

Modeling Epistemic Uncertainty in Offshore Wind Farm Production Capacity to Reduce Risk

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Financial stakeholders in offshore wind farm projects require predictions of energy production capacity to better manage the risk associated with investment decisions prior to construction. Predictions for early operating life are particularly important due to the dual effects of cash flow discounting and the anticipated performance growth due to experiential learning. We develop a general marked point process model for the times to failure and restoration events of farm subassemblies to capture key uncertainties affecting performance. Sources of epistemic uncertainty are identified in design and manufacturing effectiveness. The model then captures the temporal effects of epistemic and aleatory uncertainties across subassemblies to predict the farm availability-informed relative capacity (maximum generating capacity given the technical state of the equipment). This performance measure enables technical performance uncertainties to be linked to the cost of energy generation. The general modeling approach is contextualized and illustrated for a prospective offshore wind farm. The production capacity uncertainties can be decomposed to assess the contribution of epistemic uncertainty allowing the value of gathering information to reduce risk to be examined.

KEY WORDS: Availability; epistemic uncertainty; offshore wind farm; production capacity; risk management

1. INTRODUCTION

Global operational offshore wind capacity reached over 21 GW in 2019 with a new build program reported to be over 100 GW (Global Offshore Wind Report, 2019). The United Kingdom has the largest market share with almost 8.5 GW of operational capacity and a new build program of nearly 30 GW. Germany and China both have new build programs of around 10 GW. Currently, the United States has one operational 30 MW offshore wind project and is regarded as an emerging market with 14.5 GW of projects at different stages of maturity (Global Offshore Wind Report, 2019). Ram (2016)

& Staid and Guikema (2015) highlight the need to analyze the risks to offshore wind farms in view of the increasing importance of wind power within the global energy portfolio. In proposing an integrated approach to risk analysis motivated by the U.S. context, Staid and Guikema (2015) identify the need for existing projects to be economically and technically successful to encourage a willingness to invest in future offshore wind developments.

Similar concerns related to investment in offshore wind farms have existed in the United Kingdom (Freshfields Bruckhaus Deringer, 2013; Price Waterhouse Coopers, 2011). The contract for difference (CfD) scheme used by the U.K. Government allows developers to derisk the impact of future wholesale energy prices. This scheme guarantees the chosen developer a fixed strike price for wind farm power, whereby it receives a top-up payment when wholesale prices are lower, and it pays back if

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wholesale prices are higher. Development sites are allocated after a bidding process based on the lowest bid strike price. A developer's bid to such a scheme therefore effectively reflects their assessment of uncertainty about the future cost of generation, together with an assessment of what competitive bids might be. The steep reduction in bids over the three rounds of the U.K. CfD scheme has been driven by ever larger turbines and higher reliability. However, since each new generation of wind farms use larger turbines, innovative technologies and are possibly located further from shore, vulnerabilities might arise because of, for example, construction delays due to novel installation processes, loss of production capacity due to teething problems with technically immature designs, and reduced availability due to delays in essential maintenance given access challenges to remote sites. Uncertainties about new farm performance therefore should play in to assessing the right bid value in such auctions, and therefore the overall level of return.

Following the definitions of Der Kiureghian and Ditlevsen (2009), Tannenbaum, Fox, and Ülkümen (2017), & van der Bles et al. (2019), we class such uncertainties as epistemic since they concern phenomena not known at the time of bidding but which could, at least in theory, be known or established given more information. Given the implications for risk management, epistemic uncertainties should be distinguished from aleatory uncertainties, which are due to the intrinsic randomness of a phenomenon (Der Kiureghian & Ditlevsen, 2009). According to (Packard & Clark, 2020), epistemic uncertainty implies decision-makers could mitigate their ignorance of knowable information by adopting a predictive approach to managing. The value of modeling epistemic uncertainties to provide decision-makers with analysis will depend on the cost of information, which includes the modeling effort. Epistemic uncertainty can introduce dependencies that require sophisticated modeling effort to avoid misleading results (Bier & Lin, 2013). Currently no models exist to represent epistemic uncertainty and to support wind farm decision-makers address challenges such as that of adopting a predictive approach to assess bid values at auctions for an offshore wind farm site. Many models exist for supporting operational planning decisions associated with wind farm operations (Andrawus et al., 2007; Dalgic, Lazakis, Dinwoodie, McMillan & Revie, 2015; Duard, Domecq, & Lair, 2012; Endrerud, Liyanage, & Keseric, 2014; Hofmann & Sperstad, 2013; Phillips, Morgan, & Jacquemin, 2005;

Rademakers, Braam, Obdam and Pieterman, 2009). Such models consider only aleatory uncertainty. Of course, epistemic uncertainty can be explored in analysis using such models by considering the effect of deviations from their assumptions through sensitivity analysis on key parameters (Martin, Lazakis, Barbouchi, & Johanning, 2016; Scheu, Kolios, Fischer, & Brennan, 2017). However, sensitivity analysis results often do not provide a clear association between decisions and performance improvements, failing to give clear support for decisions to manage uncertainties. As discussed in (Bier & Lin, 2013), distinguishing between types of uncertainty is key because epistemic uncertainties introduce dependencies that have a compound effect, whereas aleatory uncertainties will average out over the farm. The larger the farm, the more significant the effects of epistemic uncertainty on estimates of performance and energy produced.

In this article, we present a new model designed to represent key epistemic uncertainties in offshore wind farm performance and to model how these uncertainties are influenced by stakeholder decisions. Our goal is to help decision-makers better understand how much control they have over risk. The model is motivated by decision-making contexts arising before an offshore wind farm is constructed, such as those relating to bids for offshore wind farm auctions. The model estimates farm performance and can be used to investigate potential mitigation actions to buy-down epistemic uncertainties. Although the prediction horizon supported by the general model is flexible, here we focus upon the early operating life of a farm because of the combined importance of cash flow discounting effects and the anticipated performance growth due to operational learning and technical innovations. Although the model will be used before real experience data are available to fine-tune farm performance and operations, it is worth underlining that there is both real engineering conceptual knowledge about new systems which could influence the perceived investment risk and subsequently the required rate of return demanded by investors. Such knowledge needs to be captured on a systematic and transparent basis, hence our model is formulated using contextual insight and quantified for specific instances using methodological processes for eliciting structured engineering expert judgment (Dias, Morton, & Quigley, 2018).

Section 2 introduces our conceptual framework. Section 3 explicates modeling choices such as the representation of epistemic uncertainties within

the stochastic process underpinning the analysis. Section 4 describes the key measure of farm performance supported by the model. Section 5 presents an illustrative use of the model grounded in a contemporary decision problem of the type facing U.K. offshore wind farms. We reflect upon the value and limitations of our modeling approach, suggesting areas for further research and development in Section 6.

2. CONCEPTUAL FRAMEWORK

2.1. Measure of Farm Performance

To predict the capacity of a wind farm to produce power, we need a performance measure that relates energy production to technical availability performance. Drawing on the general meaning of availability as the ability of a system to be in a state to perform as required, then loss of farm availability will arise when there is an inability to generate power due to failures and/or maintenance.

We define a bespoke performance measure, the availability-informed relative capacity, to be the fraction of farm power output at a specified time given the operating condition of the turbines relative to the installed power capacity of the farm. This is related, but not identical, to standard industry terms (IEEE P762, 2006; IEC 61400-26-3, 2019). These standards introduce terminology allowing for the specification of contracts between different parties involved in the operation and maintenance of wind turbines. In particular, they enable accounting of the costs of lost production depending on the underlying reasons. The appropriateness of energy based rather than purely technical availability measures for engineering models of farm performance has been examined by (Conroy, Deane, & Ó Gallachóir, 2011; Hawker & McMillan, 2015), contributing to a debate partly informed by the contracting experiences for early generation offshore wind farms (Feng, Tavner, & Long, 2010). This is a level of detail not required for this article, hence the choice of definition made here. The supplementary Appendix 2 explains how the availability-informed relative capacity relates to standard performance measures in the wind energy sector.

2.2. Model Features

The model is primarily designed to be applied prior to farm operation to estimate the availability-

informed relative capacity, enabling predicted performance to be assessed against target and action taken to reduce risk if required. Setting “Time Zero” to be the start of operation allows the timing of analysis to support decisions to be distinguished from the prediction horizon.

Fig. 1 shows the conceptual framework, with relations between key model elements across the two time phases. The diagram captures decisions (e.g., management choices), uncertainties (e.g., factors influencing availability), and performance-related metrics, encompassing both output performance measures (i.e., availability-informed relative capacity) and interim measures (e.g., reliability). The solid arrows represent information dependencies (e.g., farm restoration time will depend on logistics, travel and repair time as well as repair duration). The broken arrows represent system upgrades that might occur through time during operation. We discuss these elements of the conceptual model framework further below.

Availability will be influenced by the reliability of the farm equipment and their restoration upon failure. Equipment refers to the wind turbines, connecting cables, and balance of plant (BOP) up to, but not including, the onshore substation. Prior to construction targets will be set, while the actual reliability and restoration will be manifested during the operational period. For prior analysis, the actual reliability, and restoration, will be estimated from the model and so should not be confused with those computed using observational data once the farm is truly in operation.

Reliability will affect farm uptime (working fully or partially). Failure to work can be triggered by weaknesses or flaws affecting the equipment. All newly installed turbines are assumed to be the products of the same design and manufacturing process, and during operation are assumed to be subject to the same types of operational errors. Systemic failures due to shocks, such as design inadequacies or manufacturing faults, could be anticipated prior to operation. While failure due to human and other errors will originate in operation. We use “trigger” as a collective term for those design inadequacies, manufacturing faults or operational errors that might lead to (i.e., “trigger”) a systematic increase in, for example, the rate of failure events, and which hence reduce overall availability. These triggers are represented as uncertainties in Fig. 1.

Maintenance, planned and unplanned, will restore a farm that is down (not working) to an

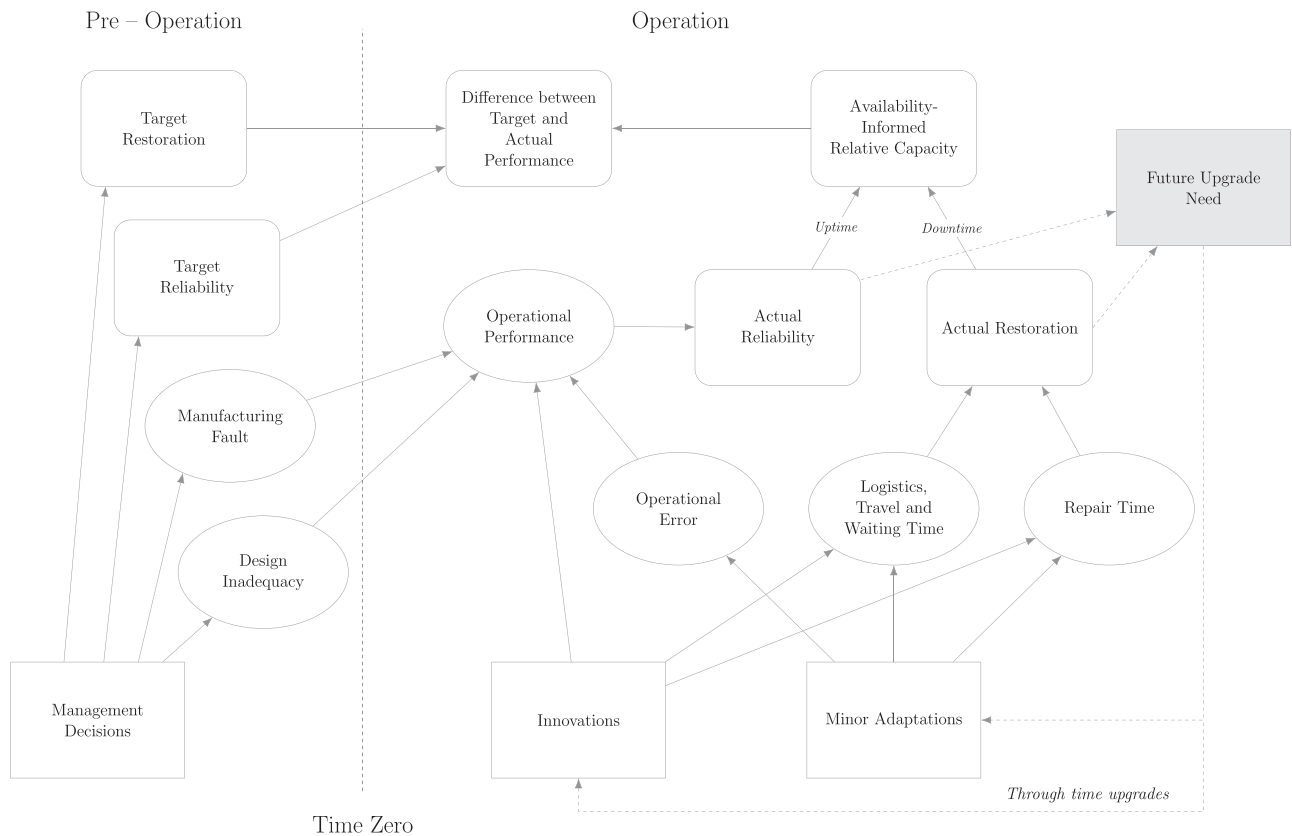


Fig 1. Conceptual framework for farm availability-informed relative capacity in terms of uncertainties (oval nodes), intervention decisions (rectangular boxes), and performance-related metrics (rounded-edge boxes). Solid arrows represent information dependencies and broken arrows represent through time upgrades.

operational state. Downtime will be affected by uncertainties in the time to complete restoration, including the logistical delays, service vessel travel times, and repair durations.

We assume the design inadequacy and manufacturing fault triggers are the main sources of epistemic uncertainty given the pre-operational state of knowledge about the novel technologies being developed to operate in new marine locations. Other uncertainties are treated as aleatory. For example, restoration can be affected by logistics and repair uncertainties some of which, although not necessarily all, might be weather-related. Since we present a generic model, here we treat weather uncertainties as aleatory. We recognize that such uncertainties might be appropriately treated as epistemic if and when the model is applied to a specific site where information may be available to learn about the local environment.

The unit of analysis for the model is subassembly level. For example, turbine subassemblies include

the gearbox, generator, blades, rotor, etc. In addition, we have BOP such as electrical cables to the on-shore substation. Modeling at the level of subassemblies allows us to represent the dependencies due to epistemic uncertainties. Each type of subassembly, such as gearboxes of the same design version, can be considered a population. Following (Bier & Lin, 2013), we distinguish between those epistemic uncertainties which introduce dependencies between individual subassemblies within a population and the aleatory uncertainties which average out over all subassemblies within a population. For example, the design inadequacy trigger can affect all equivalent subassemblies in the population implying that epistemic uncertainty due to that trigger has the potential to have a first-order effect on the uncertainty in farm performance. The larger the farm, the more substantial this effect becomes. Therefore, failing to represent epistemic uncertainty through the adequate modeling of triggers at subassembly level can lead to considerable under- or over-estimation of farm

performance and energy yield. Gaining insight in the levels of farm performance uncertainty itself is useful in many decision-making contexts, making the modeling of triggers important even when decision-makers cannot act to reduce risk.

2.3. Dependency between Epistemic Uncertainties

A trigger has an individual impact on a subassembly population if it affects subassemblies independently of others in the population, whereas it has a shared impact when all subassemblies in the population are affected equally. Furthermore, a trigger could impact in a one-off manner or dynamically through time. We assume triggers originating prior to operation have a one-off dependency, while triggers originating during operation have a temporal dependency. For example, design inadequacies are intrinsic features of a subassembly corresponding to inappropriate design or lack of understanding of the operating environment and so are assumed to be present from installation and remain unless removed through replacement or upgrade and, further, are shared by all subassemblies within a population (i.e., one-off time-dependence and shared impact). Manufacturing faults due to poor quality control and production processes are introduced during production and are assumed to affect subassemblies independently of each other in the population, and furthermore are present from installation and remain until they are actively removed (i.e., individual impact and one-off time-dependence). Operational errors are maintenance-induced and are assumed to occur independently in each subassembly (i.e., individual impact) at any time during the operation of the farm (i.e., dynamic time-dependence). Fig. 2 shows the classification.

To examine the relationships between different triggers and the subassembly failure behavior, consider a population of n equivalent subassemblies, such as gearboxes. Fig. 3 provides a graph of the uncertainties (nodes) and their dependencies (arcs). Design inadequacy is assumed to influence equally the failure propensities of all equivalent subassemblies through time. The likelihood of a manufacturing fault is assumed to depend on manufacturing process fault and to occur independently across the subassemblies in a population. Operational errors are assumed to independently affect each individual subassembly, and to represent time-varying risks which depend on factors such as maintenance history.

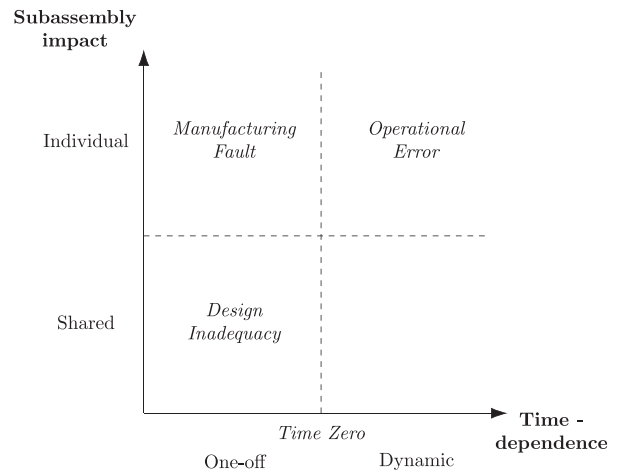


Fig 2. F Classification of assumed trigger effects on farm availability.

2.4. Interventions and Buying Down Epistemic Uncertainty

Interventions are actions intended to improve farm performance. In this article, we focus upon assessing the need for and the value of management decisions intended to buy-down epistemic uncertainties prior to operation. Generally, such actions can gain information to inform the need for design and manufacturing enhancements to improve the inherent reliability of farm equipment and processes during their development. The model also allows for interventions during operation. Such interventions may be major innovations intended to lead to a step-change in performance, such as upgrades in technologies, maintenance strategy, or logistics solutions. In addition, during operation we allow for learning as, say, operating and maintenance practices are refined with experience. Innovations and minor adaptations are treated as two classes of intervention to allow appropriate modeling of their intended effects to grow farm performance. Further mathematical details of this aspect of the model are given in (Zitrou, Bedford, & Walls, 2016).

In summary, the conceptual framework in Fig. 1 captures the relationships between choices, uncertainties, and performance over two phases of a farm life. Here we focus upon assessment of farm performance prior to operation and use modeling to examine the effect of actions intended to buy-down epistemic uncertainty. In this way, analysis can inform decision-makers of effective risk reduction strategies. More generally, the model could be used to provide

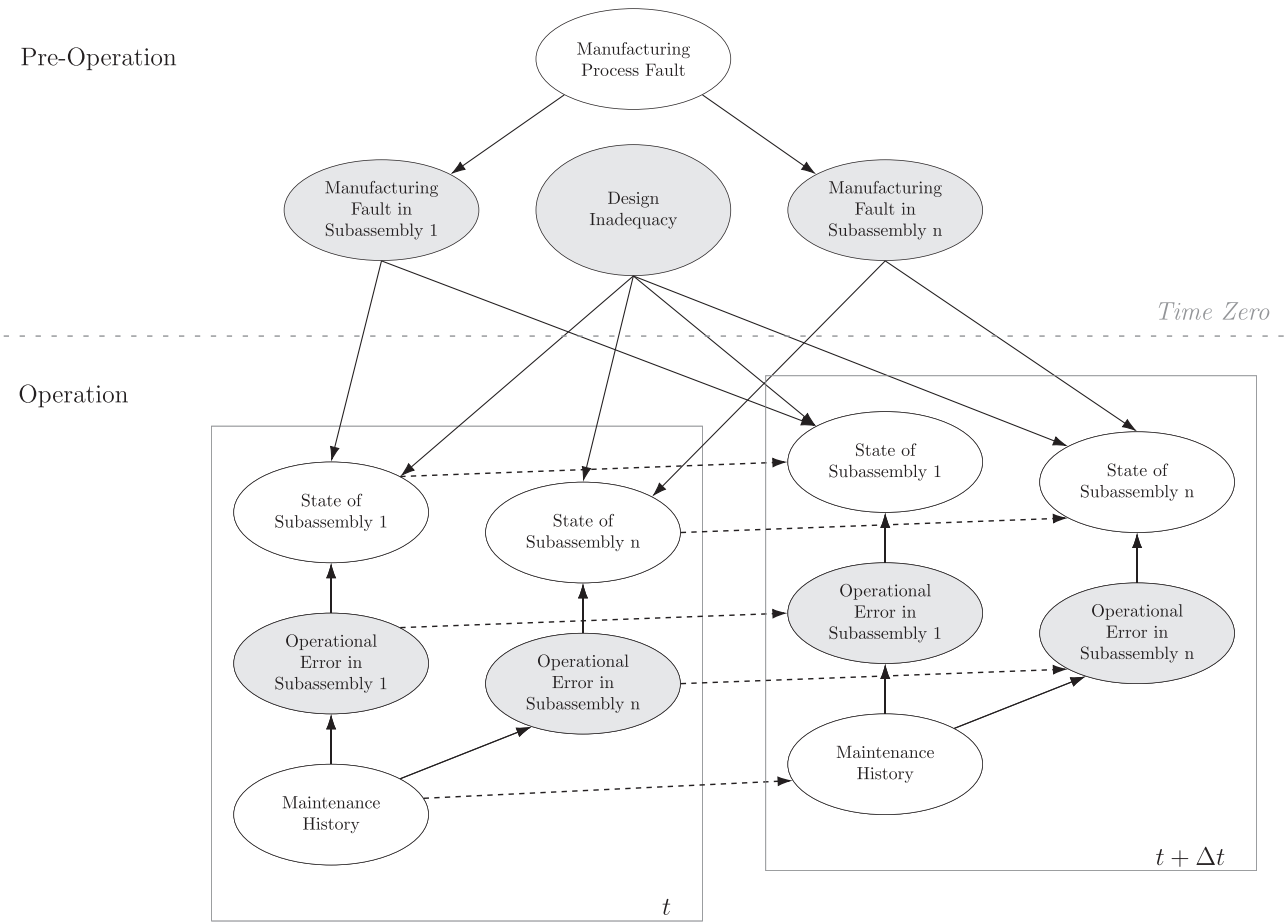


Fig 3. Graph representing dependency of triggers on subassembly state. Gray nodes portray triggers. Solid arcs represent static relationships (within the same time slice t) whereas dotted arcs represent dynamic relationships between time slices t and $t + \Delta t$

analysis to inform major upgrade decisions during operation since epistemic uncertainties might similarly arise for the equipment or processes subject to innovation.

3. STOCHASTIC MODEL

3.1. Marked Point Process (MPP) Model of Farm

Using a continuous-time MPP (Sigman, 1995) allows us to model the evolution of the wind farm failure, repair, and generation capacity processes through a stochastic model. A finite set of marks represents the different types of event affecting the farm. Marks can be conveniently thought of as multidimensional, and they include information on the realization of triggers. A realization of an MPP is a set of times with associated marks (t_n, j_n) . Consistent

with Fig. 3, we assign marks associated to triggers at the start of the farm operation ($t = 0$). These marks represent realizations of the epistemic uncertainties in the model. The epistemic uncertainties represent “the world we are in,” and the evolution of this world through the simulation model provides a single realization of the aleatory uncertainties arising given the realizations of the epistemic uncertainties.

An MPP provides a model of the history of the process up to time t as the collection of all events that occurred up to that time, denoted by \mathcal{H}_{t^-} , and allows this history to influence what happens next through the specification of the (conditional) intensity function. Thus, to specify an MPP we need to identify the set of marks and the conditional intensity function (as a function of time) given the history.

The intensity function for the system is written as a sum of intensity functions used to model the behavior of subassemblies. The complete history of the

farm might not be relevant to the failure behavior of each of these subassemblies, but part of it is, and this is the relevant history for a given subassembly. The different subassembly processes are not usually independent because previous events from one process may appear in the relevant history for another.

In order to construct a useful and usable model, we have captured what we regard as the key drivers of uncertainty while at the same time keeping the model as a simple, consistent representation of the system under study. Our set of marks includes:

- operating states representing whether subassemblies are working (up) or failed (down);
- epistemic states representing the design and manufacturing triggers, assigned once and for all at time 0;
- epistemic states representing operational error, assigned at time 0 and then changed through time using a learning model;
- subassembly failure type and repair type (major, normal, and minimal interventions), together with corresponding times;
- times of onset of partial operation (since operators may choose to de-rate a turbine);
- arrival time of maintenance resources (including logistic and weather delays).

3.1.1. MPP for Subassemblies

To model a subassembly's alternating behavior between an operable and a failed condition, we use an MPP (T_n, J_n) , $n \geq 1$ (note that we allow some subassemblies—in particular gearboxes—to have intermediate degraded states, but for simplicity here we present the approach with just two states). Let T_n denote the accumulated times to events and $J_n \in \{0, 1\}$ be marks taking values according to the type of event (failure or onset of operation) occurring at time T_n . We let $\{Y_t, t \geq 0\}$ be the subassembly state at time t , that is, the state corresponding to the mark J_n at the last event time (e.g., $Y_t = 1$ when the subassembly operates). The relevant history of the wider system that influences the intensity function for T_n can include other events such as, for example, start of repair, arrival of maintenance resources as indicated in Fig. 1, and this history up to time t is denoted by \mathcal{H}_{t^-} .

The MPP for the subassembly is described fully by the conditional event intensity $\iota(t|Y_{t^-}, \mathcal{H}_{t^-})$, which describes the instantaneous rate of occurrence of the next mark, or equivalently the next switch of value

of Y_t (Strictly speaking, Y_{t^-} is included in the history \mathcal{H}_{t^-} , but it is convenient to distinguish it).

Transitions to the failed and working states obey different stochastic laws, with the failure transition assumed to follow a failure intensity function, λ , which we define formally in Section 3.1.2: When $Y_{t^-} = 1$ (i.e., subassembly is working), we can write

$$\iota(t|Y_{t^-} = 1, \mathcal{H}_{t^-}) = \lambda(t|\mathcal{H}_{t^-}). \quad (1)$$

The quantity $\lambda(t|\mathcal{H}_{t^-})\Delta t$ is the approximate probability that the subassembly will fail in the time interval $[t, t + \Delta t)$ given that it operates just before time t ($Y_{t^-} = 1$), conditional on the history \mathcal{H}_{t^-} until this time,

$$P(Y_{(t+\Delta t)^-} = 0|Y_{t^-} = 1, \mathcal{H}_{t^-}) \approx \lambda(t)\Delta t. \quad (2)$$

For simplicity, from this point forward where there is no possibility of confusion, we write $\lambda(t)$ instead of $\lambda(t|\mathcal{H}_{t^-})$. The failure intensity $\lambda(t)$ is specified so that dependency across subassemblies, shown in Fig. 3, is appropriately modeled and the probability in Equation (2) explicitly captures the potential effect of triggers. For example, the formula used for different subassemblies will include shared variables from the history, including those representing epistemic uncertainties such as triggers.

3.1.2. Failure Intensity and Impact of Triggers

Let $h(t)$ denote the hazard rate for the time to first failure of a subassembly in the absence of triggers. Then, we can take account of the existence of triggers as follows. Let the “target” hazard rate for subassembly i at time t , denoted by $\tilde{h}^i(t)$, represent the intended subassembly reliability. An additive hazard model is used to modify the target hazard rate to take account of the effect of triggers. Thus the hazard rate for subassembly i is expressed as

$$h^i(t) = \tilde{h}^i(t) + \sum_{j=1}^3 X_j^i(t)h_j^i(t), \quad (3)$$

where $X_j^i(t)$ is an indicator variable set to 1 if subassembly i , $i = 1, \dots, n$, at time t is affected by trigger j (and 0 otherwise), and $h_j^i(t)$ is the added hazard due to trigger j where $j = 1, 2, 3$ corresponds to design inadequacy, manufacturing fault, and operational error, respectively. The added hazard describes the time to first failure of subassembly i arising from mechanisms associated to the presence of trigger j .

Combining Equations (2) and (3) gives

$$\begin{aligned} P(Y_{(t+\Delta t)}^i = 0 | Y_{t^-}^i = 1, \mathcal{H}_{t^-}) & \quad (4) \\ &= \lambda^i(t) \Delta t \\ &= \left(\tilde{h}^i(t) + \sum_{j=1}^3 X_j^i(t) h_j^i(t) \right) \Delta t. \end{aligned}$$

3.1.3. Parametric Form of Subassembly Hazard Rate

A parametric form for the hazard rates in Equation (4) has been chosen to aid the elicitation of structured engineering judgment about the impact of triggers and potential management interventions. We classify subassembly failure mechanisms as shocks (sudden failures due to single-stress events) and wear-out failures (gradual events due to damage accumulation). Initially, we assume the hazard rate is constant given the occurrence of shocks only. Then from time w we assume additionally that wear-out events occur with the hazard rate having a Weibull form from the onset of degradation. Thus the parametric form of the hazard rate, expressed in general form as $h(t)$, is given by

$$h(t) = \begin{cases} \rho, & t \leq w, \\ \rho + ab(t-s)^{b-1}, & t > w, \end{cases} \quad (5)$$

where ρ is the subassembly hazard rate for shock failures, and a and b are the scale and shape parameters, respectively, of the nondecreasing hazard rate for wear-out.

We relax the assumption that the onset of ageing occurs at a fixed time, which allows us to treat the onset time as a random variable, W , and for the purposes of this article, we assume a lognormal distribution, i.e., $W \sim \log N(\mu, \sigma)$. Under this assumption, a given population of subassemblies consists of items that start ageing at various points in time.

Maintenance activities impact subassembly reliability by modulating the virtual age (the effective age of a subassembly rather than its calendar age since installation as discussed further in Section 3.1.4) and so do not affect the shape of the hazard rate. We assume maintenance actions do not change the onset of wear variable, W , but innovations, such as subassembly replacements, may do so.

The parametric form in Equation (5) is used to model both target hazard rates (the underlying subassembly hazard rate in the absence of triggers) and the additional hazard for subassemblies affected by

triggers. Consider two situations corresponding to a subassembly reliability being above or below target over an early life time window. A relatively low rate of shock failures ρ with an onset of wear-out w after the time window characterises an above target situation. While a subassembly performing below target reliability would be subject to more frequent shock failures ($\rho' > \rho$) and/or premature and more severe wear-out ($w' < w$).

Following the above line of argument Equation (4) can be now written as

$$\begin{aligned} P(Y_{(t+\Delta t)}^i = 0 | Y_{t^-}^i = 1, \mathcal{H}_{t^-}) & \quad (6) \\ &= \left(\tilde{h}^i(t | \underline{\theta}^i) + \sum_{j=1}^3 X_j^i(t) h_j^i(t | \underline{\theta}_j^i) \right) \Delta t, \end{aligned}$$

where $\underline{\theta}^i = (\rho^i, w^i, a^i, b^i)$ are the target reliability parameters for subassembly i and $\underline{\theta}_j^i = (\rho_j^i, w_j^i, a_j^i, b_j^i)$ are the reliability parameters for subassembly i given trigger j .

The reliability parameters are set in the model at $t = 0$ for a particular subassembly and are recorded as part of the history \mathcal{H}_{t^-} . They are only reset in the case of a major intervention. Hence, the right-hand side of Equation (6) simply depends on a subset of parameters identified within \mathcal{H}_{t^-} .

3.1.4. Impact of Maintenance on Virtual Age and Downtime

Maintenance and logistics impact the model in two ways. Most obviously they affect the downtime of a subassembly, which we come to later. There is also an impact on the subsequent uptime, modeled through the hazard rate for the time to failure after the first failure. The previous sections explained how the hazard rate for time to first failure is modeled, and we use the notion of virtual age (Kijima, 1989) to specify the hazard rate for subsequent failures. The virtual age describes the effective age of a subassembly as a result of maintenance, as opposed to its calendar age which equals the amount of time passed since installation. By combining the hazard rate with virtual age, denoted by v_t , the failure intensity of the subassembly at time t —in the absence of triggers—can be written as

$$\lambda(t) = h(v_t), \quad t > 0. \quad (7)$$

In the particular case of a minimal repair (one in which the minimum repair is performed subject to making the subassembly functional again), the virtual

age immediately post the repair time equals the virtual age just prior to the repair, while in the case of complete repair the virtual age immediately after the repair is assumed to be 0 (subassembly is assumed to be as good as new).

Returning to Equation (4), we can now adapt it to account for repair type using the virtual age:

$$\begin{aligned} \lambda^i(t) = & \tilde{h}^i(v_t) + X_1^i h_1^i(v_t) \\ & + X_2^i h_2^i(v_t) + X_3^i(t) h_3^i(t), \end{aligned} \quad (8)$$

where the underlying hazard rate, and the extra hazard due to design inadequacy and manufacturing faults are assumed to be reset by the virtual age, whereas hazard from operational error is not.

The modeling approach adopted is flexible enough to incorporate a variety of failure types and maintenance models. Subassembly failures are assumed to be complete failures except in the case of gearboxes where we allow for degraded failures (because in practice a turbine will be operated in a degraded mode). The latter situation is modeled by a “time to degraded mode” and a “time from degraded mode to failure.” The restoration of the subassembly can happen in three different ways depending on whether the intervention is major, moderate, or minimal. A major intervention is where the subassembly is renewed by an upgraded version. In this case, the triggers are no longer assumed to be present and a different hazard rate may be used. A moderate intervention corresponds to complete repair (as good as new, but still subject to the same triggers as previously), and a minor adaptation corresponds to a minimal repair (as bad as old, and still subject to the same triggers).

The intervention type and subassembly type both have implications for the required logistics, which influences the overall downtime. We can accommodate delays for those repairs requiring special equipment, like a large crane, whereas we assume smaller repairs can be carried out by technicians on a vessel available to the farm. In the case of the gearbox, where we assume that a signal of degraded performance is sent to operators, the turbine is assumed to be operated at partial load in order to extend the working life (albeit with lower production capacity) until a vessel with the required equipment becomes available. These assumptions have been made for simplicity in this model, based on discussions with operators, as reflecting practice. These assumptions can be varied to make them better reflect practice as ideas change.

A key motivation for our modeling approach has been to capture the improvements to availability in operation that can be made by a combination of improving maintenance and making step changes in performance via innovations—for example, upgrading subassemblies. The costs of doing so can be large, and are the reason why upfront investment in equipment maturation is important.

3.2. Representation of Epistemic Uncertainty

Now consider the representation of the epistemic uncertainty associated with the “world we are in.” That is, in situations where specific design inadequacies, manufacturing faults, and/or other triggers might exist and, from the perspective of the wind farm operator, will impact on rates of failure and repair until upgrades (design and manufacturing) or operator learning has taken place. The residual uncertainty in the model are the aleatory uncertainties; that is, the uncertainties contingent on knowing the trigger states as captured by the distributions set out in Section 3.1.

To capture epistemic uncertainty, we treat the $X_j^i(t)$ as random variables, where $j = 1, 2, 3$ corresponds to design inadequacy, manufacturing fault, and operational error, respectively. This allows the hazard rate $h^i(\cdot)$ to take alternative forms depending on the realizations of the epistemic uncertainties at $t = 0$. Consistent with Fig. 3, we assume that X_1^i has a Bernoulli distribution with probability $0 < q_1 < 1$ and $X_1^i = X_1, \forall i$, X_2^i has a Bernoulli distribution with parameter $0 < q_2 < 1$. Finally, $X_3^i(t)$ has a Bernoulli distribution with time-dependent parameter $q_3 \cdot \varphi(t)$, where φ is a time-dependent function representing the learning effect, described in (Zitrou et al., 2016).

Uncertainties due to imperfect knowledge on the part of the analyst can be quantified in terms of prior probability distributions on the model parameters. This means representing uncertainty on the trigger probabilities, the onset of ageing parameters and so on by state-of-knowledge distributions. For the purposes of this article, we only use hyperparameters for the onset of wear-out w_j^i for subassembly i due to trigger j , using a lognormal distribution for the onset of wear-out. Since the model is implemented as a simulation where the wear-out w_j^i is sampled at $t = 0$, Equation (6) still holds.

The key advantage of explicitly representing trigger probabilities and wear-out uncertainties is that

we can explore the impact of management decisions prior to operation on the uncertainty of farm performance. This gives a route to link engineering decisions to financial risk for the wind farm developer.

4. PERFORMANCE MEASURE

4.1. Availability-Informed Relative Capacity

The performance measure output by the model, the availability-informed relative capacity introduced in Section 2, can be expressed formally as

$$C(t) = \frac{P(t)}{PO}, \quad (9)$$

where $P(t)$ is the net maximum capacity of the wind farm, modified to take account of any in-service derating for technical issues at turbine level (or within other BOP) at time t , and PO is the net maximum capacity of the wind farm. Other useful metrics can be derived, including the average and level availability-informed relative capacities. The average availability-informed relative capacity over a time interval (τ_1, τ_2) is given by

$$C_{(\tau_1, \tau_2)} = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} C(t) dt. \quad (10)$$

The level availability-informed relative capacity is the proportion of the time interval (τ_1, τ_2) when $C(t)$ is above a predetermined (acceptable) level of performance L and is given by

$$C_{(\tau_1, \tau_2)}(L) = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} \mathbb{1}\{C(t) > L\} dt, \quad (11)$$

where $\mathbb{1}(\cdot)$ is the indicator function. A value of $\alpha 100\%$ for $C_{(\tau_1, \tau_2)}(L)$ implies that $\alpha 100\%$ of the time over (τ_1, τ_2) the farm maximum output exceeds $L\%$ of the installed power.

The level availability-informed relative capacity over the interval (τ_1, τ_2) is the proportion of time $C(t)$ is above a predetermined (acceptable) level of performance L and is given by

$$C_{(\tau_1, \tau_2)}(L) = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} \mathbb{1}\{C(t) > L\} dt, \quad (12)$$

where $\mathbb{1}(\cdot)$ is the indicator function. $C_{(\tau_1, \tau_2)}(L) = k 100\%$ implies that $k 100\%$ of the time over (τ_1, τ_2) the farm maximum output exceeds $L\%$ of the installed power.

4.2. Estimating Farm Performance

Since we are interested in modeling the potential future performance of wind farms, we now need to rewrite the definition of $C(t)$ in terms of the variables defined within the model described in Section 3. For a farm comprising of n_1 turbines and n_2 BOP sub-assemblies (the BOP are assumed to be fully functional or failed, and assuming series connection with no redundancy) then we can write

$$C(t) = \frac{(\sum_{i=1}^{n_1} P_i(t))(\prod_{k=1}^{n_2} A_k(t))}{\sum_{i=1}^{n_1} PO_i}, \quad (13)$$

where $P_i(t)$ is the net maximum capacity of turbine i modified by in-service derating for technical issues, $A_k(t)$ is the point availability of subassembly k in the BOP, and PO_i is the net maximum power output of turbine i .

Our model allows us to simulate $C(t)$ given the initial states of the subassemblies and the BOP (normally assumed to be fully functional at time 0), and given the states of triggers (that is, the impact of management decisions made before time 0 as shown in Fig. 1). The simulation allows us to estimate the distribution for $C(t)$ and key parameters such as quantiles or expected value, as a function of t , and then also to evaluate the dependency and sensitivity of such quantities to the triggers. The model is coded in Matlab as a two-loop Monte Carlo simulation separating the epistemic and aleatory uncertainties in the outer and inner loops, respectively (Bier & Lin, 2013; Wu & Tsang, 2004). This computational strategy can be related back to our conceptual framework since the outer loop corresponds to the epistemic uncertainties arising in the preoperation period by simulating different possible outcomes of the manufacturing and design uncertainties, while the inner loop is a Monte Carlo simulation of the wind farm operation through life from commencement of operation given the realizations of the outer loop variables. Our simulation method is described in supplementary Appendix 3.

Decision-makers might also wish to understand the corresponding impact on energy production, hence we show how to adapt the methods used to compute the availability-informed relative capacity using simple assumptions on wind speed at a farm site.

We define $m + 1$ generation states for a turbine, where state m corresponds to full technical performance and state 0 is out of operation while other intermediary states represent different types of

degraded power production capacity, each with its own power curve (the function that gives power output as a function of wind speed). Technically these generation states are constructed by merging the combinations of the subassembly states to derive the overall state of the wind turbine. The power output can then be determined for each turbine based on its power curve.

As above, we assume BOP subassemblies have two states, operational (1) or not (0). For each turbine i , we write $X_i(t)$, $t \geq 0$, for the stochastic process with state space $\{0, 1, \dots, m\}$ representing its generation condition, $X_i(t) = j$, and $Z_k(t)$, $t \geq 0$, with state space $\{0, 1\}$ to model BOP subassembly k . We normally assume all subassemblies are in perfect operating condition at $t = 0$, which implies that $Z_k(0) = 1$ for $k = 1, 2, \dots, n_1$ and $X_i(0) = m$ for $i = 1, 2, \dots, n_2$.

Therefore, the required information to track the technical state of the farm with respect to power generation is represented by the vector of turbine and BOP states at time t ,

$$U(t) = (X_1(t), \dots, X_{n_1}(t), Z_1(t), \dots, Z_{n_2}(t)). \quad (14)$$

Now we consider the impact of wind conditions and define $V_i(t)$ as the wind speed at time t for turbine i . We define $G(t)$ as the total generation of power (MW) at time t , and $G_{ij}(t)$ as the power generated from turbine i in state j at time t given the wind speed $V_i(t)$. Assuming a power curve p_j for a turbine when in state j , this implies that $G_{ij}(t) = p_j(V_i(t))$, and we can write

$$G(t) = \left(\sum_{i=1}^{n_1} \sum_{j=0}^m G_{ij}(t) \mathbb{1}\{X_i(t) = j\} \right) \prod_{k=1}^{n_2} Z_k(t). \quad (15)$$

Therefore, the expected generation at time t , given $U(t) = (x_1, \dots, x_{n_1}, z_1, \dots, z_{n_2})$ is given by

$$E(G(t)|U(t)) = \left(\sum_{i=1}^{n_1} E(G_{ix_i}(t)|U(t)) \right) \prod_{k=1}^{n_2} z_k. \quad (16)$$

4.3. Dependency of Power Generation on Technical State

Our underlying stochastic model does not include wind speed, and so further assumptions are required to be able to express the dependence of $G_j(t)$ on $U(t)$. Given the primary intended use of this model to support decision-making on design and manufacture prior to farm operation, simplifying assumptions are appropriate. The following are made

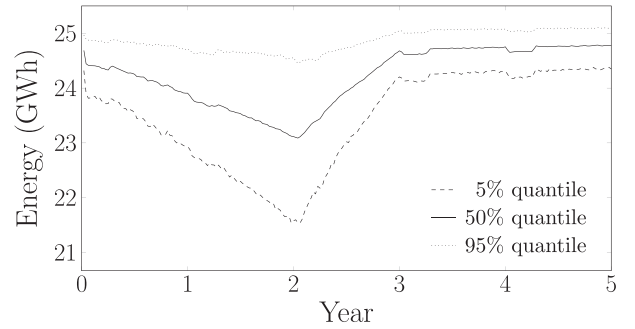


Fig 4. Estimated energy produced weekly for Scenario 1—gearbox design inadequacy trigger present from start of farm operation and gearbox upgrade is rolled out during year 3—with bounds aggregating epistemic and aleatory uncertainty.

in our illustrative example described in Section 5. First, the wind speed distribution, i.e., the distribution of $V_i(t)$, is the same for all turbines (all i) and for all t , and we denote this simply by $V(t)$. Second, the wind speed distribution is independent of the technical state of the wind farm $U(t)$. Note that these assumptions can be relaxed if required to adapt the model to other applications. The first assumption assumes no spatial impacts (e.g., shadowing of one turbine by another) and no seasonality. This assumption can be relaxed without difficulty in the model, but will lead to greater effort in specifying the required input data. If the wind speed distribution is assumed seasonal then the second assumption is not entirely valid because of the possibility of longer repair times during winter, but still remains a reasonable first-level approximation for the purposes of our example. Given again that $U(t) = (x_1, \dots, x_{n_1}, z_1, \dots, z_{n_2})$ these assumption imply that Equation (16) can be simplified as follows:

$$\begin{aligned} E(G(t)|U(t)) &= (n_1 E(G_{1x_1}(t))) \prod_{k=1}^{n_2} z_k \quad (17) \\ &= (n_1 E(p_{x_1} V(t))) \prod_{k=1}^{n_2} z_k. \end{aligned}$$

Hence, in order to calculate the expected power generation (averaged over the wind speed distribution), we only need to specify the expected power generation in each of the turbine generating states.

5. ILLUSTRATIVE USE OF MODEL

We illustrate how the model can be applied in a decision-making situation. Prior to construction of a

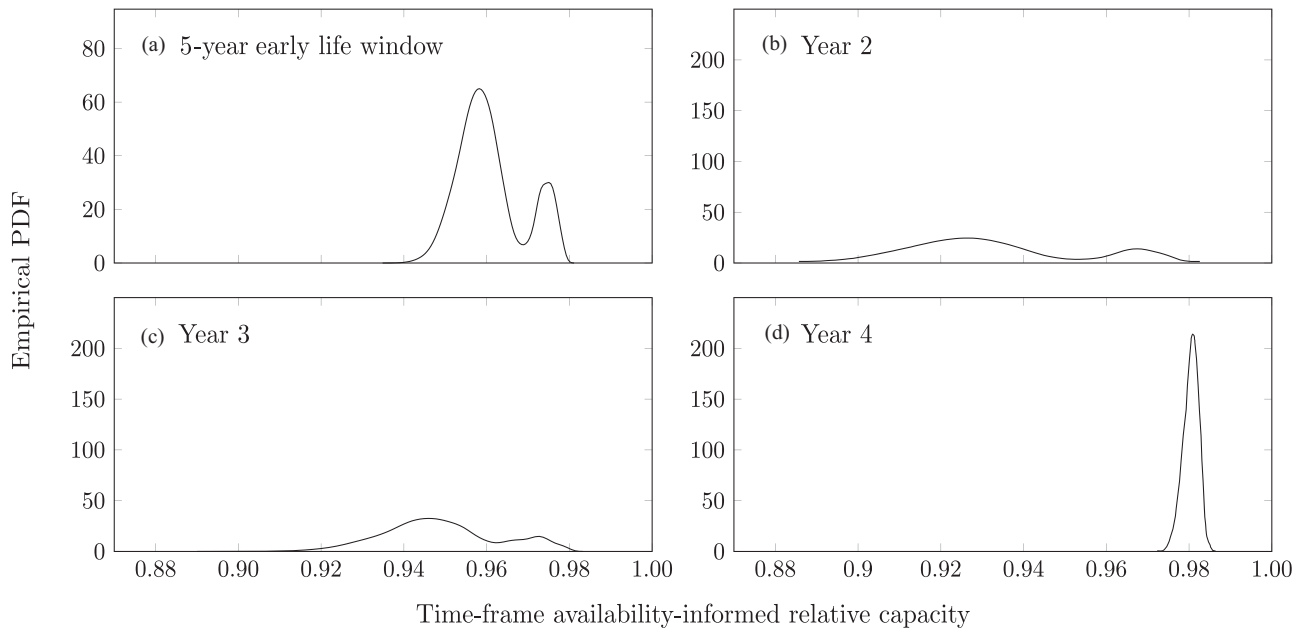
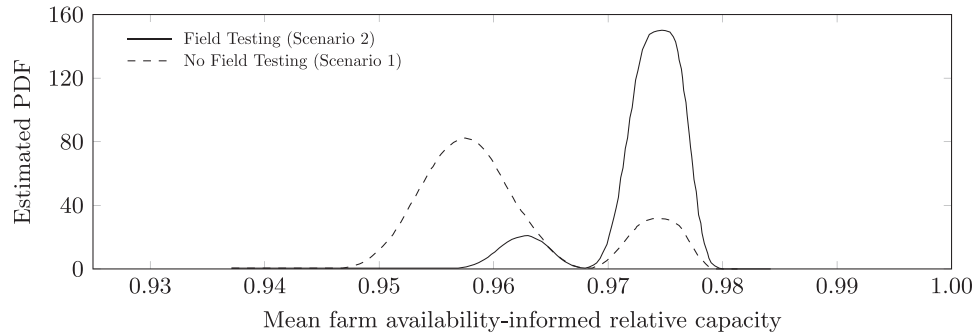
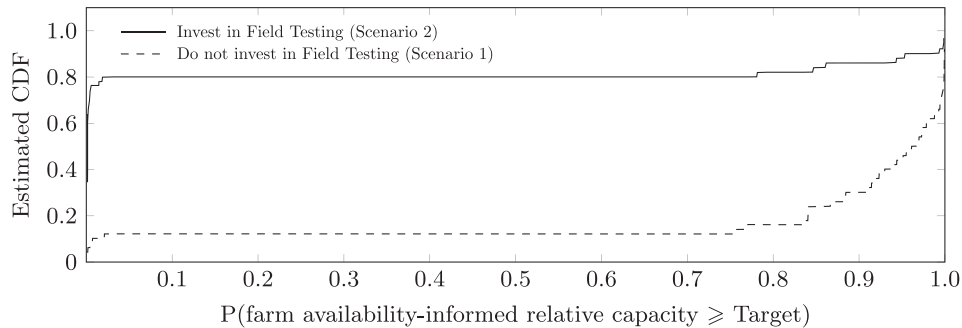


Fig 5. Empirical probability distribution functions (PDF) of estimated availability-informed relative capacity over first five years of farm operation, decomposed within years 2, 3, and 4, combining epistemic and aleatory uncertainties.



(a) Probability distribution functions (PDF) of epistemic uncertainties in expected capacity.



(b) Cumulative distribution functions (CDF) of probability farm will meet 97% performance target.

Fig 6. Comparison of epistemic uncertainty distributions for the availability-informed relative capacity estimated over the first five years of farm operation under Scenarios 1 and 2.

wind farm the model is used to predict production capacity over the first five years of operation. The purpose of the example is to show the impact of uncertainty on the availability-informed relative capacity and to provide a basis for assessing the value of information of actions (e.g., field tests) to buy-down epistemic uncertainty before the farm is operational. The example has been developed collaboratively with offshore wind energy practitioners who have informed the model setup and assessed output credibility. The model is based on the key assumptions discussed in Sections 2–4 and summarized in the index given in supplementary Appendix 5.

5.1. Tailoring the Model

The project is for a 500 MW farm with 100 5 MW turbines where the rate of failure should be no worse than expectations, which is taken to be an average time to failure of 0.26 years, or, equivalently, 3.81 failures/turbine/year. Based on discussions with experts in wind farm engineering, technology, and operation, the design inadequacy of the gearbox was identified as being of most concern and we model it as an epistemic uncertainty. The uncertainties related to the remaining subassemblies, such as the pitch system, are characterized as aleatory only. In addition, the gearbox, the generator, the main shaft bearing, and the blades are susceptible to manufacturing faults. The design inadequacy is assumed to be shared across all turbine gearboxes, while the manufacturing faults can occur independently for the respective subassemblies across different turbines.

The farm will be subject to both corrective and preventive maintenance strategies. Biannual overhauls will refurbish certain subassemblies, such as the gearbox, which is treated here as resetting the subassembly virtual age to 50% of its value prior to the intervention. Operating decisions will be taken to limit the energy output of a turbine to avoid catastrophic failure based on signals about the condition of the gearbox.

The epistemic uncertainty associated with the gearbox design inadequacy and the onset to wear-out time have been obtained as probability assessments from a panel of eight engineering experts using a structured elicitation process (Dias et al., 2018; Quigley & Walls, 2020). All experts were employed by the same renewable energy company and had relevant experience in the sector and/or with the rele-

vant technologies. Experts have been selected in collaboration with a lead technical specialist to ensure all were suitably qualified to provide probability assessments. Details of the elicitation methods used are in supplementary Appendix 4. The experts assessed the probability of a design inadequacy trigger being present to be $q_1 = 0.8$. Each expert in our panel provided their own subjective probability assessment of the number of months of operation since installation until initial signs of degradation is likely to be observed for the type of turbine affected by a gearbox design inadequacy but by no other triggers. On analysis of the elicited judgmental data, we model the variation in the time to onset of wear-out, aggregated across experts using equal weights, by a lognormal distribution with mean 1.99 and standard deviation 0.01.

Other model parameters have been populated using empirical observations from relevant generic databases. For example, subassembly hazard rates have been selected from the Reliawind analysis (Wilkinson et al., 2010) for relatively mature turbines that achieve target reliability. Classifying failures as minor, moderate, and major, in line with Faulstich, Hahn, and Tavner (2011) & Rademakers et al. (2009), allows typical duration and effectiveness of repairs on subassembly condition to be specified for each class. For example, moderate failures are assumed to require two operational days to restore a subassembly to its good-as-new condition, that is, are modeled as complete repairs.

To calculate the energy generation in this example, we specify a small number of parameters that summarize the overall impact of wind variability and technical availability of the farm. First, that a turbine has three states: fully operational; derated (when gearbox is partially operating); nonfunctional. Second, for each turbine state we specify the ratio of power output to net maximum capacity. Here, we assume the 5 MW rated turbines have a ratio = 0.3 when the turbine is fully operational, a ratio = 0.3×0.85 when the gearbox is in a partial operating state, and a ratio = 0 when the turbine is in a non-functional state. Note that these settings are made for this example only.

5.2. Selected Findings

Through analysis we explore two scenarios. Section 5.2.1 describes the situation where the current gearbox design, about which there is epistemic uncertainty about its adequacy, is used from the start

of farm operation. Section 5.2.2 examines how this epistemic uncertainty might be bought down by conducting field tests to learn if an inadequacy can be established and, if so, then action is taken to improve the gearbox design before the start of farm operation.

5.2.1. Scenario 1: Gearbox Design Inadequacy Risk Carried into Operation

Fig. 4 shows the estimated energy produced each week over the first five years of farm operation for the situation where the turbines enter service carrying a design inadequacy before an upgrade. The upgrade is rolled out in year 3 and addresses this inadequacy. The bounds show the combined epistemic and aleatory uncertainties. Following the start of farm operation, we find that production decreases until it drops to the lowest level at the end of year 2. This is intuitive given the joint effects of the gearbox design inadequacy and the manufacturing faults affecting various subassembly types. Production improves after year 2 as the gearbox upgrade is rolled out across turbines in the farm, with a return to stable performance levels in year 4.

Fig. 5 shows the empirical distribution of the combined epistemic and aleatory uncertainty in the availability-informed relative capacity. Fig. 5(a) is the distribution averaged over the first five years of farm operation together, while Figs. 5(b)-(d) are the equivalent distributions for selected years (i.e., 2,3,4) within this five-year window. The distributions in Figs. 5(b)-(d) are shown on the same vertical axis scale so that year-on-year comparisons of uncertainty can be made. Fig. 5(a), which provides a composite view for the overall first five years of farm operation, uses a different vertical axis scale for legibility. All plots use the same horizontal axis scale for the availability-informed relative capacity. Over the five-year early life period, Fig. 5(a) shows a bimodal pattern—the primary peak just below 96% with a secondary lesser peak close to 97.5%. Focusing on specific years, Figs. 5(b)-(d) show changes in both the level and the degree of uncertainty in the annual capacity distributions. As we shift from year 2 to 3, the capacity increases on average and the uncertainty decreases with both distributional shapes being bimodal. In year 4, the distribution is located at yet a higher capacity and has further reduced uncertainty. These patterns are intuitive given they represent the within year(s) availability-informed relative capacity that underpins the temporal slices of the energy pro-

duced profile shown in Fig. 4. Furthermore, they reflect the changes in capacity associated with original gearbox and the upgrade roll-out during year 3.

We can decompose the variation in the distributions of the availability-informed relative capacity in terms of the epistemic and aleatory components. Following the approach detailed in Appendix 3, the epistemic component is found by summarizing each aleatory distribution in terms of its expected value then calculating the variance across all epistemic scenarios. We find that 84% of the uncertainty in the estimated capacity over the first five years of farm operation can be classed as epistemic. This implies that epistemic uncertainty dominates the patterns shown in Figs. 4 and 5. This prompts us to examine whether this uncertainty, and hence the associated risk, can be reduced before the farm is operational.

5.2.2. Scenario 2: Buying Down Epistemic Uncertainty Before Operation

We consider the scenario where field testing can be conducted to learn about the gearbox design inadequacy before farm construction, providing an opportunity to improve this design before start of operation. We asked our panel of engineering experts to reassess the probability of a gearbox design inadequacy in view of information from an assumed field test followed by appropriate action. Their revised probability of a gearbox inadequacy for Scenario 2 was $q_1 = 0.15$ (previously, this was $q_1 = 0.8$ under Scenario 1).

Fig. 6 shows the probability distributions of the epistemic uncertainties in the expected availability-informed relative capacity over the first five years of farm operation for both scenarios. The distribution under Scenario 2 (field test and, if appropriate, action to improve gearbox design) shifts to the right of the distribution for Scenario 1 (no field test and original gearbox design used) indicating that, on average, better farm performance is estimated for the former. The degree of epistemic uncertainty is also less for Scenario 2 relative to Scenario 1. Correspondingly, the 95% intervals for the expected availability-informed relative capacity are found to be (0.962,0.977) and (0.952,0.976) for Scenarios 2 and 1, respectively. The reduction in epistemic uncertainty following field test is intuitive, while the results allow us to assess the impact of this reduction. Here, we do this by examining the level availability-informed relative capacity which allows us to

estimate the chance of meeting the specified farm target performance, which is a minimum of 97%. Fig. 6(b) shows the exceedance probabilities for Scenarios 1 and 2. That is, the cumulative probability distributions for the metric, probability that the estimated farm availability-informed relative capacity over first five years of operation is at least meeting the target level of 97%. Fig. 6(b) shows that the exceedance probability distribution for Scenario 2 is always much higher than that for Scenario 1. For example, say the farm's performance is considered to be unacceptable when there is a 20% or less chance of meeting the target. Then our findings imply that investing in field testing will decrease the probability that the farm will have an unacceptable performance from 0.8 to 0.1. That is, risk is reduced to 12.5% of its original value if we opt to conduct field testing and act appropriately on the findings.

6. CONCLUSIONS

We propose a new model to support stakeholders to better understand their degree of control over risk for a pre-construction offshore wind farm and to estimate the effectiveness of risk reduction interventions before the farm becomes operational.

The model enables a performance measure we call the availability-informed relative capacity to be estimated. This measure captures the net maximum generating capacity of the farm given the technical state of the equipment, such as the turbines. Sources of epistemic uncertainty arise in equipment design and manufacturing effectiveness. Setting our modeling unit of analysis at the subassembly level of the equipment allows us to capture the systemic effects on overall farm performance; intuitively we might expect that the larger the farm, the more substantial the combined effect of epistemic uncertainties will be. Our exposition of the underpinning stochastic model shows how the epistemic and aleatory uncertainties are represented mathematically. An illustrative example shows how the model can be used to distinguish the contributions of epistemic and aleatory uncertainties as well as to investigate the effectiveness of actions to reduce the epistemic uncertainties.

Throughout our model development, we have engaged with stakeholders with expertise in the off-shore wind sector. These included engineering subject-matter experts, operations managers, and financial and insurance practitioners. Our collabora-

tions included facilitated workshops with multiple stakeholders at model structuring and validation stages, as well as an in-depth case with a service provider to develop the example.

The characterization of uncertainties as epistemic or aleatory is not always clear because it depends on the problem context and model use. Our model, as presented in this article, represents weather as an aleatory source of uncertainty because we have developed the model for a generic wind farm. Given our intent is to apply our general model to support decisions for a specific offshore site, then there might be interest in adjusting weather-related uncertainties in the light of, say, meteorological data collected from that location, and so we would treat these uncertainties as epistemic, as well.

Treating uncertainties as epistemic implies additional modeling layers, increasing model complexity. As discussed in Section 3.2, the treatment of the trigger indicator variables as random leads to the addition of the Bernoulli models, whereas the incorporation of parameter uncertainty requires the use of distribution models and hyperparameters. As model sophistication increases, so does the modeling and computational effort required. Therefore, it is imperative that analysts make informed modeling choices to pragmatically decrease model complexity to a manageable level and increase the practical interpretation of the model structure and outputs to provide a requisite model.

Our stochastic model has been coded as a modular Matlab simulation. Inputs relate to wind farm features (e.g., number of turbines, critical subassemblies, farm layout), operating scenarios (e.g., length of the planning horizon, granularity of simulated time period, and type of intervention to address triggers) and empirical/judgmental data (e.g., trigger probabilities, target hazard parameters for each subassembly type). The representation of epistemic uncertainties also adds computational complexity. We believe our model can be extended in a number of ways to manage such computational challenges. For example, we could screen model parameters to identify those with greatest impact on output uncertainty. Or, to reduce the computations we could consider the use of emulators (O'Hagan, 2006; Wilson, Henderson, & Quigley, 2018). For example, an emulator will have as model inputs critical decision-making parameters, such as trigger likelihoods or wear-out onset times, and the emulator could be used in the place of the model to explore a range of decision-making scenarios.

Future research could also include investigation of the relative contributions of the turbine-based uncertainties presented here and the overall uncertainty of wind speeds, variation in wind resource, or long-term wind droughts. To develop the model as a decision support tool involves more consideration of issues such as modeling condition-monitoring, as well as further evaluation from the perspective of those managing risk in offshore wind farms.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix 1. Key Symbols.

Appendix 2. Relation to Energy Standard Terms

Appendix 3. Method for Model Simulation

Appendix 4. Methods for Eliciting Epistemic Uncertainties

Appendix 5. Assumptions Index