

ORIGINAL RESEARCH

Improving O&M decision tools for offshore wind farm vessel routing by incorporating weather uncertainty

Yannis Hadjoudj | Ravi Kumar Pandit 

Centre for Life-cycle Engineering and Management,
Cranfield University, Cranfield, UK

Correspondence

Ravi Kumar Pandit, Centre for Life-cycle
Engineering and Management, Cranfield University,
Cranfield, UK.
Email: ravi.pandit@cranfield.ac.uk

Abstract

The growth of offshore wind farms depends significantly on how well offshore wind turbines (OWTs) are operated and maintained in the long term. The operation and maintenance (O&M) activities for offshore wind are relatively more challenging due to uncertain environmental conditions than onshore and due to this, vessel routing for offshore on-site repair is remain complex and unreliable. Here, an improved data-driven decision tool is proposed to robust the vessel routing for O&M tasks under numerous environmental conditions. A novel data-driven technique based on operational datasets is presented to incorporate weather uncertainties, such as wind speed, wave period and wave height (significantly influence offshore crew repair works), into the O&M decision-making process. Results show: (1) The inclusion of weather conditions improves the O&M model uncertainty and accuracy, (2) the implementation of a model allowing weather conditions to evolve has been added to vary the probabilities of successful transfers throughout the day, and (3) the reduction of risk of transfer failure by 15%. These conclusions are further supported by the performance error metrics and uncertainty calculations. Last but not least, by generating a variety of policies for consideration, this tool gave wind turbine operators a systematic and transparent way to evaluate trade-offs and enable choices pertaining to offshore O&M. The full paper highlights the strengths and weaknesses of the proposed technique for offshore vessel routing as well as how the environmental conditions affect them.

1 | INTRODUCTION

Recently, the UK Government established an ambitious target in 2020 to reduce emissions in the UK by at least 68% by 2030 compared to 1990 levels [1]. Furthermore, UK's long-term goal (by 2050) is to reduce all emissions by at least 80% from 1990 levels, which means domestic emissions must be reduced by at least 3% per year [2]. With over 24% of the world's renewable energy coming from wind power, it is the second most widely used renewable energy source [3], and demand for wind energy is increasing rapidly and offshore wind output is predicted to triple by 2024 [4]. Therefore, wind energy is considered to be a formidable instrument for achieving net zero by decarbonisation to achieve the net-zero target and meet the nation's future energy demands. For instance, the installed offshore wind capacity in the EU, which was 14.6 GW in 2021, is projected to

increase by at least 25 times by 2030 [5] by leveraging the vast potential of the five EU sea basins. Therefore, by using offshore wind energy, the European green deal easily is implemented at a reduced cost.

Offshore wind turbines present a number of technological and environmental constraints that limit site accessibility for performing operation and maintenance (O&M) activities in comparison to onshore and hence attract high O&M costs [6]. Post-warranty O&M for a 4-MW offshore wind turbine costs around £648,000 per year [7], according to available data. The life cycle of an offshore wind farm is highly complex and varied due to maintenance. The variable environmental conditions along with difficult vessel access and maintenance of chosen methodologies have an impact on the overall profitability and performance of offshore wind farms [8]. Aside from that, offshore operations are more complex and

This is an open access article under the terms of the [Creative Commons Attribution](https://creativecommons.org/licenses/by/4.0/) License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2023 The Authors. *IET Renewable Power Generation* published by John Wiley & Sons Ltd on behalf of The Institution of Engineering and Technology.

expensive due to the fleet's ageing turbines and complex logistics routes [9, 10]. Therefore, for an offshore wind project, these variables are taken into account for an effective maintenance strategy.

Environmental uncertainty has a significant impact on optimising performance and minimising costs in all phases of offshore operation and maintenance (O&M) operations since it determines when operators can access the turbines. The impact of weather on three offshore wind farms in the Portuguese region was studied by Silva et al. [11], who also suggested weather time windows (of the short period) for local access to the wind farms via helicopter and rubber boat and therefore, O&M activities must be carefully planned in advance. Pandit et al. [10, 12] propose data-driven techniques for long-term weather forecasting in the context of offshore wind turbine maintenance. They used weather datasets (wave height and wind speed) to develop and compared advanced methods namely, long short-term memory (LSTM), Markov chain, bidirectional long short-term memory (BiLSTM) and gated recurrent unit (GRU) and found that LSTM is robust and computationally effective in the estimation of long-term weather forecasting as compared to other techniques. These external factors are also used to develop O&M tools for long-term logistical planning, forecasting asset availability and estimating lifetime operational expenditure (OPEX) of offshore projects, which are dealt with in more detail below.

O&M cost models, which are commonly made in Microsoft Excel and are intended to give a high-level knowledge of the project OPEX, can be a logical extension to O&M simulation tools. The O&M tools are widely referred to as O&M models, decision tools, O&M planning tools, O&M optimisation and logistical planning tools [13]. These tools are used by wind turbine industries to develop robust strategies for maintenance and planning in order to reduce OPEX and maximise asset performance by reducing uncertainties in component failures and vessel access for on-site visits. Tomaselli et al. [14] propose a numerical decision tool for the estimation of weather windows for improving offshore O&M activities. They analysed a full O&M scenario, which includes travel from the port to the offshore location, work on the turbine, and travel back to the port. The findings of the proposed decision models emphasise the tool's critical ability to compute vessel motions, which are elaborated to provide weather windows. The tool's results support the decision-making procedures that result in short- and long-term O&M plans thanks to its minimal computational time need [14]. In another article, Kolios et al. [15] report the finding of their O&M open-access decision tool initial results with a reference case study. They take into account estimating a given wind farm's availability with specific characteristics during the course of its service life, enabling the simulation of various scenarios involving reliability metrics, vessel specifications and availability, manpower requirements etc. The result demonstrates the tool's applicability and responsiveness as well as the sensitivity analysis of the jack-up vessel mobilisation time as a changing parameter because it was discovered to significantly affect the estimated availability. Dawid et al. [16] proposed decision-making robust tools for offshore effective vessel routing planning by automating the process of

logical decision-making of maintenance actions and presented case studies by collaborating with the UK offshore wind farm operators.

A comprehensive assessment of routing problem-solving techniques in the context of offshore wind turbine maintenance was presented by Irawan et al. [17]. They provide a solution based on a mixed-integer linear programme and the Dantzig-Wolfe decomposition technique (MILP). This method lacks the flexibility to account for the chance that repairs would take longer than anticipated, despite being computationally efficient. O&M simulation tools, that is, strategic O&M tools and OPEX estimation, often take a time-domain approach to long-term logistical planning [18]. This implies that the software tool simulates failures at each time step and mimics real-time decisions for performing unplanned maintenance, and planned maintenance in accordance with the specified interval. This procedure continues until the last time step is reached, simulating the completion of the life cycle of a wind turbine [19]. Furthermore, in recent years, the problem of vessel routing for offshore wind farms was addressed by Dai et al. [20], Zhang et al. [21] and Stålhane et al. [22] who used branch and bound method; Ant Colony Optimisation and path-flow model respectively. A variety of O&M simulation tools have been developed recently to support the modelling services, including Shoreline O&M Design [23], ForeCoast Marine Gamer Mode [24], Offshore TIMES [25], DNVGL O2M [26] and ECN O&M Calculator [27] to support the modelling, project planning and decision-making services. However, these are commercial products which require annual licence fees, technical support and user inputs.

2 | CONTRIBUTION TO THE KNOWLEDGE

Because of weather uncertainty and resource constraint, the vessel on-site access for O&M tasks remains a challenge for offshore wind. Additionally, these difficulties worsen due to improper advance planning and cause long unavailability and significant revenue losses. Therefore, robust O&M decision tools are needed to plan ahead vessel access for offshore wind farms, especially under weather uncertainty [28]. Pandit et al. [12] proposed two data-driven techniques (Markov chain and Long short-term memory (LSTM)) using wave height and wind speed (of three years' datasets) to forecast the long-term weather and then compare their performance in terms of accuracy and training speed. They suggested that Markov chains have a shorter training period but lower accuracy while LSTM models take longer training time (several hours) but record marginally higher accuracy. Since training time is very important and therefore suggested Markov chain is more suitable than the LSTM model for long-term weather forecasting. Dawid et al. [29] propose a novel methodology that incorporates uncertainties (expected maintenance duration) into the decision-making process on vessel routing for realistic offshore wind farm problems.

They used two case studies to evaluate the effectiveness of the proposed decision simulation tools. Results suggested that the

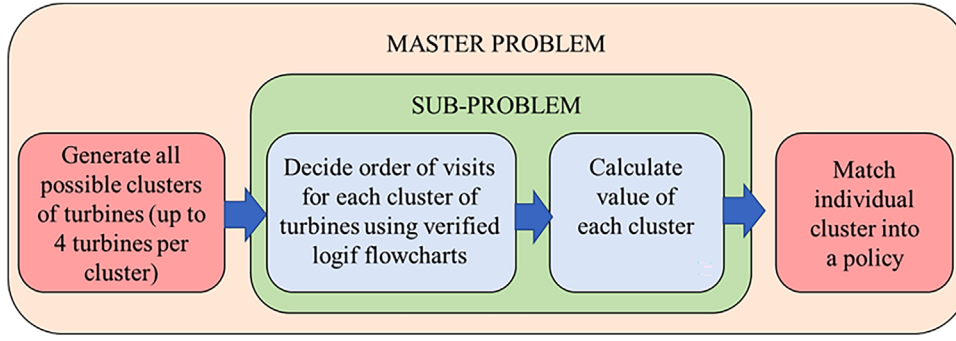


FIGURE 1 Master and Sub problem [29].

inclusion of uncertainties led to a 14% increase in the number of wind turbines maintained at the end of the day. However, they did not consider the weather uncertainties impacts which could play an important role in optimising vessel routing. By taking into account environmental conditions that can affect the transfer of maintenance teams and modifying them, this paper aims to fill this gap by improving O&M simulation tools. This paper extends [29] works where the sub-problem and master problem solutions stay the same, but uncertainty would be modified (adding more weather parameters). The sub-problem is built on case-dependent decision flowcharts, while the master problem is formulated as a mixed-integer programming problem.

This paper is structured as follows: Section 3 explains the problem formulation while Section 4 explains the data and pre-processing techniques used here. Section 5 explains the methodology that led to improving the existing work. Section 6 summarizes the various results and improvements realized. Finally, Section 7 discusses the potential improvements and limitations of this approach. The Paper concludes with Section 8.

3 | PROBLEM FORMULATION

The first step of the research is to formulate the problem by using the vehicle routing model proposed by [29] as shown in Figure 1 (illustrates the division between the inner and exterior concerns in general) which is assumed to be optimized and the only part on which modifications have been made in the estimation and consideration of uncertainties. The sub-problem was to eliminate all the clusters (set of turbines) that do not meet the constraints of the users, such as the clusters whose maintenance time is greater than the available time or whose technical constraints exceed those of the vessels.

For this, ordering decision flowcharts meeting user criteria was used. An example of a flowchart (as shown in Figure 2) for a cluster with two maintenance activities of less than 4 h.

The master problem corresponded to a mixed-integer programming problem with the following objective function as mathematically shown in Equation (1):

$$\text{maximise} \left[\sum_{k \in K} Q_k * F_{pk} \right] \quad (1)$$

$\left[\sum_{k \in K} Q_k * S_{ik} \right] \leq 1 \quad \forall i \leftrightarrow$ Each turbine is visited by one vessel only.

$\left[\sum_{k \in K} Q_k * V_{kj} \right] \leq 1 \quad \forall j \leftrightarrow$ Each cluster can only be assigned one of the vessels.

$\left[\sum_{k \in K} Q_k * D_k \right] \leq E \leftrightarrow$ The number of technicians required does not exceed the number of technicians available.

The K assembly represents the possible routes here, while i and j correspond respectively to the turbines and vessels. F_{pk} is the gain value of the cluster k , Q_k is a binary variable which takes the value 1 if the route is taken and 0 otherwise. S_{ik} is a binary variable equal to 1 if turbine i is part of route k and 0 otherwise, V_{kj} is also a binary variable which takes the value 1 if vessel j is on route k , 0 otherwise. Finally, D_k is the number of technicians needed to perform road maintenance k . Using the Gurobi Optimizer simulation tool, which employs a branch-and-cut technique to choose a group of distinct clusters that fulfil all of the requirements, the master problem was resolved [30].

3.1 | KPIs and the gain function

Equation (2) is the expression of the gain function F_p :

$$F_p = \sum_{i=1}^G (U_i - C_{r_i}) - \sum_{j=1}^V (C_{f_j} + C_{v_j}) + \left(A * P_{v_j} * U_{mean} * \frac{N_{t_j}}{\eta} \right) \quad (2)$$

where U_i is the reward for maintaining the turbine i , C_{r_i} is the cost of maintaining wind turbine i , C_{f_j} is the cost of fuel incurred by vessel j , C_{v_j} is the hire cost of vessel j , U_{mean} is the average reward across all of the turbines, N_{t_j} is the number of turbines visited by vessel j , T_{retard_j} is the delay time accumulated by vessel j and T_{total_j} is the total time to complete every action. The value function shown in Equation (2) aims to meet the KPIs listed below:

- Increase the number of wind turbine visits.
- Increasing the number of high-reward trips to wind turbines.
- Reduction of expenses.

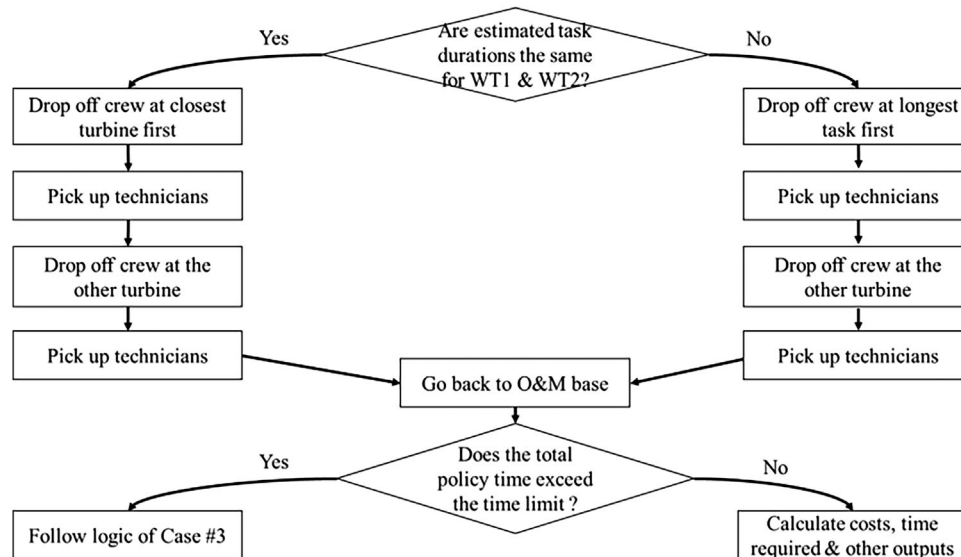


FIGURE 2 Clusters flowchart.

- Reducing the number of failed repairs (due to uncertainty realisations).

These KPIs will be used to assess the policies that the tool generates. A random number generator (RNG) and a Monte Carlo analysis were used to determine the typical number of turbines that would have been successfully maintained across a large number of repetitions if a certain strategy was adopted, given the user-specified uncertainties. Each iteration of the Monte Carlo simulation generates three random numbers, one for each turbine:

- One uses the random forest model to ascertain the real maintenance activity time.
- Determine if it will be able to transfer the crew to the turbine.
- One to determine whether the transfer of crew onto the vessel will be possible.
- One to assess if the turbine's diagnosis was accurate.

4 | DATA DESCRIPTIONS

Data plays a crucial role in the use of machine learning to improve the maintenance of a wind farm. In fact, this data makes it possible to feed machine learning algorithms and provide them with the information they need to learn and predict failures. In this section of the thesis, we will present the different data sources used in our study, as well as their nature and format.

4.1 | Data utility in O&M activities

The datasets used in this study are coming from European Centre for Medium-Range Weather Forecasts [31], Tidetechn [32], euroision [33] and open-access sources [34]. There is no confi-

dential agreement associated with these datasets and can be used in future by acknowledging them.

To develop reliable time-series weather conditions, it is crucial and vital to have access to reliable met ocean data. Sometimes the data need to be created since they are not readily available. In order to obtain numerous realistic time series of wind speed, wave period, and significant wave height, an alternate method to sensors is studied in this study and described in upcoming sections.

To identify the best vessel and equipment combination that is needed for a certain operation and to arrange the sequence of complicated offshore installation procedures. As a result, a significant number of environmental time series are required to account for environmental condition uncertainties that restrict operations. A large data collection of environmental time series is typically difficult, expensive, and occasionally impossible to acquire. When it is attainable, there are frequently missing values as a result of measuring equipment failures [35], which might affect the prediction of the duration of offshore operations. Considering the relationship between the environmental parameters is crucial for creating genuine environmental time series. Data generation makes sense at that point.

To generate those data, various tools are used. These tools include machine learning techniques like generative adversarial network (GAN) [36], generative adversarial networks, and VAE [37], variational autoencoder, as well as approaches like SMOTE [38], synthetic minority over-sampling technique, and the study of the nearest neighbours. Machine learning methods will be the ones to examine due to the nature of our data, the issue encountered by the offshore wind farm, and the complexity of the distribution of our data (weather forecasting), as they are both more efficient and more accurate than other methods. In 85% of the scenarios studied in Xu's study, some variation of GAN outperformed conventional synthetic data generating methods [39].

Generally speaking, all models are capable of accurately capturing the relationships between features. All of the models exhibit comparable performance, demonstrating that artificial data may be used to solve Machine Learning issues in place of actual data. Both meteorological and data on wind turbine failure can be generated using these data producers. They assist in training the various decision-making models for managing vessels and predicting failures, both of which are helpful for planning maintenance.

5 | METHODOLOGIES

When preparing for an offshore wind farm's operation, several uncertainties must be considered. The anticipated duration of the repair operations is unclear and might change depending on the type of maintenance action. It is uncertain if technicians can be moved from the ship to the wind turbine on days with high sea waves. Although modelling such uncertainties might be challenging, it is crucial to do so since these actual uncertainties have an impact on daily decision-making.

5.1 | Consideration of uncertainties

An approach is proposed in which uncertainties are modelled by calculating the probability of maintaining all turbines in a group. In the model proposed by Dawid et al. [29], it is assumed that the time available to perform all maintenance actions in the day (i.e. the time window) is a strong constraint, this means that the backup action is to return to the base before the deadline, even if it means leaving service actions unfinished. This hypothesis was not taken into account in our model, so the time window is no longer a strong constraint.

Considering that P_{ij} is the probability that a maintenance team will be transferred from vessel j to turbine i (depending on weather conditions and vessel used), P_{ji} is the probability that a maintenance team will transfer from the i turbine to vessel j , Pd_i is the probability that the i wind turbine has been successfully diagnosed and finally, Pr_i is the probability that maintenance will take as long as planned or less. Let G be the set of turbines assigned to vessel j , the probability that all maintenance is performed as follows:

$$P_{vj} = \prod_{i=1}^G P_{ij} * Pd_i * Pr_i * P_{ji} \quad (3)$$

The determination of transfer probabilities is made according to the weather conditions, that is, the worse weather conditions, the more likely the transfer between the vessel and the wind turbine (and vice versa) to fail. The type of boat used to transfer crews is as is typically shown in Figure 3. The transfer is generally done by the bow of the boat which clings to the base of the turbine. In the middle of the mooring point is a staircase allowing the crews to reach the windmill.



FIGURE 3 Vessel for OWTs [40].

The safety of the teams is critical in the transfer; it is unthinkable for the maintenance teams to put themselves in danger during the transfer. For this reason, safety recommendations for CTVs crew transfer vessels have been issued by several organizations including the Energy Institute of London [41]. Several environmental factors can influence the safety of the transfer, the most important being wind speed, wave height and wave period. Based on recommendations, probability takes the following values based on sea conditions.

Regarding the probability of maintenance taking as long as planned or less, the previous model proposed using a gamma distribution, but it was found that using the random forest model based on machine learning and data study could improve the estimation of maintenance time.

The random forest is a supervised learning algorithm. The term “forest” corresponds to the fact that it builds a set of decision trees, usually formed with the method “bagging”. The ‘Bagging’ method is used in ensemble learning methods to increase the accuracy and performance of ensemble learning methods. Bagging increases performance by reducing the variance of a data set. Bagging is commonly used in decision tree algorithms. It will be used in classification and regression methods because it reduces the problem of over-accuracy. It creates a different training subset from the sample of training data with replacement. Each model is driven independently, which generates results. The final result is based on majority voting after combining the results of all models as illustrated in Figure 4.

The probability of a good diagnosis of the wind turbine is maintained compared to the model proposed previously. This probability will therefore respect the information of Table 1 as shown below.

5.2 | Implementation of a temporal evolution of the weather

An experimental improvement was tested by trying to integrate the changing weather conditions as the day progressed into the model. To do this, a deep learning model was used and more particularly a generative adversarial network and its

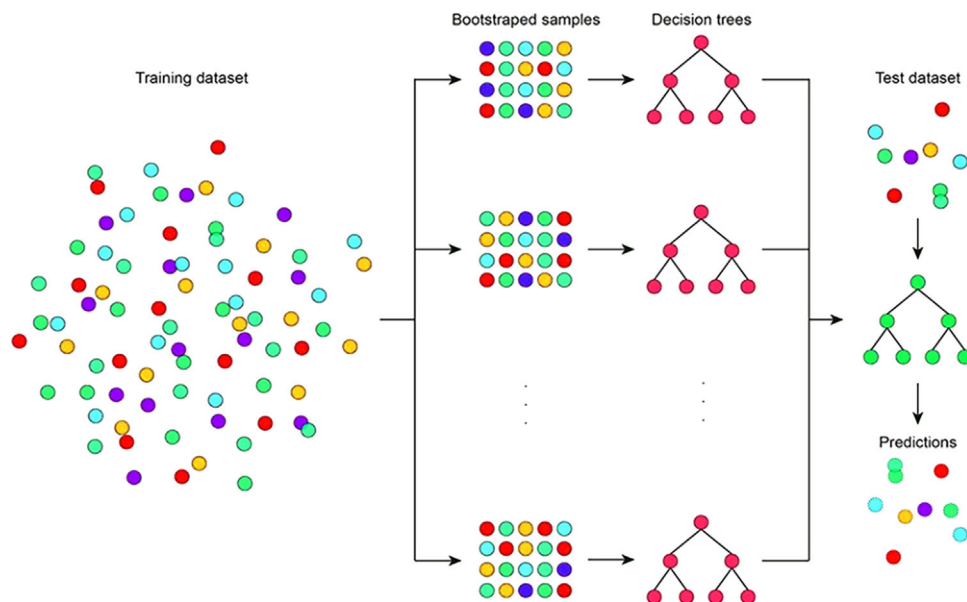


FIGURE 4 Bagging description.

TABLE 1 Probability of a successful transfer depending on conditions

Probability of a successful transfer for a vessel type 1

Wave height (m)	Wave period (s)	Wind speed (m/s)
>22	0%	0–2
2.0–2.2	25%	2–4
1.8–2.0	50%	4–5
1.6–1.8	75%	5–6
1.4–1.6	100%	6–8
0–1.4	100%	>8

improved version conditional table for GAN (CTGAN) for data table generation. Generative models have been used in a myriad of applications in different fields, from quantitative finance to modelling and ultimate risk reduction to hydro-climatic research to study the joint effects of extreme weather conditions. The power of generative models lies in their ability to encapsulate the entire dependency structure and the underlying probability distribution of the datasets. This is very useful because, using generative models, we can not only create future representations of datasets but also sample new, realistic data points that preserve the cross-correlation between the original training data sets. GANs are a new class of generative models and have been introduced by Goodfellow et al. [36] in 2014, allows to generate very accurately from a sample of data. As presented in the review literature, GANs is a type of neural network architecture for generative modelling. NAEs are pairs of neural networks. They are based on a theoretical two-player game scenario to learn the distribution and models of the training data so that the model can generate new data that preserve the character-

istics of the training data. The CTGAN version resampled the input data to improve the model's drive.

Normally, to predict the weather, a stochastic model is used. A stochastic weather generator is a statistical model that aims to produce synthetic time series of weather data of unlimited length for a location or region based on the analysis of the statistical characteristics of time in this region. Most stochastic meteorological generators use a combination of Markov procedure and frequency distribution of different meteorological variables. However, using this model, the weather conditions of the day can be simulated and directly modified in the model to best match the day that is likely to occur. The GAN offers completely different modelling of the stochastic model much simpler to set up and implement in the problem addressed as shown in Figure 5. This makes it possible to adapt the probabilities to the meteorological conditions at the time when the maintenance will take place on the given turbine and thus improve the precision of the model. After focusing on the probabilities of predicting uncertainties, and then proposing the implementation of a weather monitoring tool. Now, we need to implement all this in the gain function which will allow to insert these different elements of the equations of the problem.

5.3 | The VRP gain function

The VRP gain function is important to define as it allows to ensure that the vessel routine well meets the expectations of the users. This feature allows users to vary the risk they want, by introducing a risk factor (λ). This factor reflects the will of the manager of the wind farm, if he wishes to maximize the number of wind turbines maintained at the risk that they are not all maintained properly, or vice versa if the one wants to minimize the number of failures and maximize the chances of success. Thus,

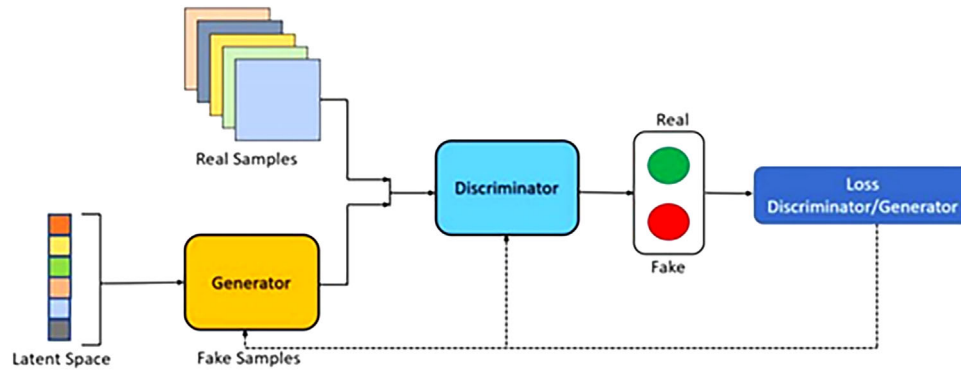


FIGURE 5 GANs description.

$\mathcal{A}$ is equal to 0, if the user considers that the probability of failure (transfer, diagnosis etc.) must not influence the path taken by the boats (usually when the conditions are good and certain). Then, the greater $\mathcal{A}$ is, the more the possibility of failure is taken into account and the more the algorithm will produce a path limiting the risks (the greater $\mathcal{A}$ is, the more the conditions are bad and uncertain). This function comes from the work done by Dawid et al [16]. It allows to give a more or less important gain value to the different turbines according to the risks that the maintenance team wants to take.

In addition, it was decided to take into account journeys which have a risk of being late but with a handicap proportional to their delay and with a delay factor (B) which the user can vary according to his requirements. So, if B is set to 0, then late journeys will not be taken into account, otherwise, the larger B is, the more later journeys will be penalized compared to other journeys. This allows users to be presented with a larger routing panel. The gain function (3) for the problem is therefore the following

$$F_p = \sum_{i=1}^G (U_i - C_{r_i}) - \sum_{j=1}^V (C_{f_j} + C_{v_j}) + \left(A * P_{v_j} * U_{mean} * \frac{N_{t_j}}{\eta} \right) - \frac{B}{N_{t_j}} * \frac{T_{retard_j}}{T_{total_j}} * U_{mean} \quad (4)$$

6 | RESULTS

To demonstrate the model's capabilities, a virtual wind farm was constructed as per [29]. The layout was a grid of 10×10 squares with 1.1 km between turbines. 80 km northeast of the wind farm's core was where the maintenance facility was located. On a certain day, twenty randomly selected turbines need maintenance. The features of each type of failure are shown in Table 2 together with their repair costs, anticipated maintenance action times, manpower requirements, and tool and spare component weights. The price of maintenance and repairs was taken from Dinwoodie et al. [37]. In this study, Dawid et al. [29] study is incorporated to depict the location of the turbines as well as

TABLE 2 Probability of correct diagnosis

	Probability of correct diagnosis
Manual reset	1
Grease top-up	1
Minor repair	0.8
Medium repair	0.9
High priority repair	0.95
Annual service	1

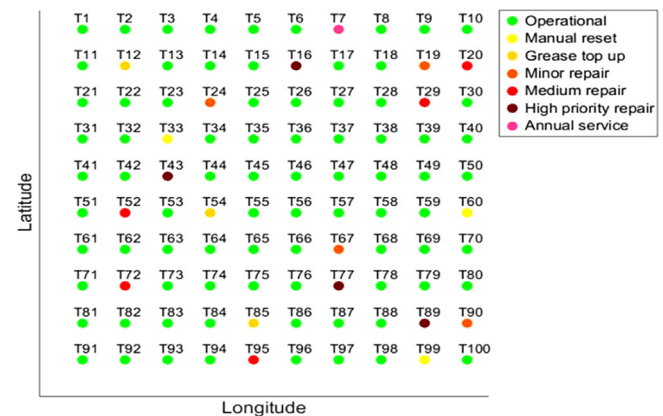


FIGURE 6 Virtual wind farm [29].

the various maintenance procedures needed for each turbine as shown in Figure 6. Details of the maintenance tasks and the result of the simulation are shown in Tables 3 and 4 respectively from the metrological centre. A turbine can be maintained, depending on the type of repair. For manual reset, minor, and medium repairs, £100,000 was given. To emphasise the need of high-priority repairs, the incentive was set at 120% of the normal repairs (£120,000). It cost £80,000 to do preventative maintenance procedures including topping out the grease and setting up an annual service [29].

The overall window of time for doing maintenance tasks on the day was 11 h, and there were 45 technicians accessible. A

TABLE 3 Details for each maintenance task of offshore wind turbines [16]

O&M tasks	Repair time (h)	Technicians required	Value (£,000)	Cost (£,000)	Weight of spares (kg)	Probability of correct diagnosis
Manual reset	2	2	100	0	0	1
Grease top-up	3	2	80	0.5	20	1
Minor repair	4	3	100	1	100	0.8
Medium repair	6	3	100	18.5	400	0.9
High priority repair	5	3	120	25	500	0.95
Annual service	6	2	80	18.5	300	1

TABLE 4 Results of the simulation

Original model							
Wave height (m) \ Wave period (s)	0–4	4–5	5–6	6–7	7–8	>8	Vessel transport
>4	0.01%	0.03%	1.85%	3.55%	3.04%	2.18%	50–80% success
3–4	0.02%	0.54%	2.67%	3.91%	2.59%	1.34%	100% success
2–3	0.07%	1.65%	6.26%	7.30%	3.94%	1.63%	
1–2	0.32%	4.77%	11.97%	9.88%	3.94%	1.19%	
0–1	1.83%	8.51%	9.39%	4.15%	1.01%	0.19%	
Sum of operability =						57.15%	
Reality							
Wave height (m) \ Wave Period (s)	0–4	4–5	5–6	6–7	7–8	>8	
>4	0.01%	0.03%	1.85%	3.55%	3.04%	2.18%	
3–4	0.02%	0.54%	2.67%	3.91%	2.59%	1.34%	
2–3	0.07%	1.65%	6.26%	7.30%	3.94%	1.63%	
1–2	0.32%	4.77%	11.97%	9.88%	3.94%	1.19%	
0–1	1.83%	8.51%	9.39%	4.15%	1.01%	0.19%	
Sum of operability =						52.06%	

20-min crew shift between the ship and the turbine was anticipated. In order to account for turning and acceleration and deceleration, the vessel speed when travelling from turbine to turbine was set at two-thirds of the cruising speed. The maximum number of turbines per vessel was capped at three due to limitations in both the technique used to solve the inner issue and the computing capability. The outcomes of the simulation of the suggested approach are shown below.

Given the computational constraints, this research is only able to use a maximum of three turbines per vessel in this research, therefore the findings of the simulation tool we offered are hardly comparable to those proposed by [29]. Nevertheless, it is interesting to consider the weather conditions that either completely prohibits some maritime operations or significantly lower the possibility of a smooth transfer between the turbine and the vessel. As a result, it is clear that the model put forth by [29] does not adequately address some scenarios because not all environmental factors are taken into account

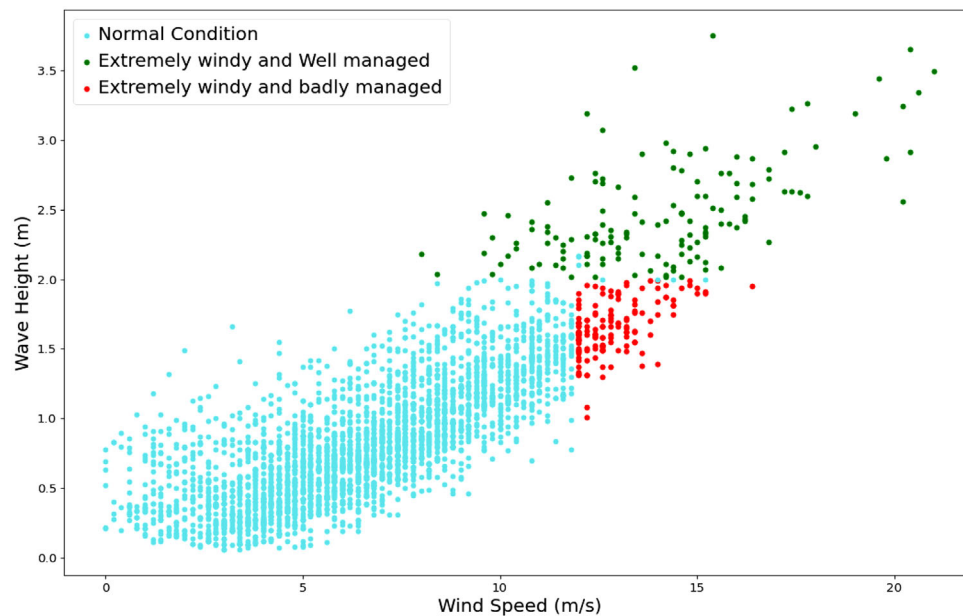
while in this study this has been covered to give a more realistic picture of O&M decision tool under environmental uncertainty.

As can be seen in Table 5, even if the waves are not very high (< 1 m), when the inter-wave period is very short (< 5 s), this can change the success probabilities of the transfer between the boat and the turbine which in the original model was always successful. Taking into account the inter-wave period, a reduction in operability time is observed, going from 57.15% to 52.06%, a difference in operability of almost 9%. The period is not the only environmental factor, which was not taken into account and could have a negative influence on operability.

Wind can have a significant impact on the operability of the wind farm and on the feasibility of maintenance. Wind speed is often correlated with wave size but sometimes there is strong wind and small waves as shown in Figure 7. Therefore, in 2016, 5% of the time high wind speed was not correlated with high waves. During this period, the original model estimates the probability of successful transfer at 100%, while following

TABLE 5 Operability depending on conditions

Policy characteristics	Case 1	Case 2	Case 3	Case 4	Case 5
Risk aversion factor (λ)	0	2.5	5	7.5	10
Planned number of turbines to be maintained ($\gamma/15$)	14	14	13	12	11
Expected policy value (not including added due to a non-zero λ) (£,000)	1249.4	1187.3	1070.5	1015.2	931.4
Number of technicians required to carry out all the maintenance actions	34	34	31	32	29

**FIGURE 7** Wind speed and wave height correlation.

the European Agency's security recommendations, the transfer under these conditions entails certain risks that need to be taken into account. Thus, below is the distribution of wind speed over the entire year of 2016 according to the wave height. The red dots correspond to the conditions during which improvements of the old model are needed while in green, these are windy conditions but well managed by the model as they are correlated to high waves. Taking these conditions into account, the model can see its accuracy compared to the windy conditions improved by 4.95%.

In the new model, taking into account the uncertainties related to the human that makes varied maintenance time and related to the boats and the weather that can lengthen the transfer time to the wind turbine improves the planning of the boat's path. This avoids the following problems that cause boats to waste time on their maintenance routes:

- -Have to wait for a service team that has exceeded the estimated maintenance time.
- -Having a transfer from the boat to the wind turbine disturbed by the weather.

- -Keep a maintenance team waiting on a wind turbine due to a delay.

These problems were not accounted for in the previous model and could therefore cause unforeseen delays at the base and a total change in planning.

The proposed methodologies allow a better estimation of uncertain values such as maintenance time thanks to Random Forest and transfer time from the boat thanks to the study of the recommendations of different maritime associations such as OCIMF. This made it possible to adapt the schedule of maintenance vessels, accordingly, making it shorter and more reliable.

6.1 | Comparative studies

As we have seen in this section, several new features have been introduced in our model to improve performance and bring us closer to reality. First, the addition of taking into account the transfer of the wind turbine to the boat can cause delays

TABLE 6 Comparison with previous models

Models	Wave height	Wave period	Wind speed	Crew transfer from the vessel to wind turbine
Previous Model	<ul style="list-style-type: none"> • Different wave heights according to the wind turbine. • Constant during the day 	<ul style="list-style-type: none"> • Does not take it into account 	<ul style="list-style-type: none"> • Does not take it into account 	<ul style="list-style-type: none"> • Depends on 2 parameters
New model	<ul style="list-style-type: none"> • Different wave heights according to the wind turbine. • Change during the day 	<ul style="list-style-type: none"> • Same wave period for the farm but changes with time 	<ul style="list-style-type: none"> • Does not take it into account • Same wave period for the farm but changes with time 	<ul style="list-style-type: none"> • Depends on 5 parameters

TABLE 7 Comparison with previous models—2

Models	Vessel routing problem (VRP) height	Time to complete a maintenance	Crew transfer from wind turbine to the vessel	Solve VRP
Previous model	<ul style="list-style-type: none"> • Decomposing in 2 problems: assignment of turbines to vessel and ordering turbine visits 	<ul style="list-style-type: none"> • Gamma distribution 	<ul style="list-style-type: none"> • Always successful 	<ul style="list-style-type: none"> • IBM CPLEX Optimizer
New model	<ul style="list-style-type: none"> • Decomposing in 2 problems: assignment of turbines to vessel and ordering turbine visits 	<ul style="list-style-type: none"> • Random Forest Model 	<ul style="list-style-type: none"> • Depends on 5 parameters 	<ul style="list-style-type: none"> • Gurobi

because of the weather and therefore impact the maintenance boat schedule. To account for this possible delay, a loss factor has been added to the gain function to ensure that transfers causing delays are avoided. Second, for maintenance time modelling, the gamma distribution is no longer used, instead, the machine algorithm Learning Random Forest was used to best represent the uncertainty related to the human. Third, a first attempt to account for weather change was first implemented in this model to try to respond to the variation in the probability of success due to the weather of some operations. Below are two tables presenting a comparison of the model presented in this paper and the previous models [29] and results are shown in Tables 6 and 7.

7 | DISCUSSION

During this research, several solutions were explored to improve the consideration of meteorological and human uncertainties. However, there are still many access improvements, some of which are presented in this section.

7.1 | Discussion regarding new-added factors

The addition of certain environmental factors improves the model's performance and the use of a deep-learning method for weather forecasting. On the other hand, the addition of these functions to the basic model allowed a better consideration of windy conditions and inter-wave intervals, thus reducing the risk that the model does not stick to real life. However, it is important not to forget the usefulness of this tool. This allows the

maintenance teams of a wind farm to determine the path that each vessel will take during the day. This algorithm is run in the morning before the start of the operation and must take as little time as possible to execute. By adding environmental factors and a forecast of the weather in real-time, the execution time is greatly increased from 215 s [42] to more than 10 min (or 600 s).

7.2 | Other ways to solve the problem

In addition, it is important to consider alternative methods to address this issue. Other algorithms such as ant columns or another version of a mixed-integer linear programming (MILP) model proposed by Irawan et al. [43] allow a new vision of the problem and special attention should be paid to it. Concerning the model presented here, a number of improvements could be made in the context of future work. This involves creating an algorithm to address the issue of scheduling turbine visits that allows for the assignment of more than four turbines per vessel without noticeably lengthening execution time.

7.3 | Other possible improvements

In the proposed model, an important element has been set aside, namely the influence of weather conditions on the speed of vessels. Poor conditions would lead to a reduction in the speed of the boat and would therefore benefit the maintenance of wind turbines that are close to each other to limit the distance travelled by vessel as much as possible. A study carried out by Carbon Trust [44] shows the influence of different

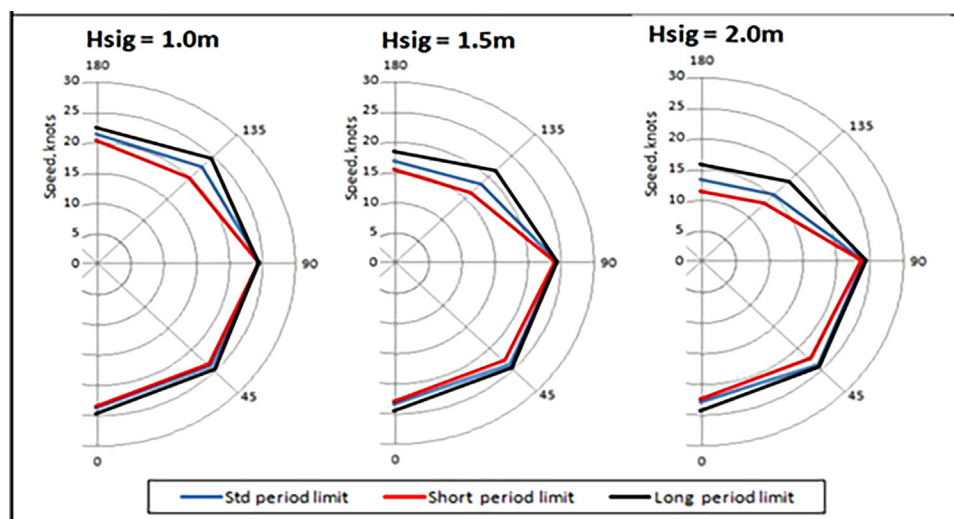


FIGURE 8 Influence on vessel speed.

environmental parameters such as the inter-wave period and the height of the waves on the vessel's speed. Figure 8 shows the evolution of the speed for a vessel of 26 m for 3 given wave sizes depending on the direction in relation to the wave and the inter-wave interval.

8 | CONCLUSION AND FUTURE WORKS

By maximising resource usage in offshore logistics planning, the decision support tool created in this study has the potential to reduce Operations and Maintenance costs. The tool is capable of presenting policies to users. This tool is based on [29] works, implementing modifications to the environmental parameters taken into account and the possibility of changing weather conditions and thereby improving the Operation and Maintenance decision tools.

Uncertainty has not yet been taken into account by experts working on vessel route optimization for offshore wind farms. The case study described in the results section shows that the cost-optimal technique will lead to fewer turbines being effectively maintained in the presence of uncertainty. Modelling offshore vessel itineraries must incorporate uncertainty since the recommended method may lead to a significant increase in maintained turbines.

With future efforts, a variety of improvements to the tool could be developed. Among these is the creation of an algorithm to address the issue of scheduling turbine visits that can allocate more than four turbines per vessel. The tool would also profit from being able to take into account the effects of weather conditions on vessel speed or the impact of wind direction.

AUTHOR CONTRIBUTIONS

Ravi Pandit: Project administration, Resources, Supervision, Writing—review and editing.

Yannis Hadjoudj: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing—original draft.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at [1. 10.15129/23f19557-8ede-4567-ac66-e4c838ca2cda2. 10.15129/c2700891-e1db-4227-841d-7aa9f8986f6f3. https://pureportal.strath.ac.uk/en/publications/decision-support-tool-for-offshore-wind-farm-vessel-routing-under/datasets/](https://pureportal.strath.ac.uk/en/publications/decision-support-tool-for-offshore-wind-farm-vessel-routing-under/datasets/).

ORCID

Ravi Kumar Pandit  <https://orcid.org/0000-0001-6850-7922>

REFERENCES

1. UK Government report titled 'UK sets ambitious new climate target ahead of UN Summit'. <https://www.gov.uk/government/news/uk-sets-ambitious-new-climate-target-ahead-of-un-summit>. Accessed 1st October 2022
2. UK Government policy paper titled 'Net Zero Strategy: Build Back Greener'. <https://www.gov.uk/government/publications/net-zero-strategy>. Accessed 1st October 2022
3. Report by Power Technology titled 'The world's most used renewable power sources'. <https://ourworldindata.org/renewable-energy>. Accessed 1st October 2022
4. Report by Earth.org titled 'What the Future of Renewable Energy Looks Like'. <https://earth.org/the-growth-of-renewable-energy-what-does-the-future-hold/>. Accessed 1st October 2022
5. EU commission report titled 'Offshore renewable energy'. <https://www.europarl.europa.eu/news/en/press-room/20220210IPR23015/boost-offshore-renewable-energy-sources-to-meet-climate-targets>. Accessed 1st October 2022
6. Pandit, R., Astolfi, D., Hong, J., Infield, D., Santos, M.: SCADA data for wind turbine data-driven condition/performance monitoring: A review on state-of-art, challenges and future trends. *Wind Eng.* (2022). <https://doi.org/10.1177/0309524%D7;221124031>

7. Ilbahar, E., Cebi, S., Kahraman, C.: A state-of-the-art review on multi-attribute renewable energy decision making. *Energy Strat. Rev.* 25, 18–33 (2019). <https://www.sciencedirect.com/science/article/pii/S2211467%D7;19300410>
8. Pandit, R., Infield, D., Peñas, M.: Accounting for environmental conditions in data-driven wind turbine power models. *IEEE Trans. Sustainable Energy* 14(1), 168–177 (2023). <https://doi.org/10.1109/TSTE.2022.3204453>
9. Ziegler, L., Gonzalez, E., Rubert, T., Smolka, U., Melero, J.J.: Lifetime extension of onshore wind turbines: A review covering germany, spain, denmark, and the UK. *Renewable Sustainable Energy Rev.* 82, 1261–1271 (2018). <https://doi.org/10.1016/j.rser.2017.09.100>
10. Astolfi, D., Pandit, R., Celesti, L., Lombardi, A., Terzi, L.: SCADA data analysis for long-term wind turbine performance assessment: A case study. *Sustain. Energy Technol. Assess.* 52, 102357 (2022)
11. Silva, N., Estanqueiro, A.: Impact of weather conditions on the windows of opportunity for operation of offshore wind farms in Portugal. *Wind Eng.* 37(3), 257–268 (2013). <https://doi.org/10.1260/0309-524X.37.3.257>
12. Pandit, R.K., Kolios, A., Infield, D.: Data-driven weather forecasting models performance comparison for improving offshore wind turbine availability and maintenance. *IET Renewable Power Gener.* 14, 2386–2394 (2020). <https://doi.org/10.1049/iet-rpg.2019.0941>
13. Gray, A.: ORE catapult report titled 'What are Operations and Maintenance Simulation Tools?'. <https://ore.catapult.org.uk/analysisinsight/what-are-operations-and-maintenance-simulation-tools/> Accessed September 2022
14. Tomaselli, P.D., Diken, M., Bolaños Sanchez, R., Sørensen, J.T.: A Decision-Making Tool for Planning O&M Activities of Offshore Wind Farms Using Simulated Actual Decision Drivers. <https://www.frontiersin.org/articles/10.3389/fmars.2020.588624/full>. Accessed 28th October 2022. (2021)
15. Kolios, A., Walgern, J., Koukoura, S., Pandit, R., Chiachio-Ruano, J.: openO&M: robust O&M open access tool for improving operation and maintenance of offshore wind turbines. In: *Proceedings of the 29th European Safety and Reliability Conference (ESREL)*, pp. 452–459. Hannover, Germany (2019)
16. Dawid, R., McMillan, D., Revie, M.: Development of an O&M Tool for Short Term Decision Making Applied to Offshore Wind Farms. *Wind Europe Summit, Hamburg, Germany* (2016)
17. Irawan, C.A., Ouelhadi, D., Jones, D., Stålhane, M., Sperstad, I.B.: Optimisation of maintenance routing and scheduling for offshore wind farms. *Eur. J. Oper. Res.* 256, 76–89 (2017)
18. Pandit, R., Astolfi, D., Tang, A.M., Infield, D.: Sequential data-driven long-term weather forecasting models' performance comparison for improving offshore operation and maintenance operations. *Energies* 15(19), 7233 (2022). <https://doi.org/10.3390/en15197233>
19. Avanesova, N., Gray, A., Lazakis, I., Thomson, R.C., Rinaldi, G.: Analysing the effectiveness of different offshore maintenance base options for floating wind farms. *Wind Energy Sci.* 7, 887–901 (2022). <https://doi.org/10.5194/wes-7-887-2022>
20. Dai, L., Stålhane, M., Utne, I.B.: Routing and scheduling of maintenance fleet for offshore wind farms. *Wind Eng.* 39, 15–30 (2014)
21. Zhang, Z.: Scheduling and routing optimization of maintenance fleet for offshore wind farms using Duo-ACO. *Adv. Mater. Res.* 1039, 294–301 (2014)
22. Stålhane, M., Hvattum, L.M., Skaar, V.: Optimization of routing and scheduling of vessels to perform maintenance at offshore wind farms. *Energy Proc.* 80, 92–99 (2015)
23. Forecoastmarine. <https://www.shoreline.no/solutions/om-design/>. Accessed 15th October 2022
24. Fraunhofer Institute for Wind Energy Systems-Fraunhofer IWES. <https://www.forecoastmarine.com/gamer-mode>. Accessed 15th October 2022
25. Fraunhofer Institute for Wind Energy Systems IWES report titled 'Strategy Report 2020–2025'. <https://www.dnv.com/services/operations-planning-o2m-for-offshore-wind-farms-5158> Accessed 15th October 2022
26. Montoya, F.S.: Dai, Report. <https://www.tno.nl/en/about-tno/organisation/units/energy-transition/> Accessed 15th October 2022
27. TNO for Innovation white paper titled 'Energy transition: a sustainable future is the only future'. Accessed 15th October 2022
28. Dawid, R., McMillan, D., Revie, M.: Development of an O&M Tool for Short Term Decision Making Applied to Offshore Wind Farms. https://www.researchgate.net/publication/312970476_Development_of_an_OM_tool_for_short_term_decision_making_applied_to_offshore_wind_farms. Accessed 15th October 2022
29. Dawid, R., McMillan, D., Revie, M.: Decision support tool for offshore wind farm vessel routing under uncertainty. *Energies* 11(9), 2190 (2018). <https://doi.org/10.3390/en11092190>
30. Cory Allen, R., Baratsas, S.G., Kakodkar, R., Avraamidou, S., Powell, J.B., Heuberger, C.F., Doga Demirhan, C., Pistikopoulos, E.N.: An optimization framework for solving integrated planning and scheduling problems for dense energy carriers. *IFAC-PapersOnLine* 54(3), 621–626 (2021)
31. ECWMF Advancing global NWP through international collaboration. Accessed 28th October 2022
32. <https://www.tidetech.org/>. Accessed 28th October 2022
33. <http://www.euroision.org/>. Accessed 28th October 2022
34. Dawid, R.: (Creator). Data for: "Decision Support Tool for Offshore Wind Farm Vessel Routing Under Uncertainty" (Revised). University of Strathclyde. *Supplementary_Material.docx*, *Wind_turbine_locations.xlsx* (2018). 10.15129/c2700891-e1db-4227-841d-7aa9f8986f6f. Accessed 28th October 2022
35. Greeff, G.: 8 - Production capability management. *Practical E-Manufacturing and Supply Chain Management* 214–242 (2004). <https://doi.org/10.1016/B978-075066272-7/50011-7>
36. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative Adversarial Nets. <https://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf> (2014). Accessed 28th October 2022
37. Rocca, J.: Understanding Variational Autoencoders (VAEs). <https://towardsdatascience.com/understanding-variational-autoencoders-vaes-f70510919f73> (2019). Accessed 28th October 2022
38. Chawla, V., Bowyer, W., Hall, O., Kegelmeyer, W.P.: SMOTE: Synthetic minority over-sampling technique. *J. Artif. Intell. Res.* 16, 321–357 (2002). <https://arxiv.org/pdf/1106.1813.pdf>
39. Xu, L., Veeramachaneni, K.: Synthesizing tabular data using generative adversarial networks. <https://arxiv.org/pdf/1811.11264.pdf> (2018)
40. DNV.GL article titled 'Sustainable ambitions for offshore wind support'. <https://www.dnv.com/expert-story/maritime-impact/Sustainable-ambitions-for-offshore-wind-support.html>. Accessed 28th October 2022
41. <https://www.energyinst.org/>. Accessed 28th October 2022
42. Carroll, J., McDonald, A., Dinwoodie, I., McMillan, D., Revie, M., Lazakis, I.: Availability, operation and maintenance costs of offshore wind turbines with different drive train configurations. *Wind Energy* 20, 361–378 (2017). <https://doi.org/10.1002/we.2011>
43. Ade Irawan, C., Staritac, S., KaiChan, H., Eskandarpour, M., Reihanehde, M.: Routing in offshore wind farms: A multi-period location and maintenance problem with joint use of a service operation vessel and a safe transfer boat. <https://www.sciencedirect.com/science/article/pii/S0377221722006415> (2022). Accessed 28th October 2022
44. Carbon Trust: Crew Transfer Vessel (CTV) Performance Plot (P-Plot) Development. <https://pdfslide.net/documents/crew-transfer-vessel-ctv-performance-plot-p-plot-transfer-vessel-ctv-performance.html> (2017). Accessed 28th October 2022

How to cite this article: Hadjoudj, Y., Pandit, R.K.: Improving O&M decision tools for offshore wind farm vessel routing by incorporating weather uncertainty. *IET Renew. Power Gener.* 17, 1488–1499 (2023). <https://doi.org/10.1049/rpg2.12689>



DSpace

<https://dspace.org/>

Improving O&M decision tools for offshore wind farm vessel routing by incorporating weather uncertainty

Hadjoudj, Yannis; Pandit, Ravi

2023-04-27

Institution of Engineering and Technology (IET)

<https://doi.org/10.1049/rpg2.12689>

Hadjoudj Y, Pandit RK. (2023) Improving O&M decision tools for offshore wind farm vessel routing by incorporating weather uncertainty. IET Renewable Power Generation, Volume 17, Issue 6, 27 April 2023, pp. 1488-1499