
Journal of the Operational Research Society

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/tjor20

# Multi-objective optimisation of multifaceted maintenance strategies for wind farms

Yikai Ma, Wenjuan Zhang & Juergen Branke

**To cite this article:** Yikai Ma, Wenjuan Zhang & Juergen Branke (2022): Multi-objective optimisation of multifaceted maintenance strategies for wind farms, Journal of the Operational Research Society, DOI: 10.1080/01605682.2022.2085066

**To link to this article:** https://doi.org/10.1080/01605682.2022.2085066

JOURNAL OF THE OPERATIONAL RESEARCH SOCIETY
https://doi.org/10.1080/01605682.2022.2085066



# Multi-objective optimisation of multifaceted maintenance strategies for wind farms

Yikai Ma, Wenjuan Zhang and Juergen Branke

University of Warwick, Coventry, UK

**ABSTRACT**
This paper proposes a way to simultaneously optimise three aspects of maintenance strategies for wind farms: the reliability thresholds that indicate when a component needs maintenance, the priority of maintenance jobs in case there are more jobs than available maintenance teams, and the use of opportunistic maintenance. We use a multi-objective evolutionary algorithm to simultaneously minimise the overall maintenance cost and the system idle time. An empirical study using a complex stochastic simulation demonstrates the benefit of such a multifaceted maintenance strategy over strategies that only consider some aspects.

**ARTICLE HISTORY**
Received 13 September 2021
Accepted 26 May 2022

**KEYWORDS**
Maintenance; metaheuristics; multi-objective

## 1. Introduction

Wind energy is an essential natural resource that is clean, renewable, and sustainable. According to EvWind (2020), the global wind energy market expanded 19% in 2019. As for Europe, wind satisfied 15% of electricity demand, and 5.1 GW (10.1 GW in EU-28) of new wind farms were installed in the first six months of 2020 (Richard, 2020). The maintenance of wind farms has attracted significant interest in recent years, as it is responsible for a large proportion of lifecycle costs. Designing a cost-effective maintenance strategy for wind farms is therefore an urgent need.

The maintenance definitions and classifications vary in the literature, and in this research, we follow the categories provided by Ren et al. (2021). There are several maintenance types, such as failure-based maintenance, preventive maintenance, condition-based maintenance and predictive maintenance. For failure based maintenance, maintenance is only carried out on a failed component. The other three types of strategies are all proactive maintenance, as they try to maintain before failures. Preventive maintenance usually refers to regular, routine maintenance, which performs maintenance activities at fixed intervals. Condition-based maintenance (CBM) and predictive maintenance both use sensors to collect data about the system state. With CBM, maintenance is performed whenever the measured signals show the target system reaches an unacceptable level. In case of predictive maintenance, maintenance activities are scheduled in advance based on the analysis of the collected signals. All maintenance strategies have their advantages and disadvantages. For example, periodic maintenance can help avoid failures but may lead to over-maintaining. The initial cost of CBM and predictive maintenance are high but can avoid unnecessary visits. For more details of the comparison of different types of strategy, the readers can refer to Ren et al. (2021). In this study, we improve the preventive maintenance for wind turbines by using predictions of the components' reliability in terms of their virtual ages. Maintenance is triggered if reliability drops below a predetermined level. The virtual age is assumed as input data in this study. When sensor data becomes available, the virtual age can be predicted based on the sensor data and the maintenance strategy becomes a predictive maintenance strategy.

Each wind turbine includes several major components, such as blade, generator, gearbox, etc. Research indicates economic and structural dependencies among units in the multi-unit system. Economic dependency means the total cost of two maintenance activities executed jointly can be lower than the total cost of doing them independently. For example, the dispatching cost of a maintenance crew and the re-start cost of the system can be saved when such opportunistic maintenance is performed. Structural dependence among units implies that a failure in one component may affect the

CONTACT Yikai Ma phd18ym@mail.wbs.ac.uk University of Warwick, Coventry, UK.
Supplemental data for this article is available online at https://doi.org/10.1080/01605682.2022.2085066

virtual age of other components in the same turbine. This study considers both dependency types in the simulation. Although there is no consensual definition of the opportunistic maintenance (Thomas et al., 2008), a strategy that exploits such opportunities to reduce maintenance costs is often called an opportunistic maintenance strategy.

In this paper, we propose to use a simulation optimisation approach to design a maintenance policy that can then be used to make daily maintenance decisions. It aims to minimise cost and system idle time simultaneously and specifies three aspects of a maintenance strategy:

- The reliability thresholds. These determine at which predicted level of a component's reliability a maintenance activity is required.
- The maintenance priority. If there are more maintenance jobs required than available maintenance teams, the jobs have to be prioritised, and the jobs with lower priority will be postponed. Here, only the types of maintenance are considered. Activities of the same kind are sequenced according to their occurrence time.
- The opportunistic strategy. This determines when a team is sent out to maintain a component at a turbine, whether they should also carry out maintenance at other components of this turbine.

We call this approach a 3-dimensional (3 *D*) multi-objective maintenance strategy. To the best of our knowledge, this is the first time three aspects of a maintenance strategy and their interactions have been considered simultaneously. We demonstrate the benefit of the 3 D maintenance strategy using a complex stochastic simulation model of a wind farm.

The rest of the paper is organised as follows. Section 2 provides a brief review of related work. Section 3 introduces the problem and describes the model used in this research. Section 4 explains the simulation process. Section 5 introduces the optimiser and reports on empirical results comparing our method to some more straightforward approaches. The paper concludes with a summary and some ideas for future work.

## 2. Literature review

Maintenance planning of an industrial system is a vast field. For example, De Jonge and Scarf (2020) review over two hundred papers about wind farms' maintenance modelling and optimisation. In this section, we will focus on the maintenance strategy for wind farms most closely related to our work. Our classification distinguishes single and multi-component turbines, the methods used to determine maintenance needs, and the number of objectives considered. Furthermore, we review the studies according to the constraints considered and the maintenance activities' level.

A wind turbine can be considered as a multi-unit system with dependencies. There are structural, stochastic, economic and resource dependencies (Rinaldi et al., 2021). Economic dependence and structural dependence are considered more often as they may be exploited by opportunistic maintenance activities (C. Zhang et al., 2019; Papadopoulos et al., 2021). For an example considering stochastic dependencies, see e.g. N. Zhang et al. (2020).

To determine when maintenance should be performed, as mentioned in Section 1, there are mainly four types of maintenance strategies. Failure-based maintenance has a low initial cost but cannot prevent failures and may lead to lower system availability. The main task of preventive maintenance is to determine the time interval between maintenance activities. For example, Carlos et al. (2013) take planned intervals between maintenance as the decision variable to schedule maintenance activities. When CBM is applied, real-time monitoring data will be collected from condition monitoring systems to detect failures. Most previous studies that apply CBM assume the monitoring systems will correctly detect all the corresponding assets' faults. Few scholars consider false alarms and the sensor detection rates (May & McMillan, 2013). For more studies about the application of CBM to wind farms, we refer the reader to Kang et al. (2019). Predictive maintenance is a more advanced maintenance strategy that uses a digital twin of a physical system to predict likely failures and schedule maintenance activities to avert the predicted failures (Canizo et al., 2017; Jiang et al., 2020; Sivalingam et al., 2018).

For a wind farm's maintenance policy, the most critical objectives are minimising cost and maximising energy production. Some papers consider the trade-off between these multiple objectives and use optimisation tools to find the best solutions. For example, Zhong et al. (2018) and Rinaldi et al. (2020) both apply a multi-objective evolutionary algorithm to maximise the system reliability and minimise maintenance cost for offshore wind farms. Ge et al. (2020) use a mixed-integer linear programming model for maintenance schedules that can maximise power generation and minimise the maintenance cost. Allal et al. (2021) propose a simulation-optimisation approach for the maintenance routine for offshore wind farms. It applies Ant Colony System to minimise the cost of the

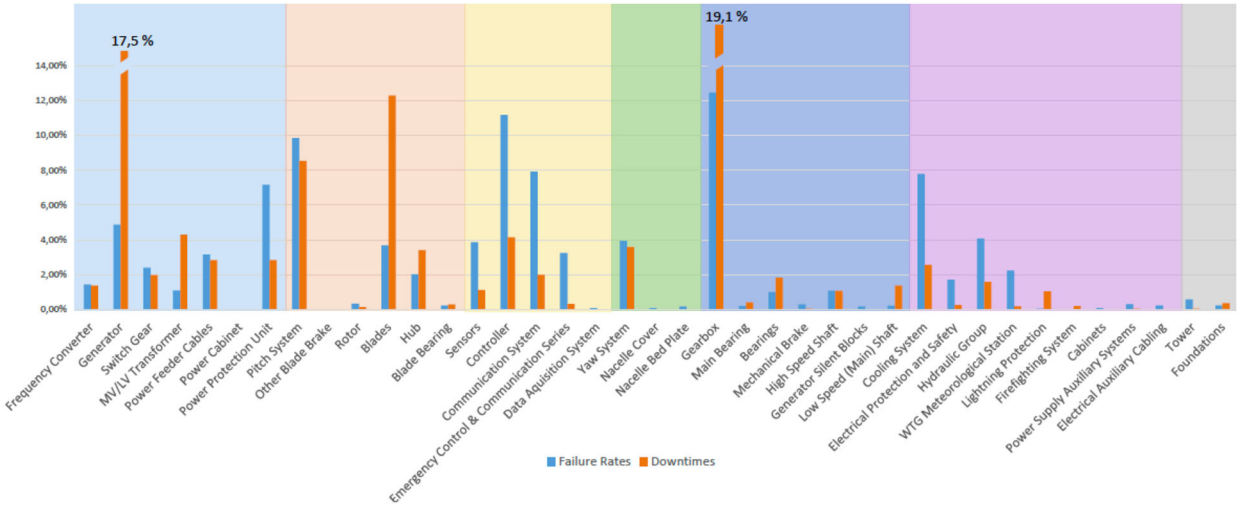


**Figure 1.** The failure rates and downtime for components in a turbine (Source: Reder et al. (2016)).

maintenance route while maximising energy production. Some papers consider multiple objectives but transform them into a single objective through linear combination, such as Carlos et al. (2013) and C. Zhang et al. (2019), or they only consider one of the objectives. For example, Nguyen and Chou (2019) propose an approach that can provide a maintenance schedule for offshore farms that can minimise maintenance costs while the study of Stock-Williams and Swamy (2019) aims to minimise energy loss.

In reality, some additional constraints can influence the maintenance activities of wind farms. A large number of previous studies considered limited maintenance teams (Abdollahzadeh et al., 2016). Yang, Li, et al. (2020) and Yang et al. (2020) consider the influence of the wind condition when scheduling maintenance of wind farms. Some studies, such as Zahedi-Hosseini et al. (2018) and Zhang et al. (2019), consider the inventory of spare parts. Some other scholars focus on the vehicles used, e.g. Stock-Williams and Swamy (2019) and Irawan et al. (2021) consider the routing and scheduling of a maintenance fleet for offshore wind farms.

The maintenance level is another critical issue to be decided by a decision-maker. Maintenance activities can be classified into perfect maintenance (replacement) which bring the component back to an as-good-as-new condition, and imperfect maintenance (repair) which will bring the component back to a better than before condition. For example, Wang et al. (2020) take two-level maintenance into account. Some other studies, such as Zhou and Yin (2019) and Yang, Li, et al. (2020), only consider a single level of maintenance by assuming all actions are replacements.

Among all papers reviewed, the one most similar to our research is Abdollahzadeh et al. (2016). We both apply reliability thresholds to determine the maintenance activities and consider opportunistic maintenance activities. However, Abdollahzadeh et al. (2016) only consider the reliability thresholds as decision variables.

Our research focuses on three types of decision variables to determine the maintenance strategy: through three sub-strategies. First, we model each component's degradation process and use its predicted reliability to determine when maintenance is triggered. This type of variable determines the reliability strategy and focuses on the health condition of a single component. Secondly, we apply an opportunistic maintenance strategy to decide which activity should be considered as an opportunistic maintenance activity. This sub-strategy treats the wind turbine as a whole and considers the dependencies among components. Thirdly, we use a priority rule to schedule maintenance teams. This sub-strategy considers the resource limitation and the priority of different maintenance types. Some previous studies consider one or two aspects, such as the reliability strategy with the opportunistic maintenance. However, to the best of our knowledge, none considers all three aspects as we do in this research. The advantage of considering all three sub-strategies simultaneously will be demonstrated in Section 5.

## 3. Problem definition, model description and optimisation model

### 3.1. Problem definition

There are several components in a wind turbine, such as the gearbox, the generator, the rotor, and the pitch system. Whether a component is regarded critical depends on its failure rate and the time needed for repair. Reder et al. (2016) provide typical failure rates and downtime for different components in different types of wind turbines. Figure 1 summarises the normalised failure rate and downtime for components in a turbine. Based on this, we select

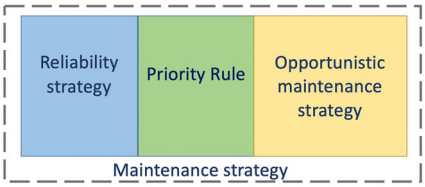


**Figure 2.** The elements of the maintenance strategy.

six critical components: the gearbox, the control system, the blade, the generator, the pitch system, and the yaw system.

In this research, we use Weibull distributions to model the time between failures. The cumulative distribution is of the form:

$$F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^{\beta}} \tag{1}$$

where $F(t)$ represents the cumulative probability of failure from time zero until time $t$, and $\alpha$ and $\beta$ are the scale and shape parameters from the Weibull distribution.

We assume that the failure probability is conditional on the virtual age of the corresponding component. The virtual age is not the real age of a component, but in practice is calculated from the cumulative operational time and collected sensor data and represents a component's current condition. In this study, we assume the virtual age will be directly provided. Let us denote the virtual age of the $j$th component in wind turbine $i$ by $VA_{ij}$. After each maintenance, the failure distribution of a component can be calculated through the failure probability distribution function conditioned on the current virtual age $VA_{ij}$.

Different types of components have different Weibull parameters. For example, Weibull parameters for $j$th component in wind turbine $i$ is $\alpha_{ij}$ and $\beta_{ij}$. The corresponding failure probability of the component with current virtual age $VA_{ij}$ is shown in Eq. (2), and is in the range $[0, 1]$.

$$F(T + VA_{ij}|VA_{ij}) = \frac{F(T + VA_{ij}) - F(VA_{ij})}{1 - F(VA_{ij})}$$
$$= 1 - \exp\left[\left(\frac{VA_{ij}}{\alpha_{ij}}\right)^{\beta_{ij}} - \left(\frac{T + VA_{ij}}{\alpha_{ij}}\right)^{\beta_{ij}}\right] \tag{2}$$

We define the reliability of a component as the probability that the component will survive for one more year (i.e. $T = 365$). Thus the reliability $R(VA_{ij})$ of a component with virtual age $VA_{ij}$ equals 1 minus the probability that it will fail in the next $T$ days.

$$R(VA_{ij}) = 1 - F(T + VA_{ij}|VA_{ij})$$
$$= \exp\left[\left(\frac{VA_{ij}}{\alpha_{ij}}\right)^{\beta_{ij}} - \left(\frac{T + VA_{ij}}{\alpha_{ij}}\right)^{\beta_{ij}}\right], \quad 0 \le R \le 1 \tag{3}$$

To simulate the actual failure times, we can use the Inverse Transform technique (Banks et al., 2005). Eq.(4) can be used to determine the time to failure (TTF), i.e. how long it will take for a failure to occur if the current virtual age is $VA_{ij}$.

$$TTF_{ij} = \alpha_{ij}\left[\left(\frac{VA_{ij}}{\alpha_{ij}}\right)^{\beta_{ij}} - \ln(1 - U)\right]^{\frac{1}{\beta_{ij}}} - VA_{ij} \tag{4}$$

where $U$ is a random variable which is uniformly distributed between $(0, 1]$.

### 3.2. Model description

As shown in Figure 2, in this research, the maintenance strategy is three-dimensional, i.e. comprised of three sub-strategies: priority rule, opportunistic maintenance strategy, and reliability strategy.

Reliability thresholds are applied to determine maintenance activities. Each component type has two reliability thresholds $RI$ and $RP$ ($RI > RP$). $RI$ is the reliability threshold for imperfect maintenance (repair), and the $RP$ is the reliability threshold for perfect maintenance (replacement). An example in Figure 3 shows how reliability of a component decreases over time. Imperfect maintenance will be triggered when the reliability decreases below $RI$. If no timely repair is performed, the reliability will eventually decrease to $RP$, and the target component will be replaced. Note that unpredicted failure can occur at any time during a component's lifetime.

When a failure occurs, the component must be replaced.

We apply the Generalised Renewal Process (GRP) proposed in Yanez et al. (2002) to model the restoration effect of maintenance. A decrease in the virtual age represents the efficiency of maintenance work. A rejuvenation parameter $q$ is applied to represent the effect of the maintenance activity. After a maintenance action on a component $ij$, the new virtual age will be:

$$VA_{ij}^{new} = VA_{ij}^{old}(1 - q_{ij}) \tag{5}$$

The value of $q \in (0, 1]$ depends on the type of component and the type of maintenance activity.

This research considers a limited number of maintenance teams. Whenever a maintenance team becomes available and several activities are due, the priority rule will determine which activity will be performed first. Table 1 shows the six priority rules considered, which only take into account maintenance types. For example, when applying priority rule 1, we will first perform the activity that replaces a failed component. If there is no failed component, we will perform a preventive replacement activity. If none of the above two activities is due, preventive

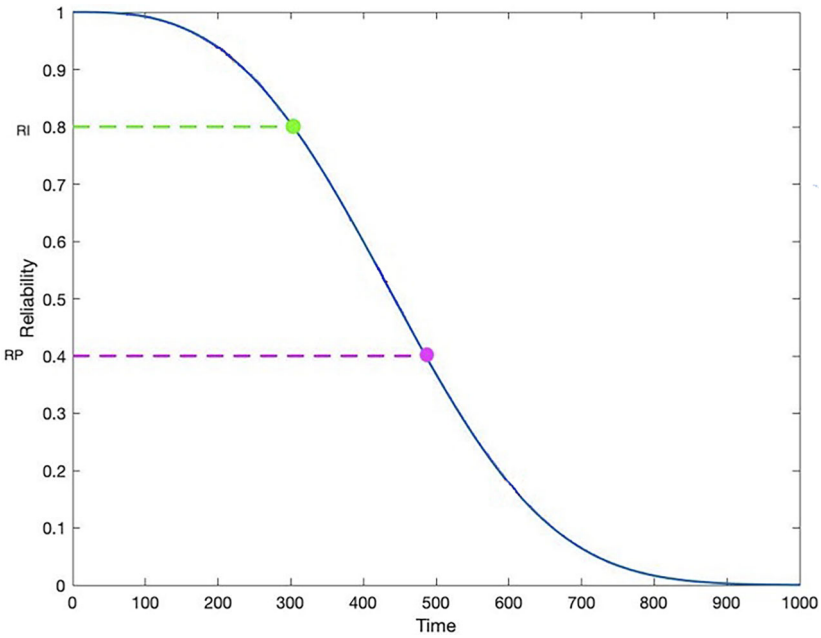


**Figure 3.** The deterioration process of a component.

**Table 1.** Priority rules.

| Priority | Rule | | |
|---|---|---|---|
| 1 | Failure > Replace > Repair | 2 | Replace > Failure > Repair |
| 3 | Replace > Repair > Failure | 4 | Repair > Replace > Failure |
| 5 | Failure > Repair > Replace | 6 | Repair > Failure > Replace |

repair work will be performed. For the same type of activity, we will prioritise according to the occurrence time.

The maintenance opportunity is initiated by a maintenance team already dispatched to a turbine. By utilising this type of opportunity, the cost of re-dispatch and system restart can be saved. Table 2 shows the three opportunistic strategies considered in this research. The classification used here has been introduced by Li et al. (2021).

When constructing the wind farm's maintenance policy, a trade-off exists between improving turbines' availability and reducing overall maintenance cost. The cost includes all expenses, such as maintenance, dispatching, and penalty cost of failures. When the system is under repair or failed, then it can't produce any energy. The downtime cost can be included in the total cost. However, when determining the objectives of maintenance strategies, we need to consider the interests from different stakeholders. For example, Schrotenboer et al. (2020) mention the misaligned objectives between the maintenance providers and wind farm owners. Some stakeholders may also consider reputation, user satisfaction, CO2 emission, and other risk-related problems. The idle time of a wind farm could be a good representation to reflect such requirements. Thus, in this research, we consider the trade-off between the overall maintenance cost and system idle time.

The general mathematical formulation of this problem is as follows:

$$\begin{aligned} &\textbf{Minimise} \quad \textit{Total Cost}\ (X, Y, Z) \\ &\textbf{Minimise} \quad \textit{Idle Time}\ (X, Y, Z) \end{aligned} \tag{6}$$

Subject to

$$\begin{aligned} &0 < RP_{i,j} < RI_{i,j} < 1 \\ &\forall i = 1, 2, \ldots, M, \quad \forall j = 1, 2, \ldots, k \end{aligned} \tag{7}$$

$X$, $Y$, and $Z$ represent the priority rule, the opportunistic strategy, and the reliability strategy. The form of $Z$ is shown in Eq. (8). Each row of $Z$ represents the $RI$ and $RP$ of each turbine. For example, the $M$th row shows the reliability thresholds for components in turbine $M$, and $RI_{M,k}$ is the reliability of imperfect maintenance for component $k$ in turbine $M$.

$$Z = \begin{bmatrix} RI_{1,1} & RP_{1,1} & \cdots & RI_{1,k} & RP_{1,k} & \\ RI_{2,1} & RP_{2,1} & \cdots & RI_{2,k} & RP_{2,k} & \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ RI_{M,1} & RP_{M,1} & \cdots & RI_{M,k} & RP_{M,k} & \end{bmatrix} \tag{8}$$

### 3.3. Optimisation method and performance assessment

If a problem has multiple conflicting objectives, we need to find a Pareto set comprised of several non-dominated or Pareto-optimal solutions, i.e. solutions that cannot be improved in both objectives simultaneously. In this research, we use two well known multi-objective evolutionary algorithms (EAs), Non-dominated Sorting Genetic Algorithm II (NSGA-II)

Table 2. Opportunistic maintenance strategy.

| Opportunistic maintenance strategy |
|---|
| 1 Each time when a maintenance work is carried out on a component, the team should also perform both repair and replacement work for the components in the same turbine with reliability lower than the corresponding thresholds. |
| 2 Each time when a maintenance work is carried out on a component, the team should also perform replacement for the components in the same turbine with reliability lower than the corresponding thresholds. |
| 3 There is no opportunistic maintenance work. The team will only perform the maintenance work on the target component. |

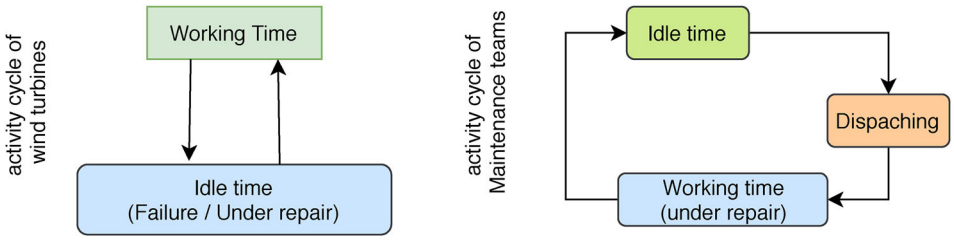


Figure 4. The activity cycles.

(Deb et al., 2002) and Indicator-Based Evolutionary Algorithm (IBEA) with additive $\epsilon$-indicator (Zitzler & Künzli, 2004) as implemented in the MATLAB platform PlatEMO (Tian et al., 2017), for the simulation-based optimisation.

To compare the quality of the results of multi-objective optimisation, we use the hypervolume indicator. The hypervolume indicator is defined as the size of the region bounded by the Pareto optimal solutions and a reference point (Zitzler & Thiele, 1999). Larger values of hypervolume generally mean a better Pareto front. For visually comparing the Pareto optimal results from different optimisation approaches, we combine results from multiple runs and compute the best, and the median attainment surfaces (Fonseca & Fleming, 1996).

## 4. Simulation process

In this research, a discrete event simulation model is used to simulate the maintenance activity of a wind farm. Figure 4 shows the activity cycles. A wind turbine can either be working or idle due to failure or maintenance work. A maintenance team can either be idle, dispatched, or working.

Figure 5 represents the activity cycles of the maintenance process of a wind farm. Three lists are used to record the state of the system and upcoming events (Table 3). The event list contains future events with a time stamp. In each iteration, the clock is advanced to the earliest event in this list, and the event is processed. The waiting list is used to record maintenance jobs waiting for an available maintenance team, and the frozen list stores events and jobs that have been put on hold because the failure of another component in the same turbine has taken precedence. The 'RS', 'OMS', and 'PR' in circles represent 'Reliability Strategy', 'Opportunistic Maintenance Strategy', and 'Priority Rule', which are configuration parameters in the simulation. The maintenance teams respond to maintenance jobs generated because a component reached its maintenance threshold specified in the Reliability Strategy or failed. They will use the Priority Rule to decide which job to do next if several jobs are waiting. And once they arrive at a turbine for maintenance, they use the Opportunistic Maintenance Strategy to decide on the components to be maintained for this turbine.

Note that it may happen that when a repair activity is performed too late, the new reliability after the repair is still lower than the corresponding *RI* threshold. When this happens, we have three options:

**Option 1 (Never check):**. If, after repair work, the new reliability is still lower than *RI*, we record the next repair activity immediately into the Waiting List. And when there are available maintenance teams, the team will refer to the priority rule and determine when to execute the next repair;

**Option 2 (Check after):** Each time after repair work, the team will check the new reliability. If the new reliability is lower than the corresponding *RI* value, the team will not perform any additional repair work and will wait until the reliability decreases to *RP* or a failure occurs;

**Option 3 (Check before):** Each time before repair work, the team will calculate the reliability after repair. If the predicted new reliability is lower than *RI*, they will skip that repair work and wait until the next replacement is due or a failure occurs.

## 5. Empirical evaluation

### 5.1. Data used in this experiment

We set the Weibull parameters following previous publications (Abdollahzadeh et al., 2016; Le & Andrews, 2016). As there are several types of

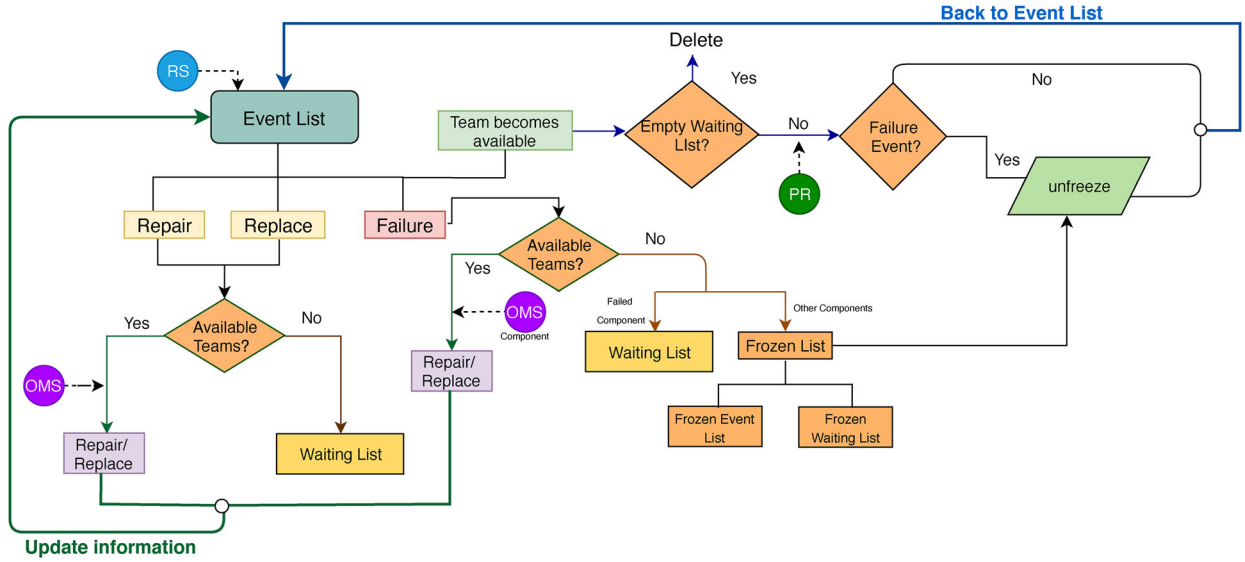


**Figure 5.** The simulation process of maintenance.

**Table 3.** Explanation of the lists used in the simulation process.

| Explanation of Lists | |
|---|---|
| **EventList** | All upcoming events for all components in the working turbines as well as the events that the teams are currently working on will be recorded in the Event List |
| **Waiting List** | Repair or replacement activities that are postponed due to insufficient maintenance team availability |
| **Frozen List** | The Frozen List can be divided into Frozen Event List and Frozen Waiting List |
| **Frozen Event List** | The events for working components in the failed turbines that are still in the Event List will be extracted to the Frozen Event List when the corresponding turbines fails |
| **Frozen Waiting List** | The events for the working components in the failed turbines that are recorded in the Waiting List will be extracted to the Frozen Waiting List when the corresponding turbines fail |

**Table 4.** Model input parameters - Weibull scale and shape parameters.

| Component | Weibull scale parameter (days) | Weibull shape parameter |
|---|---|---|
| Gearbox | 2400 | 3 |
| Control system | 1750 | 2 |
| Blade | 3000 | 2 |
| Generator | 2400 | 3 |
| Pitch system | 1500 | 2 |
| Yaw system | 1800 | 3 |

components in a wind turbine, and each of them has different characteristics. Different Weibull parameter values are applied to model the time between failures for different types of component. Table 4 shows the parameters used in this study.

The system's idle time is simply the sum of time for all turbines when the turbine is unavailable due to failure or maintenance. The maintenance time is assumed to be stochastic and follow a truncated Normal distribution with means as provided in Table 5 and a standard deviation of 0.1 times the corresponding mean value. The cost information is also provided in Table 5, obtained from previous literature (Kang et al., 2020; Le & Andrews, 2016).

Besides the cost for actual maintenance, the total cost also includes the cost of dispatching maintenance teams, the cost of restarting the system, and a penalty cost of failure. As there are interrelationships among the components in a turbine, the

**Table 5.** Model input parameters - maintenance cost and time information.

| WT component | Maintenance description | Cost (£) | Mean Time (days) |
|---|---|---|---|
| Gearbox | Repair | 25,000 | 0.9 |
| | Replace | 230,000 | 9.65 |
| Control system | Repair | 1,500 | 0.3 |
| | Replace | 95,000 | 7 |
| Blade | Repair | 1,500 | 1.5 |
| | Replace | 90,000 | 12.5 |
| Generator | Repair | 3,500 | 0.9 |
| | Replace | 60,000 | 4.5 |
| Pitch system | Repair | 5,300 | 1 |
| | Replace | 13,500 | 3.375 |
| Yaw system | Repair | 1,900 | 0.8 |
| | Replace | 14,000 | 6.25 |
| | Penalty cost of failure | 50,000 | |
| | Dispatching a team | 5,000 | 0.2 |
| | Restart the system | 5,000 | |

failure of one component may influence the deterioration process of other components in that turbine. This influence can be expressed by a faster deterioration or a sudden failure of other components. Here, as a simplified first step, the side effect is represented by a fixed increase in the virtual age (10 days) of other components in this turbine.

A maintenance work's effectiveness is modelled by a decrease in the virtual age. After imperfect repair work, the virtual age of the component is decreased by $q \times 100\%$. The value of $q$ is considered fixed and depends on the type of component, see Table 6.

Using the parameters introduced above, we experiment with a wind farm consisting of 90 wind turbines of equal characteristics with 6 critical components connected in series. Each component has a random initial virtual age, and all components are assumed to be in working condition at the start. There are 3 maintenance teams available. The maximum simulation time is 15 years (5475 days). For the NSGA-II and IBEA, the number of individuals in each generation (iteration) is set as 100, and the maximum generation number is 100.

All results reported in the next section are averaged over 11 replications with different random seeds.

### 5.2. Results and discussion

First, we use NSGA-II and IBEA with Option 2 (check after) and Option 3 (check before) to find out whether there are significant differences in the final results from the two meta-heuristics and the two options. Option 1 (Never check) is not selected, as in reality, continuous maintenance is not meaningful.

**Table 6.** The default values of maintenance effectiveness $q$.

| Critical Component | Maintenance effectiveness $q$ |
|---|---|
| Gearbox | 0.2 |
| Control System | 0.15 |
| Blade | 0.25 |
| Generator | 0.15 |
| Pitch System | 0.25 |
| Yaw System | 0.2 |

Figure 6 shows the best and median attainment surfaces. Generally, for both the best and the median attainment surfaces, the performance of IBEA is better than NSGA-II as the corresponding lines are closer to the bottom left corner, which represents lower cost and lower system idle time. Figure 7 shows values of hypervolume (HV) of Option 2 (check after) and Option 3 (check before) with NSGA-II and IBEA in each generation, respectively. Here, the reference point is set as $(90, 5\%)$. As mentioned before, larger HV values mean a better Pareto front. From Figure 7 for most generations of Option 2 (check after) and Option 3 (check before), the HV value of IBEA is larger than the one of NSGA-II. Thus the performance of IBEA is better than NSGA-II.

When comparing Option 2 (check after) and Option 3 (check before), it is not clear which one is better. As shown in Figure 6, best attainment surfaces for Option 2 and Option 3 intersect, as well as the median attainment surfaces for Option 2 and 3. If we want lower system idle time, we should choose Option 2 (check after). If we want lower cost, we would select Option 3 (check before). Option 2 (check after) performs more frequent repairs than Option 3 (check before). This can help avoid failures, which can potentially reduce system downtime but may lead to higher costs.

When we look into the details of the corresponding optimal maintenance strategies, Option 2 (check after) and Option 3 (check before) are similar but still have several differences. All Pareto optimal

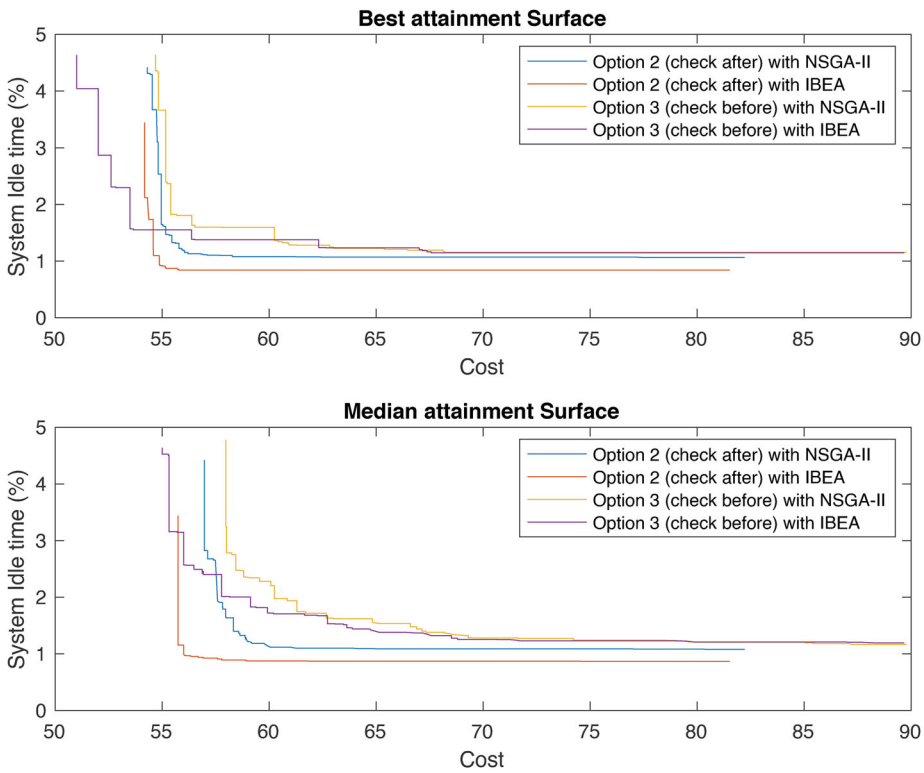


**Figure 6.** The Best and Median Attainment Surfaces.

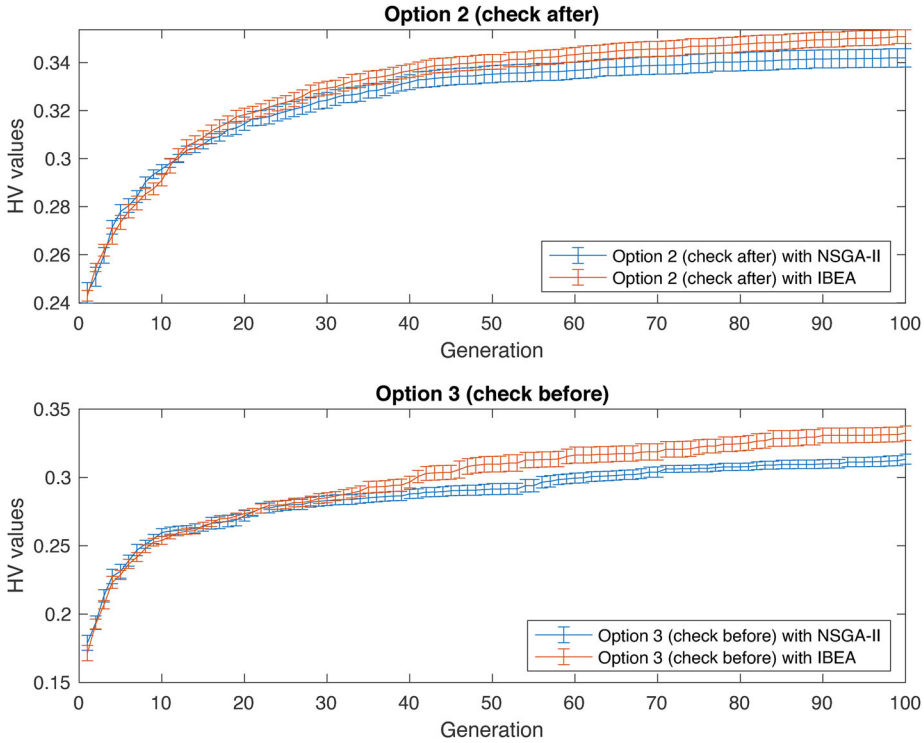


**Figure 7.** Mean HV plus/minus standard error, over generations.

results from Option 2 (check after) are from Opportunistic Strategy 2 (only take replacement as the opportunistic maintenance activity) and either Priority Rule 5 (Failure > Repair > Replace) or 6 (Repair > Failure > Replace).

The Pareto optimal solutions from Option 3 (check before) come from Opportunistic Strategy 3 (no opportunistic maintenance) in addition to Opportunistic Strategy 2. While again a large proportion of optimal solutions use Priority Rule 5 (Failure > Repair > Replace) or 6 (Repair > Failure > Replace), there are still some optimal solutions using Priority Rule 1 (Failure > Replace > Repair). Based on the Pareto optimal solutions, it seems Opportunistic Strategy 1 (take both repair and replacement as the opportunistic maintenance activity) is not a wise decision, and giving Replace priority is not a good idea. This may be because the number of maintenance teams is limited. In times of many maintenance requests, it is better to prioritise the repairs rather than conducting replacements.

To further understand the impact of the availability of maintenance teams, we select several obtained Pareto optimal strategies and track the percentage of delayed maintenance for each activity type. A maintenance delay occurs if there is no immediately available maintenance team. The delayed percentage is calculated as:

$$\textit{Delayed Percentage} = 1 - \frac{\text{timely performed maintenance activities}}{\text{all requested maintenance activities}}. \tag{9}$$

As shown in Table 7, the delayed percentages are pretty high in all scenarios, which shows the limited availability of maintenance teams has a significant influence. On the other hand, having a maintenance team on standby all the time would be costly.

Comparing the results of Option 2 (check after) and Option 3 (check before), there is no substantial difference. Priority Rule 5 seems to have a substantially higher delayed percentage of preventive repair than Priority Rule 6. This difference may be because the Priory Rule 6 favours preventive repair over the other two maintenance types. Similarly, Priority Rule 5 favours corrective replacement and has a relatively lower delayed percentage. Although both priority rules put it at the last position, the delayed percentage when applying Priority Rule 5 is significantly higher for preventive replacement. This may be because more time-consuming corrective replacement is performed on time when using Priority Rule 5, which leads to a delay of the preventive replacement.

### 5.3. Sensitivity analysis

A sensitivity analysis is performed to identify the influence of different values of input parameters on the performance of the maintenance strategy obtained from the proposed model. The maintenance cost and system idle time are computed over 100 simulation replications with different random seeds.

**Table 7.** Percentage of delayed maintenance activities for some Pareto-optimal maintenance strategies.

| | | | | | Delayed Percentage | | |
|---|---|---|---|---|---|---|---|
| Option | Oppor-tunistic | Priority | Cost | Idle Time (%) | Preventive Repair | Preventive Replace | Corrective Replace |
| 2 | 2 | 6 | 51.56 | 4.41 | 50.12% | 67.83% | 50.57% |
| | 2 | 6 | 55.61 | 2.75 | 50.06% | 71.1% | 51.13% |
| | 2 | 5 | 79.82 | 1.34 | 83.31% | 100% | 42.86% |
| | 2 | 5 | 81.26 | 1.08 | 74.87% | 100% | 41.74% |
| 3 | 2 | 6 | 55.46 | 2.41 | 41.82% | 68.38% | 49.87% |
| | 3 | 6 | 62.89 | 1.85 | 42.86% | 72.95% | 49.56% |
| | 2 | 5 | 74.89 | 1.37 | 83.65% | 100% | 43.01% |
| | 3 | 5 | 82.14 | 1.12 | 75.02% | 97.04% | 43.46% |

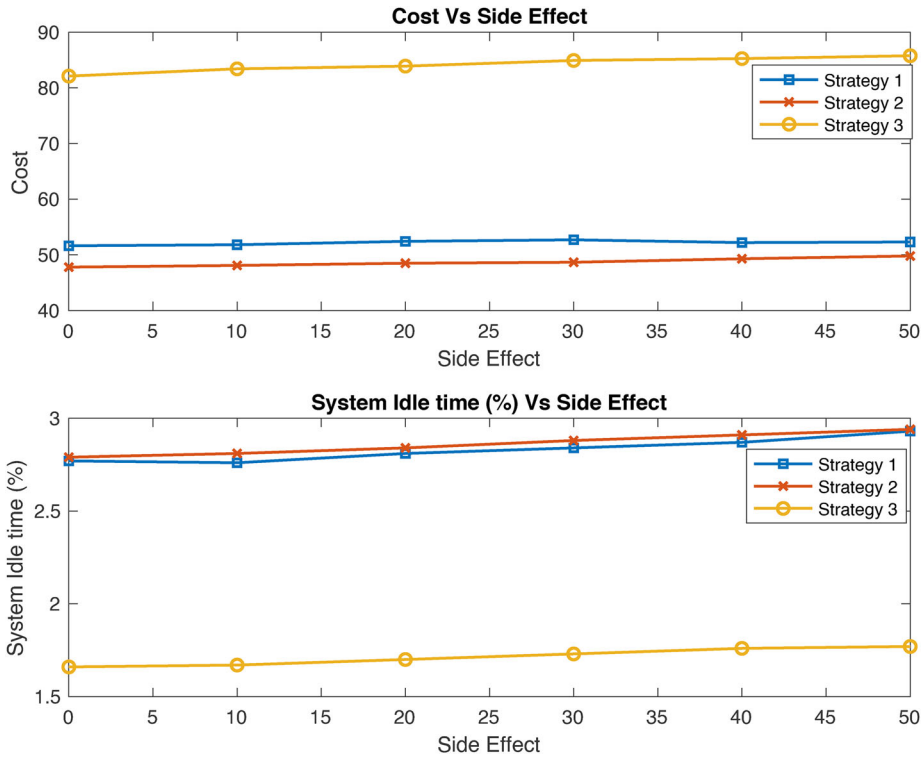


**Figure 8.** Overall Cost and system idle time with different values of the side effect parameter.

We randomly selected three Pareto optimal maintenance strategies obtained in Section 5.2, with the reliability thresholds rounded to two decimals:

- Strategy 1: $RI = [0.65, 0.77, 0.95, 0.93, \ 0.81, 0.95]$, $RP = [0.36, 0.27, 0.51, 0.31, 0.49, 0.29]$
  Opportunistic maintenance strategy 2, priority rule 6 applying option 2 (check after).
- Strategy 2: $RI = [0.84, 0.69, 0.94, 0.92, \ 0.82, 0.72]$, $RP = [0.31, 0.32, 0.57, 0.26, 0.25, 0.47]$,
  Opportunistic maintenance strategy 2, priority rule 6 applying option 3 (check before).
- Strategy 3: $RI = [0.62, 0.61, 0.82, 0.90, \ 0.77, 0.72]$, $RP = [0.31, 0.34, 0.57, 0.26, 0.55, 0.59]$,
  Opportunistic maintenance strategy 3, priority rule 5 applying option 3 (check before).

First, we check the performance of each strategy with different side effect values of one component's failure on others. The default value for the increase of VA used during optimisation was 10, and we have tested the evolved strategies with alternative values of 0, 20, 30, 40, and 50. All other variables have been kept the same.

Figure 8 shows that the impact of the side effect parameter on overall cost and system idle time are small. As expected, increasing side effects of a component's failure on others slightly increases the system idle time and overall cost. The relative ordering of the performance of all three strategies for each objective is also very stable with a change of the side effect parameter, indicating that a solution obtained with a particular parameter value would still work well under different parameter settings.

Following this, we check the sensitivity of the three strategies with respect to different values of maintenance effectiveness $q$. 25 groups of maintenance effectiveness values, each consisting of six $q$ values, have been randomly and independently generated in the range $[0.5 * q^{original}, 1.5 * q^{original}]$.

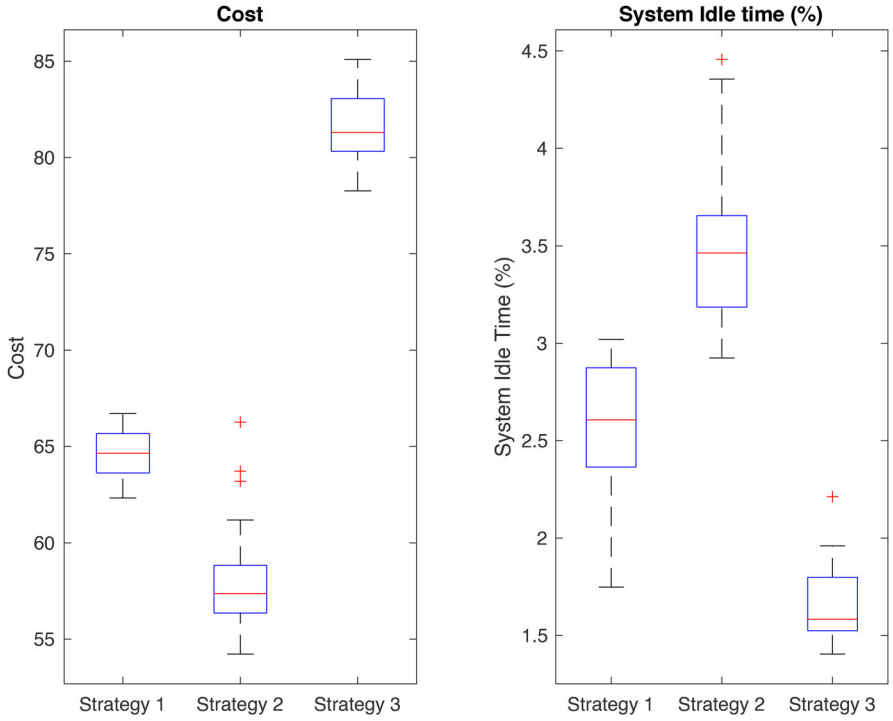


**Figure 9.** Overall Cost and system idle time with different values of the maintenance effectiveness.

**Table 8.** The results of the paired t-test.

Two-tailed paired t-test $H_0$: The mean of the paired differences equals 0 in the population

| | Strategy 1 - Strategy 2 | | Strategy 1 - Strategy 3 | | Strategy 2 - Strategy 3 | |
|---|---|---|---|---|---|---|
| | Cost | Idle Time | Cost | Idle Time | Cost | Idle Time |
| Mean difference | 6.69 | −0.95 | −16.86 | 0.89 | −23.57 | 1.84 |
| SD of difference | 3.05 | 0.52 | 2.59 | 0.41 | 3.69 | 0.44 |
| p-value | <0.01 | <0.01 | <0.01 | <0.01 | <0.01 | <0.01 |
| Effect size | 2.19 | 1.83 | 6.51 | 2.16 | 6.38 | 4.17 |

Figure 9 shows the performance of the three strategies in terms of cost and system idle time. As the boxplots indicate, the orderings of the performance of all three strategies are stable for both cost and system idle time. This again means the evolved maintenance strategies are robust to parameter variations or misspecification. To further understand the variability of the results, a two-tailed paired t-test has been performed on the difference between strategies to test whether there exists a statistical difference between these strategies. According to Table 8, all $p$ values are smaller than 0.01, which means the differences between the strategies are large enough to be statistically significant. Furthermore, the values of the effect size are also large, which indicates the differences are significant.

Finally, we check how these strategies perform depending on the number of maintenance teams (default used during optimisation was 3 teams). As shown in Figure 10, there is a transition from relatively low cost and high system idle time to relatively high cost and low system idle time. This happens because more maintenance teams will reduce the delays in maintenance, but eventually lead to over-maintenance. The relative performance of the maintenance strategies changes if the number of maintenance teams changes drastically. The maintenance strategy should be re-optimised in case of a significant change in the number of maintenance teams. Also, there exists the possibility of jointly optimising the number of maintenance teams and the maintenance strategy.

In summary, the performance of maintenance strategies is robust for stochastic values of maintenance effectiveness $q$, and the magnitude of side effects. If the number of maintenance teams changes, a re-optimisation of the maintenance strategy seems advisable.

### 5.4. Comparison with benchmark approaches

To investigate the advantages of the proposed 3 D maintenance strategy, we compare our approach with three other strategies:

- A strategy that optimises RI and RP values but never conducts opportunistic maintenance and uses the simple First Come First Serve (FCFS) priority rule.
- A strategy that also selects an appropriate opportunistic maintenance strategy but always uses the FCFS priority rule.

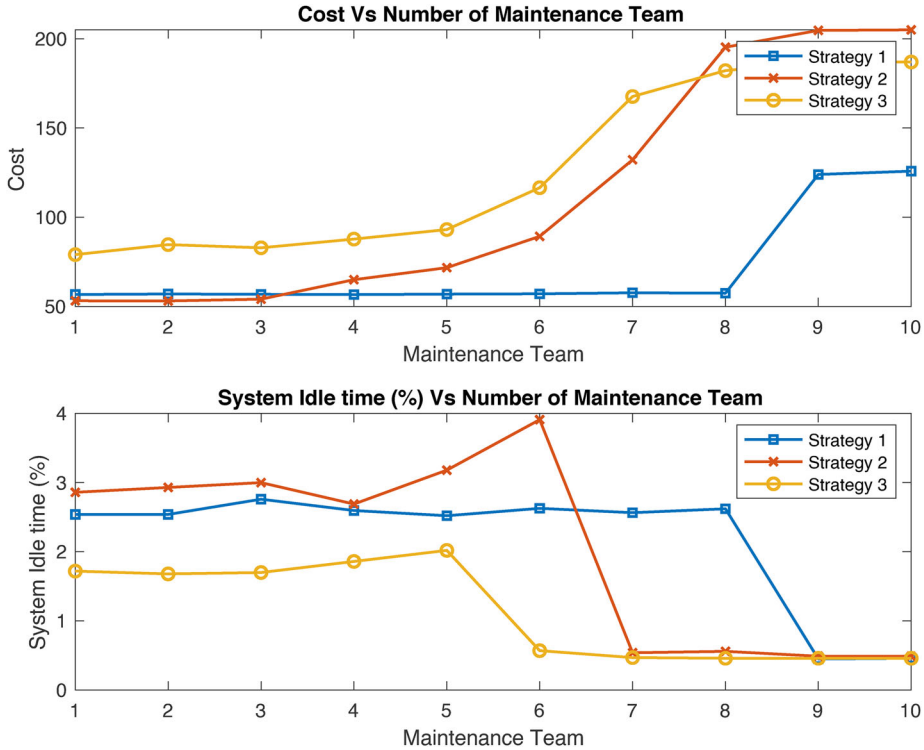


**Figure 10.** Overall Cost and system idle time with different number of maintenance teams.

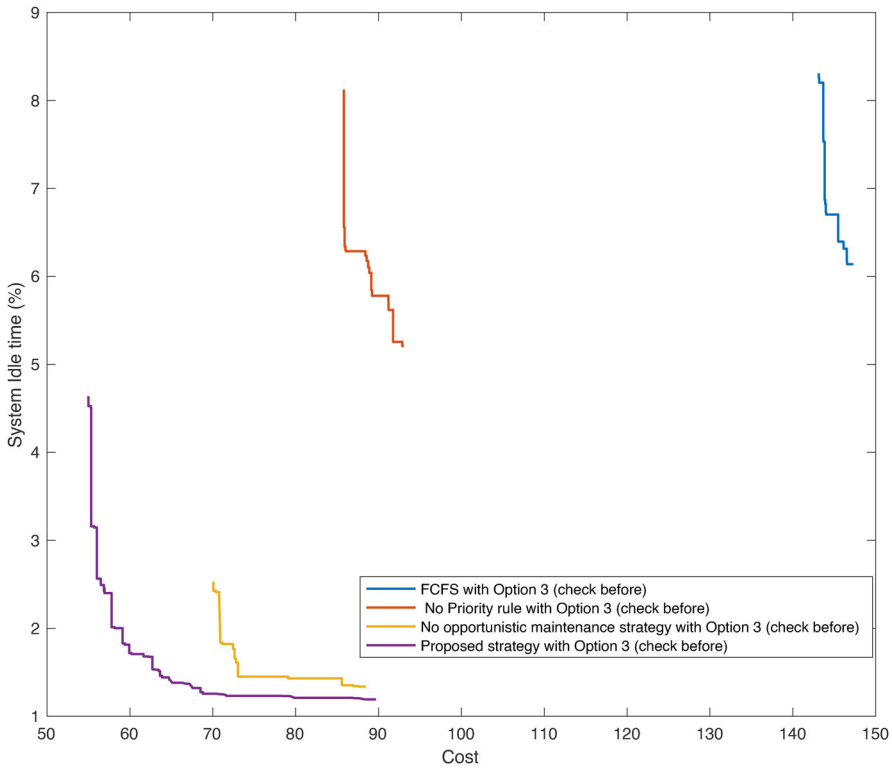


**Figure 11.** The comparison of the median attainment surfaces.

- A strategy that selects an appropriate priority rule but doesn't perform opportunistic maintenance.

As shown above, the performance of the results from IBEA outperforms the ones from NSGA-II. Thus only IBEA is applied as the meta-heuristic algorithm. Figure 11 shows the median attainment surfaces of our proposed 3 D maintenance strategy and the three benchmarks. Clearly, the median attainment surface from our proposed strategy shows significant advantages over the other alternatives. When neither opportunistic maintenance strategy nor priority rule is considered, the results have the highest cost and the longest idle time. Using one sub-strategy (priority rule or

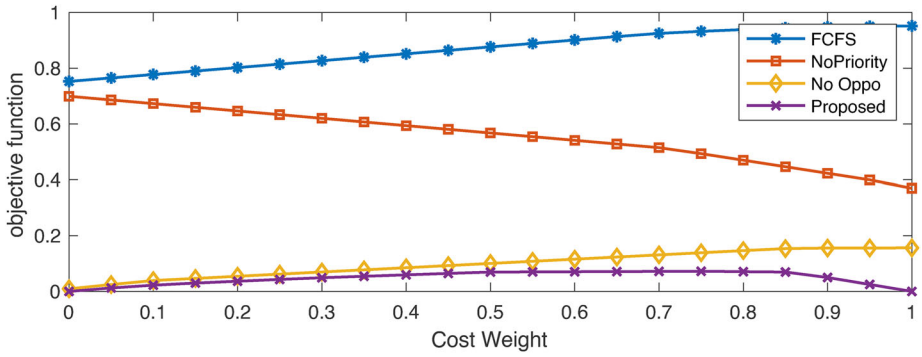


**Figure 12.** The comparison of optimal strategies when using weighted sum method.

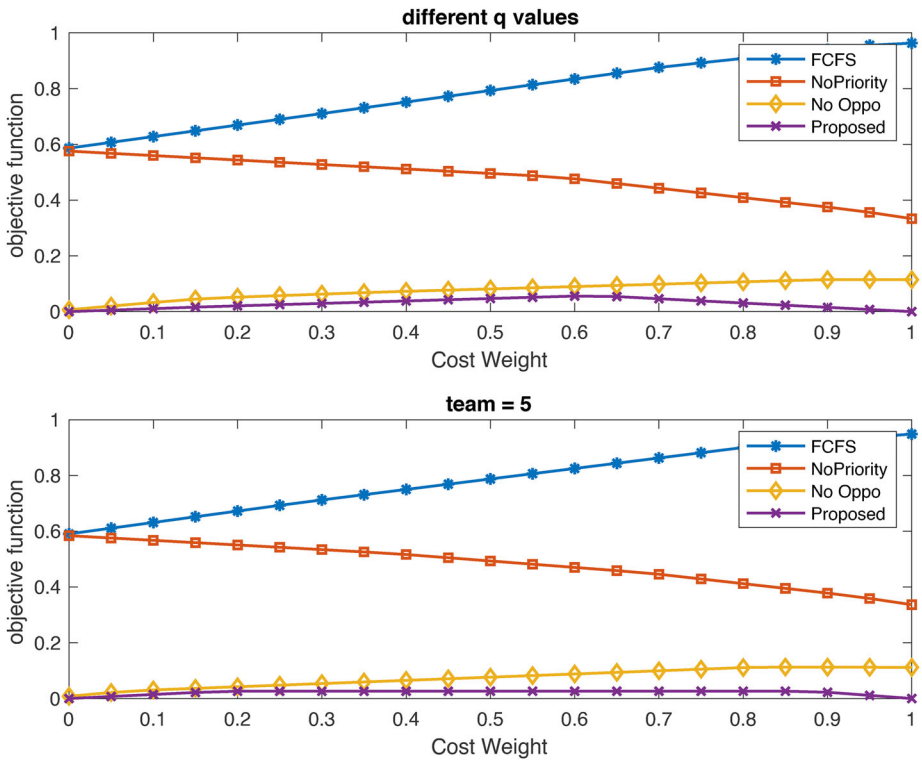


**Figure 13.** Comparison of Pareto optimal strategies for randomly selected $q$ values (top) and 5 instead of 3 maintenance teams (bottom).

opportunistic maintenance strategy) significantly decreases the cost, and the improvement through a priority rule seems to be larger, in terms of both cost and idle time, than the improvement through opportunistic maintenance (yellow Pareto front dominates the red Pareto front). This may be because, in this research, the priority rule's effect is more direct and can influence all events on the waiting list. The opportunistic maintenance strategy, on the other hand, can only impact a small subset of events (those in the same turbine). It also seems that without priority rule, the cost band of the Pareto front is quite narrow, whereas no opportunistic maintenance means a narrow idle time band. Our proposed strategy can not only provide better results than the simplified approaches, but also provide solutions with a broader range of trade-offs, giving the decision-maker more flexibility to determine whether a strategy with lower cost or lower system idle time is preferable.

To better understand the sensitivity of results to specific parameter settings, we now pick a set of 20 solutions from the Pareto front that are best with respect to a linear combination of the two objectives:

$$Objective\ Function = \min\left(\alpha \times Total\ \ Cost + (1-\alpha) \times\ Idle\ \ Time\right) \tag{10}$$

To make the values of two objectives comparable, the values are standardised to $[0, 1]$ beforehand. Figure 12 shows the results with 20 different values of $\alpha$. Obviously, the performance of the proposed 3 D strategy is still the best for all settings of $\alpha$.

Figure 13 shows the performance of the corresponding Pareto optimal strategies under two different scenarios:

a. different values of $q$, where each $q^{new}$ is randomly selected from $[0.5 * q^{original}, 1.5 * q^{original}]$;
b. increasing the available number of maintenance teams from 3 to 5.

As can be seen, these changes have only a minimal effect on the relative performance of the different maintenance strategies, demonstrating that our strategy is robust against changes in these parameters.

## 6. Conclusion

In this paper, a maintenance strategy comprising three sub-strategies is proposed to optimise the maintenance activities on a wind farm, aiming to minimise the overall cost and system idle time. The reliability strategy determines when maintenance work is triggered. The opportunistic maintenance strategy determines other components of the same turbine should be prioritised if a maintenance team is already on site. Finally, the priority rule guides the maintenance sequence of different activities when limited resources need to be allocated. The strategy considers multiple component systems, the economic and structural dependencies among components in the wind turbine, the priority of different maintenance activity types, multilevel maintenance with perfect and imperfect maintenance, the constraints of limited maintenance teams, and the time used by maintenance activities. Due to the stochastic nature of the maintenance activities, a discrete event simulation model is applied to simulate the maintenance cycle. Following this, two well-known multi-objective metaheuristics are applied to find the optimal strategy for the two conflicting objectives. The results of the comparative study show great advantage of the proposed 3 D approach over using only two of the maintenance sub-strategies, as it can keep the wind system at a higher performance level with lower overall cost and higher system availability.

The proposed maintenance strategy can be improved in multiple directions. First, considering the stochastic wind conditions can be the next step. The wind speed determines the wind farm's energy production level and the accessibility, logistic delays and time to repair. The proposed static strategy can be updated to a dynamic one with dynamic sub-strategies that change according to current wind conditions. Through doing this, the strategy can be more flexible and realistic. The proposed strategy can also be updated to a dynamic one if there are sensors to monitor the condition of the components continuously. When sensor data becomes available, we can use it to predict the components' condition continuously. The conditions can be represented by virtual age, reliability, time to failure etc. In this paper, we consider the maintenance strategy for generic wind farms. There are two kinds of wind farms, onshore and offshore wind farms. The maintenance for offshore wind turbines is more complicated due to the harsh weather and the difficulty of reaching locations. Faced with this fact, in the future, we can update the proposed policy to make it suitable for offshore wind farms by taking other real-world factors into account, such as the maintenance resource and logistics constraints, different vessels and technician competences for various tasks, and stochastic maintenance effectiveness. In further research, as shown in Rinaldi et al. (2020), we could also consider using a simplified surrogate model during optimisation to reduce the computational cost.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## ORCID

Yikai Ma http://orcid.org/0000-0002-3212-4839

## References

Abdollahzadeh, H., Atashgar, K., & Abbasi, M. (2016). Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups. *Renewable Energy*, *88*, 247–261. https://doi.org/10.1016/j.renene.2015.11.022

Allal, A., Sahnoun, M., Adjoudj, R., Benslimane, S., & Mazar, M. (2021). Multi-agent based simulation- optimization of maintenance routing in offshore wind farms. *Computers & Industrial Engineering*, *157*, 107342. https://doi.org/10.1016/j.cie.2021.107342

Banks, J., Carson, I. I., Nelson, B. L., & Nicol, D. M. (2005). *Discrete-event system simulation*. Pearson.

Canizo, M., Onieva, E., Conde, A., Charramendieta, S., & Trujillo, S. (2017). *Real-time predictive maintenance for wind turbines using Big Data frameworks* [Paper presentation]. 2017 IEEE International Conference on Prognostics and Health Management (ICPHM) (pp. 70–77). IEEE. https://doi.org/10.1109/ICPHM.2017.7998308

Carlos, S., Sánchez, A., Martorell, S., & Martón, I. (2013). Onshore wind farms maintenance optimization using a stochastic model. *Mathematical and Computer Modelling*, *57*(7–8), 1884–1890. https://doi.org/10.1016/j.mcm.2011.12.025

De Jonge, B., & Scarf, P. A. (2020, September). A review on maintenance optimization. *European Journal of Operational Research*, *285*(3), 805–824. https://doi.org/10.1016/j.ejor.2019.09.047

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

EvWind, E. (2020). *Wind energy expanded 19% in 2019, with around 60 GW of new capacity — REVE News of the wind sector in Spain and in the world*. https://www.evwind.es/2020/07/05/wind-energy-expanded-19-in-2019-with-around-60-gw-of-new-capacity/75563.

Fonseca, C. M., Fleming, P. J. (1996). On the performance assessment and comparison of stochastic multiobjective optimizers. In *International Conference on Parallel Problem Solving from Nature* (pp. 584–593). Springer.

Ge, X., Chen, Q., Fu, Y., Chung, C. Y., & Mi, Y. (2020). Optimization of maintenance scheduling for offshore wind turbines considering the wake effect of arbitrary wind direction. *Electric Power Systems Research*, *184*, 106298. https://doi.org/10.1016/j.epsr.2020.106298

Irawan, C. A., Eskandarpour, M., Ouelhadj, D., & Jones, D. (2021). imulation-based optimisation for stochastic maintenance routing in an offshore wind farm. *European Journal of Operational Research*, *289*(3), 912–926. https://doi.org/10.1016/j.ejor.2019.08.032

Jiang, Z., Bjørnholm, M., Guo, J., Dong, W., Ren, Z., & Verma, A. S. (2020). *Damage identification of a jacket support structure for offshore wind turbines* [Paper presentation]. 2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA) (pp. 995–1000). IEEE. https://doi.org/10.1109/ICIEA48937.2020.9248415

Kang, J., Sobral, J., & Soares, C. G. (2019). Review of condition-based maintenance strategies for offshore wind energy. *Journal of Marine Science and Application*, *18*(1), 1–16. https://doi.org/10.1007/s11804-019-00080-y

Kang, J., Wang, Z., & Soares, C. G. (2020). Condition-based maintenance for offshore wind turbines based on support vector machine. *Energies*, *13*(14), 3518. https://doi.org/10.3390/en13143518

Le, B., & Andrews, J. (2016). Modelling wind turbine degradation and maintenance. *Wind Energy*, *19*(4), 571–591. https://doi.org/10.1002/we.1851

Li, M., Jiang, X., & Negenborn, R. R. (2021). Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. *Ocean Engineering*, *231*, 109062. https://doi.org/10.1016/j.oceaneng.2021.109062

May, A., & McMillan, D. (2013). *Condition based maintenance for offshore wind turbines: The effects of false alarms from condition monitoring systems* [Paper presentation]. Esrel 2013.

Nguyen, T. A. T., & Chou, S.-Y. (2019, November). Improved maintenance optimization of offshore wind systems considering effects of government subsidies, lost production and discounted cost model. *Energy*, *187*, 115909. https://doi.org/10.1016/j.energy.2019.115909

Papadopoulos, P., Coit, D., & Azizezzat, A. (2021). Seizing opportunity: maintenance optimization in offshore wind farms considering accessibility, production, and crew dispatch. *IEEE Transactions on Sustainable Energy*, 1–1.

Reder, M. D., Gonzalez, E., & Melero, J. J. (2016). Wind turbine failures-tackling current problems in failure data analysis. *Journal of Physics: Conference Series*, *753*, 072027. https://doi.org/10.1088/1742-6596/753/7/072027

Ren, Z., Verma, A. S., Li, Y., Teuwen, J. J., & Jiang, Z. (2021). Offshore wind turbine operations and maintenance: A state-of-the-art review. *Renewable and Sustainable Energy Reviews*, *144*, 110886. https://doi.org/10.1016/j.rser.2021.110886

Richard, C. (2020). European installations to fall 20% below 2020 forecast. *WindPower*, https://www.windpowermonthly.com/article/1690677/european-installations-to-fall-20-below-2020-forecast

Rinaldi, G., Pillai, A. C., Thies, P. R., & Johanning, L. (2020). Multi-objective optimization of the operation and maintenance assets of an offshore wind farm using genetic algorithms. *Wind Engineering*, *44*(4), 390–409. https://doi.org/10.1177/0309524X19849826

Rinaldi, G., Thies, P. R., & Johanning, L. (2021). Current status and future trends in the operation and maintenance of offshore wind turbines: A review. *Energies*, *14*(9), 2484. https://doi.org/10.3390/en14092484

Schrotenboer, A. H., Ursavas, E., & Vis, I. F. (2020). Mixed Integer Programming models for planning maintenance at offshore wind farms under uncertainty. *Transportation Research Part C: Emerging Technologies*, *112*, 180–202. https://doi.org/10.1016/j.trc.2019.12.014

Sivalingam, K., Sepulveda, M., Spring, M., & Davies, P. (2018). *A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective* [Paper presentation]. 2018 2nd International Conference on Green Energy and Applications (ICGEA) (pp. 197–204). IEEE. https://doi.org/10.1109/ICGEA.2018.8356292

Stock-Williams, C., & Swamy, S. K. (2019). Automated daily maintenance planning for offshore wind farms. *Renewable Energy*, *133*, 1393–1403. https://doi.org/10.1016/j.renene.2018.08.112

Thomas, É., Levrat, É., & Iung, B. (2008). Overview on opportunistic maintenance. *IFAC Proceedings Volumes*, *41*(3), 245–250. https://doi.org/10.3182/20081205-2-CL-4009.00044

Tian, Y., Cheng, R., Zhang, X., & Jin, Y. (2017). PlatEMO: A MATLAB platform for evolutionary multi-objective optimization. *IEEE Computational Intelligence Magazine*, *12*(4), 73–87. https://doi.org/10.1109/MCI.2017.2742868

Wang, J., Zhang, X., Zeng, J., & Zhang, Y. (2020). Optimal dynamic imperfect preventive maintenance of wind turbines based on general renewal processes. *International Journal of Production Research*, *58*(22), 6791–6810. https://doi.org/10.1080/00207543.2019.1685706

Yanez, M., Joglar, F., & Modarres, M. (2002). Generalized renewal process for analysis of repairable systems with limited failure experience. *Reliability Engineering & System Safety*, *77*(2), 167–180. https://doi.org/10.1016/S0951-8320(02)00044-3

Yang, L., Peng, R., Li, G., & Lee, C.-G. (2020). Operations management of wind farms integrating multiple impacts of wind conditions and resource constraints. *Energy Conversion and Management*, *205*, 112162. February https://doi.org/10.1016/j.enconman.2019.112162

Yang, L., Li, G., Zhang, Z., Ma, X., & Zhao, Y. (2020). Operations & maintenance optimization of wind turbines integrating wind and aging information. *IEEE Transactions on Sustainable Energy*, *12*(1), 211–221.

Zahedi-Hosseini, F., Scarf, P., & Syntetos, A. (2018). Joint maintenance-inventory optimisation of parallel production systems. *Journal of Manufacturing Systems*, *48*, 73–86. https://doi.org/10.1016/j.jmsy.2018.06.002

Zhang, N., Fouladirad, M., Barros, A., & Zhang, J. (2020). Condition-based maintenance for a K-out-of-N deteriorating system under periodic inspection with failure dependence. *European Journal of Operational Research*, *287*(1), 159–167. https://doi.org/10.1016/j.ejor.2020.04.041

Zhang, C., Gao, W., Yang, T., & Guo, S. (2019). Opportunistic maintenance strategy for wind turbines

considering weather conditions and spare parts inventory management. *Renewable Energy*, *133*, 703–711. https://doi.org/10.1016/j.renene.2018.10.076

Zhong, S., Pantelous, A. A., Beer, M., & Zhou, J. (2018). Constrained non-linear multi-objective optimisation of preventive maintenance scheduling for offshore wind farms. *Mechanical Systems and Signal Processing*, *104*, 347–369. https://doi.org/10.1016/j.ymssp.2017.10.035

Zhou, P., & Yin, P. T. (2019). An opportunistic condition-based maintenance strategy for offshore wind farm based on predictive analytics. *Renewable and Sustainable Energy Reviews*, *109*, 1–9. https://doi.org/10.1016/j.rser.2019.03.049

Zitzler, E., Künzli, S. (2004). Indicator-based selection in multiobjective search. In *International Conference on Parallel Problem Solving from Nature* (pp. 832–842). Springer.

Zitzler, E., & Thiele, L. (1999). Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Transactions on Evolutionary Computation*, *3*(4), 257–271. https://doi.org/10.1109/4235.797969