Reliability Engineering and System Safety 152 (2016) 83–94

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

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

A model for availability growth with application to new generation offshore wind farms

Athena Zitrou*, Tim Bedford, Lesley Walls

University of Strathclyde, Department of Management Science, Graham Hills Building, 40 George Street, Glasgow G1 1QE, Scotland

ARTICLE INFO

Article history:
Received 31 January 2014
Received in revised form
8 December 2015
Accepted 10 December 2015
Available online 12 February 2016

Keywords:
Availability growth
Systemic risk
Offshore wind farm
Condition monitoring

ABSTRACT

A model for availability growth is developed to capture the effect of systemic risk prior to construction of a complex system. The model has been motivated by new generation offshore wind farms where investment decisions need to be taken before test and operational data are available. We develop a generic model to capture the systemic risks arising from innovation in evolutionary system designs. By modelling the impact of major and minor interventions to mitigate weaknesses and to improve the failure and restoration processes of subassemblies, we are able to measure the growth in availability performance of the system. We describe the choices made in modelling our particular industrial setting using an example for a typical UK Round III offshore wind farm. We obtain point estimates of the expected availability having populated the simulated model using appropriate judgemental and empirical data. We show the relative impact of modelling systemic risk on system availability performance in comparison with estimates obtained from typical system availability modelling assumptions used in offshore wind applications. While modelling growth in availability is necessary for meaningful decision support in developing complex systems such as offshore wind farms, we also discuss the relative value of explicitly articulating epistemic uncertainties.

1. Introduction

Our model is motivated by the need to support risk management decisions in offshore wind, where there is considerable innovation as the industry expands [20]. Empirical evidence indicates that availability performance of new farms has been below expectations during early operational life, with operating targets only being achieved after growing availability through the implementation of effective fixes over, typically, the first four years of operation [2]. However, responsive remedial action to improve availability not only impacts on income generation, but it also implies that extra capital expenditure is being incurred during periods when only operational expenditure had been planned. This contributes to the problem of lack of equity in the UK offshore wind energy market [40,11] since projects are in competition for capital with other investment opportunities, and hence have to be competitive in terms of risk and return.

In a bid to increase capacity and reduce Operation & Maintenance (O&M) costs, the Cost Reduction Task Force [20] recommends the use of innovative designs of high-yield, high-reliability turbines. However, new generation turbines are technically immature systems that are to operate further from the UK shore and in deeper waters than earlier versions. Hence, these new systems are subject to high physical stresses and are potentially vulnerable to systemic weaknesses in design, operation, installation and manufacturing. Therefore, paradoxically, the bid to decrease cost and accelerate offshore wind deployment actually increases some investor risks. Of course, as manufacturers and operators gain better understanding of operation and the environment, technical issues can be resolved through a series of interventions such as design upgrades, modified operational processes or changes in maintenance activities. However, commercial organisations, private investors and governments are required to make investment decisions prior to construction, before operating experience is accumulated. Our model is designed to be used in this setting. By modelling the availability growth process, we are positioned to inform the modelling of future income streams and capital and maintenance costs.

The value of growing reliability during system design and development is widely acknowledged [51]. Nevertheless, there has been no reported use of reliability growth analysis in an offshore context. Instead, modelling effort has focussed upon estimating availability performance under operational and maintenance strategies assuming that the wind farm is operating in steady-state [43,39,4,3,41,12,25,16]. Only [3] and [16] consider departures from

* Corresponding author.
E-mail addresses: athena.zitrou@strath.ac.uk (A. Zitrou), tim.bedford@strath.ac.uk (T. Bedford), lesley.walls@strath.ac.uk (L. Walls).

http://dx.doi.org/10.1016/j.ress.2015.12.004
0951-8320/

steady state by considering ageing; that is, late rather than early life. It is not possible to investigate growth using the existing availability models through sensitivity analysis since the models' structures do not allow for this. Hence, the existing models used in offshore wind do not address the issue of growing performance, which is an important modelling challenge if effective and efficient risk management decisions are to be made.

Here we develop a model for availability growth to address the particular challenges that the offshore wind sector faces. Though our model has a general formulation meaning and it should have applicability to other systems for which availability, rather than just reliability, is a key performance measure. We formulate a model to represent systematic failures triggered by weaknesses in, for example, design, manufacture and/or installation. The model, when appropriately combined with stochastic processes representing random failure and restoration events, provides a measure of availability. We assume that major interventions to address systemic weaknesses are made at discrete time points associated with what we term an innovation. By the term innovation we include, for example, re-design of system parts, major changes to installation processes, new vessel options for routine maintenance. In an offshore wind context, such innovations are likely to be scheduled to allow for the logistic delays in accessing the farm. Between innovations we allow for learning effects, since it is not unreasonable to expect maintainers and operators to continuously adapt their procedures and processes to improve the execution of routine tasks. The creation of an availability growth model allows us to explore the impact of different scenarios arising from systemic weaknesses in equipment, and to examine the cost-effectiveness of mitigation strategies.

In offshore wind, as for many other system development processes, the design is evolutionary implying that the current generation is related to the previous one [37,53]. For example, technology is largely based on modified onshore and early offshore wind turbines. In some areas, such as cable installation, there has been significant learning through method adaptation [1]. Offshore wind foundations are designed on the basis of principles applied in oil and gas, and installation of these structures is performed using mainly oil and gas vessels and procedures [47]. Nevertheless, innovation is necessary for new generation farms – such as the UK Round III sites – to deal with increased water depth and distance from shore [1]. Innovation is the driver of change between generations of product or process design, but is also of itself a major risk to future performance.

Typically a new system evolutionary design needs to meet an availability performance target at least equal to that achieved by the previous generation. On the basis of operational experience from earlier generation systems and analogous systems, it is possible for suitably qualified experts to make assessments of potential failure modes, make useful assessments of their impact (e.g. in terms of shortening lifetimes), and advise on potential mitigation strategies. By using the existing methodologies for expert judgement processes for this type of problem [49,23,7], we have structured our model through discussion with domain experts and practitioners.

In developing our model we draw upon the existing body of knowledge for reliability growth modelling and the limited consideration of availability growth. For example [9,10,26,42,17] are amongst many authors who propose models for reliability growth that is typically positioned during product development, where the goal is to improve reliability by identifying and removing weaknesses. The effect of modifications in such models is represented as a learning curve [15,10] but models also exist that allow for the representation of a series of discrete modifications through, for example, structural changes in the failure intensity [44,17]. Beyond the classical reliability growth methods for both hardware and software systems in development, there are also models proposed for supporting reliability growth during design [51] and through life [50]. These models tend to be framed from the perspective of the owner of the design blueprint.

To model availability – rather than reliability – growth, the premise of modelling needs to be extended to represent interventions that intend not only to remove the sources of potential failures, but also to reduce the restoration time. There is limited mention of such models in the literature. For example, the models found in [48,29] assess availability growth for software rather than hardware, but this is achieved exclusively through a fault removal process – implying that there are no interventions associated with the restoration process. Hence, these papers essentially apply reliability growth models to situations where restoration durations are assumed constant.

Our context requires us to draw on existing thinking about reliability growth to develop a model for availability growth that can be used not only by those with design responsibility, but also by those involved in financing and operating the system. We seek to model availability during early operational life of a system because this is the period during which many teething problems are surfaced in use and because of the limited nature of Original Equipment Manufacturer (OEM) warranties, unavailability in early life has an impact on both OEM and system operator. Our modelling approach is distinctive because we provide a single framework which integrates the effect of interventions intended to improve reliability with the effect of interventions intended to reduce restoration times, in order to estimate availability during specified time horizons. We explicitly include in the model the effect of condition monitoring, as this would allow us to predict the likely impact of investing in this type of maintenance strategy on system availability. The model output is an indicator of availability-informed capability that captures the effect of partially operating turbines on farm energy generation. Reduced output might occur, for example, when operators de-rate degraded turbines to accommodate logistic delays in gaining access for maintenance.

In this paper we describe the formulation of the growth model and illustrate its application to an offshore wind farm example. We believe this paper makes both a methodological and a contextual contribution. Methodologically we introduce a new model for system availability growth that extends current knowledge of reliability growth modelling. Contextually we show the effects of systemic risk on offshore wind farm availability, thereby addressing a shortcoming of the existing availability models proposed for operational and maintenance decision support in this industry. As presented in this paper, our model only considers aleatory uncertainty; that is, natural variability between different systems, for example the stochastic time to failure of each wind turbine. When considering the behaviour of future systems, which is when this model will be particularly useful for decision support, there are clearly also state-of-knowledge (i.e. epistemic) uncertainties. For example, in the application example given here, the design modifications are modelled as perfectly removing anticipated weaknesses. But assuming perfect fixes can be naive and by extending the model to include representation of state-of-knowledge uncertainties, we can better model the efficacy of innovations on performance. The modelling required to represent state-of-knowledge uncertainty in this setting is quite substantial and goes beyond the objectives of the present paper. In [54] we explain how the availability growth model can include representation of state-of-knowledge uncertainty, as well as aleatory uncertainty, and examine the implications of uncertainty assessment for more effective systemic risk reduction to better support dialogue between the financial and engineering stakeholders in the offshore wind sector.

This paper is structured as follows: Section 2 introduces our general rationale for availability growth modelling, while Section 3 presents the mathematical foundations of our model. Section 4 provides an example that explains how we might scope, populate and use the model for a real context based on a typical UK Round III wind farm and examines the impact of appropriately modelling growth. Section 5 concludes by reviewing the limitations as well as benefits of our approach and identifies areas of further work, including a discussion of the relative value of modelling state-of-knowledge uncertainties.

2. Modelling rationale

Technical availability is the key modelling criterion of the system (i.e. the offshore wind farm). The system is assumed to be operating fully or partially (i.e. uptime performance) or not (i.e. downtime performance). System performance depends on the performance of constituent subassemblies. Uptime performance reaches target levels when the actual reliability of subassemblies is as planned. Likewise, target downtime performance is achieved when there are no prolonged downtimes of subassemblies due to, for example, logistics or weather-induced delays.

Fig. 1 presents a visual representation of our modelling rationale showing the factors that may increase the chance of below-target uptime and/or downtime performance and subsequently impact on system availability. The factors have been identified through conversations with relevant engineers and categorised according to their effect on failure or restoration processes.

2.1. Factors influencing uptime

Inadequacies in the design, manufacturing defects or operational errors are factors that can lead to premature wear-out, increased vulnerability to external shocks, or both. Collectively we call these factors *Triggers* since they are sources of systemic risk that can reduce subassembly reliability. We define three classes of trigger as follows.

Design inadequacies are issues with system design caused either by an inappropriate blueprint for the specified operating conditions, or by design environmental parameters that poorly reflect actual operating conditions. Consider offshore wind transformers which can be placed in the bedplate exposing them to vibration. Levels of vibration are not fully understood because new generation turbines are larger and operate further from shore. This introduces risk of design inadequacy. We anticipate that upscaling offshore wind subassemblies can introduce more general issues with the design. For example, it has been observed that larger gearboxes tend to be less reliable than smaller ones [46].

Manufacturing faults occur when a shortcoming in the production process control and quality management of the manufacturer allows for defects to remain and be realised in operation. For example, offshore wind turbine blades are prone to manufacturer faults as they require a particularly labour-intensive manufacturing process, increasing the potential for human error during manufacturing.

Operational errors relate to human error during repair or installation. For offshore wind farms in particular, installation error can be an important driver of early life reliability. Activities such as the connection of transmission cables, for example, are prone to this type of issue: a combination of tight deadlines, schedule pressures and task complexity introduce the potential for faults and errors during installation that can lead to decreased cable reliability.

2.2. Factors influencing downtime

In general, restoration depends on factors such as difficulties in acquiring resources and gaining access to site. For example, harsh wind and wave conditions can render an offshore wind farm site inaccessible for extended periods of time delaying maintenance activities and extending restoration times. Offshore wind sites can also experience considerable logistic delays. Operations like gearbox replacement require expensive specialised jack-up vessels which are typically hired. So, repair is associated with procedures

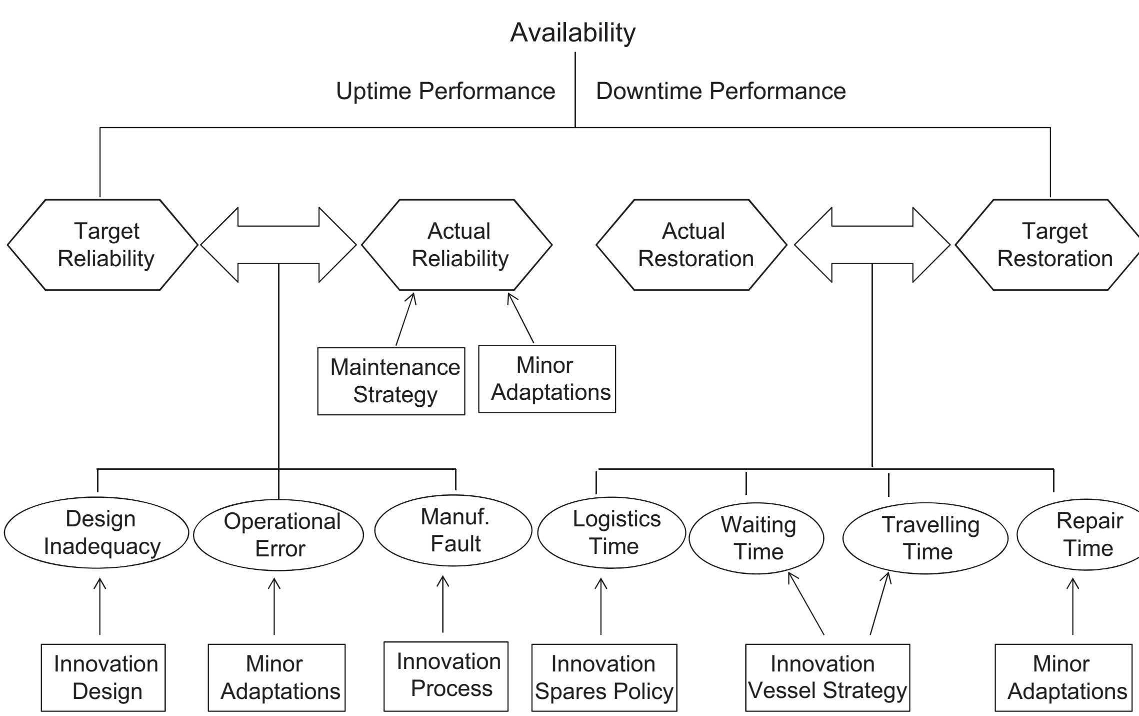

Fig. 1. Conceptual framework for availability growth model. Oval nodes represent triggers and rectangular nodes represent interventions.

such as booking and transferring the vessel between sites, which can result in additional delay.

We model such weather-induced delay as a random variable, which we call waiting time. Waiting time represents the period between when maintenance crew and resources are ready and when the trip to the site commences. The uncertainty on waiting time is determined conditionally on the failed subassembly, since the type of failure determines the period over which weather conditions need to be favourable, and on the time of the year, because waiting times are longer in the winter months – at least in the UK. We estimate the waiting time distributions using historical wind and wave data using an algorithm developed in [13].

2.3. Interventions

The model aims to capture the integrated effect of all factors affecting subassemblies on system availability, and to predict the evolution of availability as technical, operational, and organisational interventions are implemented. We classify *Interventions* in terms of their effect on availability. As in Ansell et al. [5], we separate interventions into innovations, which have a major effect on performance, and minor adjustments, which result in less radical improvement.

We define *Innovations* to be radical actions that change the basic underlying properties of the system. For example, redesigns to address design issues typify an innovation that affects subassembly reliability. We allow for the chance of achieving target reliability to differ between a new generation design and an upgrade. Innovations also relate to asset-management decisions where, for example, employing different operational strategies, such as fix on failure or charter contracts, might result in different logistic delays. Equally purchasing a new vessel might affect weather waiting times.

We define *Minor Adaptations* to be interventions that impact on the system in a more gradual manner relative to the effect of innovations. Typically, Minor Adaptations are related to learning and the accumulation of experience with the system and its operation. For example, as time progresses, maintenance crews can become more effective conducting low-level maintenance activities such as inspections and calibrations, and so may be less likely to make an error during large-scale maintenance operations such as replacements.

We also identify a third class of intervention that requires separate consideration in our model. We name this third class *Maintenance Strategy*. It represents the influence of maintenance on the condition of subassemblies and, thus, on the pattern of failures. Maintenance Strategy encompasses both the type of intervention (i.e. preventive maintenance, corrective maintenance or condition monitoring) and the effect of intervention on the system condition (i.e. perfect or imperfect repair). For example, maintenance actions such as carbon brush replacement have a minor effect on turbine condition and are modelled as imperfect repair, implying the subassembly state after maintenance is either as it was just before failure, or somewhere in between this and as good as new. Major maintenance activities, such as hub replacements, restore the subassembly to its original condition, and are modelled as perfect repairs. Our model allows for the modelling of different levels of imperfect maintenance; however, we note that it is not primarily designed to optimise maintenance logistics, as this would go beyond the level of discrimination of the model.

3. Availability growth model mathematical formulation

3.1. A parametric model for the hazard rate of a subassembly

To represent subassembly failure behaviour we classify underlying failure mechanisms broadly into shocks and wear-out. Shocks are external single stress events whereas wear-out relates to accumulated damage. We assume that subassemblies go initially through a wear-out free period where shocks dominate, which ends when wear-out begins. It is not expected for subassemblies to age prematurely, and target reliability profiles assume that wear-out occurs after early life.

We refer to the initial shock-dominating period as Stage 1, and to the succeeding wear-out and shock period as Stage 2. Let S_j be the time the subassembly leaves Stage j, for now considered fixed. The lifetime of the system is broken down into distinct intervals $[S_0, S_1)$ and $[S_1, S_2)$ where $S_0 = 0, S_2 = \infty$. Let $U(t)$ denote the system stage at time t viz.:

$$U(t) = j \Leftrightarrow S_{j-1} \le t < S_j, \quad \text{for } j = 1, 2 \tag{1}$$

First, we define the failure behaviour of the subassembly distinctly over the different lifetime stages. For j=1,2, let T_j be the elapsed time from S_{j-1}, the time the subassembly leaves Stage $j-1$, until its first failure from a mechanism relevant to Stage j. We assume T_j is a continuous random variable with cumulative distribution function F_j. Given that $U(t) = j$, the system has (conditional) hazard rate function, or Force of Mortality (FOM), given by

$$m_j(t_j) = \frac{P(t_j \le T_j < t_j + \Delta t_j)}{P(T_j > t_j)} = \frac{f_j(t_j)}{1 - F_j(t_j)}, \quad \text{where } t_j = t - S_{j-1}. \tag{2}$$

Furthermore, let random variable W_1 with distribution function G_1 represent the time when wear-out starts having an effect. A subassembly enters Stage 2 only if the onset of wear-out precedes a shock failure. Fig. 2 presents a visual representation of this reasoning.

Let random variable T with distribution function F represent the lifetime of the system, measured from the start of operation until the first failure. Assuming shocks and the onset of wear-out act as independent competing risks, we can write

$$T = \min\{T_1, W_1\} + T_2 I_{(T_1 > W_1)} \tag{3}$$

where I_A is the indicator variable of the event A. Now, the (unconditional) hazard rate of the subassembly given by

$$h(t) = \frac{P(t \le T < t + \Delta t)}{P(T > t)} = \frac{f(t)}{1 - F(t)}. \tag{4}$$

can be defined conditionally as

$$h(t) = h(t \mid \mathcal{H}_{t^-}) = m_j(t - S_{j-1}) \tag{5}$$

where $\mathcal{H}_{t^-}$ is the relevant system data observed until just before time t, such as the lifetime stage, as well as wider operation and

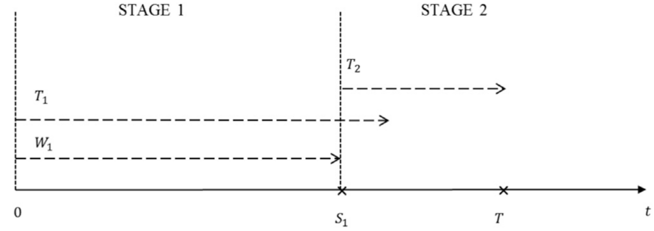

Fig. 2. Lifetime stages of a subassembly until time to first failure T. T_j is the elapsed time from S_{j-1}, the time the subassembly leaves Stage $j-1$, until its first failure from a mechanism relevant to Stage j (j=1,2). Stage 1 is a shock-dominating period. Stage 2 is a period of both shocks and wear-out mechanisms. W_1 is the time that elapses from start of operation until the subassembly starts to wear (leaves Stage 1).

maintenance information. Later this will be specified in more detail.

Shock failures, which dominate Stage 1 of the subassembly lifetime, occur at random and are represented by a constant hazard rate. Using an exponential distribution for F_1 implies that $m_1(t_1)=\rho$ is constant. Wear-out mechanisms appear when the subassembly enters Stage 2, in addition to shock failures, implying that $m_2(t_2)=\rho+h(t_2)$ where $h(t_2)$ is the wear-out hazard and can be represented by a monotonically increasing function – with time, or any other proxy of damage accumulation.

The choice of an increasing hazard rate function to represent wear-out depends on the level of knowledge of the underlying degradation mechanisms and the available data. Our model structure allows degradation to be modelled explicitly or implicitly, depending on the application. When degradation data are available allowing internal failure mechanisms to be traced, then a degradation model can be used. See, for example [32]. If sufficient degradation data to allow model specification are not available, we represent wear-out failure using parametric models for the lifetime distribution. For illustration in this paper we assume a Weibull model to represent wear-out failures, implying that $m_2(t_2)=\rho+\eta\beta(t_2-s_1)^{\beta-1}$.

Our parametric model bears similarities with other approaches. For example, we break down the time to signal into smaller segments (i.e. shock and wear-out dominated periods) to model system lifetime in more detail than the Delay Time model [8,52] and we relax the assumption made by [6] that the times at which the system enters a lifetime stage are always observable by the operator.

Fig. 3 illustrates the hazard rate for a subassembly entering Stage 2 at time $S_1=s_1$. A subassembly achieving at least target reliability will have relatively lower rate of shock failures ρ, an onset of wear-out s_1 outside the early life window, and relatively slower rate of increase in the wear-out hazard rate, as shown in Fig. 3(a). If the subassembly performs below target then it is subject to more frequent random failures ($\rho'>\rho$) throughout the whole early life and premature, more severe wear-out ($s_1'<s_1$); see Fig. 3(b).

3.2. Condition monitoring of subassemblies subject to wear-out

Condition Monitoring (CM) can indicate incipient failure by tracking measurable wear-out indicators associated with the underling degradation process and releasing a signal prior to failure; see Fig. 4. For example, wear-out of offshore wind turbine gears and bearings can increase the generation rate of particles above a certain size in gearbox oil [24]. Upon the observation of the CM signal, operators can respond by, for example, de-rating a damaged turbine, to extend its residual life and allow time to plan maintenance actions. We include CM explicitly within the availability growth model because it allows us to predict the likely impact of investing in CM on farm availability.

To capture the effect of CM on a subassembly's failure behaviour, we extend the hazard model presented in Section 3.1 to include the wear-out indicator. We assume the CM indicator starts evolving when the subassembly enters Stage 2 at time S_1 (i.e. it begins to wear). Given that the signal threshold is passed after time W_2, counted from S_1, then time $S_2=S_1+W_2$ is when the subassembly enters Stage 3. T_3 denotes the subassembly's lifetime given that a CM signal is observed. Therefore, the CM signal further partitions the subassembly lifetime, as shown in Fig. 5, into

$$0\equiv S_0<S_1<S_2<S_3\equiv\infty. \quad (6)$$

Since the degradation and indicator processes are associated, the time to the CM signal, W_2, and the conditional lifetime of the subassembly in Stage 2, T_2, should both depend on the same underlying degradation process. Let W_2 have distribution G_2. We can write $F_2(t_2)=F_2(t_2|\boldsymbol{\theta})$ and $G_2(w_2)=G_2(w_2|\boldsymbol{\theta})$ where $\boldsymbol{\theta}$ is the vector of the degradation model parameters. Given $\boldsymbol{\theta}$, T_2 and W_2 are conditionally independent random variables, then within an independent competing risks framework, the subassembly lifetime in (3) can be written as

$$T=\min\{T_1,W_1\}+\min\{T_2,W_2\}I_{(T_1>W_1)}+T_3 I_{(T_2>W_2)} \quad (7)$$

where I_A is the indicator variable of event A. Note that if upon observation of the CM signal at time S_2, an operator chooses not to act (e.g. to de-rate the turbine comprising the degrading subassembly) then random variable T_3 has the same distribution as T_2.

To apply the availability model, the anticipated effectiveness of CM (i.e. the more correlated $F_2(\cdot)$ and $G_2(\cdot)$, the more effective the CM) and the operating practice in response to the CM signal

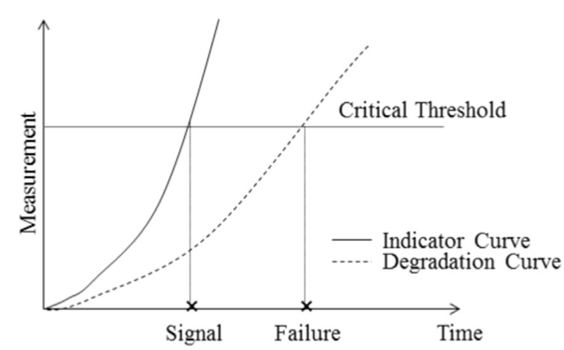

Fig. 4. Degradation process and indicator process curves: the two processes are correlated; the indicator process reaches the critical threshold before the degradation process, giving a signal prior to actual failure.

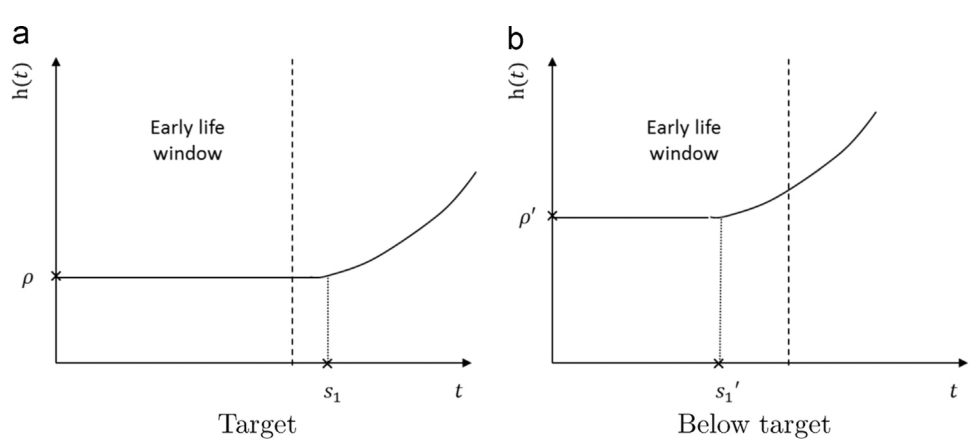

Fig. 3. Subassembly hazard rate: a subassembly with below-target reliability (b) has more frequent shock failures than in (a) and premature and/or more severe wear-out.

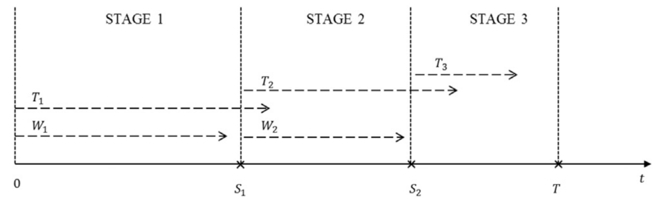

Fig. 5. Lifetime stages of a subassembly subject to condition monitoring until time to first failure T. T_j is the elapsed time from S_{j-1}, the time the subassembly leaves Stage $j-1$, until its first failure from a mechanism relevant to Stage j ($j=1,2$). Stage 1 is a shock-dominating period. Stage 2 is the period when both wear-out and shocks mechanisms are present, but before the release of a CM signal. Stage 3 is the period when both wear-out and shocks mechanisms are present, after the observation of a CM signal. W_1 is the time that elapses from start of operation until the subassembly starts to wear; W_2 is the time that elapses from the onset of wear-out until the CM signal is observed.

should be indicated. For example, a particular CM system may give a signal far in advance of failure, upon which operating performance is reduced to partial operation through some planned intervention.

3.3. Intensity of events

The hazard rate given in (2) describes the subassembly lifetime in terms of its time to first failure. Since offshore wind subassemblies are repairable systems, we use a marked point process $\{T_n, J_n\}_{n \geq 1}$ to describe their alternating behaviour between failure and repair, where $J_n = 1$ when a failure occurs at T_n and $J_n = 0$ otherwise $(n = 0, 1, 2, \ldots)$. Let $N(t)$ and $M(t)$ be the number of failures and restorations in $(0, t]$ respectively, where t is calendar time. The conditional intensity of the marked point process is defined as

$$\iota(t|\mathcal{H}_{t^-}) = \begin{cases} \lambda(t|\mathcal{H}_{t^-}) & \text{: subassembly operates just before time } t \\ \mu(t|\mathcal{H}_{t^-}) & \text{: subassembly does not operate just before time } t = 0 \end{cases}$$

where

$$\lambda(t|\mathcal{H}_{t^-}) = \lim_{\Delta t \to 0} \frac{\Pr(\text{failure in } [t, t+\Delta t)] | \mathcal{H}_{t^-})}{\Delta t} \tag{8}$$

and

$$\mu(t|\mathcal{H}_{t^-}) = \lim_{\Delta t \to 0} \frac{\Pr(\text{restoration in } [t, t+\Delta t)] | \mathcal{H}_{t^-})}{\Delta t}. \tag{9}$$

$\mathcal{H}_{t^-}$ is the history of the subassembly until, but not including, time t. History represents the information about a subassembly's past life that needs to be captured to support model computations. For simplicity, from this point forward we use $\iota(t), \lambda(t)$ and $\mu(t)$ instead of $\iota(t|\mathcal{H}_{t^-}), \lambda(t|\mathcal{H}_{t^-})$ and $\mu(t|\mathcal{H}_{t^-})$ respectively.

The intensity $\lambda(t)$, or the Rate of Occurrence of Failures (ROCOF), is the outcome of the interaction of the inherent reliability characteristics of the subassembly, described by the hazard $h(t)$, with the maintenance type (i.e. corrective or preventive) and effect (i.e. perfect or imperfect repair). The hazard defines the baseline condition of the subassembly, while the maintenance type and effect determine how this is controlled during operation. In our model, the effect of maintenance is captured via the concept of virtual age $v(t)$ [27]. We have

$$\lambda(t) = h(v(t)), \quad t > 0 \tag{10}$$

where $v(t)$ is equal to the cumulative uptime denoted with $x(t)$, where

$$x(t) = \sum_{k:J_k = 1(J_k = 0)}^{N(t)+M(t)} T_k - T_{k-1}. \tag{11}$$

For a new system $v(t) = 0$. Therefore, perfect maintenance essentially resets the virtual age of the turbine to zero, whereas minimal repair sets its value to the one it had just before failure. Several models have been developed for cases where repair effect lies between perfect and imperfect, e.g. [14], and might provide alternative formulations for the availability model.

Whereas virtual age $v(t)$ describes the effect of maintenance actions and repair, the effect of routine maintenance, such as oil changes, cleaning and lubrication, is captured implicitly by assuming that the pattern implied by the intensity in (10) assumes that such actions are undertaken properly. It is interesting to note that under the assumption of minimal repair, the hazard rate $h(\cdot)$ and the failure intensity $\lambda(\cdot)$ have the same mathematical formulation, even though they represent different quantities. It also emerges that the history $\mathcal{H}_{t^-}$ in (10) not only includes a subassembly's lifetime stage, but also its virtual age, as defined on the basis of information on the time and type of the last maintenance.

The repair intensity $\mu(t)$ can be expressed by a relationship similar to (10) where $h(\cdot)$ relates to the maintenance time distribution and $v(t)$ accounts for the amount of *continuous* time the system is under repair (i.e. cumulative downtime) as measured from the last failure event and excluding any logistic or weather delays.

3.4. Effect of interventions

3.4.1. Innovations

Since innovations are planned large-scale operations intended to have a radical effect on system performance, we model them discretely at times $S_1, S_2, \ldots, S_m$, which are assumed to be known a priori. Within the UK offshore wind energy context this is a reasonable assumption, since interventions such as design upscaling and subassembly re-fitting typically take place during the summer months, to take advantage of the relatively less severe weather conditions on site. Therefore, innovations partition the early life $(0, T]$ of the system as

$0 = < R_1 < R_2 < \cdots < R_m = T.$

Let $\iota^i(t)$ and $h^i(t), t > R_i$, denote the conditional intensity and hazard function respectively of a system after the i-th innovation $(i = 0, 1, \ldots)$. Similarly to (10), the failure intensity and hazard function are associated through equation

$$\lambda^i(t) = h^i(v(t)), \quad t > 0. \tag{12}$$

We assume the $(i+1)$-th innovation has an effect on the *basic* behaviour of the subassembly, as expressed via $h^i(\cdot)$. Innovations intend to bring the below-target reliability back to the target level and shift the subassembly profile from the one portrayed in Fig. 3(b) to the one in Fig. 3(a). This is achieved by making modelling choices to either reduce the shock failure rate $(\rho^i < \rho^{i+1})$, or delay wear-out $(S_1^i < S_1^{i+1})$, or decrease the wear-out rate. For the latter case, the wear-out rate can be modified by modulating the scale parameter of the lifetime distribution. For example, [38] makes a similar assumption when capturing enhancements in a software reliability context. Ref. [17] assumes that innovations impact the scale parameter of the Non Homogeneous Poisson Process model, whereas the shape parameter after intervention remains the same. In the context of accelerated life testing, [32,35] allow a change in stress level to impact the location of the log-lifetime (i.e. the scale parameter of the lifetime distribution), rather than the failure mechanism as expressed via the shape parameter of the lifetime distribution. However, these assertions are typically formed on the basis of statistical analysis, and the assumption that increased stress impacts only on one parameter is not always appropriate – see [31,33] and references therein.

To impose the orderings implied by the effect of innovations on shocks and wear-out, we intentionally use a simple version of the model and assume the following mathematical relationships:

$$\rho^{i+1} = \phi_i \rho^i,\ S_1^{i+1} = (1+\phi_i) S_1^i \quad \text{and} \quad \eta^{i+1} = \phi_i \eta^i \tag{13}$$

where η^i is the scale parameter of the lifetime distribution of a system subjected to i innovations and $0 < \phi_i \le 1$ is a fix-effectiveness parameter. One can produce a more elaborate model by defining as many fix-effectiveness parameters as the number of parameters affected by the innovation, or simplify the model further by assuming that $\phi_i = \phi$ for every i. Regardless of the choice, determining the intensity in (10) requires information on the number of innovations undertaken to be included in history $\mathcal{H}_{t^-}$.

As an example, consider a subassembly subject only to wear-out with hazard rate

$$h^0(v(t)) = \eta\beta(v(t))^{\beta-1}, \tag{14}$$

and, suppose that the subassembly is subject only to corrective maintenance with minimal repair and negligible restoration times. These assumptions imply that $v(t) = t$ and that

$$\lambda(t) = h^i(t) = \phi^{i-1}\eta\beta t^{\beta-1} \quad \text{for some } 1 \le i \le m. \tag{15}$$

Fig. 6 shows these assumptions result in a stepwise change in the subassembly intensity.

3.4.2. Minor adaptations

Recall that the hazard in (10) expresses the failure behaviour of a subassembly subject to routine maintenance. As experience accumulates and operators learn, maintenance practices are adjusted and procedures are improved. These changes, referred to as minor adaptations, can have an almost continuous positive effect on system performance as expressed by the failure or restoration intensities. We model this effect in terms of function $\varphi(\cdot)$.

The failure intensity of a subassembly after the i-th innovation and subject to minor adaptations is now given by

$$\lambda(t) = h^i(v(t))\varphi(t). \tag{16}$$

A number of formulations for $\varphi(t)$ can be used to represent this ‘learning effect’ due to minor adaptations. Here, we choose a function that is bounded and non-increasing function of t to represent the decreasing chance of failure resulting from learning,

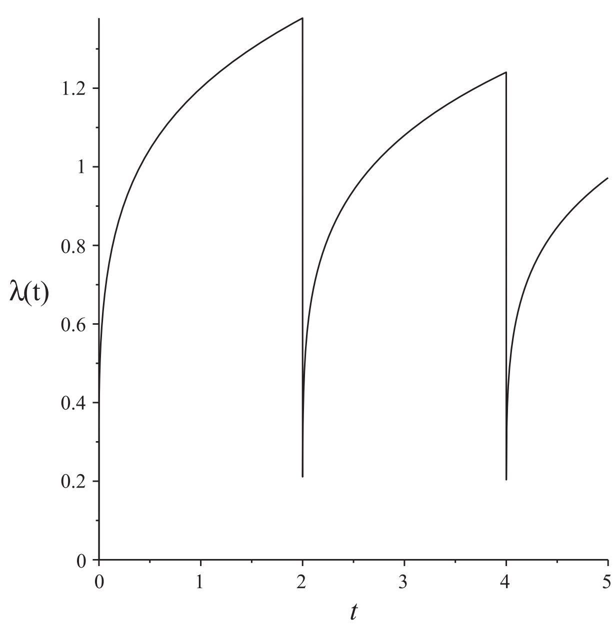

Fig. 6. Innovations ($\phi = 0.9$) occur every two time periods. The lifetime of the system is represented by a Weibull distribution with shape parameter $\beta = 1.5$ and scale parameter $\eta = 0.5$. The system is subject to corrective maintenance with minimal repair and restoration times are assumed negligible.

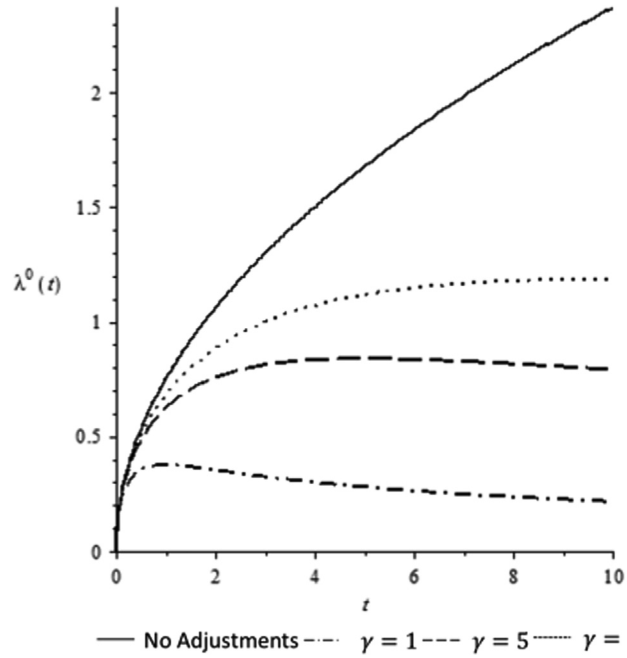

Fig. 7. Effect of learning on failure intensity when minor adaptations occur continuously. In this example: system lifetime is represented by a Weibull distribution with shape parameter $\beta = 1.5$ and scale parameter $\eta = 0.5$, and the system is subject to corrective maintenance only with minimal repair and negligible restoration times.

and we have

$$\varphi(t) = 1 - \frac{t}{t+\gamma}. \tag{17}$$

Since learning is the result of accumulated operating experience, it is reasonable to assume that minor adaptations depend on calendar time t, and the history $\mathcal{H}_{t^-}$ should include this information to allow determination of the failure intensity. In Fig. 7 one can see how the failure intensity of the subassembly used in the simple example described previously is modified due to minor adaptations, before any innovations take place.

3.5. Estimation of system availability performance

A performance indicator we call *availability-informed capability* is derived as an output of the mathematical model. Our capability measure aims to capture the effect of partial performance of subassemblies on the system output, in particular the effect of partial operation of wind turbines on the energy output from the farm. Since the power generated by a farm is the aggregate of the power generated by individual turbines, the *availability-informed capability* is defined as the fraction

$$C_{\text{farm}}(t) = \frac{\sum_{i=1}^{n} P_i(t)}{\sum_{i=1}^{n} PO_i(t)} \tag{18}$$

where $P_i(t)$ is the average output power of turbine i at time t (calculated by applying the power curve of a turbine to a reference wind speed distribution at hub height), given the turbine's operating condition, and $PO_i(t)$ is the average output power of turbine i at time t assuming it is fully operational. Therefore the *average* farm availability-informed capability over some interval (τ_1, τ_2) is given by

$$C_{(\tau_1,\tau_2)} = \frac{1}{\tau_2 - \tau_1}\int_{\tau_1}^{\tau_2} C_{\text{farm}}(t)\,\mathrm{d}t. \tag{19}$$

A full explanation of this performance indicator and a discussion of why it is regarded as a meaningful measure of production

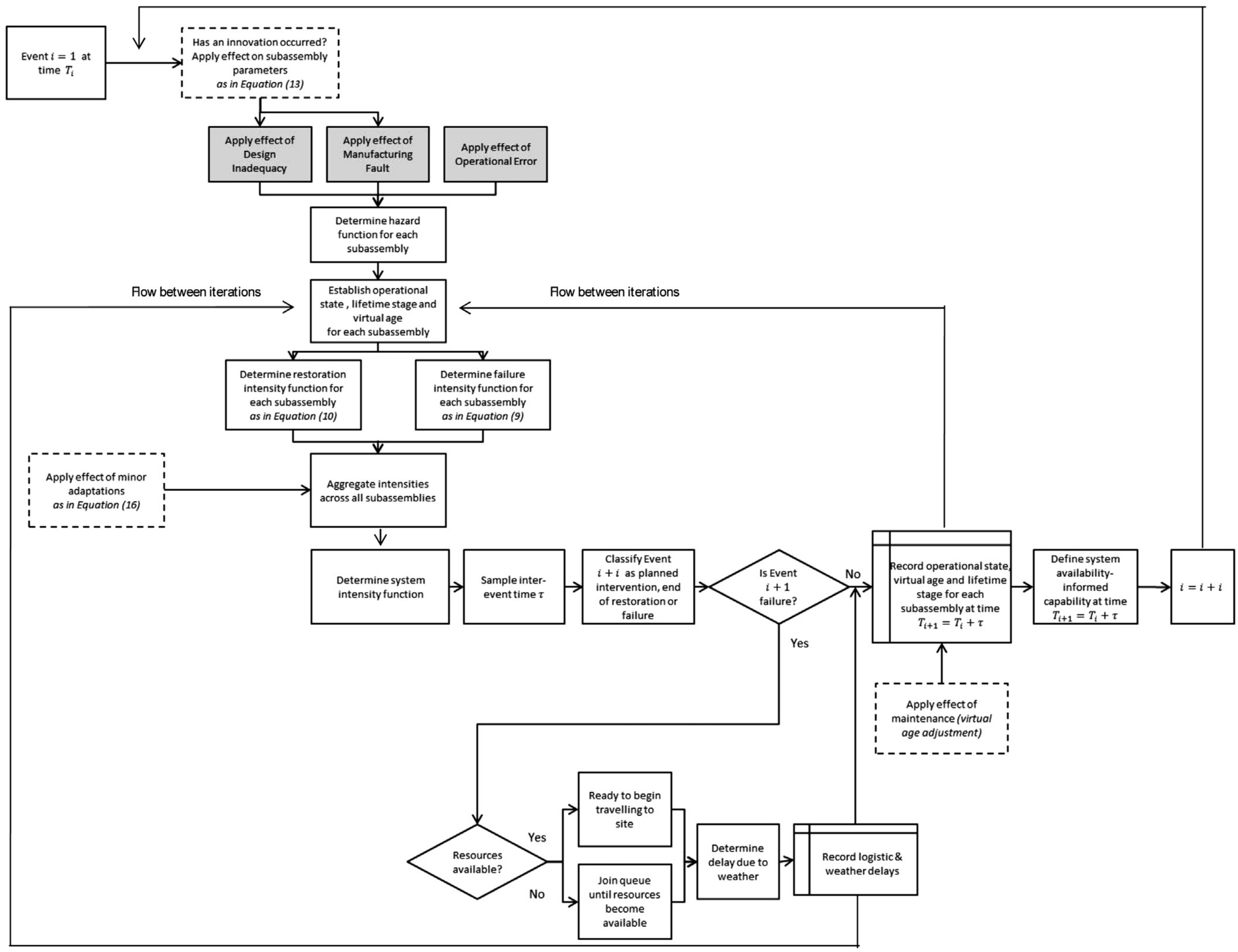

Fig. 8. High-level logic of simulation of events through time. Solid lines represent relationships between variables; dotted lines represent interventions to grow availability; grey nodes denote triggers of systemic risk.

capability in the context of financial analysis of offshore wind farms is given in [54].

A capability estimate is computed by representing the mathematical model as a point process simulation. The flowchart in Fig. 8 provides the high level logic of the simulation of events through time and shows the types of events simulated and the relationships between them. For example, exposure to the triggers of systemic risk, shown by the shaded nodes, influences the failure events of subassemblies by modulating the hazard function, as does the condition of the subassembly (i.e. the virtual age) that gets modulated by maintenance. History represents the combined information about, for example, the number of past innovations and calendar time.

4. Example

We now illustrate the application of the availability growth model for a new generation offshore wind farm. Unlike other availability modelling approaches used in an offshore wind context, our model allows for the representation of both the gradual effect of minor adaptations, introduced through the accumulation of operating experience, as well as the more radical effect of innovations, such as the replacement of subassemblies with inherent weaknesses with improved versions. In our example we compare model outputs under two scenarios: when systemic risk due to design weaknesses is considered (i.e. growth is explicitly modelled) and when this type of risk is omitted (i.e. as in current availability models for offshore wind). The aim of this comparison is to demonstrate the consequence of failing to represent systemic risks, as well as the subsequent availability growth resulting from restorative action, in estimating farm technical performance, energy output and hence expected financial return.

Our example is based on a typical large-scale Round III UK offshore wind farm and our modelling has been developed in collaboration with wind energy experts. Specifically, we translated the conceptual framework shown in Fig. 1 into a process to support the customisation of the general model for the particular context as follows: firstly, we defined the system and its critical subassemblies, for which the model was to be built and scoped the availability growth model; secondly, we articulated the reliability and restoration targets for the system subassemblies based upon the achievable performance of similar relevant parts which have accrued operational experience; thirdly, we considered the causes and effects of failure so that we appropriately model the triggers on the uptime performance, as well as the impact of interventions on uptime and downtime performance.

4.1. Scoping the wind farm system model

Our UK round III wind farm, currently at pre-construction stage, will comprise 150 5MW turbines. The turbines have novel design features and are larger scale than earlier versions. Eight subassemblies (i.e. gearbox, generator, frequency converter, transformer, main shaft bearing, blades, tower, foundations, collection cable and transmission cable) have been identified as critical through discussion with subject experts, because they are considered to be subject to high technical and physical risk. We model each of the critical subassemblies explicitly and treat the remaining non-critical subassemblies as one modelling group.

Availability-informed capability is to be estimated for the first five years of operation, which is the UK warranty period. The farm is intended to start operation in the summer months. Engineering experts have identified the gearbox and the frequency converter as being at high risk because these are the subassemblies more likely to have design weaknesses. Therefore, in the modelling we examine scenarios associated with the prevalence of systemic risk associated with such design weaknesses and the impact of intervention strategies both on availability levels and financially in terms of energy production loss.

We set the target reliability for offshore turbines to equal that achieved by mature onshore turbines since this is consistent with engineering requirements. Analysis of relevant data shows that onshore turbines achieve a failure rate of 3.81 failures/year. This failure rate includes failures of any subassembly and severity, and can be broken down to rates for specific subassemblies [22]. We use a turbine breakdown similar to that used in onshore analyses, which allows us to set the target reliability for each offshore subassembly equal to the level achieved by its onshore counterpart. Table 1 gives values for the target failure rates for the critical subassemblies, whereas the target failure rate for the non-critical group is the sum of the rates of the non-critical subassemblies comprising the group [22].

Following [41,18], we categorise the effects of failure into minor, moderate and major. Restoration durations depend on the failure severity and are taken to be 6 h, 1 day and 2 days for a minor, moderate and major failure respectively. The proportion of failures of different severities for each of the critical subassemblies is also shown in Table 1 and, again, is based on the experience from onshore farms which is considered requisite for our offshore context in this example.

Our farm maintenance strategy includes preventive and corrective actions. The turbines will be subject to bi-annual overhauls during which subassemblies are refurbished and for modelling purposes we treat this as re-setting the subassembly virtual age to 50% of its value prior to the refurbishment. Condition monitoring (CM) will be installed on the gearboxes and will provide continuous data giving information about the state of the subassembly with an average run length between signal and occurrence of failure of approximately 1.5 months. Finally, minor adaptations are assumed to improve subassembly reliability in a gradual manner. The minor adaptation parameter γ has been chosen on the basis of providing a reasonable learning curve effect based on historical experience from related farms.

Observation of the CM signal will allow operators to de-rate the turbine to limit its output in order to extend its life until the next scheduled maintenance and to reduce the chance of a hard failure. If the fault signalled by the CM cannot be rectified remotely, then the affected subassemblies join the list of jobs awaiting repair. More generally, corrective repair will be conducted on a first come, first served basis and will be constrained by the available maintenance resources and the logistical accessibility. Weather delays are determined as described in [13] for subassembly failure types. For example, the average waiting time for a major gearbox failure is 9 days during the summer months and 18 days during the winter months. The condition to which an affected subassembly returns after maintenance depends on the severity of failure determined previously. A minimal failure is treated with minimal repair and the subassembly is returned to an as-bad-as-old condition, while moderate and major failures result in repairs that are believed to return the subassembly to 85% and 60% of what its condition was just before failure respectively.

As mentioned, the major concerns about the new turbine to be installed in our wind farm are the design weaknesses in the gearbox and the frequency converter. These weaknesses, should they exist, will be prevalent in all turbines in the farm, therefore they will trigger all similar subassemblies to wear prematurely and will therefore be a source of systemic risk. To represent systemic weaknesses in the model, it is necessary to determine the reliability of subassemblies, in terms of hazard functions, given the presence of triggers. In our example we used a structured expert judgement elicitation process to obtain point value estimates of the parameters for the hazard-induced hazard functions of each critical subassembly. Note that the expert judgement information was obtained as part of a larger exercise reported in [55]. Table 2 shows the point values used in this application for the scenario where systemic risk due to design weaknesses is to be explicitly modelled.

Our example aims to highlight the importance of representing systemic risks in farm availability performance – which is a novel feature of our growth model. Therefore we now examine the scenario where upgrades intended to address design weaknesses of the gearbox and frequency converter designs are rolled out across the turbines in the farm in Year 2 (i.e. a trigger exists) and compare it to a baseline scenario where there are no systemic weaknesses (i.e. the trigger does not exist).

Table 1
Subassemblies, target and apportioned failure rates. Source: data from [22,41,18].

Subassembly	Target failure rate	Failure apportionment		
		Major	Moderate	Minor
Gearbox	0.228 f/yr	0.09	0.27	0.64
Generator	0.266 f/yr	0.10	0.26	0.64
Frequency converter	0.456 f/yr	0.04	0.18	0.78
Transformer	0.076 f/yr	0.04	0.16	0.8
Main shaft bearing	0.038 f/yr	0.25	0.15	0.6
Blades	0.114 f/yr	0.04	0.21	0.75
Tower	0.114 f/yr	0.01	0.19	0.8
Foundations	0.038 f/yr	0.01	0.19	0.8
Non-critical group	2.47 f/yr	0.01	0.19	0.8
Collection cable	1×10^{-6} f/km/yr			
Transmission cable	1×10^{-6} f/km/yr			

Table 2
Point estimates of parameters based on expert judgement to reflect the effect of premature wearout due to design inadequacy of gearbox and frequency converter. The CM indicator relates to gearbox degradation. Unit of time is a year.

	Gearbox	Frequency converter
Shocks	$\lambda = 0.019$	–
(Exponential)		
Wear-out onset	$\mu = 0.335$	$\mu = 0.992$
(Normal)	$\sigma = 0.01$	$\sigma = 0.01$
Signal	$\eta = 15$	–
(Weibull)	$\beta = 1.5$	–
Full operation	$\eta = 5.15$	$\eta = 2.2$
(Weibull)	$\beta = 1.19$	$\beta = 1.2$
Partial operation	$\eta = 5$	–
(Weibull)	$\beta = 1.5$	–

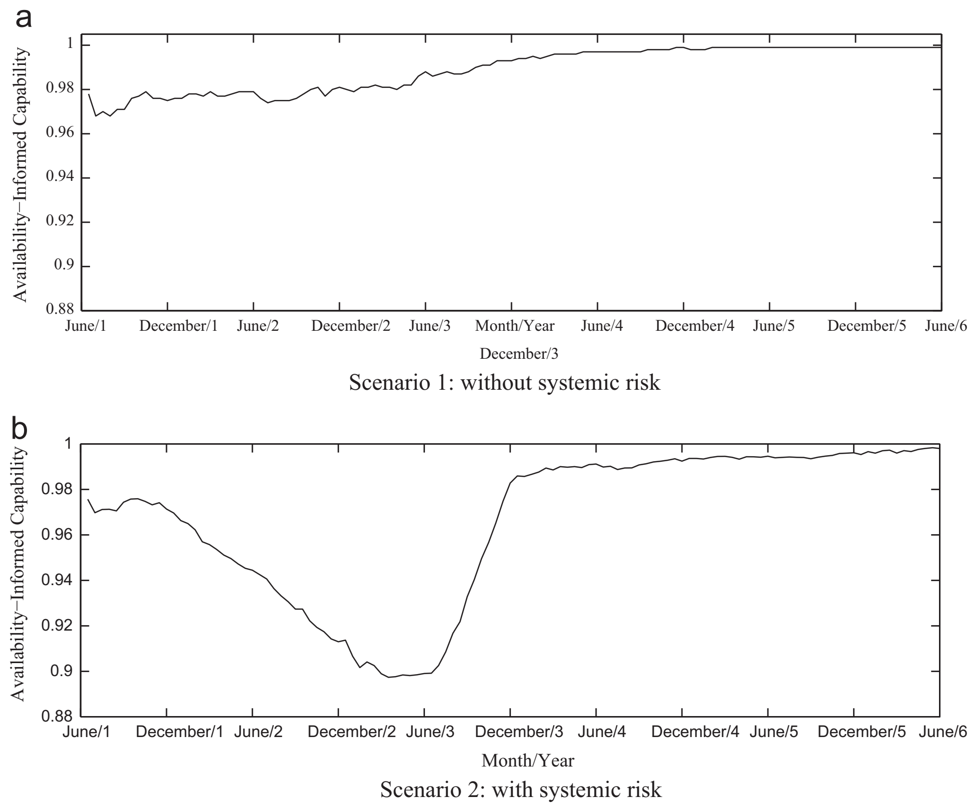

Fig. 9. Estimated early life availability-informed capability for simulated scenarios: (a) no recognised gearbox and frequency converter design weaknesses; (b) design inadequacy weaknesses result in deteriorating farm performance over the next two years; performance reaches target levels once issues are removed through implementation of innovations.

4.2. Findings

Our modelling provides performance profiles for the farm over the first five years of operation, starting in summer of Year 0, for both scenarios. The model has been developed as a modular simulation in Matlab, making it feasible to replace or to extend modelling features. Monte Carlo simulations based on the computational model logic shown in Fig. 8 are used to calculate the aleatory uncertainty on the availability-informed capability on a two-weekly basis using $N=100$ runs. This is a limited number of simulation runs but the choice was made as a practical trade-off between simulation runtime and estimation accuracy. Further, since our primary goal here is to examine patterns in availability performance profiles, we have shown only the 50% quantiles in the model output plots.

Fig. 9 illustrates the 50% quantiles of bi-weekly availability-informed capability profiles under the two scenarios. When systemic design weaknesses are not considered explicitly in the analysis, Fig. 9(a) shows that performance is below the typical target of 97% capability for the first quarter of Year 1, before gradually improving due to the effects of minor adaptations to achieve an availability of around 99%. However, as Fig. 9(b) shows, the systemic effects of design inadequacies can reduce early farm performance to a level below 90% capability. Our results show that the predicted farm performance deteriorates prematurely during the first two years of operation until innovations in the form of the design upgrades are undertaken during the summer months of Year 2. Following the successful mitigation of systemic risk, performance increases gradually. Fig. 10 shows the equivalent estimated failure intensity rate for the farm for our two scenarios. The common learning effects due to minor adaptations of, for example, procedures lead to pattern of reduction in the failure intensity under Scenario 1. The impact of systemic risk due to the design weaknesses appears as an increasing failure intensity over the first two years of operation before decreasing substantially over the last half of Year 3 when the full effects of the design modification combined with the minor adaptations are achieved across the farm.

By applying the wind speed distribution on the power curve of a turbine, the total farm energy production and associated revenue can be estimated. Table 3 provides the results under our two scenarios. If the energy price is £155 per MWh, and without modelling triggers of systemic risk, then the expected revenue over the first 5 years of operation is computed to be 1760 million pounds. However when systemic risk is properly accounted for in the analysis, the farm generates a revenue of 1722 million pounds over the same period. This implies that failing to model growth in availability, but instead assuming that steady-state performance can be achieved from the outset, can lead to an overestimation of farm revenue in the range of 38 million pounds even before taking into account the cost of innovations. In this example these costs would be those accrued in the re-design and re-fitting of 150 problematic frequency converters and gearboxes.

The example shows clearly what kind of impact systemic risks can have on wind farm financial performance. Current modelling of offshore wind farm availability does not take account of growth due to the risks associated with innovation, leading to over-optimistic planning and high costs of mitigation. Simply having awareness of this type of problem during planning and contracting can focus minds on maintaining options to deal with the nature of this issue.

5. Conclusions and further work

We have presented an availability growth model for a system, such as an offshore wind farm, where innovations might be made

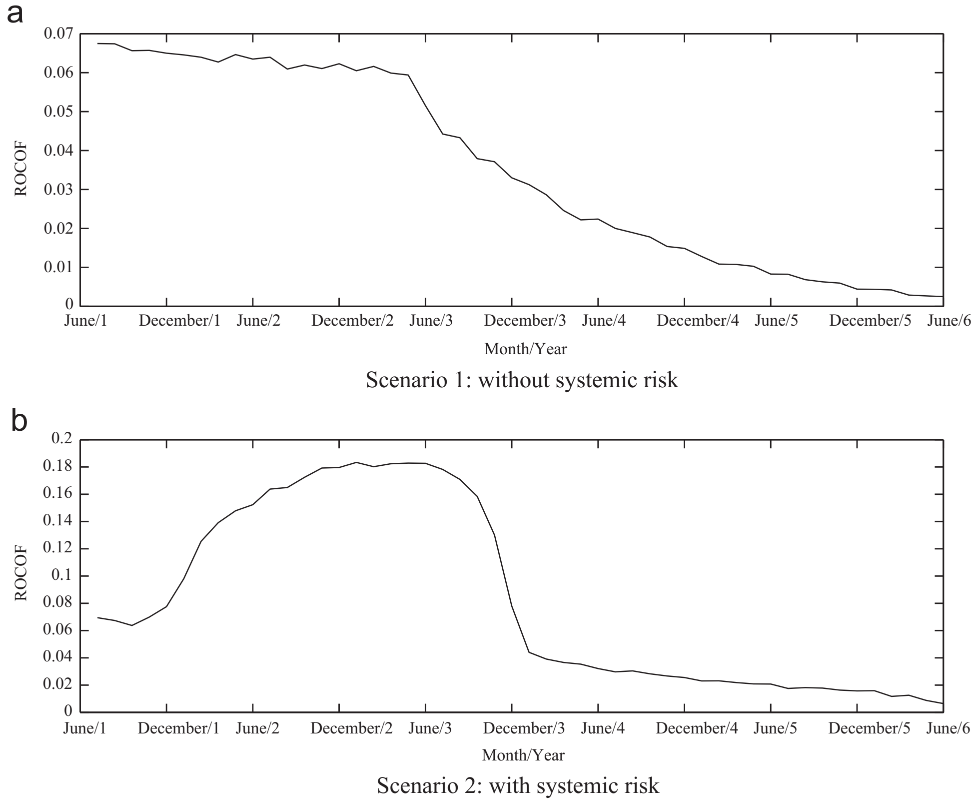

Fig. 10. Estimated early life failure intensity rate denoted by ROCOF for simulated scenario: (a) no recognised gearbox and frequency converter design weaknesses; (b) design inadequacy weaknesses result in increasing rate over the next two years before reducing after effect of innovation.

Table 3
Expected farm output over early life assuming average wind speed under two scenarios and an energy price of £155 per MWh.

Scenario	Early life output	
	Energy (GWh)	Revenue (million £)
No triggers	11,355	1760
Triggers	11,109	1722

during early operation to improve performance and estimates of availability are required prior to entry into service. Importantly, this includes exploration of mitigation strategies for the initial period of operation, should availability problems emerge, and should influence logistics planning and options on service provision. While our availability growth model has been motivated by, and its application illustrated for, the offshore wind problem, the generic structure of the model means that it can be adapted to other domains where commercially unproven technology or processes are used. The model presented is designed to provide insight into the effectiveness of interventions on growth in system performance by providing availability estimates under different scenarios. Our example for a typical UK Round III wind farm highlights the importance of being able to meaningfully assess farm performance over early life when systemic risks due to design, maintenance and operational weaknesses may still exist. The model provides a means of measuring the impact of systemic risk on availability performance and can be used to quantify the financial implications of underestimating performance relative to target.

The model, as presented here, considers only aleatory uncertainties and allows the exploration of different scenarios with decision makers. This is useful for dealing with managers in industry as it allows them to explore the implications of issues that they are aware of, but are not currently modelling. A more sophisticated mathematical approach which uses epistemic uncertainties to create a more formal rational decision-making model framework is developed in a further paper [54]. However, this further approach inevitably requires that decision makers 'buy-in' to the expert uncertainty assessments which have to be gathered from a variety of different stakeholders. Since the availability growth scenario approach presented here already enables decision makers to explore key problems without having to commit to a more conceptually sophisticated and complex approach, it is genuinely useful both to deal with those problems where the more complex approach would probably not make a difference, and also to motivate them to go on to the more complex approach when it is needed. Our point of view in this regard is consistent with that expressed by I.J. Good [21] who said that a rational decision maker should take account of the cost of the decision analysis (to all parties) as well as the direct costs and benefits of the decision.

Our current model code is based on the set of assumptions described. While reasonable for our example domain, they might need to be developed for other application areas. Further, the implementation of sensitivity or uncertainty analysis would require further consideration of the simulation model computation so that appropriate numbers of simulation runs can be efficiently generated to provide suitably accurate results. For example, future work could involve the use of metamodels such as emulators [36,28] to approximate the simulation model and to speed up computation.

Our example provides insight into how the general growth model can be customised for a particular system by articulating the modelling choices. For example, the classification of subassemblies to critical and non-critical, as well as the specific triggers considered, was achieved using the structured judgement of wind energy experts, and can be modified to reflect the systemic risks relevant to a particular situation. Similarly, the condition monitoring characteristics, which we represented by the timing of the signal relevant to failure and the operational response, can be modified to represent actual maintenance of a given system. To build a meaningful model for decision makers requires engagement with relevant engineering experts to both qualitatively structure the model and to quantify selected parameters. We have developed a scientific protocol to support collection and preparation of data details of which are provided in [55]. Ongoing work includes further engagement with stakeholders experienced in offshore wind farm engineering, technology and operations to conduct validation studies of the availability growth model and supporting data management processes.

Acknowledgements

This research was supported by EPSRC Grant EP/I017380/1. We gratefully acknowledge the support from Mr. Graeme Hawker, Dr. Keith Bell, Prof. David Infield and Dr. Julian Feuchtwang and thank them for their help in understanding and modelling the offshore wind farm problem. Special thanks should go to Dr. Kevin Wilson, for supporting the construction of the MATLAB code. We should also like to thank the engineers, farm operators and developers that shared their valuable insights and experiences with us. Datasets associated to the simulations discussed here are available from http://dx.doi.org/10.15129/b8c056e4-b73a-4ac4-a4fe-af8e5bd54804.

References

[1] Towards round 3: building the offshore wind supply chain. Technical report, The Crown Estate; June 2012.
[2] Offshore wind operational report 2013. Technical report, The Crown Estate; 2013.
[3] Andrawus JA, Watson J, Kishk M. Wind turbine maintenance optimisation: principles of quantitative maintenance optimisation. Wind Eng 2007;31(3):101–10.
[4] Andrawus JA, Watson J, Kishk M, Adam A. Determining an appropriate condition-based maintenance strategy for wind turbines. In: 2nd joint international conference on sustainable energy and environment. p. 270–75.
[5] Ansell J, Walls L, Quigley J. Achieving growth in reliability. Ann Oper Res 1999;91:11–24.
[6] Bedford T, Dewan I, Meilijson I, Zitrou A. The signal model: a model for competing risks of opportunistic maintenance. Eur J Oper Res 2011;214:665–673.
[7] Bedford T, Quigley J, Walls L. Expert elicitation for reliable system design. Stat Sci 2006;21(4):428–80.
[8] Christer AH, Wang W. A delay-time-based maintenance model of a multi-component system. IMA J Math Appl Bus Ind 1995;6:205–22.
[9] Cozzolino JM. Probabilistic models of decreasing failure rate processes. Nav Res Logist Q 1968;15:361–74.
[10] Crow LH. Reliability analysis of complex repairable systems. Technical report, SIAM; 1974.
[11] Freshfields Bruckhaus Deringer. European offshore wind 2013: realising the opportunity. Technical report; 2013.
[12] Dinwoodie I, McMillan D. Sensitivity of offshore wind turbine operation and maintenance costs to operational parameters. In: 42nd ESReDA seminar on risk and reliability for wind energy and other renewable sources; 2012.
[13] Dowell J, Zitrou A, Walls L, Bedford T, Infield D. Analysis of wind and wave data to assess maintenance access to offshore wind farms. In: Steenbergen RDJM, Van Gelder PHAJM, Miraglia S, Vrouwenvelder ACWM, editors, Proceedings of the ESREL2013 Conference safety, reliability and risk analysis: beyond the horizon. CRC Press; 2013. p. 743–50.
[14] Doyen L, Gaudoin O. Classes of imperfect repair models based on reduction of failure intensity or virtual age. Reliab Eng Syst Saf 2004;84:45–56.
[15] Duane JT. Learning curve approach to reliability monitoring. IEEE Trans Aerosp 1964;2:563–6.
[16] Duard F, Domecq C, Lair W. A probabilistic approach to introduce risk measurement indicators to an offshore wind project evaluation improvement to an existing tool: ECUME. Energy Proc 2012;24:255–62.
[17] Ebrahimi N. How to model reliability growth when times of design modifications are known. IEEE Trans Reliab 1996;R-45:45–58.
[18] Faulstich S, Hahn B, Tavner PJ. Wind turbine downtime and its importance for offshore deployment. Wind Energy 2011;14:327–37.
[20] Offshore wind cost reduction task force. Offshore wind cost reduction task force report. Technical report; 2012.
[21] Good IJ. Good thinking: the foundations of probability and its applications. University of Minnesota Press; 1983.
[22] Hendriks B. Reliawind. Presentation in EWEC 2010, Warsaw, Polland; 2010.
[23] Hodge R, Evans M, Marshall J, Quigley JL, Walls L. Eliciting engineering knowledge about reliability during design-lessons learnt from implementation. Qual. Reliab. Eng. Int 2001;17(3):169–79.
[24] Hyers RW, Mcgowan JG, Sullivan KL, Manwell JF, Syrett BC. Condition monitoring and prognosis of utility scale wind turbines. Energy Mater: Mater Sci Eng Energy Syst 2006;1(3):187–203.
[25] Quail F, Dinwoodie I, McMillan D. Analysis of offshore wind turbine operation and maintenance using a novel time domain meteo-ocean modeling approach. In: Proceedings of ASME turbo expo 2012; 2012.
[26] Jewell W. Bayesian extensions to a basic model of software reliability. IEEE Trans Softw Eng 1985;11:1465–71.
[27] Kijima M. Some results for repairable systems with general repair. J Appl Probab 1989;26:89–102.
[28] Kleijnen JPC. Kriging metamodeling in simulation: a review. Eur J Oper Res 2009;192:707–16.
[29] Laprie JC, Kanoun K. X-ware reliability and availability modeling. IEEE Trans Softw Eng 1992;18(2):130–47.
[31] Meeker WQ, Escobar LA. A review of recent research and current issues in accelerated testing. Int Stat Rev/Rev Int Stat: Spec Issue Stat Ind 1993;61(1):147–68.
[32] Meeker WQ, Escobar LA. Statistical methods for reliability data. New York, Chichester, Weinheim, Brisdane, Singapore, Toronto: John Wiley & Sons, Inc.; 1998.
[33] Meeker WQ, Meeter C. Optimum accelerated life tests with a nonconstant scale parameter. Technometrics 1994;36(1):71–83.
[35] Newby M. Accelerated failure time models for reliability data analysis. Reliab Eng Sys Saf 1988;20:187–97.
[36] O'Hagan A. Bayesian analysis of computer code outputs: a tutorial. Reliab Eng Syst Saf 2006;91:1290–300.
[37] Pahl G, Beitz W. In: Wallace K, editor. Engineering design: a systematic approach. Berlin: Springer-Verlag; 1996.
[38] Pham L, Pham H. Software reliability models with time-dependent hazard function based on Bayesian approach. IEEE Trans Syst Man Cybern 2000;30:25–35.
[39] Phillips JL, Morgan CA, Jacquemin J. Understanding uncertainties in energy production estimates for offshore wind farms. In: Copenhagen offshore wind 2005; 2005.
[40] PriceWaterhouseCoopers. Offshore proof: turning windpower promise into performance. Technical report; 2011.
[41] Rademakers LWMM, Braam H, Obdam TS, Pieterman RPvd. Operation and maintenance cost estimator (OMCE) to estimate the future O&M costs of offshore wind farms. Technical report ECN-M–09-126, ECN: Energy Research Institute in the Netherlands; 2009.
[42] Robinson D, Deitrich D. A new non-parametric growth model. IEEE Trans Reliab 1987;R-36:411–8.
[43] Rowe Stephen J, Dello Stritto Frank J, Brendling William J, Grittner Steven. Simulating operating & production efficiencies for deep water field developments. In: Offshore technology conference, Houston, Texas; 2000.
[44] Sen Ananda. Estimation of current reliability in a Duane-based reliability growth model. Technometrics 1998;40:334–44.
[46] Tavner P, Spinato F. Reliability of different wind turbine concepts with relevance to offshore application. In: European wind energy conference, Brussels; 2008.
[47] Offshore wind power summary report low carbon innovation coordination group, Technology Innovation Needs Assessment (TINA); February 2012.
[48] Tokuno K, Yamada S. Markovian software availability modeling for performance evaluation. In: Christer AH, Osaki S, Thomas LC, editors, Stochastic modelling in innovative manufacturing. Berlin: Springer-Verlag. p. 246–56.
[49] Walls LA, Quigley JL. Building prior distributions to support Bayesian reliability growth modelling using expert judgement. Reliab Eng Syst Saf 2001;74(2):117–28.
[50] Walls LA, Krasich M, Quigley JL. Comparison of two models for managing reliability growth during product design. IMA J Manag Math 2005;16(1):12–22.
[51] Walls L, Quigley JL, Marshall J. Modelling to support reliability decisions during new product development with applications in the aerospace industry. IEEE Trans Eng Manag 2006;53(2):263–74.
[52] Wang W. An overview of the recent advances in delay-time-based maintenance modelling. Reliab Eng Syst Saf 2012;106:165–78.
[53] Zaaijer MB, Van Bussel GJW. Integrated analysis of wind turbine and wind farm. In: 2nd symposium offshore wind energie, Hannover, Germany; 9 September 2002.
[54] Zitrou A, Bedford T, Walls L, Wilson K. Modelling epistemic uncertainty on availability assessments of a new generation offshore wind farm. Department of Management Science, University of Strathclyde; 2015, in preparation.
[55] Zitrou A, Bedford T, Walls L. Quantification and modelling of epistemic uncertainties for availability risk of future offshore wind farms using expert judgment. In: Nowakowski T, Mlynczak M, Jodejko-Pietruczuk A, Werbinska-Wojciechowska S, editors, Proceedings of the European safety and reliability conference on safety and reliability: methodology and applications, ESREL 2014. CRC Press/Balkema; 2015. p. 805–12.