

where C_{tec}, C_{pen} and C_{tra} are the technicians, penalty cost and travel cost respectively, which are formulated as follows:

$$C_{tec} = \sum_{\gamma} \sum_{u}^{U} n_u^{\gamma} \cdot c_{\gamma} \tag{2}$$

$$C_{pen} = \sum_{u}^{U} \left(t'_u - \hat{t}_u \right) \cdot c_u \tag{3}$$

$$C_{tra} = \sum_{i \in U \cup B} \sum_{i' \in U \cup B} c_{vii'}^{\varphi} \cdot y_{vii'}^{\varphi} \tag{4}$$

where $y_{vii'}^{\varphi}$ is a binary variable. If $y_{vii'}^{\varphi} = 1$ means the vessel v of type φ travel from node i to i'; If $y_{vii'}^{\varphi} = 0$, otherwise.

The constraints are given as follows:

$$\sum_{w}^{W} n_v^{wt} \leqslant \sum_{b}^{B} \sum_{\varphi} \widetilde{nv}_{\varphi}^{b} \tag{5}$$

$$n_v^{bt} \leqslant \sum_{\varphi} \widetilde{nv}_{\varphi}^{b} \tag{6}$$

$$n_v^{t} \leqslant \tilde{n}_v \tag{7}$$

$$\sum_{w}^{W} \theta_v^{wt} \leqslant 1 \tag{8}$$

$$\sum_{v} \sum_{t} \sum_{w} (\theta_v^{wt} \cdot \theta_u^{t}) = 1 \tag{9}$$

$$\sum_{v} \sum_{\varphi} \sum_{i' \in U} y_{vii'}^{\varphi} = 1, \forall i' \in U \tag{10}$$

$$\sum_{b \in B} \sum_{i \in U} y_{\varphi bi}^{v} = \sum_{b \in B} \sum_{i' \in U} y_{\varphi i' b}^{v} \geqslant 1, \forall b \in B \tag{11}$$

$$y_{\varphi ii}^{v} = 1, i \in U \tag{12}$$

$$\overleftarrow{m_{vwj}^{t}} \leqslant \overrightarrow{m_{vw(j+1)}^{t}}, \forall j \in J \tag{13}$$

$$\overleftarrow{m_{vwj}^{t}} - \overrightarrow{m_{vwj}^{t}} = \zeta_{vwj}^{t} \geqslant m_u + m_v \tag{14}$$

$$m_{ii'} = 0, \forall i \in B, \forall i' \in U \tag{15}$$

$$y_{vii'}^{\varphi} \left(t_i' + m_{vii'}^{\varphi} + m_v^{\varphi} - t_{i'}' \right) = 0, \forall i, i' \in U \cup B \tag{16}$$

$$y_{vii'}^{\varphi} \left(n_{vi}^{\gamma} - n_u^{\gamma} - n_{vi'}^{\gamma} \right) = 0, \forall i \in U, \forall i' \in U \cup B \tag{17}$$

The explanation of the constraints is as follows:

Constraint (5): The number of vessels that provide service for all the wind farms will not be greater than the maximum number of vessels at all bases;

Constraint (6): The total number of vessels for each period is not greater than the ones available at the O&M base;

Constraint (7): The total number of technicians of vessel for each period is not greater than the capacity of vessel;

Constraint (8): A vessel cannot provide service for more than one wind farms at a period;

Constraint (9): A turbine is only maintained once in the planning horizon;

Constraint (10): Node i' (turbine) is visited only once by vessel v of type φ from node i;

Constraint (11): All the vessels will start from the arbitrary O&M base and get back to any available base after servicing the last maintained turbine. Meanwhile, the O&M bases could be visited more than once;

Constraint (12): A vessel travels directly from the delivery node to the pickup node (which is the same turbine) if the vessel needs to be present during the maintenance operation;

Constraint (13): The discrete weather window for the maintenance routing and scheduling;

Constraint (14): The arbitrary time window is greater than the maintenance time of turbine u and transfer time for technicians and equipment from vessel v to a turbine;

Constraint (15): The time when the vessel leaves the O&M base is forced to be 0;

Constraint (16): The time difference between node i and node i' is only related with the travel time and transfer time;

Constraint (17): The quantity change of technicians (for each type) on the vessel when arriving at node i'.

3 The Hybrid Heuristic Optimization Algorithm

Due to the complexity and flexibility of the maintenance routing and scheduling for offshore wind farms, the optimization problem in this article is divided into two parts, as shown in Fig. 2. The first part mainly establishes the mapping relationship between the bases and wind farms and determines the certain number of wind farms that the vessel will service. Then, the scheme of vessel allocation is transferred to the second part to optimize the maintenance route. Conversely, the costs of the maintenance route are utilized as the evaluation of the first part and thus, as a guide of vessel allocation.

To address this problem, it is necessary to introduce an artificial intelligence method to seek the optimal solution space. The authors choose PSO as the optimization approach for its adaptability and quick converging capacity (Mazadi et al., 2012). Because the purpose of the article is to find the optimal open and multi-depot maintenance route to minimize the cost of O&M with the scheduling of vessel allocation and multiple round trips, there are no former relevant research models and the optimization issue for the optimization of maintenance routing and scheduling for offshore wind farms; thus, it is unknown which optimization method is more appropriate. PSO is selected partly because it has been used in solving some similar problems, such as component clustering, and it is found to be more robust. Additionally, the authors prefer PSO for its high efficiency in maintaining the diversity of the swarm, ease in adjusting parameters, and no requirement for differentiable optimization problems. However, the traditional PSO algorithm (Eberhart and Kennedy, 2002) is usually utilized for the continuous function, and it has a high probability of falling into a local optimum. Therefore, a modified PSO, named mixed PSO (MPSO), is proposed in this article to maintain the diversity of the swarm and strengthen the search performance.

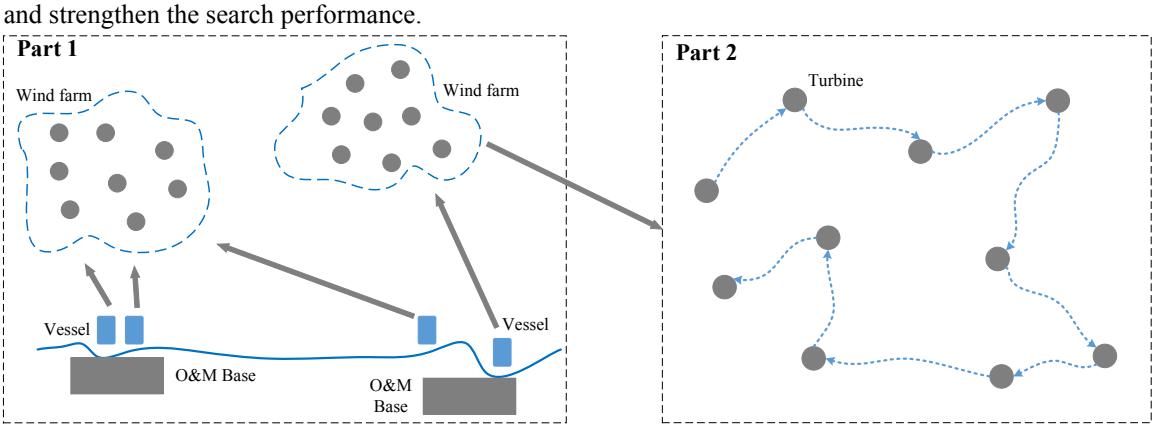


Fig. 2. The scheme of vessel allocation

The second part is for an open maintenance route optimization with discrete weather windows. It underlines the optimization of maintenance and delivery routes with multi-depot under the premise of a vessel scheduling plan. Compared with other bioinspired optimization methods, the WPS algorithm has better convergence and robustness, especially for high-dimensional functions. As the maintenance route for offshore wind farms, it is a typical high-dimensional problem in which the dimensions increase quickly with the number of turbines to be maintained and the vessels. Therefore, the WPS algorithm is chosen for modification for the proposed problem in this article.

3.1 Mixed PSO

1) Numerical initialization

The particles are initialized to constitute an $F \times H$ Euclidean space, where F is the number of particles, and H equals the number of vessels. The state of the *i*th particle can be described as $X_i = (x_{i1}, x_{i2}, \cdots x_{iH})$, and $x_{id}(d \in H)$ is the position in the H-dimensional variable space, namely, the number of wind farms for the *d*th vessel. As the feature of discrete vessels and wind farms, the initial position and velocity of each particle are assigned randomly, and the positions of particles are mandatorily set as an integer. All particles are traversed based on parameter i, and the number of iterations is traversed based on parameter $Iters$.

Then, each particle is input to the DWPS as an input parameter, and the fitness function of the particle can be evaluated by DWPS. The position under different iterations is updated by the speed of the particles, which is as follows:

$$vel_{id}^{Iters+1} = \tau \cdot vel_{id}^{Iters} + c_1 \cdot (pos_{id}^{best} - x_{id}^{Iters}) + c_2 \cdot (pos_{d}^{best} - x_{id}^{Iters}) \tag{18}$$

$$pos_{id}^{Iters+1} = \begin{cases} 1, \rho_{id} < \dfrac{1}{1+\exp(vel_{id}^{Iters})} \\ 0, \rho_{id} \geqslant \dfrac{1}{1+\exp(vel_{id}^{Iters})} \end{cases} \tag{19}$$

$$x_{id}^{Iters+1} = x_{id}^{Iters} + pos_{id}^{Iters+1} \tag{20}$$

where $vel_{id}^{Iters+1}$ is the velocity in dth dimension of the particle i at the $Iters$ th iteration; x_{id}^{Iters} is the position in dth dimension of the particle i at the $Iters$ th iteration; $pos_{id}^{Iters+1}$ is the value of position change in dth dimension of the particle i at the iteration of $(Iters+1)$th; pos_{id}^{best} is the best position in dth dimension of the particle i in history; pos_{d}^{best} is the best position in dth dimension of the particle swarm; τ is the inertia coefficient; and c_1, c_2 are acceleration coefficient which c_1 is the extent to which particles affect themselves, and c_2 is the capability to share the information between particles; ρ_{id} is an empirical parameter.

To improve the search performance of the MPSO algorithm, the inertia coefficient τ adopts an adjustment strategy that decreases linearly with the number of iterations. The value of the inertia coefficient τ can be expressed as follows:

$$\tau = \frac{\tau_{\max} - Iters \cdot (\tau_{\max} - \tau_{\min})}{Iters_{\max}} \tag{21}$$

where $\tau_{\max}$ and $\tau_{\min}$ are the extreme values of τ, and they can be obtained by experience; $Iters$ is the current iterations and the maximum number of iterations $Iters_{\max}$ should be set to effectively control the running time of the algorithm.

2) Individual crossover

In the process of numerical initialization, the position at each iteration of each particle is recorded. Apparently, if the position x_{id}^{Iters} is beyond the solution space, the iteration of the ith particle ends. Otherwise, the iteration ends when it reaches $Iters_{\max}$ iterations. After the numerical initialization, each particle has a set of positions with no more than $Iters_{\max}$ elements, denoted by $S_i^{Iters}(Iters \leqslant Iters_{\max})$, and the optimal particle in the individual optimum particle and the swarm need to be obtained. Owing to the generated particle values, the allocation scheme of vessels is fixed. In this article, we use the WPS iteratively to evaluate the fitness function of each particle with small variables (iteration times, searching numbers, number of artificial wolves, etc.). With the help of WPS, the particles are determined and evaluated, and the occupation of computing resources and time is also acceptable.

Step 1: Taking the best certain number of elements in set S_i^{Iters}, denoted by $Ind_{\text{sum}}(Ind_{\text{sum}} \in [F/(\alpha_1+1), F/\alpha_1])$, as the crossover particles (except the individual optimum particle), and α_1 as the proportion of individual crossover particles, the initial fitness function of the jth ($j = 1, 2, \cdots, Ind_{sum}$) particle is Fit_j.

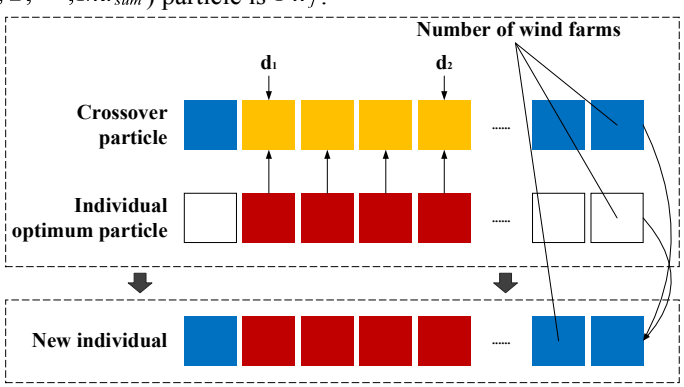


Fig. 3. The operation of individual crossover

Step 2: Choose two arbitrary positions in the individual optimum particle, namely, d_1 and d_2. Traverse all the crossover particles with j as an index and replace the sequence of $[d_1, d_2]$ in the crossover particles with the sequence at the same position in the individual optimum particle. The operation of an individual crossover is shown in Fig. 3.

Step 3: Calculate the corresponding fitness function of a new individual particle, denoted by Fit_j'. If $Fit_j' > Fit_j$, update the sequence of the jth particle; otherwise keep the original position.

Step 4: Set $j = j+1$ and repeat the steps above until $j = Ind_{sum}$.

3) Swarm crossover

To move close to the optimal particle of the population, the operation of swarm crossover between the individual particles and the optimal particle of the swarm is proposed. The primary process of swarm crossover is the same as the individual crossover, and the only difference is that the crossed object is replaced by the optimal particle of the population, as shown in Fig. 4.

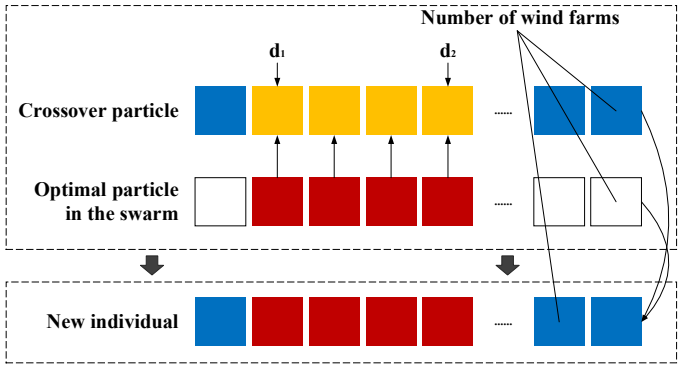


Fig. 4. The operation of swarm crossover

4) Mutation

Step 1: Take the best certain number of elements in set S_i^{Iters}, denoted by $Mut_{\text{sum}}\left(Mut_{\text{sum}} \in [F/(\alpha_2+1), F/\alpha_2]\right)$, as the mutation particles, and α_2 is the proportion of mutation particles. The initial fitness function of the *j*th ($j=1,2,\cdots,Mut_{sum}$) particle is Fit_j.

Step 2: Choose two arbitrary positions, namely, d_3 and d_4. Traverse all the mutation particles with j as the index and exchange the position of d_3 and d_4. The operation of the mutation is shown in Fig. 5.

Step 3: Calculate the corresponding fitness function of a new individual particle, denoted by $Fit_j^{'}$. If $Fit_j^{'} > Fit_j$, update the sequence of the *j*th particle; otherwise keep the original position.

Step 4: Set $j=j+1$ and repeat the steps above until $j=Mut_{sum}$.

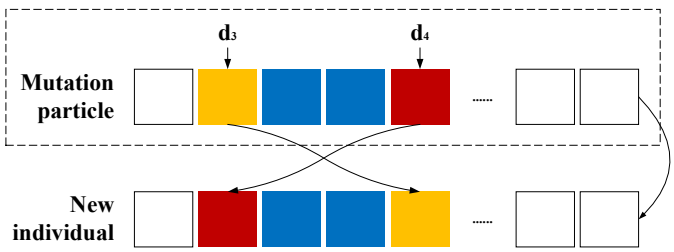


Fig. 5. The operation of mutation

5) Output the optimized solution

The optimized solution $X_i^{best}=(x_{i1}^{best}, x_{i2}^{best}, \cdots, x_{iH}^{best})$ is output, and the x_{id}^{best} is the best number of wind farms for which the *d*th vessel provides service. The procedure of MPSO is shown in Fig. 6.

```
Input: The initial parameters, including F(number of particles), H(number of vessels), W(number of
wind farms), Iters_max(number of iterations), ρ_id(empirical parameter), τ_max(maximum of inertia
coefficient), τ_min(minimum of inertia coefficient), α_1(proportion of individual crossover particle),
α_2(proportion of mutation particle)

Output: An optimized maintenance mapping relationship between vessels and wind farms.
        Generate an initial particle swarm {individual i, i=1,2…,F} randomly, and compute the
fitness functions of initial particle swarm;

**************The fitness value of the particle swarm**************
for i=1:1:F
  %%%%Allocate vessels to 3 windfarm based on the individual
  if the number of available vessels in any windfarm < 1
    Exchange the unavailable vessels with others or randomly choose some vessels of the windfarm
    with the most available vessels.
  end
  Calculate the cost of three windfarms by wolves algorithm
  Solve the total cost of the current allocation plan;
end

**************The initialization of the particle swarm**************
for i=1:1:F
  for Iters=1:1:Iters_max
    Generate a particle sequence randomly and evaluate the speed and position in the next iteration.
    if (the position value <= W) && (the position value >= 1)
      Record the position in the next iteration;
      Iters=Iters+1;
      else if (the position value > W) || (the position value < 1)
        break;
      end
    end
  end
end

**************The individual crossover process of the particle swarm**************
Sort these costs of all the existing individuals and find the best individual;
%%%%Each individual interacts with the optimal one of itself
for j=1:1: Ind_sum
  Generate two individual crossover positions randomly ;
  Get the subsequence of the individual optimum particle between the two positions;
  Get the subsequence of the crossover particle between the two positions;
  Replace the subsequence of the crossover particle by the individual optimum particle;
  %%%%Allocate vessels to 3 windfarm based on the individual
  if the number of available vessels in any windfarm < 1
    Exchange the unavailable one(s) with others or randomly choose some vessels of the wind farm
    with the most available vessels.
  end
  Calculate the fitness value of the new individual;
  if the fitness of new individual < the fitness of original individual particle
    Record the new individual particle;
    else
    Keep the original position;
  end
end

**************The swarm crossover process of the particle swarm**************
for j=1:1: Swa_sum
  Generate two swarm crossover positions randomly ;
  Get the subsequence of the swarm optimum particle between the two positions;
  Get the subsequence of the crossover particle between the two positions;
  Replace the subsequence of the crossover particle by the swarm optimum particle;
  %%%%Allocate vessels to 3 windfarm based on the individual
  if the number of available vessels in any windfarm < 1
    Exchange the unavailable vessels with others or randomly choose some vessels of the wind farm
    with the most available vessels.
  end
  Calculate the fitness value of the new individual;
  if the fitness of new individual < the fitness of original individual particle
    Record the new individual particle;
    else
    Keep the original position;
  end
end

**************The mutation process of the particle swarm**************
for j=1:1: Mut_sum
  Randomly generate two mutation positions;
  Exchange the points of the two positions in the individual;
  %%%%Allocate vessels to 3 windfarm based on the individual
  if the number of available vessels in any windfarm < 1
    Exchange the unavailable one(s) with others or randomly choose some vessels of the wind farm
    with the most available vessels.
  end
  Calculate the fitness value of the new individual;
  if the fitness of new individual < the fitness of original individual particle
    Record the new individual particle;
    else
    Keep the original position;
  end
end
```

Fig. 6. The flow diagram of Mixed PSO

3.2 Discrete WPS

Bioinspired optimization methods are becoming common among researchers due to their simplicity and extensibility. The WPS algorithm, one of the relatively new optimization algorithms, is inspired by the social hierarchy and hunting behaviour of wolves in nature.

The wolves cooperate well with each other and attack their competitors and prey (Zhou et al., 2018; Chen et al., 2018, 2017). The whole process of the hunting activity of a wolf pack can be summarized as 1) initializing wolves, 2) searching for wolves, 3) summoning wolves, 4) sieging wolves, and 5) eliminating wolves and updating wolves.

The original WPS algorithm can be directly used in real-valued unconstrained global optimization problems (Xi et al., 2016; Emary et al., 2018; Ren et al., 2019). All operations of the WPS algorithm are suitable for continuous functions. However, the MTSP is an integer programming problem with complex constraints. Therefore, it cannot be directly applied to the MTSP. To solve this problem, we propose a novel WPS algorithm with a two-dimensional code representation, named the DWPS algorithm for solving the maintenance routing for offshore wind farms.

1) Numerical initialization

In the initialization operation, each artificial wolf is encoded as a two-dimensional code, namely, X_{iu}^{Iters} and X_{iv}^{Iters}, respectively. X_{iu}^{Iters} is the sequence of turbines corresponding to the artificial wolf i, and X_{iv}^{Iters} is the sequence of vessels. The fitness function of each artificial wolf is determined by the two-dimensional code. An example of the two-dimensional code representation is shown in Fig. 7.

Step 1: Generate Num artificial wolves randomly with i as an index. Set $X_{iu}^{Iters} = \varnothing, X_{iv}^{Iters} = \varnothing\,(i \leqslant Num)$. Set the maximum number of generations as $Iters_{\max}$ to effectively control the running time of the algorithm.

Step 2: Generate the initial number of turbines that need to be serviced randomly, denoted by X_{i1}^{Iters}. Then, calculate the following sequence of turbines utilizing the chaotic search as follows:

$$z_{i(k+1)}^{Iters} = \mu \cdot z_{ik}^{Iters}(1 - z_{ik}^{Iters})\ (k = 1, 2, \cdots, U-1) \tag{22}$$

where μ is the control parameter. Assume that $0 \leqslant z_{ik}^{Iters} \leqslant 1$, and the system has been proven to be entirely chaotic if $\mu = 4$.

Owing to the discrete feature of the turbine sequence, the $z_{i(k+1)}^{Iters}$ is mapped mandatorily into an integer, and thus the $X_{i(k+1)}^{Iters}$ is obtained.

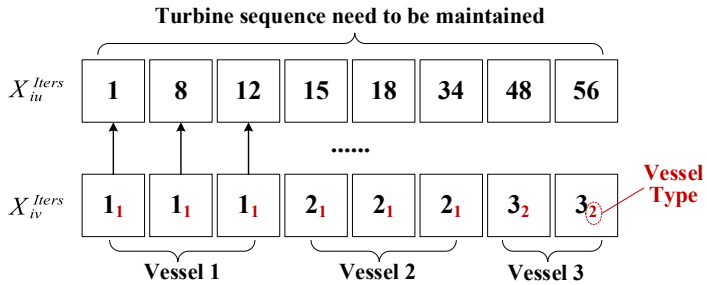


Fig. 7. Example of the two-dimensional code for 8 turbines with 3 vessels

Step 3: According to the turbine sequence X_{iu}^{Iters}, the vessel sequence X_{iv}^{Iters} is obtained by satisfying constraints such as the limitation of spare weight, the discrete weather window and technicians.

Step 4: If $i < Num$, update $i = i + 1$, and return to Step 1; otherwise, continue to Step 5.

Step 5: Calculate the fitness function of each artificial wolf by equation (1). The number of the leader wolf is recorded as m, and its corresponding fitness function value is $Fit_{best} = Fit_m$.

2) Wolves searching

Take all artificial wolves (except the leading wolf) as the searching wolves and explore the prey in the h directions of the surroundings to search for a better solution in the solution space explanatorily. The initial fitness function of the *i*th searching wolf is Fit_i. Since each element is regarded as a discrete turbine in the sequence X_{iu}^{Iters} of the artificial wolf, the process of searching wolves is redefined in this article.

Step 1: Choose one turbine randomly in the $X_{iu}^{Iters(h)}$ sequence of the *i*th artificial wolf, denoted by d_5 in the direction h. The position of its closest turbine is d_6. Reverse the order of the elements between d_5 and d_6, and thus, a new sequence of artificial wolf i is obtained, as shown in Fig. 8.

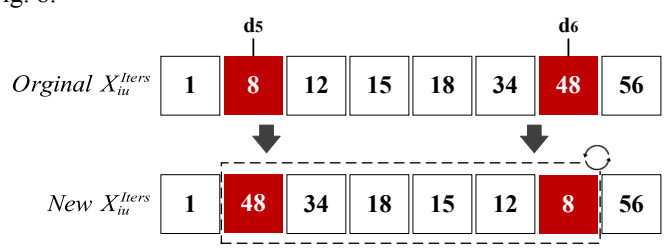


Fig. 8. The search operation of the DWPS algorithm

Step 2: Calculate the fitness function of $X_{iu}^{Iters(h)}$, denoted by Fit_i^h. If $Fit_i^h \leqslant Fit_i$, update the sequence of artificial wolf i and its corresponding fitness value; otherwise, keep the original position.

Step 3: Set $h = h + 1$ and back to step 1 until $Fit_i \leqslant Fit_m$ or the maximum cycle-index $T_{\max}^{search}$ is reached. Update the number of the leader wolf as m'.

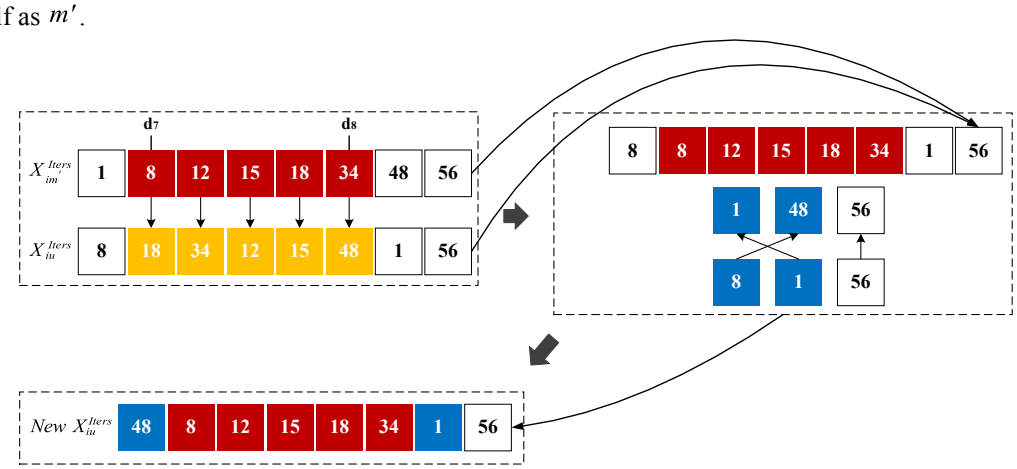


Fig. 9. The summoned operation of the DWPS algorithm

3) Wolves summoned

Take all artificial wolves (except the leading wolf) as the summoned wolves, and the leader wolf shares the experience with other wolves by summoning. The initial fitness function of the *i*th summoned wolf is Fit_i.

Step 1: Choose two turbines as the dominant sequence of the leader wolf to share with the other summoned wolves, and the positions of the two turbines are denoted by d_7 and d_8. Then, replace the corresponding position of all summoned wolves.

Step 2: According to the constraint of equation (10), update the remaining positions in the sequence of summoned wolves i to ensure that all the turbines are visited only once.

Step 3: Calculate the fitness function of the summoned wolf after updating the sequence, denoted by $Fit_i^{'}$. If $Fit_i^{'} \leqslant Fit_{m'}$, then update the number of the leader wolf as m''; otherwise, continue to summon until the maximum cycle-index $T_{\max}^{summon}$ is reached. The summoning operation of the DWPS algorithm is shown in Fig. 9.

4) Wolves sieging

Take all artificial wolves (except the leading wolf) as the sieging wolves, and the sieging wolves aim to move close to the leader wolf m''.

Step 1: Choose one turbine randomly as the sieging number in the leader wolf m''. The positions of the sieging and leader wolf are denoted by d_9 and d_{10}. Similarly, the initial fitness function of the *i*th sieging wolf is Fit_i.

Step 2: Compare the position of d_9 and d_{10}. If $d_{10} > d_9$, then the order of the sieging wolf is changed and the position of d_{10} is moved up by $step_{siege}$.

Step 3: Calculate the fitness function of sieging wolf i after updating the sequence, denoted by $Fit_i^{'}$. If $Fit_i^{'} \leqslant Fit_{m''}$, then update the number of the leader wolf as m'''; otherwise, continue to siege until $d_9 = d_{10}$ or the maximum cycle-index $T_{\max}^{siege}$ is reached. The sieging operation of the DWPS algorithm is shown in Fig. 10.

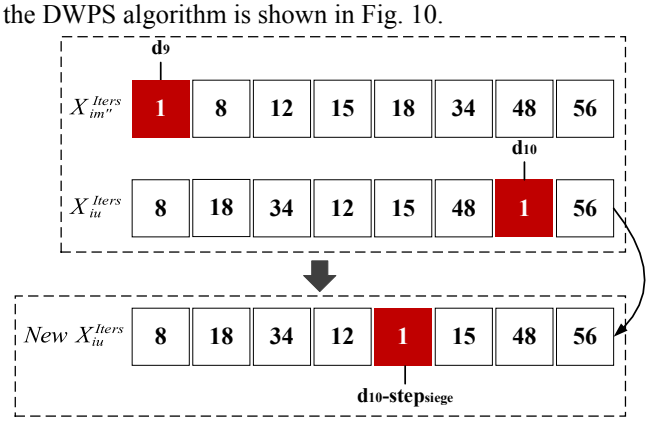


Fig. 10. The sieging operation of the DWPS algorithm

```
Input: The initial parameters, including: Num(number of artificial wolves), W(number of wind
farms) Iters_max(maximum number of generations), T_max^search (maximum cycle-index in
searching), T_max^summon maximum cycle-index in summon), and T_max^siege (maximum cycle-index in
sieging)

Output: A optimized maintenance sequence and cost

**************The initialization of the wolf pack**************
for i=1:1:Num
  Generate the first number of initial wolf pack {wolf i, i=1,2…,Num}, and obtain the followed
  sequence by chaotic search;
  Generate the vessel sequence by satisfying constraints;
  Calculate the fitness functions of initial wolf pack;
end

**************The fitness value of the wolf pack**************
for i=1:1:Num
  %%%%The fitness of the initial wolf
  for j=1:1:W
      Calculate the cost of three wind farms;
      Evaluate the total cost of the current distribution plan;
  end
  Sort these costs of all the distribution and find the minimum cost;
  The fitness of this wolf is the minimum cost in its sequence, regarded as the leader wolf;
end
```

```
**************The optimization operation of the wolf pack**************
%%%% The optimization process
for i=1:1:Iters_max// The number of cycles to optimize
  %%%%The searching wolves
  for j=1:1:Num-1// the number of searching wolves
    for q=1:1: T_max^search //The times of searching of each wolf
      Choose one position randomly and its nearest position, denoted by d5 and d6;
      Reverse the order of the elements between d5 and d6;
      Calculate the fitness function of new artificial wolf;
      if the fitness of the new artificial wolf < the fitness of original artificial wolf
        Record the new artificial wolf;
        else
        Keep the original position;
      end
      Update the number of the leader wolf as m'
    end
  end
  %%%%The summoned wolves
  for j=1:1:Num-1// the number of summoned wolves
    for q=1:1: T_max^summon //The times each wolf is summoned
      Choose two positions randomly, denoted by d7 and d8;
      Replace the corresponding positions of all summoned wolves between d7 and d8;
      Update the remaining positions in the sequence of summoned wolves;
      Calculate the fitness function of new artificial wolf;
      if the fitness of new artificial wolf < the fitness of leader wolf
        Record the new artificial wolf;
        else
        Continue;
      end
      Update the number of the leader wolf as m''
    end
  end
  %%%%The sieging wolves
  for j=1:1:Num-1// the number of sieging wolves
    for q=1:1: T_max^siege //The times each wolf sieges
      Choose one position randomly in the leader wolf, and the positions of sieging and leader
      wolf are denoted by d9 and d10;
      Compare the position of d9 and d10;
      if (d9 > d10)
        Change the order of the sieging wolf, moved towards the leader wolf by step_siege;
        else if (d9 < d10)
          Change the order of the sieging wolf, moved towards the leader wolf by step_siege;
          else if (d9 == d10)
          continue;
          end
        end
      end
      Calculate the fitness function of new artificial wolf;
      if the fitness of the new artificial wolf < the fitness of the leader wolf
        Record the new artificial wolf;
        else
        Continue;
      end
      Update the number of the leader wolf as m''';
    end
  end
  %%%%Wolves eliminated and updated
  Calculate the number of eliminated wolves;
  Sort the wolf pack according to the cost in descending order;
  Eliminate the last certain numbers of wolves and randomly generate some new sequences as
  new wolves to ensure the amount of artificial wolves are constant;
  Solve the new cost of the new wolves;
end
```

Fig. 11. The flow diagram of Discrete WPS

5) Wolves eliminated and updated

After completing the above four steps, calculate all the fitness functions of the artificial wolves and rank them from the best to the worst. Eliminate the worst artificial wolves according to a certain proportion and generate the new artificial wolves to ensure that the number of artificial wolves is constant. Additionally, if $Iters \leqslant Iters_{\max}$, set $Iters = Iters + 1$; otherwise, finish the DPWS algorithm and output the optimized solution. The procedure of discrete WPS is shown in Fig. 11.

4 Computational Analysis

We carried out extensive experiments to examine the performance of the proposed solution approaches. In the computational experiments, we generated a challenging dataset where three offshore wind farms were considered in the experiment. Each offshore wind farm consisted of 48 turbines, and the number of turbines that needed to be maintained was 16 turbines within 7 periods (days), which means that the experiment involved 48 turbines for three offshore wind farms and that optimal maintenance routing and scheduling were required.

4.1 Numerical analysis

The dataset generated represents the maintenance routing and scheduling problem with a discrete weather window and open routing problems with multi-depots that was illustrated in Fig. 1. It was constructed to illustrate the functionalities of the

optimization model. As with the dataset, the experiment was abstracted into three O&M bases (b_1, b_2 and b_3) and three wind farms (w_1, w_2 and w_3). We assumed that each base was limited to providing services for finite offshore wind farms. 1) Base b_1 provided service for wind farms w_1, w_2 and w_3. 2) Base b_2 provided service for wind farms w_1 and w_2. 3) Base b_3 provided service for wind farms w_2 and w_3. According to the harsher climate conditions, the weather window was discretized in the experiment. Table V presents the information on the weather window within periods. For example, as the vessel v_4 served wind farms 1 and 2, the available weather windows for vessel v_4 were 0-4 hours, 6-10 hours within the initial three days and 0-6 hours for the last four days.

TABLE V
DISCRETE WEATHER WINDOW FOR EACH VESSEL WITHIN PERIODS

Vessel	Day	Weather window (h)		
		Wind farm 1	Wind farm 2	Wind farm 3
$v_1 - v_3$	1-7	12	12	12
v_4	1-3	[0-4][6-10]	[0-4][6-10]	--
	4-7	6	6	--
v_5	1-3	[0-4][6-10]	[0-4][6-10]	--
	4-7	6	6	--
v_6	1-3	--	[0-4][6-10]	[0-4][6-10]
	4-7	--	8	8
v_7	1-3	--	[0-4][6-10]	[0-4][6-10]
	4-7	--	8	8

Table VI presents the specification (φ), load capacity (ϖ_v), personnel capacity ($\tilde{n}_v$), vessel speed (sp_φ) and fuel cost (fc_φ) used in the experiment. If $a_v^{b\varphi} = 1$, the vessel v of type φ at O&M base b could deliver the maintenance spare parts and technicians. If $a_p^{b\gamma} = 1$, the technician p of type γ at O&M base b could provide maintenance.

TABLE VI
SPECIFICATION, QUANTITY AND THE RELATED INFORMATION OF VESSELS

Vessel	Vessel type	O&M base	Load capacity	Person capacity	Vessel speed	Fuel cost
v_1	$\varphi = 1$	b_1	1.5	12	18	225
v_2	$\varphi = 2$	b_1	2	12	11	250
v_3	$\varphi = 2$	b_1	2	12	11	250
v_4	$\varphi = 1$	b_2	1.5	12	18	225
v_5	$\varphi = 2$	b_2	2	12	11	250
v_6	$\varphi = 1$	b_3	1.5	12	18	225
v_7	$\varphi = 2$	b_3	2	12	11	250

TABLE VII
SPECIFICATION, QUANTITY AND THE RELATED INFORMATION OF VESSELS FOR WIND FARM 1

No.	Turbine	Maintenance time	Spare weight	Penalty cost	Last period	Vessel present	Type of technicians		
							$\gamma = 1$	$\gamma = 2$	$\gamma = 3$
1	u_1	4	700	1900	3	0	2	0	1
2	u_2	3	700	1500	2	0	0	1	1
3	u_3	5	300	1600	4	1	3	0	0
4	u_4	2	900	1900	1	0	1	0	2
5	u_5	4	600	1200	1	0	1	2	2
6	u_6	5	900	1600	1	1	3	0	0
7	u_7	2	900	1800	4	0	2	2	1
8	u_8	2	500	1100	1	0	3	0	1
9	u_9	3	400	1300	1	0	0	1	1
10	u_{10}	2	600	1500	3	0	0	1	1
11	u_{11}	4	800	1400	2	1	1	3	0
12	u_{12}	2	700	1900	1	0	0	2	1
13	u_{13}	3	600	1900	2	0	3	2	0
14	u_{14}	4	800	1600	3	0	1	2	0
15	u_{15}	4	400	1500	3	1	3	0	1
16	u_{16}	3	800	1800	2	0	3	1	0

Table VII illustrates an example of the turbines to be maintained for wind farm 1, where the maintenance time (m_u), weight of spare (ϖ_u), penalty cost (c_u), last period ($\hat{t}_u$), vessel present (a_v^u) and the number of technicians (n_u^γ) are given. The binary values of the present vessel are also given in Table VII. If $a_v^u = 1$, the vessel v was required to be present when servicing turbine u;

$a_v^u = 0$, otherwise. To be more realistic, the required transfer time (m_v) for technicians and spare parts from a vessel to a turbine was set to 30 minutes. The number of each type of technician available in each O&M base was equal to 4, and the spare parts needed to service the turbines were always available.

TABLE VIII
COST BREAKDOWN FOR THE SOLUTION ATTAINED BY THE PROPOSED APPROACH

Wind farm	Vessel	Total cost	Last operation time	Penalty cost	Technician cost	Travel cost	U.R of weather window	Unavailability	Parameter
w_1	v_5		5	0	10275	15199.92			$F=100$
w_2	$v_2\ v_3\ v_4$	74633.68	3	0	11875	12657.62	0.7922	0.0208	$Num=1000$
w_3	$v_1\ v_6\ v_7$		3	0	17375	7251.14			

Maintenance routing of vessels

	Day 1	Day 2	Day 3	Day 4	Day 5
v_1	$b_1 \to w_3(4) \to w_3(1) \to w_3(4) \to b_1$	$b_1 \to w_3(3) \to b_1$	$b_1 \to w_3(15) \to w_3(14) \to w_3(15) \to b_1$		
v_2	$b_1 \to w_2(4) \to w_2(1) \to b_2$	$b_2 \to w_2(5) \to w_2(3) \to b_1$	$b_1 \to w_2(2) \to w_2(8) \to b_2$		
v_3	$b_1 \to w_2(11) \to w_2(13) \to b_1$	$b_1 \to w_2(12) \to w_2(7) \to w_2(14) \to w_2(12) \to b_1$			
v_4	$b_2 \to w_2(15) \to w_2(10) \to b_2 \to w_2(9) \to b_1$	$b_1 \to w_2(6) \to w_2(16) \to b_2$			
v_5	$b_2 \to w_1(5) \to w_1(6) \to b_1 \to w_1(4) \to w_1(5) \to b_2$	$b_2 \to w_1(9) \to w_1(1) \to w_1(2) \to b_2 \to w_1(8) \to w_1(2) \to w_1(1) \to w_1(9) \to b_2$	$b_2 \to w_1(10) \to w_1(3) \to w_1(11) \to w_1(10) \to b_1$	$b_1 \to w_1(15) \to w_1(12) \to w_1(7) \to w_1(1) \to w_1(2) \to b_1$	$b_1 \to w_1(16) \to w_1(14) \to b_1 \to w_1(13) \to w_1(16) \to w_1(16) \to b_1$
v_6	$b_3 \to w_3(11) \to w_3(10) \to b_3$	$b_3 \to w_3(5) \to w_3(13) \to w_3(5) \to b_3$	$b_3 \to w_3(12) \to w_3(9) \to b_3$		
v_7	$b_3 \to w_3(7) \to w_3(2) \to w_3(7) \to b_3$	$b_3 \to w_3(8) \to w_3(6) \to w_3(16) \to w_3(8) \to b_3$			

Table VIII presents the optimal experimental results of the proposed method with $F=100, Num=1000$. Three types of costs are presented: travel cost, technician cost and penalty cost. According to the weather conditions in the period, the detailed routes of vessel v_1 to v_7 for each day were arranged. As Table VIII shows, vessel v_4 first visited turbines v_{15} and v_{10}, and needed to be present for maintenance and then returned to O&M base b_2. When the weather window was available, the vessel v_4 started from base b_2 and visited turbine v_9, then finally returned to O&M base b_1. The maintenance routing of v_2, v_3 and v_4 for offshore wind farm 2 is shown in Fig. 12 and proves intuitively that the algorithm is appropriate for solving the open and multi-depot VRP.

Additionally, the utilization rate of the weather window is also shown in Table VIII owing to the discrete weather window. The utilization rate of the weather window represents the proportion of the maintenance schedule within the available time range. A higher utilization rate means more efficient maintenance activities. According to the optimization process, the optimal utilization rate of the weather window was 0.7922, and the relationship among the utilization rate of the weather window, generation and iterations are shown in the discussion section.

Considering that the maintenance time of the turbine is inevitable, the unavailability of the system can be divided into two parts. If the turbine is maintained before $\hat{t}_u$, the unavailability time is m_u; otherwise, the unavailability time is $m_u + (t'_u - \hat{t}_u)$. Hence, the unavailability of the system is defined as follows:

$$Unavailability = \sum_u \frac{m_u + \max\left[0, (t'_u - \hat{t}_u)\right]}{T} \tag{23}$$

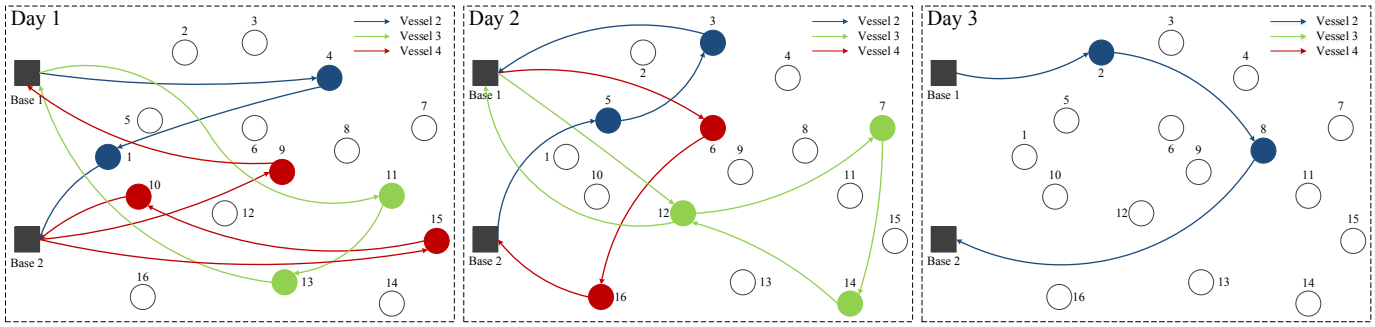


Fig. 12. The optimal solution of maintenance routing for offshore wind farm 2

Table IX shows the cost breakdown for the best ten solutions of all feasible maintenance routing and scheduling on the experimental dataset. The table reveals that on average, the travel cost and the technician cost contributed the highest proportion to the total cost by nearly 99 percent, followed by the penalty cost by 1 percent. The optimal solution not only considers the single cost but also the global cost. Additionally, as with the optimization with the proposed approach, the optimal result is revealed with $F=100, Num=1000$, and the proposed method with $F=50, Num=500$ and $F=10, Num=100$ produces a relative deviation of 0.0568 percent and 0.1053 percent, respectively.

TABLE IX
EXPERIMENTS RESULTS OF THE PROPOSED METHOD

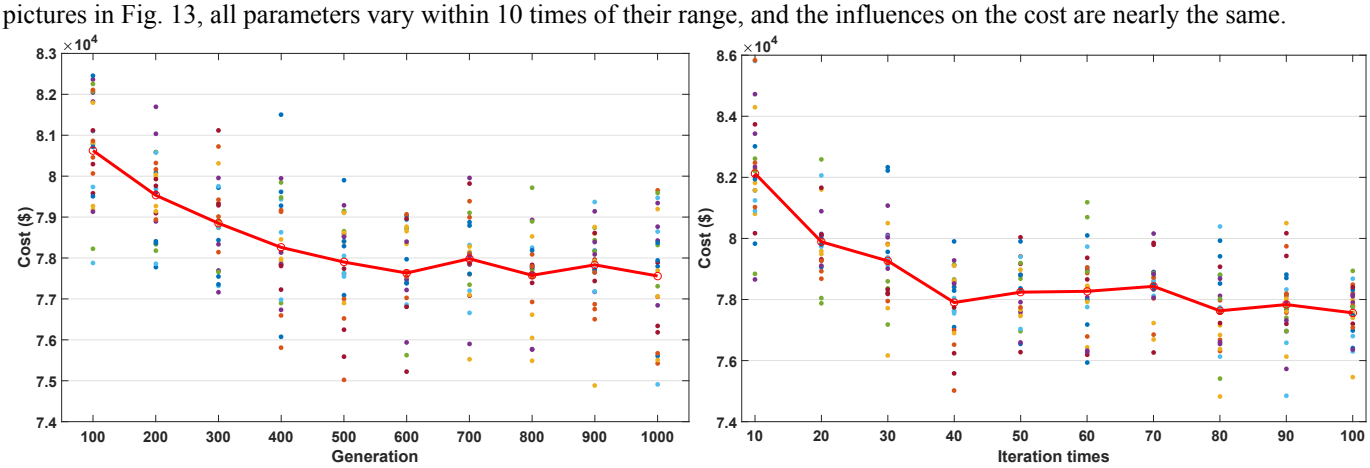
No.	$F=100, Num=1000$				$F=50, Num=500$				$F=10, Num=100$			
	C_{pen}	C_{tec}	C_{tra}	C	C_{pen}	C_{tec}	C_{tra}	C	C_{pen}	C_{tec}	C_{tra}	C
1	0	39525	35108.68	74633.68	0	29525	46068.15	75593.15	1600	42000	37350.64	80950.64
2	1300	33375	40238.68	74913.68	2300	40625	34164.08	77089.08	1400	39450	43803.68	84653.68
3	0	39875	35545.69	75420.69	0	40850	39050.93	79900.93	1300	40225	42410.61	83935.61
4	0	38925	36585.38	75510.38	2400	36650	41611.32	80661.32	0	40950	43359.37	84309.37
5	1400	40075	36317.26	77792.26	0	39875	38644.58	78519.58	0	39650	42369.98	82019.98
6	0	39650	37194.49	76844.49	1700	39175	39368.83	80243.83	1300	40375	42425.91	84100.91
7	3300	39425	37378.42	80103.42	0	38850	39256.03	78106.03	1400	40150	39785.62	81335.62
8	0	39650	36691.32	76341.32	0	39650	35611.32	75261.32	1300	40000	39727.44	81027.44
9	1600	29525	48531.19	79656.19	1600	38850	42690.46	83140.46	0	39300	41797.59	81097.59
10	0	39525	36077.66	75602.66	0	39175	41068.83	80243.83	0	39350	42132.39	81482.39
Avg	760	37955	37966.88	76681.88	800	38322.5	39753.45	78875.95	830	40145	41516.32	82491.32
Prop.	0.99	49.49	49.52		1.02	48.59	50.41		1.01	48.67	50.32	
Dev.			0.0000				0.0568				0.1053	

4.2 Discussion

1) Sensitivity of the approach

As mentioned in Section 3, the proposed hybrid heuristic optimization technique is used to find the optimal maintenance routing and scheduling for offshore wind farms. Owing to the number of artificial wolves Num, iteration times $Iters_{\max}$ and number of searches h being important parameters in the algorithm, a sensitivity analysis is executed on the experiment. The cost of maintenance with various values of Num, $Iters_{\max}$ and h are shown in Fig. 13.

Fig. 13 shows that the hybrid heuristic algorithm is available for the optimization of maintenance routing and scheduling for offshore wind farms. As the parameter increases, the solution space is searched increasingly more comprehensively, and thus, the total cost of the maintenance is further optimized with a downturned trend and eventually tends to be smooth. Compared with the pictures in Fig. 13, all parameters vary within 10 times of their range, and the influences on the cost are nearly the same.



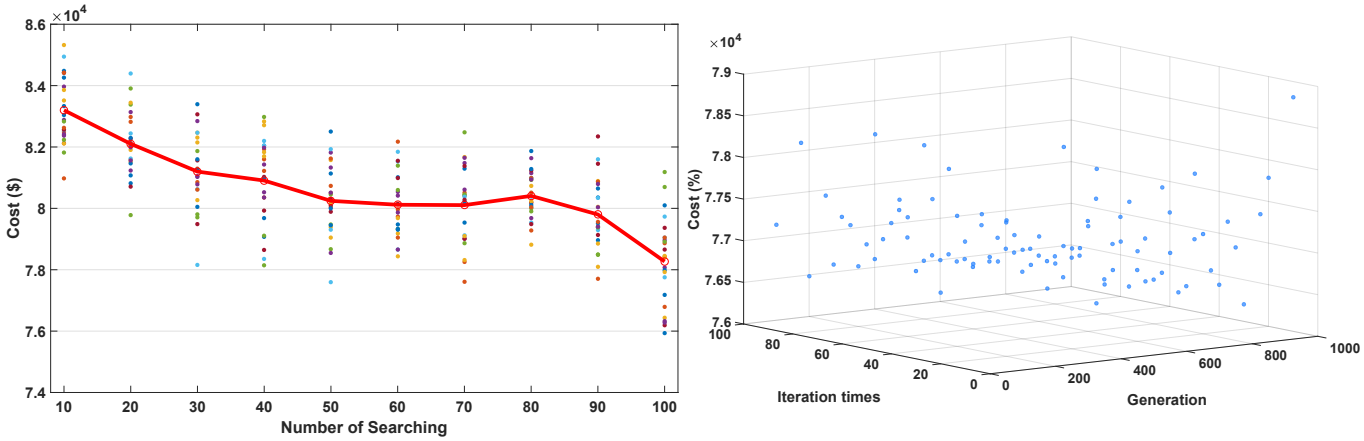


Fig. 13. The relationship curve between the simulation parameter and maintenance cost

2) *Effectiveness of the approach*

The effectiveness of the algorithm is verified by conducting analyses of the cost of maintenance routing with a fixed vessel allocation scheme. Utilizing the DWPS algorithm, the change in cost is proposed with the various unavailability and utilization of weather windows. As shown in Fig. 14, each point presents an optimal maintenance route with the fixed vessel allocation scheme, and the points are mainly concentrated in areas with better results. The approach provides a more intuitive method for decision makers to trade-off between the numerous indicators.

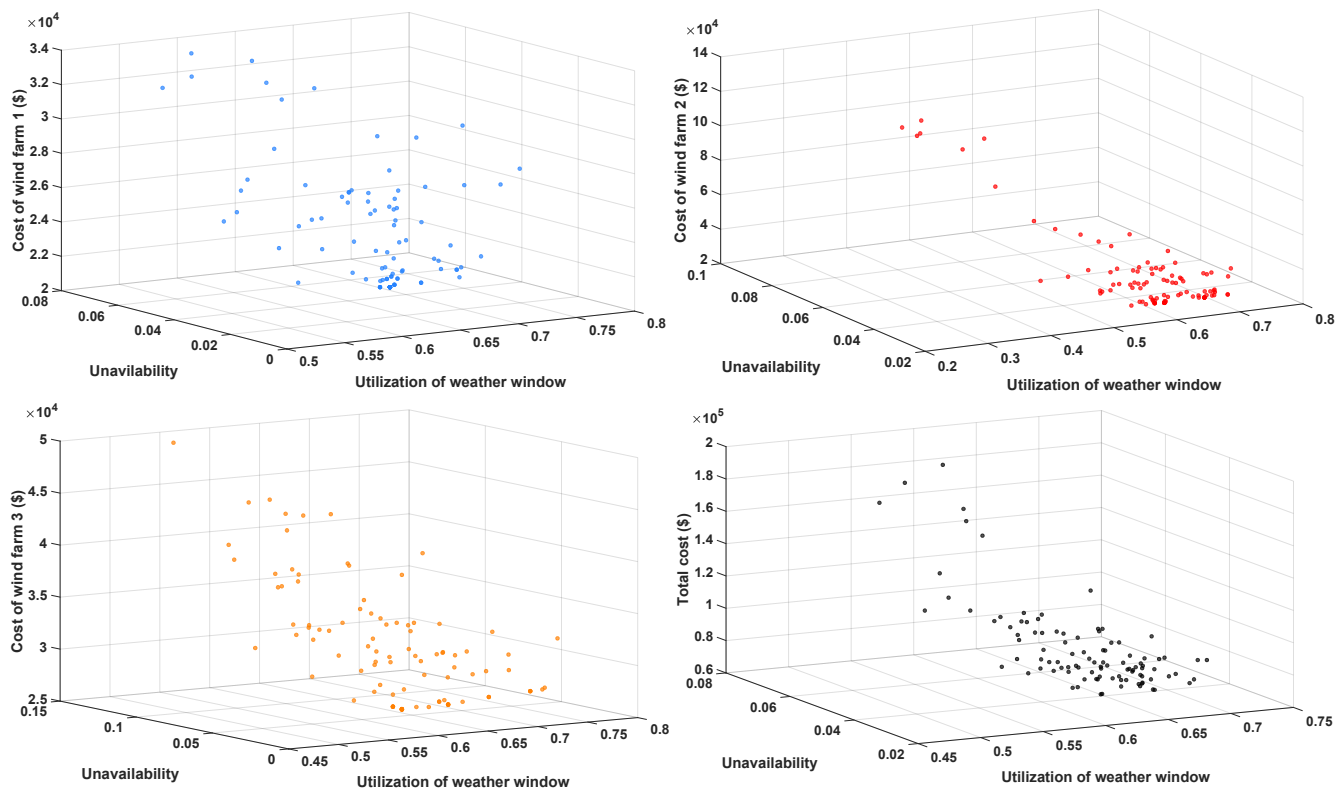


Fig. 14. The effectiveness of the approach

3) *Comparison with other approaches*

Owing the maintenance routing and scheduling for offshore wind farms is a NP-hard problem, the constraints play a critical role in the optimization of model. Present literatures have proposed several approaches to solve this problem, but none of the proposed approaches can cover all the characteristic like the range of time window, number of bases and wind farms, the closed/open route and the single/round trip, shown as Table X. With the advantage of MPSO and DWPS integrated, this manuscript can propose an open and multi-depot maintenance route to minimize the cost of O&M with the scheduling of vessel allocation and multiple round trips.

TABLE X
COMPARISON WITH SOME PREVIOUS WORKS REPORTED IN THE LITERATURE

Study	Method	Database	Characteristics				Computation Time/s	Cost/€
			Time window	Bases and wind farms	Routing	Round trip		

Zhang (2014)	Duo-ACO	Turbines: 8 Wind farm: 1 Period: 6	Continuous	Single	Closed	Single	--	9641.6
Akbari et al., (2017)	MILP	Turbines: 24 Wind farm: 3 Period: 7	Continuous	Multiple	Closed	Single	3465.71	41839.74
Dai et al., (2015)	Mathematical computation	Turbines: 8 Wind farm: 1 Period: 3	Continuous	Multiple	Closed	Single	10000	7606.13
Proposed Method	MPSO+DWPS	Turbines: 48 Wind farm: 3 Period: 7	Discrete	Multiple	Open	Multiple	5623.56	74633.68

5 Conclusion and Further Work

In this paper, a hybrid heuristic optimization technique of maintenance routing and scheduling for offshore wind farms is proposed. Integrated with MPSO and DWPS, the optimal vessel configuration is selected, and the maintenance routing is developed simultaneously to minimize the total cost comprising travel, technicians and penalty costs. The algorithm explores all combinations of turbines that are feasible for servicing in a period with a discrete time window and divides the optimization problem into two parts. Utilizing the MPSO, the relationships between the bases and wind farms are established, and the certain number of wind farms that the vessel will service is determined. Then, according to the open multi-depot VRP with a discrete weather window problem, the maintenance and delivery routes under the premise of a vessel scheduling plan can be proposed by DWPS. Ultimately, a numerical analysis with 3 wind farms and 3 bases is designed to verify the practicality of the approach. Based on the results and discussion, the approach proposed in the article has the capability of providing an optimal maintenance routing and scheduling plan with the lowest cost.

The main contributions of this paper are as follows: 1) to extend the routing and scheduling problem with discrete window time and consider several logistics bases and the possibility of servicing more than one wind farm with the same fleet; 2) to introduce the open and multi-depot VRP into maintenance routing and scheduling for offshore wind farms with pickup/delivery; 3) to propose a new hybrid heuristic optimization technique integrated with MPSO and DWPS to support the multiple round trips to the bases during maintenance. Meanwhile, there are many possible extensions to enhance the approach proposed in the article to make it more applicable to both offshore wind farms in operation and under development, such as the group or opportunistic maintenance scheduling, uncertainty and variability of the weather conditions.

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