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Offshore wind turbine reliability and operational simulation under uncertainties

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Abstract

The fast-growing offshore wind energy sector brings opportunities to provide a sustainable energy resource but also challenges in offshore wind turbine (OWT) operation and maintenance management. Existing operational simulation models assume deterministic input reliability and failure cost data, whereas OWT reliability and failure costs vary depending on several factors, and it is often not possible to specify them with certainty. This paper focuses on modelling reliability and failure cost uncertainties and their impacts on OWT operational and economic performance. First, we present a probabilistic method for modelling reliability data uncertainty with a quantitative parameter estimation from available reliability data resources. Then, failure cost uncertainty is modelled using fuzzy logic that relates a component's failure cost to its capital cost and downtime. A time-sequential Monte Carlo simulation is presented to simulate operational sequences of OWT components. This operation profile is later fed into a fuzzy cost assessment and coupled with a wind power curve model to evaluate OWT availability, energy production, operational expenditures and levelised cost of energy. A case study with different sets of reliability data is presented, and the results show that impacts of uncertainty on OWT performance are magnified in databases with low components' reliability. In addition, both reliability and cost uncertainties can contribute to more than 10% of the cost of energy variation. This research can provide practitioners with methods to handle data uncertainties in reliability and operational simulation of OWTs and help them to quantify the variability and dependence of wind power performance on data uncertainties.

KEYWORDS
failure cost, fuzzy logic, offshore wind energy, operational simulation, reliability, uncertainty

1 | INTRODUCTION

Offshore wind energy has grown rapidly in the last decade, and it is still expected to rise in the coming years. From just over 2 GW in 2009, the global installed capacity of offshore wind energy has increased more than 11 times to over 23 GW in 2018 (Figure 1), representing an annual

ABBREVIATIONS: AEP, annual energy production; CAPEX, capital expenditure; FIS, fuzzy inference system; GW, gigawatt; LCOE, levelised cost of energy; MCS, Monte Carlo simulation; MW, megawatt; NPV, net present value; O&M, operation and maintenance; OPEX, operational expenditure; OWT(s), offshore wind turbine(s); TEP, total energy production; TSMCS, time-sequential Monte Carlo simulation.

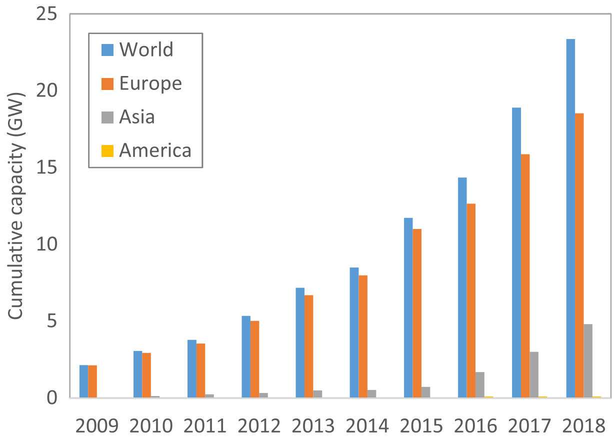


FIGURE 1 Offshore wind energy installed capacity growth (2009–2018) [Colour figure can be viewed at wileyonlinelibrary.com]

growth rate of over 30%.[1] Currently, approximately 80% of the installed capacity of offshore wind comes from Europe, with the United Kingdom (8.3 GW) and Germany (6.4 GW) leading the industry. In the next decade, the United Kingdom aims to meet a third of the country's electricity demand from offshore wind with a total expected generation capacity of 30 GW in 2030.[2] Asian economies aim to build up to 100 GW of offshore wind power by 2030.[3] The United States also has a plan to increase its offshore wind energy and reach 22 GW by 2030 with a series of projects in its north-eastern coast.[4] The fast-growing offshore wind energy sector brings opportunities for providing a green and sustainable energy but also challenges in offshore wind turbine (OWT) modelling and management.

Operational simulation can provide useful information for performance evaluation, cost of energy estimation and operation and maintenance (O&M) planning and optimisation of OWTs. The O&M of offshore wind is complex and costly. It is generally higher than its onshore counterpart and contributes approximately 30% to the cost of energy.[5–8] OWT O&M modelling and simulation are complex, as they involve several factors such as component reliability, turbine system characteristics, wind speed data, maintenance strategy and costs.[9,10]

Wind turbine component reliability is a critical input to the operational simulation of OWTs. Existing operational simulation models often assume a fixed failure rate or failure probability for the wind turbine. In the literature, reliability data are often collected and analysed for the turbines that have been operating for several years,[11,12] whereas the operational simulation needs to model and predict the operation of future OWTs. The lack of data problem has been an issue in the research community, which has been mentioned in previous studies.[12,13] Particularly, operators and manufacturers tend to keep reliability and cost data for themselves, and there have been very few sources of offshore reliability data published. Data sometimes are published, but information about wind farm/wind turbine is commonly anonymised.[14,15] The problem may be less severe for wind farm developers as they can have some data directly from manufacturers. However, data uncertainty is still a problem as for newly developed wind turbines with limited operating experience, and its true reliability and failure cost are not known with certainty. In addition, reliability of wind turbine components can vary greatly depending on manufacturer, technology, location of deployment and maintenance strategy. This fact creates a challenge for researchers and practitioners in investigating and modelling the OWT reliability and operation.

Furthermore, several factors are involved when dealing with failure and repair cost estimation, and this cost represents a major portion of the total O&M cost of OWTs.[16,17] In operational simulation, the cost per failure of a wind turbine is often required as an input to be specified in advance. Cost data for OWT failures and repairs are not easy to obtain because of the competitive nature of the offshore wind industry. A recent paper[14] reported the average material cost for repair. However, there are several other factors such as repair logistics, equipment, manpower and detailed component failure consequences, which can all contribute to the failure cost. The uncertainty of failure cost makes it challenging to specify a single crisp value for this input explicitly. Thus, the need for a method to represent the cost data uncertainty in OWT reliability modelling and O&M cost estimation is viable.

In the literature, it has been shown that simulation is a powerful and flexible tool for analysing OWT operation, and several O&M simulation studies have been performed.[18] Although input data uncertainty is a critical factor that wind energy system operators need to deal with,[19] existing simulation models vastly ignore the uncertainties of data in reliability and O&M cost evaluation.[9,20–32] Therefore, this paper focuses on modelling two types of uncertainties related to reliability data and failure cost of OWT components. An OWT simulation framework employing a time-sequential Monte Carlo simulation (TSMCS), probabilistic techniques and fuzzy logic is proposed to evaluate the impacts of reliability and failure cost uncertainties on the OWT availability, energy production and cost of wind energy.

Existing operational simulation models take deterministic values of input reliability and cost data, and it is common to vary the input data and perform a sensitivity analysis to estimate output performance. Sensitivity analysis can be effective to estimate the change of output depending by changing each of the input variables. However, if there is a probabilistic variation of reliability data, a method to quantify the statistical information of OWT output performance is needed. Moreover, sensitivity analysis relies on the assumption that a change of one variable is independent from that of other variables. Sensitivity analysis is not useful when there are associations between different variables, such as component capital cost, downtime and cost per failure in this case. Thus, the contributions of this paper are the methodologies for handling input data uncertainty while considering the relationship between different input variables, including a probabilistic reliability data modelling and a fuzzy cost inference system.

The remaining part of this paper is organised as follows. Section 2 provides a literature review on the existing operational simulation of both onshore wind turbines and OWTs, their objectives and methods used. Section 3 presents two types of uncertainties related to reliability and cost data and an OWT operational simulation framework incorporating these types of uncertainties into the TSMCS to estimate the operational and economic performance of OWTs. A case study on a future 10-MW direct-drive OWT is presented, and the impacts of two types of uncertainties are analysed in Section 4. Finally, Section 5 concludes this research.

2 | LITERATURE REVIEW

Wind turbine and wind farm operational simulation is a thriving research topic that has been the focus of many studies since the early 2000s. The first work on wind farm operational simulation was performed within the Dutch Offshore Wind Energy Converter (DOWEC) project,[20] which focused on accessibility, that is, the possibility that wind turbines are accessible when maintenance is required. A Monte Carlo simulation (MCS) was developed to evaluate wind farm availability and examine the relationship between accessibility and availability. Using the reference wind farm in DOWEC project,[20] the Energy Research Centre of the Netherlands (ECN) developed an ECN O&M tool for estimating the costs of offshore wind farms and has continuously updated it in subsequent publications.[21,22,27] The ECN tool was developed using a 'what-if analysis' with several options for different types of maintenance to estimate the O&M costs of offshore wind farms.

A group of researchers at Texas A&M and Texas Tech University simulated wind farm O&M using the discrete event system specification (DEVS) simulation.[23,26,32] The DEVS simulation is a hierarchical approach allowing the construction of components, wind turbines and wind farm models and coupling them together to simulate failure and maintenance events. A wind turbine may be in either operating or failed state, which can be simulated by assuming that the state transition probabilities of its components are given. McMillan and Ault[24] used MCS to simulate the failures of wind turbines and analysed the benefits of condition monitoring. Focusing on two maintenance strategies, namely, corrective maintenance and preventive maintenance, Santos et al.[25] used Petri net and MCS for determining the best preventive maintenance intervals. By employing a sequential MCS, a reliability and operation simulation framework is developed to analyse several OWT performance indicators such as energy not supplied, failure cost and cost of energy depending on its component reliability data.[9]

In the literature, there are some offshore wind farm operational simulation models aiming to support maintenance and logistics planning. The Norwegian Offshore Wind power lifecycle cost and benefit tool (NOWIcob), developed by the SINTEF Energy Research Centre, used an event-based MCS to simulate the wind farm O&M costs considering weather, maintenance and logistics.[30] Endrerud et al.[28,29] presented a logistics decision support model using an agent-based simulation for O&M of offshore wind farms. This model was later integrated into a commercial tool, Shoreline.[33] Dalgic et al.[31] extended the ECN and NOWIcob models by defining in details four sets of input data related to climate, vessel specifications and fleet configuration, wind farm/wind turbine information and different types of costs. All the maintenance and logistics models require extensive input data, which are not always available, and assumptions on known reliability and deterministic cost data. With these assumptions, different maintenance strategies can be simulated to identify the best strategy for the specific and given context.

Although there are uncertainties of input parameters related to reliability and cost in wind turbine operational simulation, all of the above simulation models assume that these parameters are given. To date, there has been only one paper by Scheu et al.[34] that considers the reliability uncertainty in wind turbine operational simulation, where the wind farm availability was investigated for nine types of distribution of wind turbine failure time. This study revealed that the availability could vary significantly by simply changing the failure distribution. However, Scheu et al.[34] is more of a theoretical study as they used classical failure distributions with given mathematical formulation, and discussion on how practical reliability data can be used in their study was not provided. In addition, the cost uncertainty and analysis have been vastly ignored in the literature. Thus, this paper attempts to bridge the gap by investigating the methods for modelling and simulation of both reliability and cost uncertainties in OWT reliability and operational simulation. The modelling and simulation methods in this research will provide OWT operators and wind power performance analysts with approaches to handle data uncertainty and to quantify its impacts on the variation of OWT operational and economic performance.

3 | UNCERTAINTIES MODELLING AND OWT OPERATIONAL SIMULATION

In general, a comprehensive OWT reliability and operational simulation takes input data, including component reliability data, wind turbine system characteristics, wind speed data and failure cost information, and simulates the operation of the wind turbine throughout its lifetime (Figure 2). Several performance indices, that is, the output of the simulation, such as availability, energy production and cost of energy, can be estimated from the operational simulation. The core parts in the OWT operational simulation include (i) reliability models to simulate the failure and repair

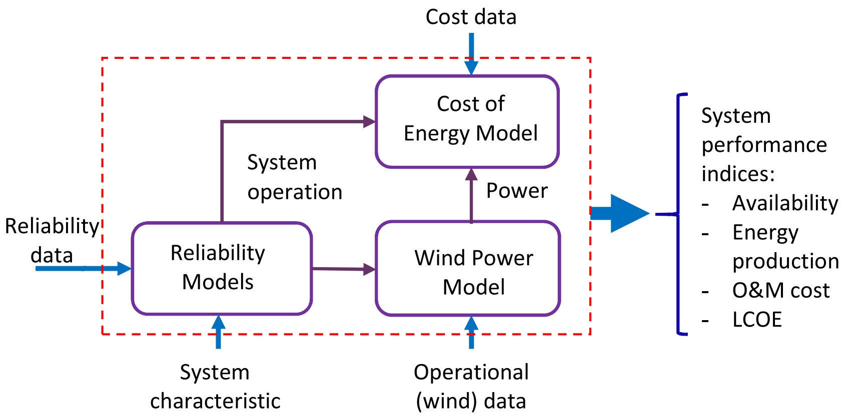


FIGURE 2 General offshore wind turbine (OWT) operational simulation (no uncertainties) [Colour figure can be viewed at wileyonlinelibrary.com]

(or maintenance) of the wind turbine components; (ii) a wind power model to estimate the power output of the wind turbine; and (iii) a cost of energy model to evaluate its economic performance.

In this paper, we assume that the OWT characteristics and wind speed data are given, and we focus on the modelling and analysis of OWT performance under the reliability and failure cost uncertainties.

Although some of the large OWTs recently developed have limited operating experiences, their reliability can be estimated with some degree of uncertainty. The basis for estimating the reliability of new OWT components can come from the fact that existing wind turbines are not entirely similar but have some common characteristics with the new wind turbine. Thus, this paper presents methods for modelling data uncertainty and investigates their impacts on the performance of OWTs.

In the remaining part of this section, two types of uncertainties related to reliability and failure cost data are described and modelled. Then, they are integrated into an OWT operational simulation framework for estimating the operational and economic performance of the wind turbine under uncertainties.

3.1 | Component reliability data uncertainty

Component reliability data are important inputs for OWT operational simulation. Reliability data include failure rate λ and repair rate μ; the former represents the failure frequency per unit time repair, and the latter is a multiplicative invert of the expected downtime per failure *d*. In operational simulation, the failure and repair processes of wind turbine components are simulated using reliability data and a degradation model based on the assumption of the Markovian process for failure and repair transitions. In existing simulation studies, deterministic values of failure and repair rates are used to represent the component reliability; that is, parameters of component reliability distributions are assumed to be known with certainty.

In this paper, the failure rates and expected downtimes of OWT components are not known with certainty. Instead, only some reference reliability databases in the literature are available, and a method allowing probabilistically sample failure rate and downtime from multiple distributions is presented. This model is applicable for the situation where the future OWT is not entirely similar to but has some common characteristics with and can be referred to existing wind turbines reported in the literature. A probabilistic reliability data matrix is introduced to represent the probabilities that a component's reliability is similar to its reliability from existing databases. If there are n components and m_f available reference failure rate databases, the probabilistic reliability data matrix for failure rate, $\mathbf{P}_f$, is presented in Equation 1.

$$\mathbf{P}_f = \begin{bmatrix} p_{11}^f & p_{12}^f & \dots & p_{1m_f}^f \\ p_{21}^f & p_{22}^f & \dots & p_{2m_f}^f \\ \dots & \dots & \dots & \dots \\ p_{n1}^f & p_{n2}^f & \dots & p_{nm_f}^f \end{bmatrix}. \qquad (1)$$

Each element p_{ij}^f in the probabilistic reliability data matrix represents the probability that the failure rate of component *i* is similar to its failure rate from database *j*.

Similarly, if there are m_d reference reliability databases for downtime, the probabilistic reliability data matrix for downtime, $\mathbf{P}_d$, is presented as in Equation 2.

$$\mathbf{P}_{\boldsymbol{d}} = \begin{bmatrix} p_{11}^d & p_{12}^d & \dots & p_{1m_d}^d \\ p_{21}^d & p_{22}^f & \dots & p_{2m_d}^d \\ \dots & \dots & \dots & \dots \\ p_{n1}^d & p_{n2}^d & \dots & p_{nm_d}^d \end{bmatrix}, \tag{2}$$

where p_{ij}^d represents the probability that the expected downtime of component i is similar to its expected downtime from database j.

An important characteristic of the two matrices $\mathbf{P}_{\boldsymbol{f}}$ and $\mathbf{P}_{\boldsymbol{d}}$ is that the total sum of all elements in a row is equal to 1; that is, for each component $i, i = 1, 2, \ldots, n$, in the OWT, we have the following expression:

$$\sum_j p_{ij} = 1, \forall j \in J. \tag{3}$$

In Equation 3, J is the set of all available reliability databases. The value of each element in the probabilistic reliability data matrices, $\mathbf{P}_{\boldsymbol{f}}$ and $\mathbf{P}_{\boldsymbol{d}}$, can be either determined by expert judgements or estimated from available reliability data. When simulating the operation of a new OWT, the turbine designers and developers (experts) can specify the likelihood that a component's reliability gets a value of its reliability in a reference reliability database. In addition, there are reviews on existing wind turbine reliability databases,[12,35] which investigate a large population of wind turbines and provide averages and ranges of failure rate and downtime. Data obtained from this large population can be used to estimate the reliability data uncertainty and probabilistic reliability matrices $\mathbf{P}_{\boldsymbol{f}}$ and $\mathbf{P}_{\boldsymbol{d}}$. In the following part of this section, mathematical formulations for estimating p_{ij}^f in the failure rate probabilistic matrix $\mathbf{P}_{\boldsymbol{f}}$ are presented. The elements in $\mathbf{P}_{\boldsymbol{d}}$ can be calculated similarly.

Let $\bar{\lambda}_i$ and $R_{\lambda,i}$ be the mean and range of failure rate drawn from the large reliability data population for component i. A failure rate deviation of database j from the mean failure rate for component i is calculated as in Equation 4.

$$\Delta_{ij} = \left| \lambda_{i,j} - \bar{\lambda}_i \right|. \tag{4}$$

From Equation 4, we can measure the degree of uncertainty by defining an indicative uncertainty factor q_{ij} of database j, representing the proportion of failure rate deviation over its range, as follows:

$$q_{ij} = \frac{\Delta_{ij}}{R_{\lambda,i}}. \tag{5}$$

It is noted that the failure rate deviation is always less than the failure rate range, that is, the difference between the largest and the smallest in the population. Thus, q_{ij} always takes a positive value between 0 and 1.

Among the population, the possibility that the failure rate of component i is taken from database j can be represented using the following equation:

$$p_{ij}^f = k_i \left(1 - q_{ij}\right) = k_i \left(1 - \frac{\Delta_{ij}}{R_{\lambda,i}}\right), \tag{6}$$

where k_i is a normalising coefficient to make $\sum\limits_j p_{ij}^f = 1$, that is,

$$\sum_j p_{ij}^f = \sum_j k_i \left(1 - \frac{\Delta_{ij}}{R_{\lambda,i}}\right) = 1. \tag{7}$$

If there are m_f available reference reliability databases for failure rate, Equation 7 can be rewritten as

$$k_i \left(m_f - \frac{\sum_j \Delta_{ij}}{R_{\lambda,i}}\right) = 1 \Rightarrow k_i = \frac{R_{\lambda,i}}{m_f R_{\lambda,i} - \sum_j \Delta_{ij}}. \tag{8}$$

From Equations 6 and 8, we have

$$p_{ij}^f = \frac{R_{\lambda,i}}{m_f R_{\lambda,i} - \sum_j \Delta_{ij}} \left(1 - \frac{\Delta_{ij}}{R_{\lambda,i}}\right). \tag{9}$$

As the probability $p_{ij}^f \in (0,1)$ and $\sum_j p_{ij}^f = 1$, the random selection of failure rate data can be performed using an MCS with random numbers. The OWT component failure rate can be generated using a series of n random numbers following the uniform distribution $r_i \sim U(0,1), i = 1,2,\ldots,n$. The failure rate of component i is drawn from database j if

$$\sum_{k=0}^{j-1} p_{ik}^f < r_i \leq \sum_{k=0}^{j} p_{ik}^f. \tag{10}$$

3.2 | Failure cost uncertainty

In OWT operational simulation, component failure cost is an important factor in estimating the total failure cost, which is later used for levelised cost of energy (LCOE) estimation. In the literature, component failure cost is either estimated as a percentage of its capital cost[9,24] or discretised by the types of repair and maintenance methods.[31,36] In both cases, the cost per failure is assumed to be known with certainty. However, it is challenging to specify this cost value in practice, as it can vary widely depending on component failures, downtime, materials, maintenance manpower and repair equipment. Therefore, in this section, instead of using a crisp, that is, single and given, value for component failure cost, fuzzy numbers and a fuzzy inference system (FIS) are used to represent the relationship between component capital cost, downtime and component failure cost.

3.2.1 | Fuzzy set theory and uncertainty representation

In fuzzy set theory,[37,38] a fuzzy set $\tilde{A}$, built from a reference set of real numbers $U \in \mathbb{R}$, is defined as follows.

$$\tilde{A} = \{x_i, \mu_A(x_i)\}, \tag{11}$$

where $x_i \in U$, and $\mu_A : U \to [0,1]$ is the membership function of A; the value $\mu_A(x) \in [0,1]$ is called the degree of membership of x in A. Figure 3 shows an example of a triangular fuzzy membership function, which can be represented by three real numbers a,b and c.

Intuitively, the fuzzy set theory implies that an element can either belong to a set or not, and the possibility that an element belongs to the fuzzy set is the membership function value. In Figure 3, a value between (a,b) has the degree of membership between 0 and 1 and thus can 'partially' belong to set A.

In the literature, fuzzy logic has been applied to the problem of wind turbine speed control, such as in Jauch et al.[39] and Bououden et al.[40] It was also used to diagnose and identify failure modes on the basis of symptoms of wind turbine components.[41] To the authors' best knowledge, it has not been developed for quantifying the uncertainty and evaluating the wind turbine failure cost. Thus, in this study, a FIS is presented to predict the failure cost on the basis of component capital cost and random downtime sampled from the MCS.

3.2.2 | Failure cost FIS

One of the applications of the fuzzy set theory is to build FISs or fuzzy expert systems, which can be used to acquire expert knowledge in the form of logical statements called fuzzy rules.[38] In fuzzy rules, the variables can take linguistic 'values' in word or sentence from natural language,

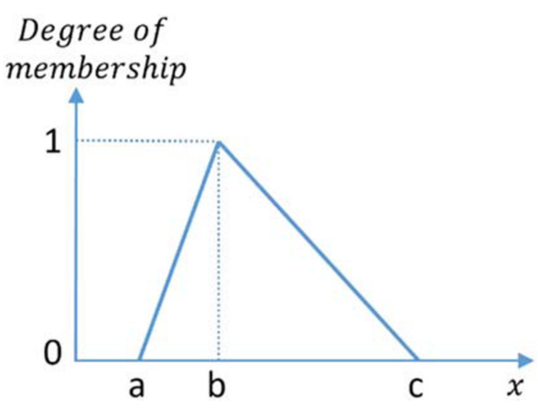


FIGURE 3 Membership function of fuzzy numbers [Colour figure can be viewed at wileyonlinelibrary.com]

for example, low, medium and high; and the relationship between different variables is represented using 'if–then' clauses. In this paper, a FIS is built to represent logical relationships between component capital cost, downtime per failure and its failure cost, as shown in Figure 4.

The inputs of the fuzzy failure cost estimation include downtime and component cost (capital cost). Downtime data can be generated from the MCS of operation using reliability data (Section 3.3). Component capital cost (c_i) data are available from manufacturer factsheet or industrial reports such as that of BVG Associates.[42]

The fuzzy failure cost estimation also works on the basis of FIS logical rules representing the failure cost uncertainty and its 'fuzzy' relationship with downtime and component cost. In this paper, the FIS rules describe the inference logic between the FIS inputs (downtime and component cost) and output (failure cost), as shown in Figure 5. Intuitively, it is assumed that the failure consequence in terms of cost will be more severe for more extended downtime and higher component cost.

In Figure 5, the FIS rules present the relationship between downtime, component cost and failure cost in a matrix form. Each coloured cell contains an inference relation with an underlying 'if–then' statement, for example, 'if component cost is high and downtime is long, then the failure cost is high' and 'if component cost is low and downtime is long, then the failure cost is medium'. In general, FIS is quite flexible, as several types of logic rules and operators such as and, or, not can be defined depending on expert knowledge and available information.

A FIS is developed by two essential elements of fuzzy membership functions and FIS rules. Whereas FIS rules are constructed using intuitive logic with linguistic relation, fuzzy membership functions can be estimated using data.[43] A procedure for developing the FIS for failure cost estimation is presented as follows.

1 Generate random downtime data for fuzzy numbers.
2 Partition the data into groups and estimate the membership function in each group.
3 Define the fuzzy logic rules and relations between input and output.
4 Define fuzzy operators and defuzzification method for output failure cost estimation.

In this paper, we employ the MCS and reliability data to generate data for fuzzy membership function construction. The purpose of this simulation is to obtain a set of downtime samples for determining the fuzzy numbers to represent the downtime. The Gaussian membership function[44] is used to estimate the parameters of fuzzy membership function:

$$\mu_A(d_i, c, s) = e^{-\frac{(d_i - c)^2}{2s^2}}, \tag{12}$$

where c and s are two parameters representing the mean, that is, central point, and standard deviation of the Gaussian membership function and d_i is a downtime sample data point from the MCS. A reference simulation case in the literature with levels of repair time and cost such as minor, medium and major[36] is used to partition the simulated data into groups that match the qualitative levels in the FIS rules' matrix. Assume that there are K groups of reference data and r_k is the reference data in group k; the central point c_k, that is, $\mu_A(c_k) = 1$, in each group can be estimated using Equation 13.

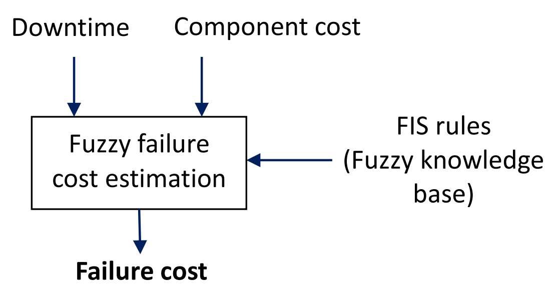


FIGURE 4 Fuzzy failure cost estimation [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 5 Fuzzy inference system (FIS) rules in the fuzzy failure cost estimation [Colour figure can be viewed at wileyonlinelibrary.com]

	Component cost		
Downtime	Low	Medium	High
Short	very low	low	medium
Medium	low	medium	medium
Long	medium	medium	high
Very Long	medium	high	very high

$$c_k = r_k \frac{\left(\sum_i d_i\right)/I}{\left(\sum_k r_k\right)/K}, \tag{13}$$

where I is the total number of data points generated from the MCS. A membership function should take a value between 0 and 1, and its cumulative value is equal to 1. A Gaussian function with a standard deviation of the group's standard deviation can be used for representing a membership function of generated data.

Once the central points and standard deviations of membership functions in all groups are determined, the FIS rules in 'if–then' statements (Figure 5) are added to construct the FIS. Finally, the computational unit within FIS employs the FIS rules, fuzzy operators and defuzzification methods[38] to estimate the FIS output. The output of FIS is the failure cost, which can further be used to evaluate the wind turbine economic performance indicators. The FIS for failure cost estimation is integrated into OWT operational simulation framework as presented in the next section.

3.3 | OWT operational simulation framework under uncertainties

The two types of uncertainties in Sections 3.1 and 3.2 are integrated into an OWT reliability modelling and operational simulation framework (shown previously in Figure 2) to evaluate the operational and economic performance of the OWT as in Figure 6.

In the proposed reliability modelling and operational simulation framework, reference reliability data, that is, $\{\lambda\}$ and $\{\mu\}$, from existing reliability surveys are inputs for probabilistic reliability data uncertainly modelling (Section 3.1). A TSMCS is used to generate multiple sequences of random failure/repair events of the OWT using the component and system reliability models. More details about the TSMCS are presented in Section 3.3.1. The output of TSMCS can be used to estimate the system availability as well as the system operation and downtime to feed into the wind power model for energy production (Section 3.3.2) and fuzzy failure cost estimation (Section 3.2), respectively. The wind speed and wind power models employ historical wind speed data to create a time series of future wind speed using an autoregressive moving average (ARMA) model.[45] The wind power model is, then, coupled with the TSMCS for estimating the energy production. At the same time, downtime and component capital cost are used in the fuzzy failure cost estimation for evaluating the variable failure cost of OWT. The simulation can be run for the entire OWT lifetime, for example, 20 years, and finally, the energy production and the total failure cost are integrated into the LCOE estimation to calculate the LCOE of OWT.

It is noted that the wind speed and other weather conditions may have an influence on component degradation and thus affect its failure probability. Some papers have found that there are correlations of component reliability and environmental conditions such as Tavner et al.[46,47] In this work, we focus on data uncertainty modelling and investigate the impacts of data uncertainty on OWT operational simulation, and it is assumed that the wind speed and other weather conditions have no influence on the failure rate. Also, in other simulation models, focusing on maintenance and logistics often requires met-ocean data to do the planning of activities, as this type of data may relate to the OWT accessibility and selection of transportation vessels. This paper mainly focuses on reliability modelling and the impacts of reliability uncertainty on the performance of OWTs. The impacts of maintenance logistics and met-ocean data, in this work, are assumed to reflect in the downtime per failure and its uncertainty as presented in Section 3.1.

3.3.1 | Component degradation model and TSMCS

As mentioned earlier, in this paper, the failure and repair of each component in the OWT are assumed to follow a two-state Markov process as in Figure 7.

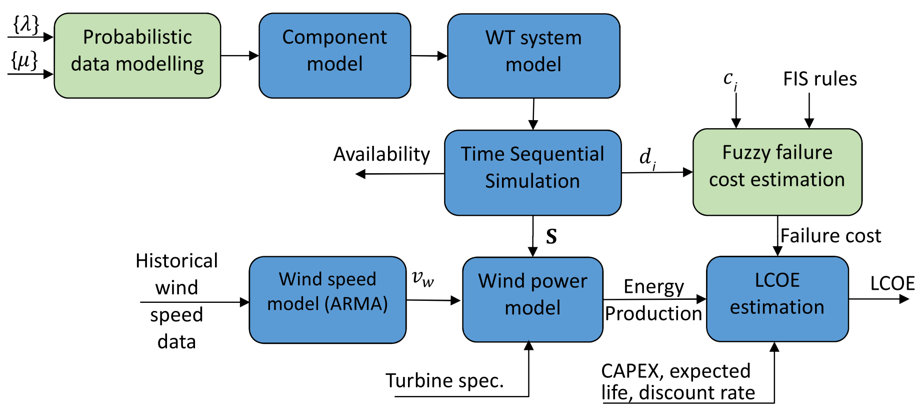
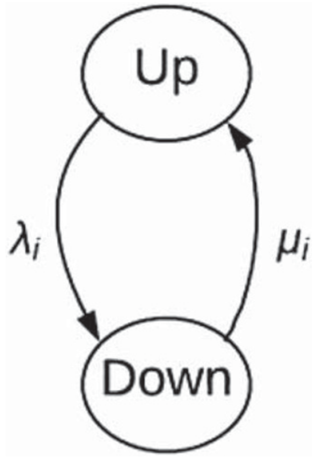


FIGURE 6 Offshore wind turbine (OWT) operational simulation (with uncertainties) [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 7 Component degradation model



A failure of the component brings it from the working or 'Up' state to the failure or 'Down' state with failure rate λ_i , whereas a repair brings it from the 'Down' state to the 'Up' state with a repair rate μ_i. From the Markov degradation process, an MCS is employed to simulate the failure time t_i^f and repair time t_i^r of a component i, as follows.

$$\begin{gathered} t_i^f = -\frac{1}{\lambda_i}\ln(r_1), \\ t_i^r = -\frac{1}{\mu_i}\ln(r_2), \\ r_1, r_2 \tilde{U}(0,1). \end{gathered} \tag{14}$$

The failure and repair times of each component are generated sequentially until the total failure and repair times reaches the turbine operational lifetime and therefore is called a TSMCS. The OWT in this paper is regarded as a series system of several s-independent components. The system is in the 'Up' state if and only if all of its components are in the 'Up' state. The illustration of getting a system operating sequence from two components' operating sequences is shown in Figure 8.

In Figure 8, the first time index, for example, t_{11}, is similar to the first time to failure generated by the MCS. Subsequent time indices are accumulated from repair or failure times as in the set of equations in Equation 14.

After several simulation runs, expected values for different performance indicators are calculated as in Section 3.3.3. The number of SMCS runs, N, is determined by setting a threshold for relative error, ε, as in Dao et al.[9]

$$\varepsilon = \frac{\sigma_{\text{TEP}} \times Z}{\mu_{\text{TEP}}\sqrt{N}} \le \alpha, \tag{15}$$

where μ_{TEP} and σ_{TEP} are the mean and standard deviation of a performance indicator, such as the total energy production (TEP); Z is a value representing the confidence level, for example, Z = 1.96 for 95% confidence level; and α is a desired accuracy threshold.

3.3.2 | Wind power model

The wind power output of an OWT depends on its reliability and wind speed at the site location. For a normal working turbine, the relationship between hourly wind speed at time t,that is, v_t, and wind turbine power output at the same time, that is, P_t, is shown in Equation 16.

$$P_t = \begin{pmatrix} \frac{1}{2}\rho C_p A_r v_t^3 \text{ when } v_{\text{cut-in}} \le v_t < v_{\text{rated}} \\ P_{\text{rated}} \text{ when } v_{\text{rated}} \le v_t \le v_{\text{cut-out}} \\ 0 \qquad \text{otherwise} \end{pmatrix}, \tag{16}$$

where P_{rated} is the rated power; C_p is a power coeffient; ρ is the air density; A_r is the rotor swept area; and v_{rated}, $v_{\text{cut-in}}$ and $v_{\text{cut-out}}$ are rated, cut-in and cut-out wind speed, respectively.

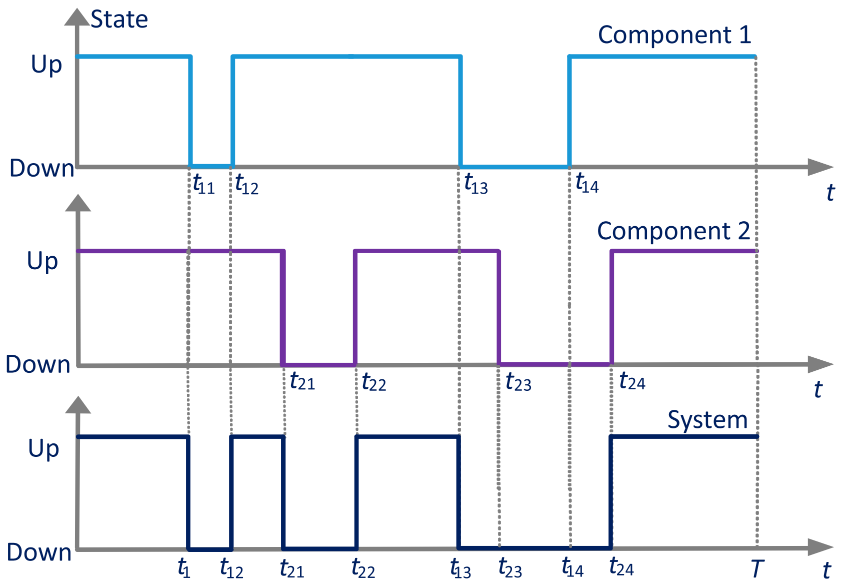


FIGURE 8 Illustration of the offshore wind turbine (OWT) and its components operation using time-sequential Monte Carlo simulation (TSMCS) [Colour figure can be viewed at wileyonlinelibrary.com]

It is noted that the actual power output is a combination of its operational simulation, that is, a sequence of 'Ups' and 'Downs', and the theoretical power output as in Equation 16. The wind turbine generally generates power when wind speed is between v_{cut-in} and $v_{cut-out}$. However, when a failure occurs, that is, the turbine is in the 'Down' state, there is no power output regardless of the current wind speed. Therefore, the actual power output at time t considering the reliability is

$$P_w(t) = P_t \times \delta(t), \tag{17}$$

where $\delta(t)$ is a zero–one function, taking the value 1 when the wind turbine is in the 'Up' state and 0 when the system is in the 'Down' state.

3.3.3 | Wind turbine operational and economic indicators

In this paper, a set of wind turbine operational and economic indicators are used to evaluate the performance of the OWT and investigate the impacts of uncertainties. These indicators include availability, energy production, failure cost and LCOE.

- Time-based availability: From the TSMCS, the total time that the system is in either 'Up' or 'Down' state can be estimated, and the system time-based availability (A_T) is calculated as the ratio between the total up time and the total time in simulation.

$$A_T = \frac{\sum t_{up}}{\sum t_{up} + \sum t_{down}}. \tag{18}$$

- TEP and annual energy production (AEP) and energy-based availability: The *TEP* generated by the OWT in its entire lifetime is

$$TEP = \sum_{t \in T} \Delta t \times P_w(t), \tag{19}$$

where Δt is the timestep, that is, the interval between two consecutive time points, that the wind speed and wind power estimated in Equation 16. The TSMCS is performed in the entire turbine's lifetime, T, which is typically 20–25 years. It is assumed that there are 8760 h per year, and the AEP of year y can be calculated for year y with a set of time T_y.

$$AEP_y = \sum_{t \in T_y} \Delta t \times P_w(t), \tag{20}$$

where $T_y = [1+8760(y-1), 8760y], y = 1,2,\ldots$. It is noted that $TEP = \sum_y AEP_y$.

From the energy production, the energy-based availability (A_E) can be estimated as

$$A_E = \frac{TEP}{EP_{\max}}, \tag{21}$$

where $EP_{\max}$ is the maximum theoretical energy production that can be calculated using the theoretical power curve shown in Equation 16. It is seen that availability and energy production are purely technical and operational performance indicators; there are no economic factors involved in the calculation of these performance indicators. Two other economic indicators are also examined as follows.

- Total failure cost: The total failure cost, C_F, is the summation of all individual failure costs of each component in a wind turbine's entire lifetime.

$$C_F = \sum_{t \in T} \sum_i c_{f,i}(c_i, d_i), \tag{22}$$

where the component failure cost $c_{f,i}(i, d_i)$ is estimated using the fuzzy failure cost estimation based on the component capital cost c_i and downtime d_i.The fuzzy logic and estimation used data generated from the MCS. Similar to the AEP, the annual failure cost, $C_{F,y}$, can also be calculated for each year y.

$$C_{F,y} = \sum_{t \in T_y} \sum_i c_{f,i}(c_i, d_i), \tag{23}$$

and $C_F = \sum_y C_{F,y}$.

- LCOE: LCOE is the total net present value (NPV) of annual costs, $NPVC_y$, over the total NPV of annual energy yield, $NPVE_y$:

$$LCOE = \frac{\sum_y NPVC_y}{\sum_y NPVE_y} = \frac{\sum_y \frac{CAPEX_y + OPEX_y}{(1+r)^y}}{\sum_y \frac{AEP_y}{(1+r)^y}}, \tag{24}$$

where $CAPEX_y$ is the capital expenditure (CAPEX) allocated to year y to acquire and install the OWT; $OPEX_y$ represents the annual operational expenditure (OPEX) in year y; AEP_y is the AEP in year y; and r is the discount rate.

In this paper, it is assumed that CAPEX is given and OPEX includes a fixed OPEX, which represents the fixed costs such as rental, administration and insurance, and a variable OPEX associated with failures and repairs of the wind turbine. The calculation of OPEX in year y is shown in Equation 25.

$$OPEX_y = OPEX_{Fix} + C_{F,y}, \tag{25}$$

where $C_{F,y}$ is the cost from the operational simulation and failure cost estimation as shown in 23.

4 | CASE STUDY, RESULTS AND DISCUSSIONS

In this section, a numerical study using reliability data from the literature is performed to investigate the impacts of uncertainties on OWT operational and economic performance. An exemplar 10-MW direct-drive, which is suitable for offshore application, is selected. The wind turbine specification is taken from Bak et al.[48] and presented in Table 1.

TABLE 1 Wind turbine specifications

Parameter	Value
Power rating	10 MW
Rotor diameter	178.3 m
Cut-in wind speed	4 m/s
Rated wind speed	11.4 m/s
Cut-out wind speed	25 m/s
Power factor (C_p)	0.45

In this paper, the data of six major components in the main wind turbine power generation chain are considered, namely, rotor blades, pitch, drivetrain, generator, converter and other electrical. Three different reliability data sources, namely, LWK, CIRCE and Strath,[11,13,14] are selected for reliability data uncertainty analysis. They are carefully selected from our recent wind turbine reliability data review.[12] The main reason for selecting these data sources is that they contain detailed failure statistics of wind turbine subassemblies reported on the basis of the same wind turbine taxonomy from the Reliawind project.[49]

Although the three selected reliability data sources were all collected in Europe, the reliability statistics reported for each component shows a clear disparity in different databases. They can truly illustrate the uncertainty in reliability data depending on the source of data collection, and that is suitable for the demonstration purpose of this case study, where cross-comparison and analysis of the impacts different reliability levels on OWT operational and economic performances are performed. Among the three databases, Strath is a recent offshore reliability data sources by the University of Strathclyde.[14] LWK and CIRCE are among the most comprehensive databases with detailed insights being analysed in a number of publications,[50–53] making them accessible to vastly general readers and, thus, are selected in the case study. Interestingly, in Tavner et al.,[50] it was observed that the reliability tends to decrease for larger turbines in Faulstich et al.[11] However, the group of wind turbines with the smallest power rating actually had the highest failure rate in Reder et al.[13] By examining each database closely, a clear trend of reliability and power rating is not observed, and thus, input component reliability data are directly taken from three databases available in the literature[11,13,14] and are summarised in Table 2.

In Table 2, the selected databases are classified into 'low–medium–high' failure rates and 'short–long' downtimes. This classification is based on the values of the wind turbine failure rate/downtime in one database compared with that of other databases. In this case study, it represents intuitive names of databases that are convenient for the results analysis and uncertainty comparison when the combination of reliability data takes place (in Sections 4.1 and 4.2). In practice, a database can have a mixture of reliability for different components, and the presented method will work for any combination of input reliability data.

Data for LCOE estimation, such as CAPEX and component cost, are taken from the recent guide to offshore wind farm by BVG Associates for a 10-MW wind turbine for offshore application[42]; fixed OPEX is taken from BEIS report for Round 3 offshore wind in the United Kingdom predicted for 2020.[8] Input wind speed data and the offshore site for wind data to be extracted are from Renewables.ninja[54] and the Dogger Bank wind farm in the United Kingdom,[55] respectively. The OWT is expected to operate for a duration of 20 years (which is also the simulation time span), and the discount rate for LCOE estimation is 10%. Table 3 shows the input cost data in this study.

To analyse the impacts of cost uncertainty, a FIS is designed to represent the linguistic relationships between component cost, downtime per failure and the failure cost. Four levels of downtime (short, medium, long and very long), three levels of component cost (low, medium and high) and four levels of failure cost (low, medium, high and very high) are used with reference failure cost data from.[36] The Gaussian membership functions[44] are employed to represent the downtime and cost data uncertainty. Table 4 shows the details of 12 FIS rules in this case study.

TABLE 2 Input reliability data

	Failure rate (failures per turbine per year)			Downtime (h)	
Component	CIRCE[13] (low)	LWK[11] (medium)	Strath[14] (high)	LWK[11] (short)	CIRCE[13] (long)
Rotor blades	0.044	0.194	0.755	42.123	190.73
Pitch	0.029	0.088	1.076	25.147	98.092
Drivetrain	0.016	0.030	0.633	118.185	165.846
Generator	0.029	0.140	0.999	74.361	320.636
Converter	0.006	0.053	0.180	29.867	74.171
Electrical	0.061	0.270	1.322	34.53	74.031

TABLE 3 Input CAPEX, OPEX and component cost

Cost element/component	Value (£ thousand)
CAPEX (per MW)	2670
Fixed OPEX (per year)	962
Rotor blades	1450
Pitch	100
Drivetrain	400
Generator	2000
Converter	300
Electrical	400

Abbreviations: CAPEX, capital expenditure; MW, megawatt; OPEX, operational expenditure.

TABLE 4 Fuzzy logical rules

If downtime is	And component cost is	Then failure cost is
Short	Low	Low
Short	Medium	Low
Short	High	Medium
Medium	Low	Low
Medium	Medium	Medium
Medium	High	Medium
Long	Low	Medium
Long	Medium	Medium
Long	High	High
Very long	Low	Medium
Very long	Medium	High
Very long	High	Very high

4.1 | Impacts of reliability data uncertainty

From three failure rate databases and two downtime databases presented in Table 2, 12 possible scenarios (simulation cases) of fixed and uncertain reliability data can be formed, and the proposed operational simulation is performed for all 12 cases. There are six simulation cases with fixed failure rates and fixed downtimes, that is, no uncertainty included; three cases where the failure rates are fixed and downtimes are uncertain; two cases where the failure rates are uncertain and downtimes are fixed; and one case where both failure rates and downtimes are uncertain.

In order to evaluate the impacts of reliability data uncertainty, each simulation case is repeatedly run, and the mean and standard deviation of operational and economic indicators presented in Section 3.3.3 are calculated for all 12 cases. This experiment is designed for analysing the impacts of the probabilistic reliability data selection used for assigning the component reliability data as in Section 3.1. For each selection of reliability data, several realisations of OWT operational lifetime are simulated in the TSMCS to ensure the relative error for TEP being less than the desired threshold of 0.01% (see Equation 15, Section 3.3.1). The simulation is developed in Matlab R2018 and built-in Fuzzy logic toolbox. It is run in a multiple-core Intel Xeon CPU 2.40-GHz server, 256GB of RAM, and Linux operating system. The number of simulation runs and CPU performance summary is presented in Table 5.

On average, it requires more than 3340 TSMCS runs for the TEP to converge to the desired accuracy of 0.01%. A random operational profile of the OWT is generated per TSMCS run, and the CPU time per TSMCS run is relatively short, that is, approximately 0.32 s. However, the TSMCS needs to run repeatedly to guarantee the desired accuracy as well as for the reliability data uncertainty evaluation. In total, more than 167 000 operational profiles, that is, simulated lifetimes, are generated per simulation case to obtain the mean and standard deviation of five operational and economic indicators as in Figure 9.

In Figure 9, the standard deviations are plotted to show the impact of reliability data uncertainty for 12 possible simulation cases (six of them are fixed input reliability data, and six other cases are with different levels of uncertainty). This figure is useful to (i) illustrate the differences in the variation between fixed and uncertain reliability data and (ii) compare the variation between different levels of reliability data.

TABLE 5 Summary of the simulation performance

Parameter	Value
Error threshold (%)	0.01
Ave. number of TSMCS runs per data selection	3340
Ave. CPU time per data selection (s)	1082
Total number of operational profiles per scenario	167 004
Total CPU time per scenario (s)	54 099

Abbreviation: TSMCS, time-sequential Monte Carlo simulation.

The left-hand-side subfigures (Figure 9A,C,E,G,I) show the mean values of five performance indicators of interest and indicate the general relationship between reliability data, that is, failure rate and downtime, and the operational and economic performance of the OWTs. Similar patterns can be observed in time-based availability, energy-based availability and AEP; that is, high failure rates and long downtimes lead to low average availability and energy production and vice versa. For the total failure cost and LCOE figures, high failure rates and long downtimes lead to high total failure cost and LCOE, with mean values in cases with uncertainty line between the case with low reliability and the case with high reliability. This well agrees with the fact that high failure rate increases the number of failures and long downtime reduces the total operating time, and both lead to a decrease in OWT operational and economic performance.

The right-hand-side subfigures (Figure 9B,D,F,H,J) provide information about the impacts of reliability data uncertainty on the indicators of interest. The impacts of reliability data uncertainty are measured by the standard deviation of each indicator. In all subfigures, the variation for six cases without reliability data uncertainty is minimal, which implies that the MCS produces robust results; that is, the variation caused by the MCS is negligible and appropriate for uncertainty analysis. The variation is the highest where both failure rate and downtime are uncertain. Interestingly, where there is either failure rate uncertainty or downtime uncertainty, the variation is bigger for the cases with low reliability, that is, high failure rate or long downtime. This not only means reliability data uncertainty can cause a large variation in the OWT operational and economic performance but also implies that low reliability magnifies the impacts of reliability data uncertainty on its performance.

4.2 | Impacts of failure cost uncertainty

Further experiments are performed for two cases: (i) the cost per failure is fixed at 10% of the component capital cost, that is, $c_{f,i} = 0.1c_i$, and (ii) cost per failure is uncertain and estimated using the FIS as presented in Section 3.2. The mean and variation of availability, mean AEP, total failure cost and LCOE in both cases are presented in Figure 10.

In Figure 10 horizontal axis, 'Low', 'Medium' and 'High' indicate the level of failure rate database when downtime is uncertain; 'Short' and 'Long' indicate the level of downtime database when failure rate is uncertain; and 'Both' indicates both failure rate and downtime are uncertain.

There are disparities in the impacts of cost uncertainty on the operational and economic performance of OWTs in this case study. Similar patterns of mean and standard deviations can be observed in Figure 10A,B,C. The variations are not clearly distinguishable, which means that there is no correlation between cost uncertainty and the obtained A_T,A_E and *AEP*. This is because A_T,A_E and *AEP* are purely operational performance indicators, which are dictated by wind turbine reliability data but not the failure cost. However, the impacts of failure cost uncertainty are observed in Figure 10D,E, where standard deviations of total failure cost and LCOE are higher for the case with cost uncertainty compared with the case without cost uncertainty. Additionally, a similar pattern to Figure 9 is observed; that is, the wind turbine reliability also has impacts on the cost uncertainty; that is, the variation is more significant in turbines with higher rates of failure and longer downtimes.

It is noted that in this study, the OPEX uncertainty can be reflected via the total failure cost. As shown in Equation 25, OPEX includes a fixed OPEX and variable OPEX associated with the failures of the wind turbine. Because the fixed OPEX is assumed to be a constant in all cases, the main driving factor in the overall OPEX impact is the total failure cost uncertainty, which is presented in Figure 10D.

In order to quantify the impacts of reliability and cost data uncertainties on different performance indicators of OWTs, the coefficient of variation, that is, ratio between standard deviation and mean, are calculated for six different cases and presented in Table 6.

In general, a higher coefficient of variation means higher impacts of the uncertainty on the performance indicator of interest. Table 6 indicates that the impacts of uncertainty vary vastly with wind turbine reliability as well as with different performance indicators. The uncertainty increases as the reliability decreases; that is, the coefficients of variation are large for high failure rate and long downtime databases and vice versa. The case where both downtime and failure rate are uncertain produces the highest variation. These results can be explained as follows.

- For operational indicators such as availability and energy production, high failure rates, that is, low-reliability components, lead to frequent failures of OWTs, which reduce the operational time and the energy produced. The availability is generally high, that is, close to 1, and the energy

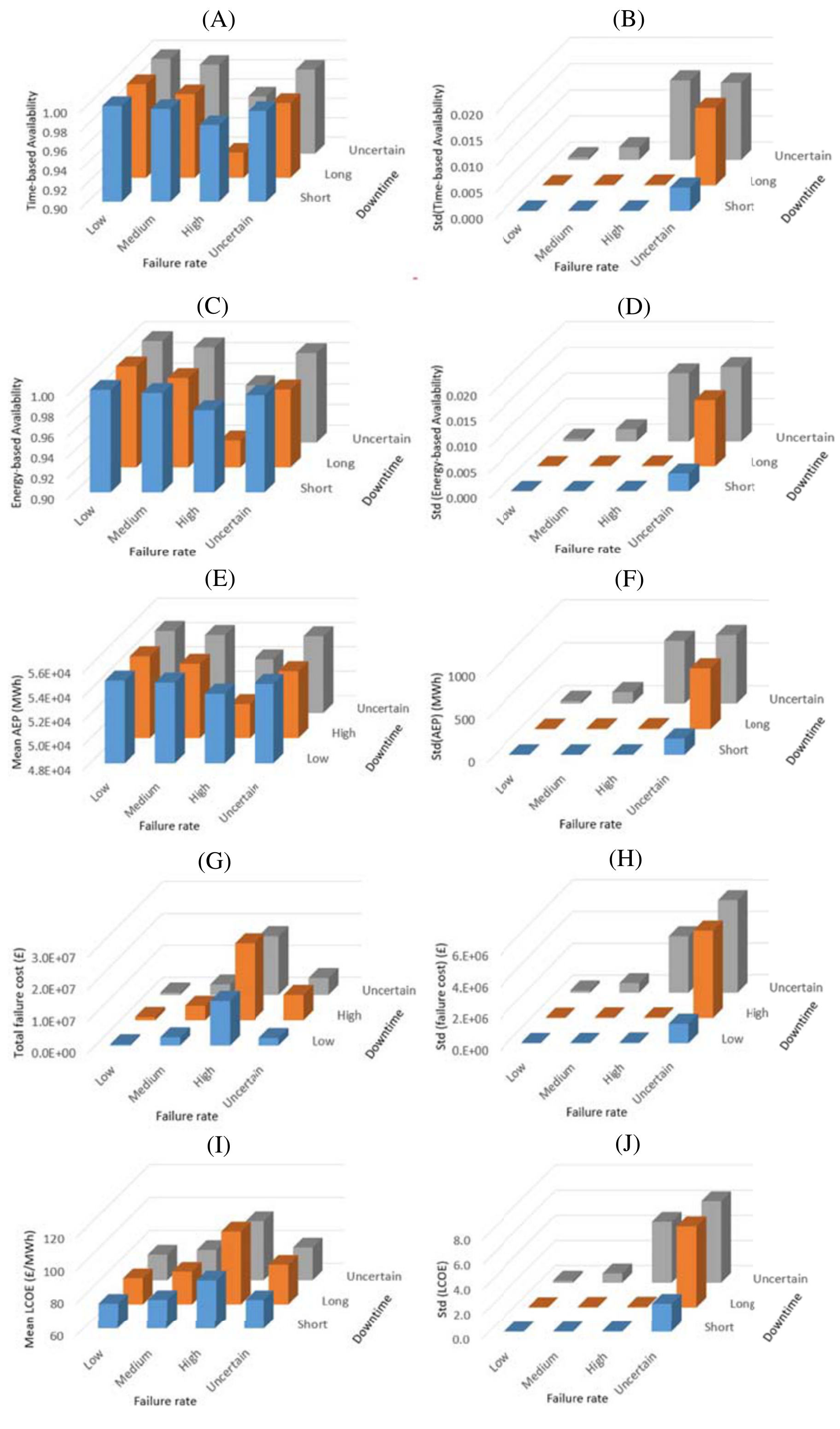


FIGURE 9 A–I, Impacts of reliability data (i.e., failure rate and downtime) uncertainty [Colour figure can be viewed at wileyonlinelibrary.com]

production is large; thus, the coefficient of variation for these operational indicators is not as large as that of other two economic indicators (Table 6).

- For economic indicators such as total failure cost and LCOE, high failure rates also cause more failures, and that leads to high total failure cost and LCOE, as shown in Figures 9 and 10. Meanwhile, the combination of uncertain cost and long downtime can create some special circumstances, where the cost per failure is very high, corresponding to very long downtime. These special circumstances contribute to the increase of standard deviation and coefficient of variation of total failure cost and LCOE (Figure 10 and Table 6).

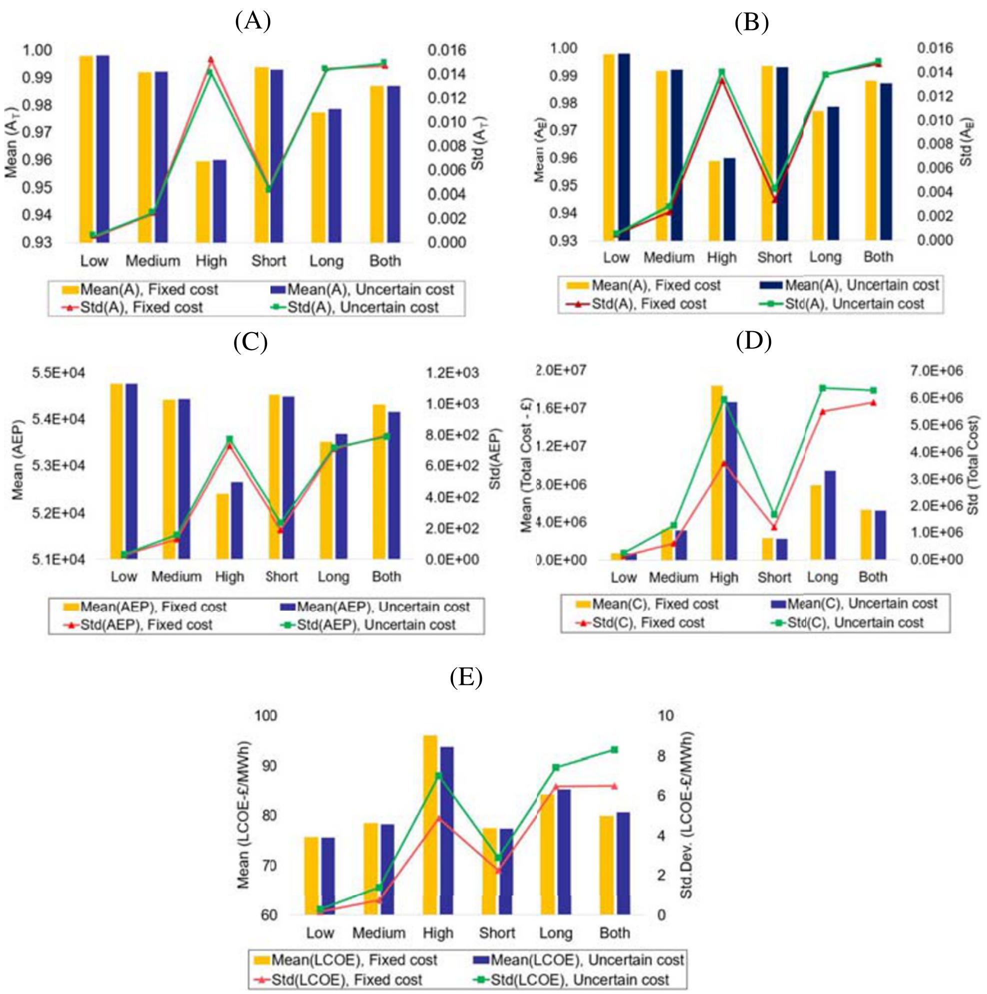


FIGURE 10 A–I, Impact of failure cost uncertainty [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 6 Coefficient of variation

Failure rate/downtime uncertainty combination		Coefficient of variation (%) Availability	Mean AEP	Total failure cost	LCOE
Uncertain downtime	Low failure rate	0.06	0.06	36.19	0.39
	Medium failure rate	0.25	0.29	40.96	1.79
	High failure rate	1.47	1.47	29.64	7.47
Uncertain failure rate	Short downtime	0.44	0.43	74.06	3.71
	Long downtime	1.48	1.41	66.56	8.69
Both uncertain		1.51	1.49	117.8	10.29

Abbreviations: AEP, annual energy production; LCOE, levelised cost of energy.

- When the failure rate and/or downtime data are uncertain, the generated number of failures and downtime vary greatly with different reliability data selections, and that creates a wider range of both operational and economic indicators. Thus, the coefficients of variation in uncertain-cost cases are greater compared with those in the fixed-cost cases.

In addition, the coefficient of variation is relatively low in two operational performance indicators of availability and AEP (up to 1.51%), whereas it is very high for failure cost (from approximately 30% to 120%). The former can partly be explained by the way operational performance indicators are estimated; that is, failure cost is not taken into consideration in estimating availability and AEP. Meanwhile, a possible reason for the latter is that both reliability data and cost uncertainties directly dictate the total failure cost, and, therefore, its variation is notably high. LCOE is a measure that considers both failure cost and energy production, and its coefficient of variation can vary between 0.39% (where the failure rate is low, and downtime is uncertain) and 10.3% (where both downtime and failure rate are uncertain).

TABLE 7 Characteristics of failure cost distribution

Parameter	Value
Mean (£)	1.83e+5
Median (£)	1.20e+5
Standard deviation	2.16e+5
Coefficient of variation	1.18
Skewness	2.40

To further understand the failure cost variation, the random failure cost distribution from the fuzzy cost evaluation is investigated. The TSMCS is run repeatedly until the relative error is less than 0.01%, and the fuzzy failure cost data results are extracted. The failure cost distribution is presented in Table 7.

The obtained results indicate that the failure cost distribution is positively skewed (right skewed) with the median value less than its mean value. This implies that more failures with low cost are observed. This is true in operational practice, as the wind turbine can experience many minor repairs with low cost, that is, less than the mean failure cost, whereas there are fewer failures with high cost. The failure cost can be fitted by a nonparametric distribution, for example, Kernel distribution, rather than by a parametric distribution. These interesting statistics of the cost per failure from the fuzzy cost estimation are meaningful for the wind farm developers and operators, especially the cost data analysts, as it shows the variation and nonparametric distribution of the cost per failure during OWT operational lifetime.

5 | CONCLUSIONS

Uncertainty is an inherent characteristic in operational simulation of OWTs but is rarely considered. This paper models two types of uncertainties related to reliability and cost data and incorporates them into an OWT operational simulation framework. A probabilistic reliability data matrix is proposed to model the reliability data uncertainty, and the fuzzy logic is used for failure cost uncertainty. These are integrated into an OWT reliability and operational simulation framework under uncertainties, and the TSMCS is employed to investigate the impacts of uncertainty on the operational and economic performance of OWTs.

The case study and results show that OWT performance indicators such as availability, energy production and LCOE vary vastly with varying degrees of uncertainty in the input reliability data. The variation reduces for databases with highly reliable components, which implies that improving reliability not only enhances operational performance and lowers LCOE but also reduces the variation in OWT performance prediction. In addition, it is seen that the total failure cost variation is substantial when the cost uncertainty is also considered, and that leads to LCOE variation at up to 10.3% of the mean LCOE. This research can enable OWT modellers and operators to handle data uncertainties and to quantify the impact of reliability and cost data uncertainties on wind turbines' operational and economic performance.

This paper focuses on uncertainty modelling and assumes that the failure rates of wind turbine components are not affected by the wind speed and other weather conditions. To incorporate the impact of environmental conditions, one would need to develop a model that can quantify the changes in failure rate depending on wind speed and test the validity of the model. Such models representing the relationship between failure rate and weather conditions would be another interesting area of research and are suggested for future study.

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NOMENCLATURE

λ	failure rate of the turbine
λ_i	failure rate of component *i*
$\lambda_{i,j}$	failure rate of component *i* in database *j*
Δ_{ij}	failure rate deviation of component *i* in database *j*
$\delta(t)$	a zero–one function taking the value of 1 when the system works and 0 when the system fails
μ	repair rate of the turbine
μ_i	repair rate of component *i*
ρ	air density
A_E	energy-based availability

A_T time-based availability
A_r rotor swept area
C_F total failure cost calculated for the entire OWT lifetime
$C_{F,y}$ total failure cost in year y
C_p power coefficient
$c_{f,i}$ cost per failure of component i
c_i capital cost of component i
d_i downtime per failure of component i
k_i normalising coefficient for reliability data uncertainty estimation
m_d number of reference downtime databases
m_f number of reference failure rate databases
N number of simulation runs in the TSMCS
n number of components in the wind turbine
$\mathbf{P}_d$ probabilistic reliability data matrix for downtime
$\mathbf{P}_f$ probabilistic reliability data matrix for failure rate
p_{ij}^d probability that the downtime data of component i are drawn from database j
p_{ij}^f probability that the failure rate data of component i are drawn from database j
P_{rated} rated power output
P_t theoretical power output
P_w actual power output
q_{ij} reliability uncertainty factor of component i and database j
$R_{\lambda,i}$ failure rate range of component i considering different databases
r discount rate
t_i^f random time to failure of component i
t_i^r random time to repair of component i
v_t wind velocity at hub height

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