Ocean Engineering 225 (2021) 108752

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

An optimization framework for daily route planning and scheduling of maintenance vessel activities in offshore wind farms

Iraklis Lazakis *, Shahroz Khan

Department of Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, Glasgow, G4 0LZ, United Kingdom

ARTICLE INFO

Keywords:
Offshore wind farm
Service operation vessel (SOV)
Crew transfer vessel (CTV)
Optimal route planning
Reduction of fuel consumption
Maintenance operation
Maintenance cost reduction

ABSTRACT

To increase energy production, offshore wind farms are currently installed far from shore, providing a challenge for vessels to undertake maintenance tasks from the designated hub port. Service Operation Vessels (SOVs) are utilized to carry out the offshore wind turbines maintenance tasks, which act as a servicing station having required technicians and daughter crafts (i.e. Crew Transfer Vessels (CTV)) onboard to facilitate on-time and on-demand servicing of wind turbines. This paper proposes an optimization framework, called OptiRoute, for daily or short-term maintenance operations based on route planning and scheduling while minimizing the cost under different operational constraints. Different heuristic and clustering techniques are developed and integrated to make the framework computationally effective. OptiRoute considers climate data, vessels specifications, failure information, wind farm attributes and cost-related specifics. The series of the overall operational tasks are divided into sequential sessions, including maintenance crew pick-up and drop-off tasks while the vessel routing optimization is performed for all sessions separately. OptiRoute reliability is tested by employing different Case studies while a user-friendly Graphical User Interface (GUI) is also developed to depict the various maintenance scheduling scenarios. Experimental results reveal that OptiRoute can efficiently increase the operational window especially when SOV and CTVs are used together.

1. Introduction

Recent advancements in the offshore wind turbine technology play a significant role in shaping the world economics and energy-dependent industries, thereby moving progressively towards greener energy resources. However, even with the rapid advancements towards efficient offshore wind turbine design, these are still not cost-effective compared to other renewable energy resources, such as solar energy (Güney (2019)), and are not affordable especially by the developing countries (Ghimire and Kim (2018)). This is not only due to the high manufacturing and installation cost of the turbines but also because of the associated high maintenance and operation cost, which accounts significantly in Case of offshore wind farms (Li et al. (2016)). In order to address this challenge, there have been many efforts put forward to develop efficient methods and digital frameworks for planning maintenance operations of offshore wind farms. However, the offshore wind sector is still lagging to effectively adopt and integrate these tools in their day-to-day operations mainly due to the inherent challenges to simulate realistic operational scenarios. Moreover, most of the current efforts and studies in this field focus on simulating the long-term life cycle operational and maintenance planning under the presence of strong assumptions (Hofmann (2011)).

Apart from the high cost, the ineffective planning of maintenance operations with large vessels like Service Operation Vessel (SOV) and Crew Transfer Vessels (CTV) can result in high fuel consumption leading to an increment of overall maintenance cost and more importantly, this also contributes towards the carbon footprint of the offshore wind farms. According to a study by Kaldellis and Apostolou (2017), the operational and maintenance activities may account up to 5–10% of the total greenhouse emissions throughout the life cycle of an offshore wind farm.

Therefore, the planning of the daily operations and maintenance work in an offshore wind farm is an essential but complex and challenging problem (Irawan et al. (2017)). One of the key factors that significantly affect the overall maintenance cost is the route planning and scheduling of the maintenance fleet to transport technicians and spare parts to each turbine requiring the maintenance work on a daily or short-term basis. In general, the main objective of the operational planning task is to provide an optimal maintenance vessel routing and a

* Corresponding author.
E-mail addresses: iraklis.lazakis@strath.ac.uk (I. Lazakis), shahroz.khan@strath.ac.uk (S. Khan).

https://doi.org/10.1016/j.oceaneng.2021.108752
Received 27 September 2020; Received in revised form 4 February 2021; Accepted 10 February 2021
Available online 5 March 2021

maintenance schedule for a particular day within the planning horizon for any type of maintenance activity, which is identified prior to the optimization. The optimization is carried out while minimizing the overall maintenance cost and maximizing the wind farm availability. Various factors/constraints affect the optimal planning of the maintenance activities within an offshore wind farm including weather conditions (such as significant wave height and wind speed), availability, type and size of maintenance vessels, failure type, maintenance crew, spare parts, etc. Once these constraints are taken into account, the decision has to be made on (1) type of vessels to be used to carry out the particular maintenance work and (2) the visiting sequence of the turbines by the vessels used during the suggested maintenance work.

Generally, in practice and for a particular day, the maintenance operation starts with a report indicating the list of turbines requiring maintenance or repair work. Then for each turbine and failure type, the number and type of technicians, spare parts and estimated time to complete the maintenance work are identified. Furthermore, the specific vessel type to carry out the maintenance work and visit the wind turbines, as well as the requirement for the vessel to stay in close proximity (or not) during the maintenance work, is also specified. Later on, taking into account the prevailing climate and other operational constraints, an operations department member of staff creates a transfer plan (Stock Williams and Swamy (2019)) and provides it to the maintenance team. The travelling sequence of the vessels visiting the various wind turbines is manually determined either before or during the maintenance work. If the vessel is required to stay close to the turbine during the maintenance work, its waiting/stand-by location is usually determined by the vessel captain. Stock-Williams and Swamy (2019) state that for 10 maintenance tasks there can be approximately 3.6 million possibilities for the creation of an operational plan. Therefore, manually planning of these activities can be extremely cumbersome and time-consuming.

There exist a substantial amount of literature work, which addresses this particular challenge either using optimization (Dai et al. (2015); Irawan et al. (2017); Stock-Williams and Swamy (2019)) or simulation (Abdollahzadeh et al. (2016); (Dalgic et al., 2015a–c); Li et al. (2016); Martin et al. (2016)) tools. The majority of the existing studies are simulation-based ones, simulating the maintenance operations for the entire life cycle of the wind farm. On the other hand, the routing optimization problem addressed in the literature is overwhelmingly complicated, which mostly results in high computational cost and local optimal solution (Laporte (2009)). However, to the best of the authors' knowledge, no existing optimization-based work reflects a complete realistic scenario on the usage of SOV, CTV or their combination for the daily route planning, also including an estimation of the vessels fuel consumption, which is one of the important economic advantages of the entire offshore wind farm's maintenance planning operation. Considering the complexity and criticality of the problem, there is a need for a computationally robust and effective operational planning framework. Therefore, the present study proposes the development of an optimal operational planning framework, *OptiRoute*, which provides, both on-board the ships and at the on-shore Operations and Maintenance base the capability to plan and assess offshore wind farm operations in advance based on optimal route planning, vessel positions, weather conditions as well as considering the expected fuel consumption and associated cost.

The main contributions of the present work include:

1. A novel optimal operational planning methodology based on the two types of vessels, SOV and CTV, used separately or combined.
2. A computationally effective heuristic optimization and cluster strategy for optimal daily or *short-term* route planning and scheduling under the presence of operational constraints.
3. Verification of the proposed framework under different operational scenarios.
4. Development and implementation of a User Graphic Interface (UGI) to depict above scenarios.

In the proposed framework, daily route planning and scheduling occur by considering five sets of input parameters related to the climate, maintenance fleet, wind farm, turbine failure and cost. A novel optimization and planning strategy is developed after carefully analyzing the currently practised operational planning at different wind farms, which is integrated into the proposed framework in order to provide a complete realistic daily route planning and scheduling of maintenance vessels. Furthermore, to make the framework computationally effective, the optimization problem is simplified by dividing the planning task for any particular day into two sessions; technician drop-off and pick-drop sessions. Then a k-mean clustering (Capó et al. (2017)) and iterative optimization (Kelley (1999)) based strategies are developed to ensure the usage of the optimum number of vessels and to effectively plan both sessions while satisfying the vessels' operational constraints.

In this respect, the present paper is structured as follows: section two demonstrates the related work and existing literature on the suggested issue in hand. Section three further elaborates on the novel proposed optimization framework of the daily route planning and scheduling of maintenance vessel activities in offshore wind farms. Section four presents the results and discussion on a number of different Case studies related to the above framework and finally, section 5 provides the final comments and suggestions for future work concluding the present paper.

2. Relevant literature

There are various efforts put forward by different researchers to address the operational challenge of offshore wind farms. As mentioned previously, existing studies can be broadly categorized into two categories: simulation-based ones ((Abdollahzadeh et al. (2016); (Dalgic et al., 2015a–c); Erguido et al. (2017); Li et al. (2016); Martin et al. (2016); Sarker and Faiz (2016); Wang et al. (2019); Zhang et al. (2019)), which simulate the operational planning of the entire life of the wind farm based on the predictive turbine failure and optimization based ones (Dai et al. (2015); Dawid et al. (2017); Gutierrez-Alcoba et al. (2019); Irawan et al. (2017); Raknes et al. (2017); Schrotenboer, uit het Broek, Jargalsaikhan, and Roodbergen (2018); Stålhane et al. (2015); Stock--Williams and Swamy (2019)), which try to optimize the maintenance scheduling problems for the predetermined preventive, corrective and condition-based maintenance tasks. In this section, we describe some of the current literature which focuses on the daily route planning and scheduling problem for offshore wind farms.

Recently, a metaheuristic optimization methodology was proposed by Stock-Williams and Swamy (2019) to determine strengths and weaknesses in any maintenance plan and provides an estimation on investment from implementation, which follows the analogy of the travelling salesman problem for route planning in an offshore wind farm. The authors argue that compared to heuristic and exact optimizers, metaheuristics are more flexible while they also are problem independent optimization techniques as it does not require any amendments in the optimizer itself with the change of objective. Therefore, compared to heuristic, these should be adopted to address the operational problem in offshore wind farms. However, due to their random search nature, metaheuristics do not ensure an optimal solution to the problem and require a large number of iterations to find a near-optimal solution, which makes them computationally expensive. In Dai et al. (2015), the authors proposed a mathematical model for vessel routing and scheduling problem of maintenance vessel for an offshore wind farm in order to determine the optimal routes from the maintenance port to the failed turbines to transfer the maintenance technicians. Optimization was performed using a commercial software Xpress optimizer and maintenance operation was performed with two different vessels. Recently, based on Dai's work, Irawan et al. (2017) proposed a maintenance operational planning method for multiple wind farms and the optimization problem was solved by using the mixed-integer linear programming. However, unlike the proposed framework, Dai et al. (2015) and Irawan et al. (2017) suggested the planning and initiation of the maintenance operations from the hub port. Moreover, he above maintenance works neither address the problem of specifically using SOVs and CTVs nor include the vessels stay and waiting time at the wind turbine location and process of performing a far or short-stay.

Stålhane et al. (2015) proposed two different optimization models, such as arc-flow, which is based on a commercial software using a branch-and-bound technique to solve the optimization, and the path flow, which used a heuristic-based method to generate an optimal subset of routes and schedules for the vessels. An Adaptive Large Neighborhood Search (ALHS) heuristic for the short term operational planning was proposed by Schrotenboer et al. (2018). ALHS optimizes the vessel routes for technician pick-up and delivery in order to investigate the technician sharing between different wind farms over multiple periods. A similar approach was also utilized by Raknes et al. (2017), however, instead of starting the maintenance work from the maintenance port, Raknes et al. (2017) have taken into account the vessel stay at the wind farm during multiple shifts.

A clustering-based heuristic algorithm was proposed by Dawid et al. (2017). In their approach, the failed turbines were first clustered, which were then sorted based on the total number of technicians required by the turbines in each cluster and a maintenance vessel was utilized in order to plan the maintenance operations in each cluster. Along with the operational planning and vessel scheduling, some authors (Stålhane et al. (2019)) have also integrated the optimization of the size and type of the maintenance fleet. However, along with the usage of SOVs and CTVs, none of the aforementioned works incorporates the different operation modes of the maintenance vessels, such as fast transit, transit and dynamic positioning mode. Moreover, most of the existing works use commercial optimizers which also limits their usage.

Apart from the specific optimization-based approaches maintenance operation and route planning is also performed based on the human factors, for instance, a hybrid human error assessment and reduction technique is proposed by Islam et al. (2020) to estimate human error probability (HEP) for marine and offshore systems. A data-driven study was performed by Musharraf et al. (2020), which used a decision tree algorithm to create a set of decision rules. These rules were then used to describe how people use different attributes of emergency scenarios to choose an egress route. Furthermore, similar to the concept of SOV, Rahman et al. (2020) developed an Offshore Resource Centre (ORC), which acts as a service station at sea and carries anything required for short- and long-term maintenance including technicians and materials. This enables the maintenance operations to be carried out quickly and effectively, thereby increasing the offshore wind farm productivity. Here the concept of ORC is proposed in a more generic form and in a broader sense have risk reduction objectives to provide an intermediate point for helicopters and also provide forward staging or response asset for an emergency. In another recent study, Rahman et al, Colbourne, and Khan (n.d.) also performed a risk-based cost-benefit analysis of the ORC.

3. Proposed framework

In this section, the algorithmic detail of OptiRoute will be first introduced. After describing the basic terminologies, the proposed mathematical model for daily route planning with SOV and CTV in line with the cluster and optimization techniques and OptiRoute's user interface will be introduced.

Fig. 1 shows the workflow of OptiRoute with its inputs and outputs. The overall optimization workflow of the proposed framework, considers four different sets of input parameters such as the climate, vessel specifications and fleet configuration, wind farm attributes, the turbines failure attributes and cost. These inputs are then processed during an optimization process in order to optimize the daily routing of SOVs and CTVs so as to plan the maintenance tasks for the failed wind turbines. The whole operational task is completed with multiple SOVs, CTVs and/or combination of both. Based on the inputted data, the framework starts the optimization process with the objective to minimize the fuel consumption and maximize the wind farm availability, while using the least number of maintenance vessels.

3.1. Basic terminology and problem description

Let a wind farm $\mathscr{W}$ consist of N wind turbines. On a particular day there exist a set $\mathscr{J}$ of n turbines requiring maintenance work, which we shall call as failed turbines (i.e. $\mathscr{J} = \{J_j, j = 1, 2, \ldots, n\} \subset \mathscr{W}$). The

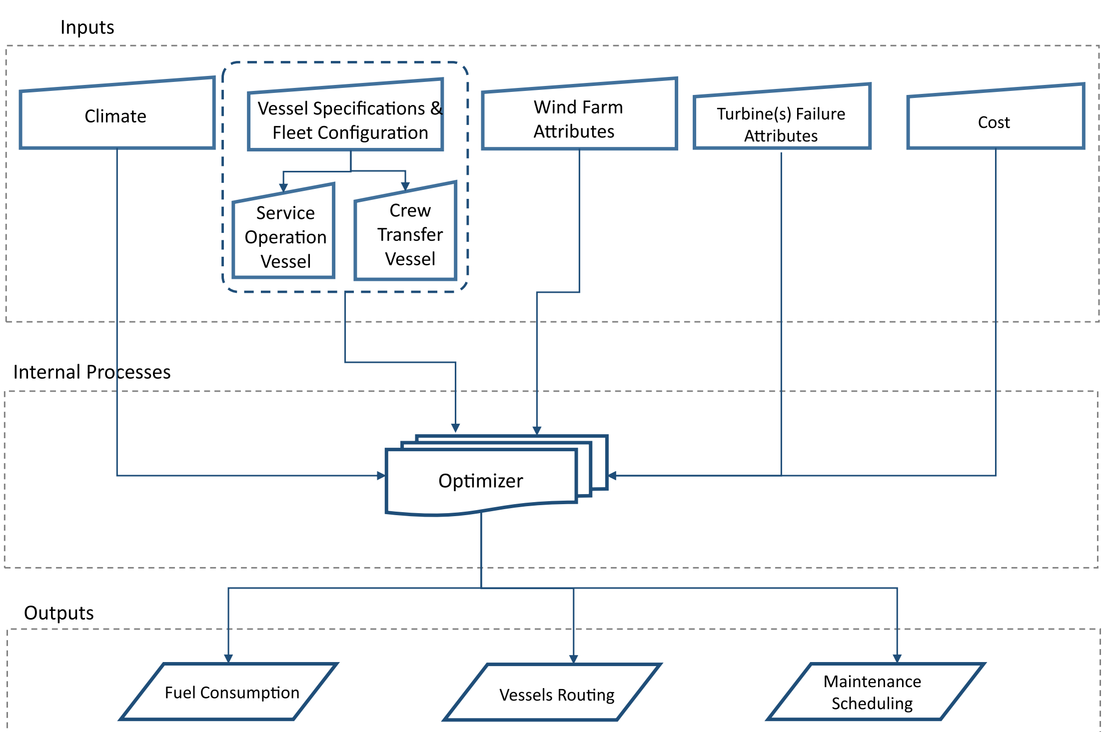

Fig. 1. Proposed OptiRoute framework workflow.

objective for the proposed framework is to complete the maintenance work for $\mathscr{J}$ within the planning horizon using a single or multiple SOVs ($\mathscr{V}^{sov} = \{V_v^{sov}, v = 1, 2, \ldots, n_{sov}\}$), CTVs ($\mathscr{V}^{ctv} = \{V_v^{ctv}, v = 1, 2, \ldots, n_{ctv}\}$) or combination of both, while minimizing the total distance travelled (D_{total}) and fuel consumption (F_{total}), thereby minimizing the overall operational cost. Furthermore, to complete the maintenance work within the planning horizon, the total time (T_{total}) taken to complete the maintenance work should be less than or equal to the available weather window.

To start the route planning and scheduling for $\mathscr{J}$, the framework requires a set of user specified input parameters $\mathbf{I} = \mathscr{I}^e \cup \mathscr{I}^v \cup \mathscr{I}^w \cup \mathscr{I}^{\mathscr{J}} \cup \mathscr{I}^c$ associated with the weather ($\mathscr{I}^e = \{I_1^e, \ldots, I_4^e\}$), maintenance vessels ($\mathscr{I}^v$), wind farm ($\mathscr{I}^w = \{I_1^w, \ldots, I_4^w\}$), failed turbines ($\mathscr{I}^{\mathscr{J}}$) and fuel cost ($\mathscr{I}^c$). For each turbine in $\mathscr{J}$, the framework requires a separate subset of input parameters such as $\mathscr{I}^{\mathscr{J}} = \{I_i^J, i = \{1, 2, \ldots, 8\}, \forall J \in \{1, 2, \ldots n\}\}$. Moreover, if multiple SOVs or CTVs are considered to be utilized then the framework considers that all the SOVs and CTVs are of similar characteristics and requires vessel specification parameters for SOV ($\mathscr{I}^{sov}$) and CTV ($\mathscr{I}^{ctv}$) separately (i.e. $\mathscr{I}^v = \mathscr{I}^{sov} \cup \mathscr{I}^{ctv}$). After defining $\mathscr{J}$, the framework first creates two sets of turbines $\mathscr{J}_{sov}$ and $\mathscr{J}_{ctv}$, each one is a subset of $\mathscr{J}$ (i.e. $\mathscr{J}_{sov}, \mathscr{J}_{ctv} \subset \mathscr{J}$) containing the turbines which are required to be serviced by $\mathscr{V}^{sov}$ and $\mathscr{V}^{ctv}$, respectively.

During the simulation, the framework finds an optimal travelling sequence for $\mathscr{V}^{sov}$ and $\mathscr{V}^{ctv}$ to serve $\mathscr{J}$ while taking into account the operational constraints and minimizing the overall fuel consumption in litres, thereby, minimizing the overall distance travelled by vessels and increasing the weather window. Fig. 2 illustrates the route planning of the maintenance vessels using the proposed framework. As discussed earlier, the proposed optimization framework is used for daily and short-term planning and scheduling of maintenance work. In this respect, it is assumed that the user/operator is already aware of the specific failure type, therefore, similar to (Gutierrez-Alcoba et al. (2019); Raknes et al. (2017); Stock-Williams and Swamy (2019)) no specific failure model is directly integrated within the proposed framework.

The optimization process for route planning commences by sorting the turbine based on their distance from the current location of the maintenance vessels, which can be either in port or at standby location. Instead of considering distance as an input, the proposed framework considers the locations of turbines (J), maintenance hub port (R) and standby positions (S) of SOV as longitudinal (P_{lon}) and latitudinal (P_{lat}) coordinates ($i.e.\mathscr{P} = \{\mathscr{P}^L = \{P_{lat}^L, P_{lon}^L\}, \forall \in \{J, R, S\}\}$). The Haversine Distance Formula (HDF) Bradley (1942) was utilized to precisely calculate the distance between turbines, port and standby positions. Therefore, the location of a j^{th} turbine in $\mathscr{J}$ is represented using longitudinal P_{lon} and latitudinal P_{lat} coordinates i.e. $\mathscr{P}^J = \{\mathscr{P}^{J_j} = \{P_{lon}^{J_j}, P_{lat}^{J_j}\}, \forall j \in \{1, 2, \ldots n\}\}$ and the Haversine distance $D(\mathscr{P}^{J_p}, \mathscr{P}^{J_q})$ between two failed turbines J_p and J_q is measured using Equation (1), where $\mathscr{P}^{J_p}$ and $\mathscr{P}^{J_q}$ represents the position of J_p and J_q, respectively.

$$\Delta P_{lat} = P_{lat}^{J_p} - P_{lat}^{J_q}$$

$$\Delta P_{lon} = P_{lon}^{J_p} - P_{lon}^{J_q} \tag{1a}$$

$$\Omega = \sin^2\left(\frac{\Delta P_{lat}}{2}\right) + \cos\left(P_{lat}^{J_p}\right) \times \cos\left(P_{lat}^{J_q}\right) \times \sin^2\left(\frac{\Delta P_{lon}}{2}\right)$$

$$\lambda = 2 \times \operatorname{atan2}\left(\sqrt{\Omega}, \sqrt{1-\Omega}\right) \tag{1b}$$

$$D\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right) = \Omega \times \lambda \cdot (3) \cdot \tag{1c}$$

HDF measures the great-circle distance (in meters m) between two points using their longitudes and latitudes, which is the shortest distance over the earth surface. Unlike other distance formulas, such as the spherical law of cosines (Banerjee (2004)), the HDF is well-conditioned even for the numerical computation of small distances. As in reality, the voyage of a vessel between two turbines is not performed in a straight line, therefore, a contagious factor η of the percentage of overall distance travelled by vessels was also added to induce the effect of curvy motion of the maintenance vessels while travelling among the turbines. So, the curvy Haversine distance between J_p and J_q is measured using Equation (2)

$$D\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right) = \Omega \times \lambda \times \left(1 + \frac{\eta}{100}\right) \tag{2}$$

The time taken (in hours h) and vessels' fuel consumed (in litres lt) to travel between J_p and J_q is calculated using Equations (3) and (4).

$$T\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right) = \frac{D\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right)}{S_o} \tag{3}$$

$$F\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right) = T\left(\mathscr{P}^{J_p}, \mathscr{P}^{J_q}\right) \times F_o \tag{4}$$

where S_o and F_o is the vessel speed in meter per hours (m/h) and fuel consumption in litre per hours (l/h) at fast transit (o_1), transit (o_2) and dynamic position (o_3) operational mode (i.e. $S_o, F_o \in \{o_1, o_2, o_3\}$), which will be discussed in detail later in this section.

3.2. Framework input parameters

As described in the previous section the suggested optimization framework considers a set of input parameters such as the weather, maintenance fleet, wind farm, turbine failure and cost. Below, we give a

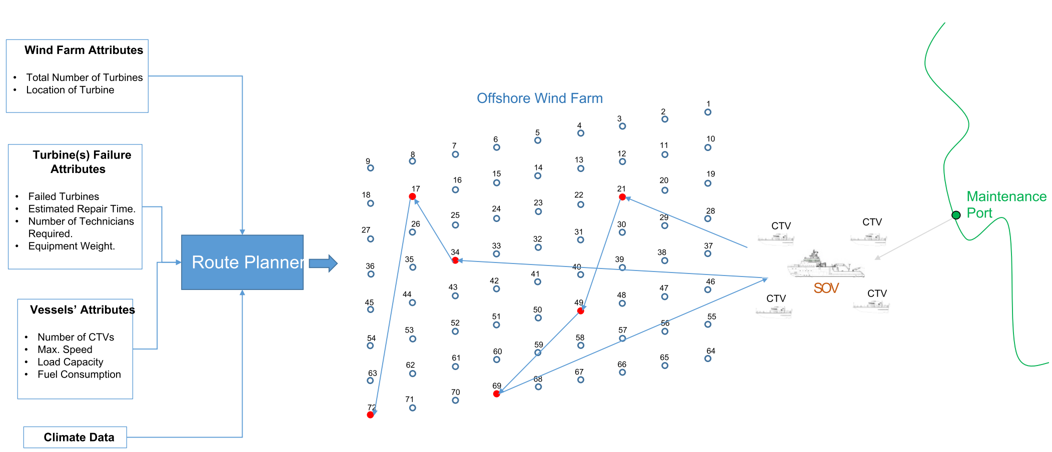

Fig. 2. Illustration of route planning with maintenance vessels under the given input parameter sets.

brief description of each set of input parameters.

3.2.1. Climate inputs ($\mathscr{I}^e$)

For the climate inputs, there is a single weather window per day for maintenance vessels. Therefore, significant wave height and average wind speed with at least a minute resolution for the whole day are taken into account. To start the maintenance work, the predicted average wind speed and significant wave height must be lower than the maximum operation wind speed and significant wave height of the vessels. The starting time of the maintenance work is also essential to initiate the optimization process. If this time is not provided then the sunrise time is considered as the start time of the maintenance work. Furthermore, if the average significant wave height and wind speed are less than the vessels maximum limit for the whole day, then the weather window is considered as the one between maintenance work's start time and sunset time. The weather window also reflects the best time to carry out the maintenance work as it is particularly related with good accessibility to the turbine. Table 1 provides a set of input parameters associated with climate.

3.2.2. Turbine failure inputs ($\mathscr{I}^J$)

The daily planning of the maintenance work requires the identification of failed turbines to be served on a particular day. Therefore, the main input required by the framework is the turbine failure information, which contains the set of turbines ($\mathscr{J}$) needed to be maintained on any particular day; type of vessel used to perform maintenance work; the number of technicians required to complete the maintenance work (I_1^J); vessels' stay information at the turbines; predicted total time it takes to complete the maintenance work; etc. For each failed turbine in $\mathscr{J}$, a set of the input parameter, shown in Table 2, are essential for the framework to plan the vessels' optimal routing. Moreover, the total repair time for a turbine includes time taken by the technician to (1) reach the turbine, (2) finish the maintenance work and (3) test the turbine.

Here, it is noteworthy that the equipment weight and the number of technicians are considered as operational constraints while planning the maintenance operations with CTVs. These will be only taken into account by the framework if the user selects to employ a CTV for the whole operational planning task or a set of turbines.

In the proposed framework, the decision on the selection of the vessel for a turbine is made by the user. However, it is recommended to use SOV for a turbine if it requires an equipment replacement, which weights more then the CTV's load-carrying capacity or if the type of the failure associated with the turbine is of major failure, which requires long repair time and more number of technicians.

Another important parameter that greatly affects the operational planning is the identification of whether the vessel is required to be present at the turbine during the maintenance operation. From the daily maintenance planning of real Case studies of an existing wind farm, it was observed that after delivering the technicians, a vessel may perform either a near-stay (i.e. staying close to the turbine) or a far-stay (i.e. staying at a specified location far from the turbine but close to the wind farm). Therefore, to represent a more realistic scenario, if the vessel stays at the turbine then the framework considers the type of stay (near-stay or far-stay) for each turbine. The near-stay location of the vessel is represented as a measure of its overall unit length. On the other hand, if far-stay is chosen then the location of this needs to be inputted as well.

Table 1
Set of input parameters related to the climate data required during the optimization process.

No	Parameters	Notation	Description	Units
1	Average Significant Wave height	I_1^e	Average significant wave height on a particular day with minimum minute resolution	m
2	Average Wind Speed	I_2^e	Average wind speed on a particular day with minimum minute resolution	m/s
3	Sun-rise time (Maintenance start time)	I_3^e	Sun-rise time on the particular day (Time maintenance work will start)	$hh:mm$
4	Sunset time (Maintenance end time)	I_4^e	Sunset time on the particular day (Time at which maintenance work should be completed and vessels come back to port or standby location)	$hh:mm$

Table 2
Set of input parameters related to the failed turbines requiring maintenance.

No	Parameters	Notation	Description	Unit
1	Required Technicians	I_1^J	Number of technicians required to complete the maintenance work	*persons*
2	Equipment Weight	I_2^J	Weight of the spare parts or maintenance equipment	*kg*
3	Required Repair Time	I_3^J	Total time required to complete the maintenance work for each turbine	$hh:mm$
4	Transport Means	I_4^J	Vessel type required to carry out the maintenance jobI_5^J	*vessel*
5	Vessel Stay at Turbine		Turbine requirement for the vessel to stay close to the turbine during maintenance work	N/A
6	Vessel Stay Type	I_6^J	Indication if the vessel will stay far away from the turbine	N/A
7	Vessel Far Stay Location	I_7^J	Location of the vessel	*latitude&longitude*
8	Vessel Short Stay Location	I_8^J	Location of the vessel equal to its unit length	*latitude&longitude*
9	Failure Type	I_9^J	Failure type of the turbine (minor or major)	*failure*

3.2.3. Vessel specification inputs ($\mathscr{I}^v$)

Another set of critical inputs are related to the maintenance vessels' specifications. As the operational planning is performed using SOV and CVT, so the specification for these two vessel types is required as input as well.

Offshore support vessel (I^{sov}): Table 3 shows the input related to SOVs specifications. In the current study, it is considered that there is only one SOV available, however, the framework can be used with multiple SOVs in order to increase the weather window. For an SOV, three different operational modes/tasks are considered: fast transit, transit and dynamic positioning. These tasks are segmented based on the SOV's operational speed and fuel consumption. During the development of the proposed framework, it was observed that the SOV is on fast transit task while moving outside the wind farm and it is on the transit task while travelling within the wind farm. The dynamic position mode of the vessel is also included, which is only used when SOV approaches towards the turbine to deploy the gangway to transfer technicians and equipment to the wind turbine. This mode is also used when SOV requires to perform a near-stay at the turbine.

Crew Transfer Vessel (I^{ctv}): Inputs related to the CTVs are shown in Table 4. As mentioned before, in an offshore wind farm, SOV act as a service platform and CTVs are launched from SOV if they are required to be utilized during the maintenance work within the wind farm. Therefore, the maintenance work starting location for the CTVs is the same as for the SOV's. Moreover, in the Case of CTVs, the technician and equipment carrying capacity of CTV are considered as operational constraints.

Table 3
Set of input parameters related to the performance attributes of service operation vessels.

No	Parameter	Notation	Description	Unit
1	Number of SOVs	I_1^{sov}	Number of SOVs available at the present day	*vessel*
2	Max. Significant Wave Height	I_2^{sov}	Limiting significant wave height for the SOV	*m*
3	Max Wind Speed	I_3^{sov}	Limiting wind speed for the SOV	m/s
4	Available Technicians	I_4^{sov}	Total number of technicians available at SOV to perform the maintenance work	*persons*
5	SOV's Available Hours	I_5^{sov}	Number of hours SOV is available for the maintenance work at the present day	$hh:mm$
6	Avg. DP and Technician Transfer Time	I_6^{sov}	The average time is taken by SOV to approach turbine during the DP mode, to deploy the gangway and to transfer the technicians	$hh:mm$
7	Transient Speed	I_7^{sov}	Speed of the SOV within the wind farm	*kn*
8	Fast Transient Speed	I_8^{sov}	Speed of the SOV outside the wind farm	*kn*
9	Transient Task Fuel Consumption	I_9^{sov}	SOV fuel consumption during the transit task	lt/hr
10	Fast Transient Task Fuel Consumption	I_{10}^{sov}	SOV fuel consumption during the fast transit task	lt/hr
11	DP Fuel Consumption	I_{11}^{sov}	SOV fuel consumption during at the DP mode	lt/hr
12	SOV Current Location	I_{12}^{sov}	Location of SOV before the start of maintenance work	*latitude&longitude*
13	SOV Maintenance End Location	I_{13}^{sov}	Location of SOV after finishing the maintenance work	*latitude&longitude*

Table 4
Set of input parameters associated to the performance attributes of crew transfer vessels.

No	Parameter	Notation	Description	Units
1	Number of CTVs	I_1^{ctv}	Number of CTVs available at the present day	*vessel*
2	Max. Significant Wave Height	I_2^{ctv}	Limiting significant wave height for the CTV	*m*
3	Max Wind Speed	I_3^{ctv}	Limiting wind speed for the CTV	m/s
4	Technicians Capacity	I_4^{ctv}	Maximum number of technicians CTV can take on board	*persons*
5	Component Capacity	I_5^{ctv}	Maximum component carrying capacity of CTV	*kg*
6	Technician Transfer Time	I_6^{ctv}	Average time taken by CTV to transfer the technicians	$hh:mm$
7	Transient Speed	I_7^{ctv}	Speed of the CTV within the wind farm	*kn*
8	Fuel Consumption	I_8^{ctv}	CTV fuel consumption during the transit task	lt/hr

3.2.4. *Offshore wind farm inputs* ($\mathscr{I}^w$)

The framework takes into account the location of the turbines, port and SOV standby location as longitudinal and latitudinal coordinates. Table 5 shows the input parameters related to the wind farm and vessel locations.

Table 5
Input parameters associated with the offshore wind farm having turbines requiring maintenance operations.

No	Parameter	Notation	Description	Units
1	Number of Turbines	I_1^w	Number of turbines in the offshore wind farm	*turbines*
2	Turbines Location	I_2^w	Location coordinates of each turbine in the wind farm	*latitude&longitude*
3	Port Location	I_3^w	Location coordinates of the maintenance port	*latitude&longitude*

3.2.5. *Cost input* ($\mathscr{I}^c$)

As the framework optimizes the operational work while minimizing the total distance and fuel consumption, therefore, only cost associated inputs for the framework is the costs of the SOV and CTV engine fuel (Table 6).

3.3. *Maintenance planning with SOV*

To simplify the operational planning problem, the whole planning task is partitioned into two sessions; drop-off and pick-up sessions. Drop-off session begins when the SOV leaves the port or its standby location and ends when the technicians are dropped-off at the last turbine, only if the last turbine does not require SOV to stay. However, if the last turbine requires SOV to stay then the drop-off session finishes after SOV completes the near- or far-stay for the last turbine. After the drop-off session, the pick-up session begins, which includes route planning to pick up the technicians from the turbines. This session is planned excluding the turbines which require SOV to stay. This session ends when the SOV reaches the inputted standby location. The optimization is performed separately for both sessions and the fuel consumption, cost and overall time taken to complete the maintenance work is the sum of both drop-in and pick-up sessions. The pseudo-code of this heuristic route planning approach using SOV is provided in Algorithm 1 and explained below.

Before planning any of the two sessions, the framework first checks if average significant wave height and average wind speed are less then the vessels' limiting significant wave height and average wind speed ($I_1^e < I_2^{sov}$ and $I_2^e < I_3^{sov}$). If this condition is satisfied then the framework first starts planning the drop-off session. In drop-off session, first, the framework identifies the present location of SOV, which can be either at port or standby $\mathscr{P}^L, L \in \{R, S\}$. Afterwards, a turbine (J_a) having the minimum distance from $\mathscr{P}^L$ is identified. It is placed first in the travelling sequence ($\mathscr{T}_{sov}$) of SOV and eliminated from $\mathscr{J}_{sov}$ if it requires to stay at the turbine. So during maintenance planning, this turbine will be visited first. This was done in order to take into account the SOV's different operating mode (i,e. o_1, o_2 and o_3). Outside the wind farm, the SOV performs a fast transit task (i.e. to travel from port/standby location to J_a) and inside the wind farm, the SOV employs the transit task, which is considered when the SOV travels among the turbines. As the SOV has different operational speed at these modes, therefore, the fuel consumption, the time taken to travel and the overall cost are different at these modes as well.

As stated before, it was observed from a real scenario of an existing wind farm that when the SOV is required to stay at the turbine, it either stays somewhere near the turbine or at a specific location, which is far from the turbine but close to the wind farm. The SOV waits at these

Table 6
Cost associated input parameters required by the purposed framework to calculate the cost of the fuel consumed during the maintenance planning.

No	Parameter	Notation	Description	Unit
1	SOV Fuel Cost	I_1^c	Present day cost fuel used by SOV	$\$/lt$
2	CTV Fuel Cost	I_2^c	Present day cost fuel used by CTV	$\$/lt$

locations to pick up the technicians before travelling to other turbines. As mentioned in subsection 3.2.2, to include this behaviour of the SOV, the framework takes two further inputs by the user. The SOV is required to stay at a turbine then the user has to identify whether it will be staying close or far from the turbine. These two scenarios are categorized as near-stay and far-stay by the framework. For near-stay, the SOV stays at a distance equal to one unit of the overall length, which is industry standard. It is noteworthy that to move at this distance, the framework takes into account the dynamic positioning mode and calculates the fuel consumption based on this mode. Whereas, if the SOV has to perform a far-stay waiting then the user is required to input the location co-ordinates where the SOV will stay during the maintenance work of that turbine. In this Case, the fuel consumption for the SOV to travel to this location is calculated based on the transit task.

Algorithm 1. The pseudo-code of route planning algorithm using SOV

Algorithm 2. The pseudo-code of pick-up session planning for SOV

If the time taken by the SOV to travel to the far-stay location is more than the total repair time required by the turbine (i.e. $I_3^{J_a} < 2 \times T(I_7^{J_a}, \mathscr{P}^{J_a})$) then it is recommended to select the near-stay waiting option instead of the far-stay one. Moreover, to increase the operational window, SOV leaves the far-stay location before the maintenance work is finished. For instance, consider that the maintenance work at a particular turbine finishes at 13:00 h and it takes the SOV half an hour to reach to that turbine from its far-stay location. Then the SOV will leave the far-stay location at 12:30 h to pick up the technicians so that it reaches the turbine on time. This option increases the operational window to a substantial amount. The waiting time $T_{sov}^{J_a}$ for the SOV at J_a during the far-stay ($I_7^{J_a}$) or near-stay ($I_8^{J_a}$) is equal to

$$I_3^{J_a} - 2 \times T\left(I_7^{J_a}, \mathscr{P}^{J_a}\right) \quad \text{or} \quad \mathrm{I}_3^{J_a} - 2 \times \mathrm{T}\left(\mathrm{I}_8^{J_a}, \mathscr{P}^{J_a}\right), \tag{5}$$

respectively, which is the turbine's total repair time ($I_3^{J_a}$) minus twice the time taken by the SOV to reach the stay locations. If J_a requires vessel to stay, then time taken to complete the maintenance work for J_a is the sum of time taken by the SOV to travel to J_a ($T(\mathscr{P}^L, \mathscr{P}^{J_a})$); time taken to perform far or near-stay ($T(I_7^{J_a}, \mathscr{P}^{J_a}$ or $T(I_8^{J_a}, \mathscr{P}^{J_a})$; waiting time $T_{sov}^{J_a}$; and twice of average dynamic position and crew transfer time I_6^{sov}. After approaching close to a turbine, the SOV then uses its dynamic positioning mode to get close to the turbines and deploys the gangway to transfer the technicians. Afterwards, it un-deploys the gangway and retreats from the turbine using again its dynamic positioning mode. Therefore, I_6^{sov} includes, time to approach and retreat from the turbine; to deploy and un-deploy the gangway and to transfer the technicians.

After identifying the first turbine, SOV is set on the transit mode (o_2) and the travel sequence for the rest of the turbines is planned. All the remaining turbines are enumerated again based on the distance from the first turbine under the transit mode. From this enumeration, a turbine (J_b) having minimum distance is selected and placed second in the travelling sequence $\mathscr{T}_{sov}$. Similar to J_a, based on the vessel stay requirement for J_b, travel time and time taken to complete the maintenance work and accordingly, fuel consumed to reach this turbine is calculated. Similarly, the travel sequence of all the turbines in $\mathscr{J}_{sov}$ is identified for the drop-off session. The total time taken by the SOV during the drop-off session is the sum of travel time from initial SOV location to and between the turbines; time taken to reach the far or near-stay locations; and the total repair time of the turbines, which require for the vessel to stay. After completing the drop-off session, optimal planning for the pick-up session is carried out.

During the pick-up session, the first turbine is the one that is visited last during the drop-off session. Similar to drop-off, all the combinations of travel patterns between the remaining turbines were enumerated and the combination which gives the lowest fuel consumption and satisfies all the constraints is selected. During this process, the turbines requiring SOV to stay are eliminated. It is also noteworthy that SOV starts the pick-up session only when all the turbines have completed the maintenance work. As the prime objective for the framework is to minimize the fuel consumption, however, it will be significantly increased if the SOV travels to the turbines which finish the maintenance work early. If all the turbines require the SOV to stay then no pick-up session will be planned and the SOV will go back to its inputted standby location after picking-up the technicians from the last turbine.

If after finishing the drop-off and pick-up session, the total time to complete the maintenance works increases the available weather window (or exact time at which maintenance work finishes T_M is higher than the inputted maintenance work finish time I_4^e) then a different heuristic strategy is adopted to increase the available weather window. In this technique, a set of failed turbines $\mathscr{J}_{sov}'$ is determined for those maintenance works that can be finished within the specified time, where $\mathscr{J}_{sov}' \subseteq \mathscr{J}_{sov}$. The pseudo-code of this technique is provided in Algorithm 3.

In this technique, if $T_M > I_4^e$ then all the turbines in $\mathscr{J}_{sov}$ are first sorted based on the distance from I_{12}^{sov}. The first turbine in the sorted set of $\mathscr{J}_{sov}$ is removed and inserted to $\mathscr{J}_{sov}'$, which is then inputted to Algorithm 1 along with $\mathscr{J}$. If T_M for the first turbine is less than I_4^e, then it is taken as the first turbine in the travelling sequence. Otherwise, the second turbine is removed and inserted to $\mathscr{J}_{sov}'$. This process is repeated for all the n turbines until a turbine satisfying the condition $T_M < I_4^e$ is identified. If no turbine satisfies this condition then the framework indicates that no turbine can be completely maintained at the present day. Afterwards, the remaining turbines in $\mathscr{J}_{sov}$ are sorted based on the previously selected one and closest one is added to $\mathscr{J}_{sov}'$. At this stage, there are two turbines in $\mathscr{J}_{sov}'$, which is inputted to Algorithm 1 to calculate T_M. If $T_M > I_4^e$ then that turbine is eliminated from $\mathscr{J}_{sov}'$ and another closest one is added to it. Similarly, this process is repeated until there are no turbines left in $\mathscr{J}_{sov}$.

Algorithm 3. The pseudo-code of route planning algorithm using SOV when all turbines cannot be maintained within a single weather window

3.4. Maintenance planning with CTV

The operational planning for CTVs is carried in a similar way as for the SOV. The main difference compared to the operational planning of SOV is that the number of available CTVs can be much higher. Along with the weather window, there are constraints on the number of technicians that a CTV can carry and on the weight of the equipment (or spare parts). Moreover, during operational planning, the framework prefers to use less number of CTVs, instead of using multiple CTVs. The initial location for CTVs to start the operational work is the SOV as CTVs are launched from there. The pseudo-code for route planning of CTVs is shown in Algorithm 4.

During the drop-off session planning, the total number of technicians H_{total} required by the turbines $\mathscr{J}_{ctv}$ which will be visited by the CTV is calculated first. If H_{total} is higher than the technician capacity (I_1^{ctv}) of the CTV then it performs multiple journeys to and from the SOV to deliver the technicians in multiple journeys. However, the number of these journeys should be kept to a minimum number. Therefore, a heuristic approach is proposed to perform route planning for CTVs, while ensuring a minimum number of CTV journeys and the optimal number of technicians in its every journey. In each trip, the CTV has to carry a precise number of technicians that will be delivered to respective turbines.

In Case of $H_{total,} > I_1^{ctv}$, to decide the number of trips and technicians in each trip, the proposed framework first sorts the $\mathscr{J}_{ctv}$ based on the distance from I_{12}^{sov}. In the first trip ($t = 1$), CTV carries $h_1 = I_1^{ctv}$ technicians and goes to the first turbine J_a in $\mathscr{J}_{ctv}$ if the number of available technicians on the CTV is greater or equal to the technicians required by

J_a ($I_1^{J_a}$) then this turbine is placed first in the travelling sequence f_1, which is also eliminated from $\mathscr{J}_{ctv}$. Otherwise, this turbine is ignored for this trip and the CTV will move to the next neighbouring turbine. Now $h_1 - I_1^{J_a}$ technicians are being left in the turbine. Afterwards, the turbine in $\mathscr{J}_{ctv}$ are again sorted based on distance J_a and the CTV visits the first turbine and if available at the CTV, required technicians are dropped-off at the turbines. Similarly, this process is repeated for all n turbines.

If after visiting all the turbines, there are technicians left on the vessel (i.e. $h_1 > 0$) then the aforementioned process is repeated but this time CTV carry $h_1 = I_1^{ctv} - 1$. If no technicians are left then $h_1 = I_1^{ctv} - 1$ technicians CTV will carry its first trip. Later, the CTV will go to the SOV to pick up the required number of technicians for the remaining turbines and f_2 travel sequence will be planed. insert.

3.4.1. Clustering strategy

If multiple CTVs are available for the particular day and if the overall time taken (T_M) by a single CTV to complete the maintenance work is more than the inputted time (I_4^e) then the k-means clustering technique (Capó et al. (2017)) is utilized to divide the turbines into groups/clusters based on their distances from the SOV. For each cluster, a CTV is utilized to accommodate the turbines but the total number of clusters cannot be more than the number of available CTVs.

First, the turbines to be maintained are divided into two clusters of turbines using k-means clustering and for each cluster Algorithm, 4 is utilized. If the T_M for any of the set is greater then I_4^e the number of clusters φ is increased by one and again Algorithm 4 is run for each cluster. φ continue increasing until for all clusters $T_M > I_4^e$. However, when φ gets equal to the total number of available CTVs and there also exists a cluster for which $T_M > I_4^e$, then planning of that cluster is performed using a technique similar to Algorithm 3. The pseudo-code of the clustering techniques is presented in Algorithm 5.

Algorithm 4. The pseudo-code of route planning algorithm using a single CTV

3.5. Maintenance planning with combined SOV and CTV

The framework can also be used to plan maintenance operations using both SOV and CTVs. In this Case, the user is required to indicate the type of vessel which will be used to serve the turbine. The framework first creates the two sets of turbines, one for SOV and one for CTV and route planning for both sets is performed separately. It was observed during the experimentation that operational window increases when SOV and CTV are used together.

Algorithm 5. The pseudo-code of route planning algorithm using multiple CTVs

3.6. User-interface of OptiRoute

A Graphical User Interface (GUI) was also developed based on the proposed techniques using the C++ programming language and the Microsoft Visual Studio platform. The GUI consists of a main graphical window and an input and output dialog box. The main window, shown in Fig. 3, is an OpenGL (Shreiner et al. (2013)) based interface for the visualization of the turbines and planning of the vessel routing during the maintenance work.

To start the operational planning for a particular day, the user first accesses the input dialog box, which is shown in Fig. 4 (a). The user then enters all the required inputs associated with climate, vessel configuration and location. A separate dialog box is created to input the turbine attributes and failure data, which can be seen in Fig. 4(b) and can be accessed from the input dialog box. The framework outputs, such as total cost, overall fuel consumption, and total time taken to complete the maintenance work and travel sequence of the vessel can be viewed from the output dialog box (Fig. 4(c)).

Instead of using the input dialog boxes, the user can also use a standard input Microsoft Excel file with different sheets for input categories.

4. Results and discussion

In this section, the proposed optimization framework using different test cases is presented and verified. It has to be noted that a variety of test cases are presented in order to demonstrate the applicability of OptiRoute. The mentioned cases have been also conducted after consultation with a major SOV owner/operator.

4.1. Optimization framework verification

In this subsection, a number of Case studies and output results are presented for different test cases. Six different test cases were carried out to demonstrate the reliability and efficiency of the framework. First, four test cases represent the operational planning using an SOV under different parametric configuration. The operational planning using CTV is given in the fifth test case. The last test case demonstrates the operational planning when both CTV and SOV are used simultaneously. The

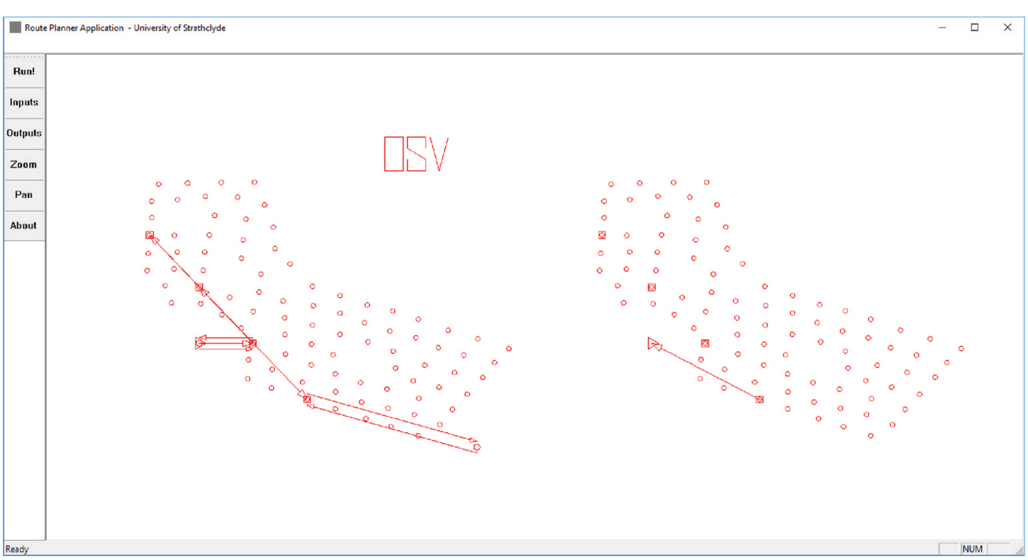

Fig. 3. Graphical window of the framework user interface.

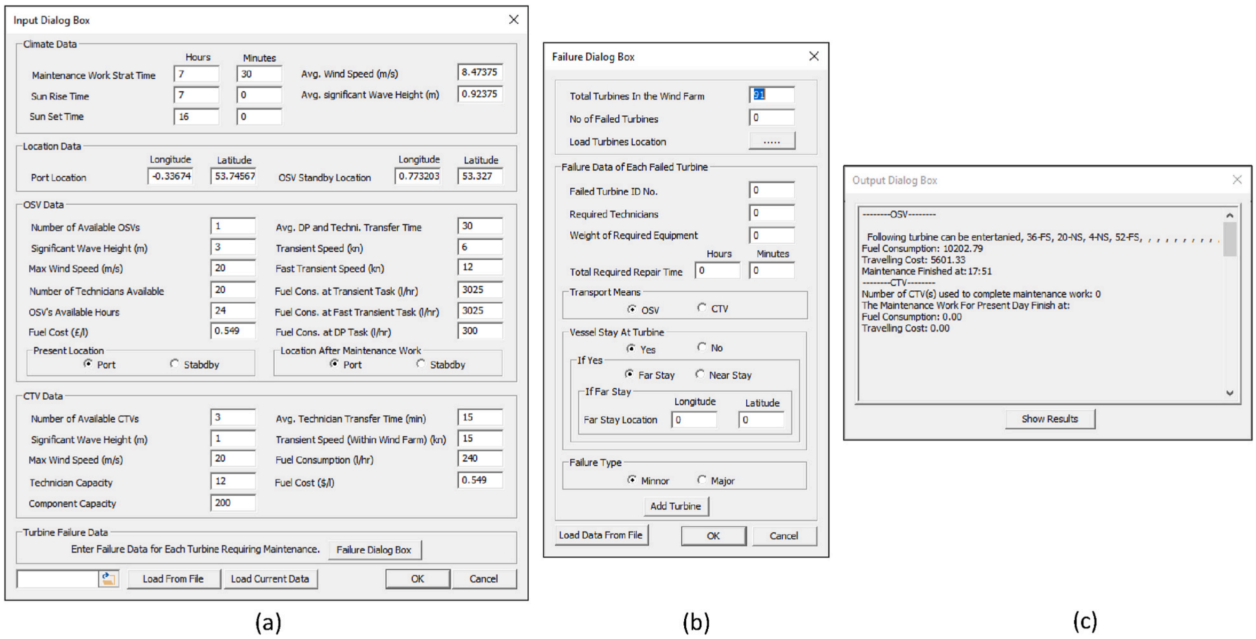

Fig. 4. Input and output dialog boxes of the framework. (a) Climate and vessel specification inputs, (b) Wind farm and turbine failure inputs and (c) output dialog box of the framework.

input data related to climate, SOV, CTV, wind farm and cost utilized to run these test cases are presented in Tables 7–11, respectively, which is obtained from an existing wind farm based in the United Kingdom. Name and location of this wind farm are not mentioned due to confidentiality reasons.

As shown in Table 7, the maintenance work in each Case study starts at 05.00 h and has to be finished before the sun-set time. The single weather window is considered with average significant wave height and wind speed of 1.07 m and 10.42 m/s, respectively, which is the weather data of a particular day and obtained from internal communications with the vessel owner/operator. Only one SOV and three CTVs are considered and the maximum operational wind speed and wave height for both vessel types are higher than the average significant wave height and wind speed. For the SOV, the average time to approach the turbine and to deploy the gangway for technicians transfer is assumed to be equal to 30 min and the technician transfer time for CTV is set to 15 min through communication with industry experts. There are 91 turbines in the wind farm whose location layout is shown in Fig. 4, which is plotted using their actual longitudinal and latitudinal coordinates showing on the x- and y-axis, respectively.

It should be noted that all the results provided in Figs. 1–11 are the framework actual outputs and plots correspond to the framework graphical interface.

4.1.1. *Employing SOV only*

Case Study I: In this case, Table 12 gives the input specifications of this test case and Fig. 6 depicts the graphical results of the optimised route plan. The wind turbines highlighted in red require maintenance work to be carried out with the SOV while the arrows show the way in and back from the standby location to the wind turbines. Four turbines; Turbine-4, Turbine-20, Turbine-36 and Turbine-52, are considered to be maintained using the SOV. All the turbines required the SOV to stay, among these turbines two of them require SOV to perform the short stay

Table 7
Values of climate associated input parameters used during the Case studies for the verification of the proposed framework.

No	Parameter	Value	Unit
1	I_1^e	1.107925	*M*
2	I_2^e	10.42373	m/s
3	I_3^e	05:00	*hh* : *mm*
4	I_4^e	19:00	*hh* : *mm*

Table 8
Initial values of SOV parameters set during the Case studies for the verification of the proposed framework.

No	Parameter	Value	Unit
1	I_1^{sov}	1	*vessel*
2	I_2^{sov}	1	*m*
3	I_3^{sov}	20	m/s
4	I_4^{sov}	20	*persons*
5	I_5^{sov}	24:00	*hh* : *mm*
6	I_6^{sov}	00:30	*hh* : *mm*
7	I_7^{sov}	6	*kn*
8	I_8^{sov}	12	*kn*
9	I_9^{sov}	3025	lt/hr
10	$I_1^{sov}0$	3025	lt/hr
11	$I_1^{sov}1$	300	lt/hr
12	$I_1^{sov}2$	Standby (??)	*latitude&longitude*
13	$I_1^{sov}3$	Standby (??)	*latitude&longitude*

Table 9
Initial values of CTV parameters set during the Case studies for the verification of the proposed framework.

No	Parameters	Values	Units
1	I_1^{ctv}	3	*vessel*
2	I_2^{ctv}	1	*m*
3	I_3^{ctv}	20	m/s
4	I_4^{ctv}	12	*persons*
5	I_5^{ctv}	200	*kg*
6	I_6^{ctv}	00:15	*hh* : *mm*
7	I_7^{ctv}	15	*kn*
8	I_8^{ctv}	240	lt/hr

Table 10
Values of wind farm inputs.

No	Parameters	Value	Unit
1	I_1^w	91	*turbines*
2	I_2^w	See Fig. 5	*latitude&longitude*
3	I_3^w	53.74567 & −0.336741	*latitude&longitude*
4	I_4^w	53.26392494 & 0.794134381	*latitude&longitude*

Table 11
Values of cost related inputs used during the Case studies for the verification of the proposed framework.

No	Parameters	Values	Units
1	I_1^c	0.549	$\$/lt$
2	I_2^c	0.549	$\$/lt$

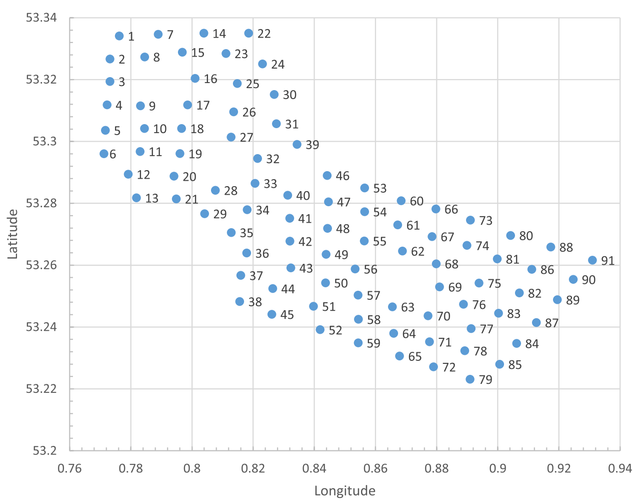

Fig. 5. Plot showing the location of the turbines of an offshore wind farm on longitudinal and latitudinal axes.

while the remaining two necessitate far stay during maintenance operations. To pick-up the technicians, the SOV performed a far stay for two of them while for the other two it remained close to the turbine. All turbines required minor repair work, apart from Turbine-36 for which the estimated total repair time is 6 h. The locations of the SOV at the start and after finishing the work is different. The output results of the framework in Fig. 10 show that the maintenance work finished at 18:51 h with overall fuel consumption of 10,202.79lt. All the turbines are maintained and technicians are recovered with the following SOV travailing sequence: 36-FS → 20-NS → 4-NS → 52-FS. Here, NS and FS represent the Near-Stay and Far-Stay, respectively.

Case Study II: Table 13 presents the failure data utilized for this test case in which no turbine requires for the SOV to be present during the maintenance operations. Maintenance work for each turbine requires a varying number of technicians. Fig. 7 shows the results of the framework in which turbines highlighted in red require maintenance work to be carried out with SOV and the arrows show the way in and back from standby location to the turbines. The initial standby location is represented with a solid triangle. Similar to case study I, maintenance work is carried out using the SOV, however, none of the turbines requires SOV to stay. In total 7 turbines, Turbine-4, Turbine-5, Turbine-6, Turbine-12, Turbine-23, Turbine-45 and Turbine-50, require minor maintenance work. The maintenance work starts at 05:00 h and finishes at 14:55 h and all the turbines are maintained with overall fuel consumption of 11,387.81lt. The travel sequence of the SOV during the drop-off session is 12-D → 6-D → 5-D → 4-D → 23-D → 50-D → 45-D. Here, the D symbol represents the delivery of the technicians. As all the turbines do not require SOV to stay, therefore, optimizing the drop-off session, the route planning for the SOV to pick-up the technicians is carried out. The SOV's travel sequence during the pick-up session is 45-P → 50-P → 12-P → 6-P → 5-P → 4-P → 23-P, where symbol P represents the technicians pick-up. The SOV has the same start and return location.

Case study III: Failure data utilized in this test case and its results are shown in Table 14 and Fig. 8, respectively. Table 14 provides the input specifications of the failed turbines. Among these turbines only one, require SOV to perform the short stay and remaining two necessitate far stay during maintenance operations. Maintenance work for each turbine requires a varying number of technicians. Fig. 8 shows the graphical results for this test case in which turbines highlighted in red require maintenance work to be carried out with SOV and the arrows show the way in and back from standby location to the turbines. In this test case, four turbines require maintenance work, which is carried out with the SOV. Three turbines require the SOV to stay near them and one of them requires a far-stay. Similar to case study I, SOV's initial standby location and standby location after finishing the maintenance work are different. Turbine-4, Turbine-9, Turbine-21 and Turbine-22 are recovered with the following SOV travel sequence: 21-FS → 9-NS → 4-NS → 22-FS. The overall fuel consumption for this case study is 5264.31lt and

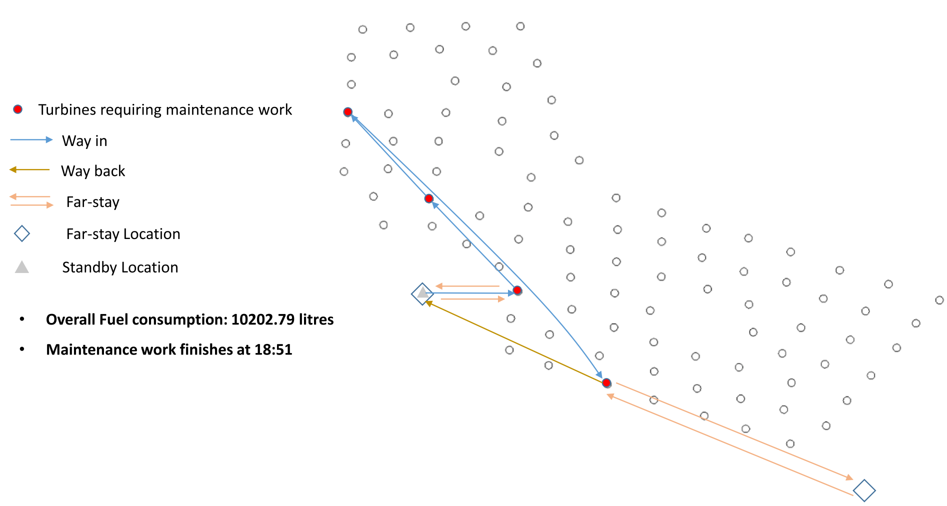

Fig. 6. Results of Case study I.

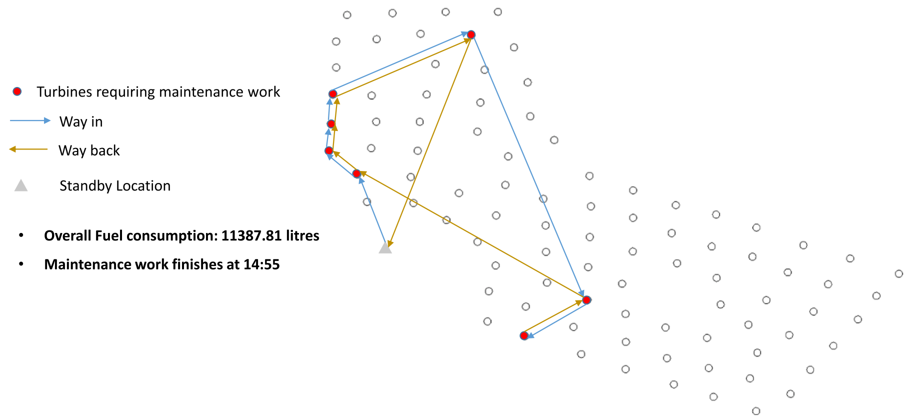

Fig. 7. Results of Case study II.

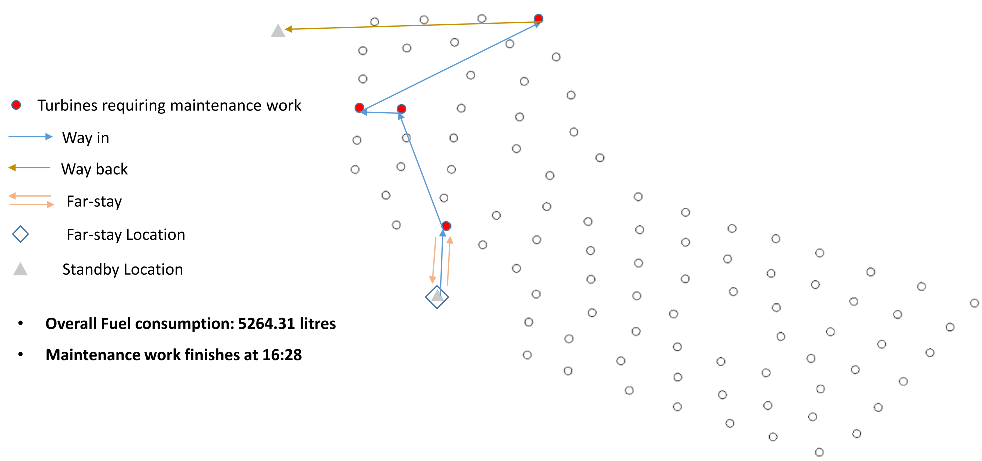

Fig. 8. Results of Case study III.

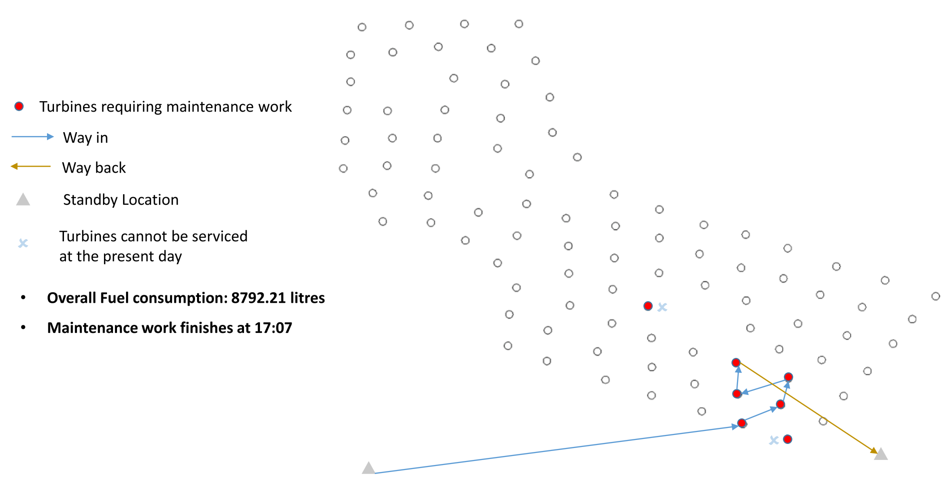

Fig. 9. Results of Case study IV.

maintenance work is finished at 16:28.

Case study IV: Similar to the previous three test cases, in this test case, seven turbines, Turbine-56, Turbine-70, Turbine-71, Turbine-72, Turbine-77, Turbine-78 and Turbine-79, required minor maintenance work using SOV. Table 15 presents the input specifications and the failure data utilized for this test case. Fig. 9 shows the results of the framework and turbines highlighted in red require maintenance work to be carried out with SOV and the arrows show the way in and back from standby location to the turbines. All turbines require SOV to perform a near stay during maintenance with the different initial and final

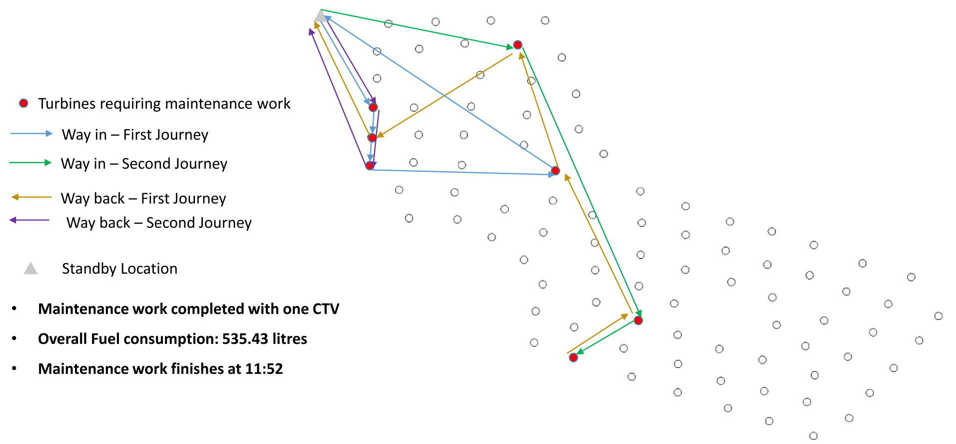

Fig. 10. Results of Case study V.

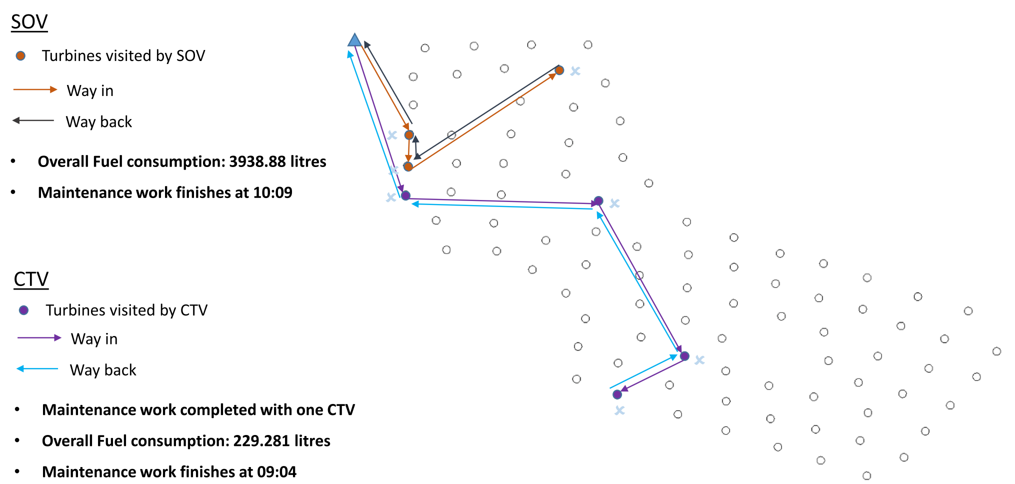

Fig. 11. Results of Case study VI. In this case maintenance work is carried out in combination of SOV and CTV.

Table 12
Data input used for Case study I in which maintenance work is carried out with SOV for four turbines.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 4$	3	0	01:05	SOV	Yes	Near-Stay	–	82 m
$J_2 = 20$	4	0	00:30	SOV	Yes	Near-Stay	–	82 m
$J_3 = 36$	3	200	06:02	SOV	Yes	Far-Stay	53.26392494 & 0.794134381	–
$J_4 = 52$	3	0	01:00	SOV	Yes	Far-Stay	53.218 & 0.917	–

Table 13
Data input used for Case study II in which maintenance work is carried out with SOV for seven turbines.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 4$	3	0	01:05	SOV	No	–	–	–
$J_2 = 5$	4	0	00:30	SOV	No	–	–	–
$J_3 = 6$	4	0	02:02	SOV	No	–	–	–
$J_4 = 23$	3	0	00:30	SOV	No	–	–	–
$J_5 = 45$	4	0	01:00	SOV	No	–	–	–
$J_6 = 50$	3	0	01:00	SOV	No	–	–	–
$J_7 = 12$	3	0	01:45	SOV	No	–	–	–

Table 14
Data input used for Case study III in which maintenance work is carried out with SOV for four turbines.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 4$	3	0	01:50	SOV	Yes	Near-Stay	–	82 m
$J_2 = 9$	4	0	03:30	SOV	Yes	Near-Stay	–	82 m
$J_3 = 21$	3	0	02:02	SOV	Yes	Far-Stay	53.26392494 & 0.794134381	–
$J_4 = 22$	3	0	00:30	SOV	Yes	Near-Stay	–	–

Table 15
Data input used for Case study IV in which maintenance work is carried out with SOV for seven turbines.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 56$	3	0	01:05	SOV	Yes	Near-Stay	–	–
$J_2 = 70$	5	100	02:30	SOV	Yes	Near-Stay	–	–
$J_3 = 71$	3	250	02:02	SOV	Yes	Near-Stay	–	–
$J_4 = 72$	3	0	01:30	SOV	Yes	Near-Stay	–	–
$J_5 = 77$	3	0	01:20	SOV	Yes	Near-Stay	–	–
$J_6 = 78$	4	0	00:30	SOV	Yes	Near-Stay	–	–
$J_7 = 79$	4	0	02:10	SOV	Yes	Near-Stay	–	–

destination, which is depicted with a grey solid triangle. All the turbines required SOV to perform the near-stay. SOV started the maintenance from the port, therefore, out of seven turbines, Turbine-56 and Turbine-79 cannot be served on the present day and the maintenance work for these two turbines is shifted to the next day. The maintenance work finishes at 17:07 with the SOV's travelling sequence as follows: 72-NS → 78-NS → 77-NS → 71-NS → 70-NS. The overall fuel consumption in the case is 8792.21*lt*.

4.1.2. CTVs only - case study V

In this sub-section, we discuss a Case study for CTVs. The maintenance work is carried out using a single CTV while none of the turbines requires the vessel to stay at the turbine. Failure data and input specifications for this test case are shown in Table 16 and the results obtained from the optimization framework for this case are given in Fig. 10. Turbines highlighted in red in Fig. 10 require maintenance work to be carried out in two different journeys of CTV. The arrows show the way in and back from SOV to the turbines. None of the failed tribunes requires CTV to stay during maintenance and it comes back to SOV after completing maintenance work, whose location is depicted with a solid grey triangle. The maintenance starts after the CTV is launched from the SOV. To transfer the technicians, CTV performs two journeys from the SOV. In the first trip, the CTV carries 11 technicians and delivers them to turbine 4, 5, 6 and 32. After delivering the technicians to these turbines, the CTV goes back to the SOV and picks up 7 more technicians and delivers them to turbines 23, 50 and 57. The travel sequences of CTV during the first and second journey of the drop-off session are SOV→ 4-D → 5-D → 6-D → 32-D → SOV and SOV → 23-D → 50-D → 45-D → SOV, respectively. Similarly, the travel sequence is SOV→ 45-D → 50-D → 32-D → 23-D → 5-D → SOV and SOV → 4-D → 6-D → SOV respectively, for the first and second journey during the pick-up session. The maintenance work starts at 05:00 and finishes at 11:50 with overall fuel consumption of 535.43 L.

It should be noted that the maintenance work finish time for this Case is less compared to the previous cases. This is due to the fact that travel time for the CTV is less compared to SOV and that no turbine requires a CTV to stay at the turbine. Therefore, the maintenance work for all the turbines is carried out in parallel and finishes in less amount of time.

4.1.3. Employing a combination of SOV and CTV - case study VI

In this Case, we discuss a test case in which both a CTV and an SOV are used in parallel. The failure data and input specification (given in Table 17) used in this test case are similar to the one used in case study V. However, the maintenance work for turbines 4, 5 and 32 is carried out using an SOV. It is noteworthy that the maintenance work finishes approximately 2 h earlier when a CTV and an SOV are used together. The overall fuel consumption of the SOV and CTV is 3938.88*lt* and 22.281*lt*, respectively. The results of this test case can be seen in Fig. 11.

4.2. Overall results

In this sub-section, the overall results and findings of all the Case studies are discussed as shown in Table 18. In the first four cases, the SOV is used for maintenance work of different turbines under different parameter settings. For the first three cases, all the turbines were visited by the SOV and the maintenance work was completed within the given weather window. SOV is also utilized for the fourth case study, but the initial position of the SOV before starting the maintenance work was considered as the hub port. Therefore, the SOV is unable to visit Turbine-56 and Turbine-79 within the given weather window. The overall fuel consumption of case study II is higher compared to the other cases as in this case the number of turbines visited by the SOV is higher. Furthermore, the failure data used in case study V and VI is the same, however, the overall time to finish the maintenance work in case VI is smaller than in case V. During the experimentation it was observed that the overall time taken to perform the maintenance work is less and a higher number of turbines can be accommodated when SOV and CTV are used together in comparison to the other test cases. Thanks to the effective heuristic strategy used in the proposed framework, the computational time to perform optimization for all the test cases was less than a minute. This time may increase if there is a larger number of turbines that have to be visited, however, it will be still efficient enough to allow daily and spontaneous route and maintenance planning for both SOV and CTV. Although, a comparative study would further verify the proposed approach and help to analyse the quality of the solutions it was not possible due to the novelty of the problem. As discussed before, to the best of the authors' knowledge non of the existing approaches for route planning of maintenance vessels of wind turbines replicates the realistic scenario and tackles the similar aspects of the problem, such as usage of combined SOVs and CTVs under the various operation modes of vessels, while including different weather windows.

5. Conclusions and future work

The present study proposes an optimization framework for the daily operational planning of the maintenance fleet on an offshore wind farm. A heuristic optimization technique was developed and integrated within the framework. The new framework optimizes the entire maintenance

Table 16
Data input used for Case study V in which maintenance work is carried out with CTV for seven turbines.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 4$	3	0	01:50	CTV	No	–	–	–
$J_2 = 5$	2	0	00:30	CTV	No	–	–	–
$J_3 = 6$	4	0	02:02	CTV	No	–	–	–
$J_4 = 23$	2	0	03:30	CTV	No	–	–	–
$J_5 = 32$	2	0	01:00	CTV	No	–	–	–
$J_6 = 45$	3	0	01:50	CTV	No	–	–	–
$J_7 = 50$	2	0	01:45	CTV	No	–	–	–

Table 17
Data input used for Case study VI in which maintenance work is carried out with combination of SOV and CTV.

Turbines	Parameters							
	I_1^J	I_2^J	I_3^J	I_4^J	I_5^J	I_6^J	I_7^J	I_8^J
$J_1 = 4$	3	0	01:50	SOV	No	–	–	–
$J_2 = 5$	2	0	00:30	SOV	No	–	–	–
$J_3 = 6$	4	0	02:02	CTV	No	–	–	–
$J_4 = 23$	2	0	03:30	SOV	No	–	–	–
$J_5 = 32$	2	0	01:00	CTV	No	–	–	–
$J_6 = 45$	3	0	01:50	CTV	No	–	–	–
$J_7 = 50$	2	0	01:45	CTV	No	–	–	–

Table 18
Summarised results for all Case studies I-VI

Results	Case Study I	Case Study II	Case Study III	Case Study IV	Case Study V	Case Study VI (SOV/CTV)
Non-visited turbines	None	None	None	56,79	None	None
D_{total} (KM)	41.28	39.50	17.95	50.41	51.29	40.84
T_{total} (hours)	13.85	9.91	11.46	12.12	6.87	5.15/4.16
T_M (hh:mm)	18:51	14:55	16:28	17:07	11:52	10:09/09:04
F_{total} (litres)	10,202.79	11,387.81	5264.31	8792.21	535.43	3938.88/229.281
Total Cost ($)	5601.33	6251.90	2890.10	4826.92	293.95	2288.32

task sequence in order to reduce the overall fuel consumption and increase the overall wind farm operational window. During the optimization process, the climate data, such as average significant wave height and average wind speed for a particular day, is used to plan a single weather window. The framework also considers the inputs related to the vessels' specifications and their fuel consumption. To simulate an actual scenario, a different number of inputs related to wind turbines were also considered during the optimization. The optimization for the CTVs and SOV is performed separately and the whole maintenance operation task is divided into two sessions; pick-up and drop-off ones. The framework first optimally plans the drop-off session and if required, the framework then plans the pick-up session. The fuel consumption for both sessions is calculated to obtain the overall fuel computation for a particular day. The reliability and feasibility of the framework were tested using a number of test cases while it was observed that the new framework can reduce overall fuel consumption and increase the operational window to a great extent. It was also observed that the operational window increases if SOV and CTVs are used together.

In future, the proposed framework can be further enhanced by considering the type of technicians available for the maintenance work and a cluster strategy used to cluster the wind turbines which have similar failure attributes. Moreover, the suggested framework can be integrated with a simulator to optimize the operational activities for the entire life cycle of the wind farm providing the corresponding life cycle technical and financial outputs. Along with the concept of Offshore Resource Centre Rahman et al. (2020), we also intend to integrate a failure model, similar to Scheu et al. (2017), within the proposed framework.

CRediT authorship contribution statement

Iraklis Lazakis: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Shahroz Khan:** Methodology, Software, Formal analysis, Validation, Investigation, Data curation, Writing – original draft, Visualization.

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.

Acknowledgements

The authors would like to thank Dr Yalcin Dalgic for all the discussions and assistance at initiating this study as well as the NEXUS partners for providing the information required for the completion of this study. The work presented in this paper is partially funded by NEXUS (Next generation support vessels providing safe and more efficient offshore wind farm services) project. NEXUS Project has received research funding by the European Union's Horizon 2020 research and innovation programme under agreement No. 774519. This publication reflects only the authors' views and the European Union is not liable for any use that may be made of the information contained herein.

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