Quantification and Modelling of Epistemic Uncertainties for Availability Risk of Future Offshore Wind Farms using Expert Judgment

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ABSTRACT

Understanding the level of control one has over risk is important in the context of financial decision-making associated with new offshore wind farm projects. Effective risk management requires a new model to adequately address systemic risk, which is important for two reasons. First, if systemic risk, which impacts across all turbines, is ignored then overall farm performance will be over-estimated. Second, the epistemic uncertainty associated with systemic risk reduces as we learn from relevant data and information gathered from, for example, relevant testing.

We have developed a novel availability growth model that takes into account the sources of systemic risk to provide a more accurate estimation of farm performance over early life. Our model focuses on early operating life because the impact of systemic risk is more prevalent when teething problems arise and are resolved through remedial actions at the price of additional investment. Our model can be used to understand the scale of uncertainties involved in wind farm development and, thus, inform decisions to grow availability and buy-down risk. The model captures the specific effect of epistemic issues on the wind farm subassemblies, as well as their aggregated effect on overall farm performance. Our model has a general structure that can be adjusted to reflect a particular application.

This paper explains how we have designed and implemented a structured expert judgment elicitation process to identify key uncertainties for a particular offshore wind farm context and to quantify model parameters associated with epistemic uncertainties.

We overview our contextual model to set the scene before describing the mathematical approach to modelling the epistemic uncertainties. We explain our general protocol of expert judgment elicitation, which involves a qualitative stage to identify key subassemblies for which there is large to moderate epistemic uncertainty, followed by a quantitative stage to elicit probabilities for key variables and parameters. For example, the uncertainty distribution on the parameters of the trigger induced hazard function for each subassembly and the relative weights of the influencing factors to obtain the best estimate of the trigger probabilities. We discuss how we gathered judgmental data from a panel of experts with experience in wind farm engineering, technology and operations for a UK Round III wind farm application. Figure 1, for example, shows key subassemblies and the triggers to which they are susceptible from this panel elicitation.

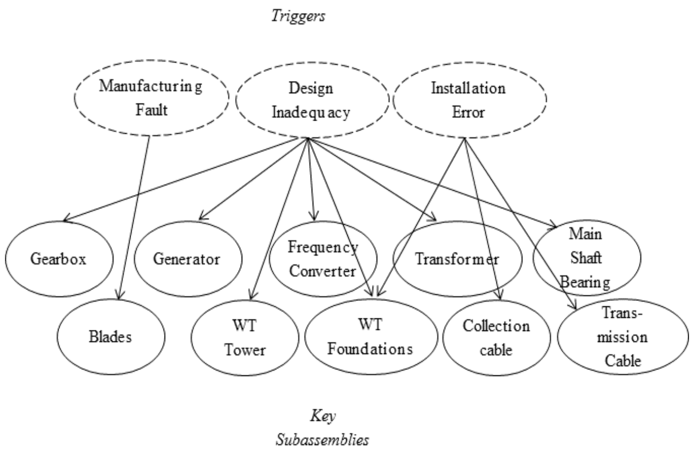

Figure 1. Illustrative output of qualitative elicitation stage.

subassemblies triggers susceptibility

We instantiate our model using the subjective assessments of epistemic uncertainties made by our expert panel and present selected outputs of modelling. Figure 2, for example, compares the distributions of the mean early-life farm availability-informed capability under the two decision scenarios: with and without field testing. In the worst case scenario, the mean farm capability might drop to 95% if no field testing is undertaken. But if field testing is undertaken, this capability will increase to 96%. Our model requires further validation study to mature our framework for practical implementation

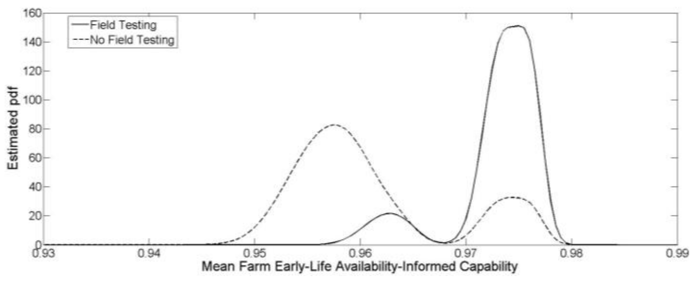

Figure 2. Epistemic probability distribution function on the mean farm capability averaged over first 5 years of operation under the two decision scenarios with and without field testing.

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ABSTRACT: We develop a model to capture state-of-knowledge, as well as aleatory, uncertainties associated with off-shore wind farm technologies, processes and environments. Our goal is to better understand systemic technology risks and support investment decisions for effective, efficient risk management. Typical epistemic uncertainties present in the offshore wind context are articulated. A protocol for eliciting expert judgment to quantify variables representing epistemic uncertainties and other relevant model parameters is presented. We discuss the elicitation of judgments from an expert panel of energy company technical specialists and show an application of our model to a generic new design offshore wind farm.

1 INTRODUCTION

The UK government has set ambitious renewable energy targets to address the issue of increased carbon emissions [Department of Energy & Climate Change, 2013]. To meet these targets, capacity is being increased by, for example, building off-shore wind farms which use novel large-scale, complex technology and are sited further from shore. However, deploying innovative technology in partially understood environments introduces the potential for systemic weaknesses associated with the design, manufacturing and operation of wind farm systems. Since weaknesses increase the perceived levels of risk related to offshore wind projects they inhibit capacity growth and act as a barrier to investment.

Understanding of the level of control one has over risk is important in the context of financial decision-making associated with new offshore wind farm projects. Effective risk management requires a new model to adequately address systemic risk, which is important for two reasons. First, if systemic risk, which impacts across all turbines, is ignored then overall farm performance will be over-estimated. Second, the epistemic uncertainty associated with systemic risk can be reduced by as we learn from relevant data and information gathered from, for example, relevant testing.

We have developed a novel availability growth model that takes into account the sources of systemic risk to provide a more accurate estimation of farm performance over early life [Zitrou & al, to appear]. Our model focuses on early operating life, which usually covers the first five years of operation, because the impact of systemic risk is more prevalent when teething problems arise and are resolved through remedial actions at the price of additional investment. Our model can be used to understand the scale of uncertainties involved in wind farm development and, thus, inform decisions to grow availability and buy-down risk. In particular, the farm performance estimates obtained through modelling can be used to support assessment of the risk-return profile of offshore wind projects at a pre-construction phase. Our model has a general structure that can be adjusted to reflect a particular application and requires to be populated using an appropriate mix of expert judgment and empirical data.

In this paper we explain how we have designed and implemented a structured expert judgment elicitation process to identify the key uncertainties for a particular offshore wind farm context and to quantify selected model parameters associated with epistemic uncertainties. In Section 2 we overview our contextual model to set the scene before describing the mathematical approach to modelling the epistemic uncertainties. In Section 3 we explain our general protocol of expert judgment elicitation, while in Section 4 we discuss how we gathered judgmental data from a panel of experts with experience in wind farm engineering, technology and operations for a UK Round III wind farm application. In Section 5 we show how the subjective assessments of epistemic uncertainties made by our expert panel can be used to instantiate the model and present selected outputs of modelling. We conclude in Section 6 by discussing the methodological and practical implications of our results.

2 MODELLING FARM PERFORMANCE

2.1 *Conceptual Framework*

Our model is designed to represent the key sources of epistemic uncertainties from a risk-management perspective. The model captures the specific effect of epistemic issues on the wind farm subassemblies, as well as their aggregated effect on overall farm performance. Compared to the standard uncertainty analysis, where epistemic uncertainty is represented by varying the model parameters over intervals, the output from our model has a practical interpretation and, therefore, can be used meaningfully to inform decision-making.

Figure 1 provides a diagrammatic representation of our model framework. Farm performance is measured in terms of its availability-informed capability. We introduce this measure to merge farm energy capacity with the technical availability because we believe that this better supports uncertainty analysis. Availability informed capability is a function of the uptime, whether full or partially operating states, and downtime performance. Oval nodes represent the uncertainties affecting performance, with shaded nodes being specifically the epistemic uncertainties affecting reliability and hence uptime performance. That is, design inadequacy, operation error and manufacturing fault, which we collectively refer to as "triggers" because they act as initiators of failure events that will reduce reliability and they represent factors about which we shall gain knowledge through experience. Other uncertainties, such as waiting and repair times, are treated as aleatory. The boxes represent interventions taken to grow performance and reduce uncertainty, and include major innovations such as design changes as well as minor adaptations such as refinements of operational procedures.

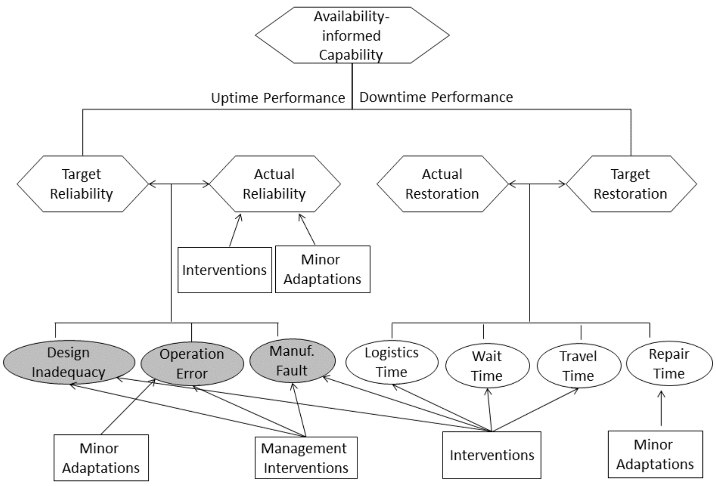

Figure 1. Conceptual model framework of model.

uncertainty epistemic intervention

2.2 *Mathematical Foundations*

We represent uncertainties in our model at the level of the farm subassemblies, such as gearboxes, generators, blades. The combined effects of uncertainties at the subassembly level are then aggregated to the wind farm level through the model structure.

2.2.1 *Failure intensity function*

The failure intensity $\lambda(t)$ is a function of the inherent reliability properties of the subassembly at start of life, $t = 0$, denoted by the hazard rate, $h(t)$, and the modification of these properties through maintenance and other interventions prior to some time, *t*, which can be represented by the virtual age, v_t. Therefore by combining the hazard rate with the virtual age, the failure intensity of the subassembly at time *t* is given by:

$$\lambda(t) = h(v_t), \quad t > 0 \tag{1}$$

2.2.2 *Parametric model for hazard rate*

We assume two classes of subassembly failure mechanism, shock and wearout, which occur in sequential phases. During the first phase shock failures occur at a constant rate, ρ. The second phase relates to wearout which, for the purposes of this paper, we assume to have a Weibull rate, with scale parameter *a* and shape parameter *b*. We assume that the transition between the first and second phases occurs at time *w*. Thus the parametric form of the hazard rate at time *s* is given by:

$$\begin{array}{ll} \rho & \text{if } s \le w \\ \rho + ab(s-w)^{b-1} & \text{if } s > w. \end{array} \tag{2}$$

Extending our reasoning to capture the additional risk due to triggers, we write the hazard rate as:

$$h(v_t) = \tilde{h}(v_t \mid \underline{\theta}) + \sum_{j=1}^{3} X_j(t) h_j(v_t \mid \underline{\theta}_j) \tag{3}$$

where components $h_j(\cdot)$ for $j = 1,2,3$ represent the risk added to the subassembly due to their exposure to triggers and the parameters are represented by $\underline{\theta}$. We assume that triggers cause affected subassemblies to fail more frequently due to shocks and/or age prematurely. We also assume that hazards $\tilde{h}(\cdot)$ and $h_j(\cdot)$ ($j = 1,2,3$) have the same parametric model as in Equation (2). To represent epistemic uncertainty, variables $X_j(t)$ in Equation (3), and also the parameters, are assumed to be uncertain. This allows hazard $h(\cdot)$ to be take alternative formulations, allowing for the possibility of different (epistemic) scenarios.

Triggers can have different properties in terms of the way they impact on subassembly reliability. For example, design inadequacies and manufacturing faults might affect subassemblies from the moment turbines start operating, implying:

$$X_1(t) = X_1,\ \forall t \text{ and } X_2(t) = X_2,\ \forall t \tag{4}$$

Bernoulli distributions with parameters p_1 and p_2 can be used to model the variables $X_1(t)$ and $X_2(t)$ respectively. In contrast, an operational error may manifest itself after a maintenance operation at any time during operational life implying that $X_3(t)$ has again a Bernoulli distribution, but is “switched on” with a given probability after a maintenance action. In the model, design triggers simultaneously impact all turbines, manufacturing triggers impact independently on individual turbines subassemblies, and (maintenance) operational triggers occur independently at each subassembly maintenance event.

2.2.3 *Trigger probabilities*

We discuss a functional relationship that allows us to assess what trigger probabilities we should adopt for a given subassembly class. We assume that the susceptibility of subassemblies to a trigger depends on a number of factors relating to design, operational and environmental characteristics. We call these attributes, denoted by A_i for $i = 1,\ldots,n$, and assign to each one a scale. For example, the chance of a manufacturing fault developing may depend quality control processes applied during manufacturing (i.e. Quality Control), the degree to which novel process principles are used in the manufacturing process (i.e. Process Novelty) and the track record of the manufacturer (i.e. Manufacturer Status) as depicted in Figure 2. Each of these attributes has a number of levels which have been defined in conjunction with domain experts. For example, Manufacturer status has five levels, ranging from a new manufacturer with lack of relevant track record through to an established manufacture with a long positive track record producing a given subassembly.

To assess a trigger probability, the analyst chooses the appropriate level for each attribute that influences the particular trigger. The probability can then be determined by using a log-linear model, viz:

$$p_j(\mathrm{x}_1,\ldots,\mathrm{x}_\mathrm{n}) = q_j r_1^{\mathrm{x}_1-1}\ldots r_n^{\mathrm{x}_\mathrm{n}-1} \tag{5}$$

where x_i is the level of attribute A_j, q_j is the trigger probability for the worst case scenario (i.e. attribute levels are at the minimum) and r_i is the proportion by which the trigger probability changes when A_j moves by one level whilst the levels of A_k for $k \neq j$ remain fixed.

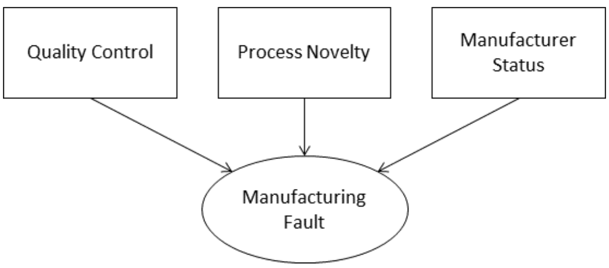

Figure 2. Attributes influencing Manufacturing Fault trigger

2.3 *Quantification and Model Implementation*

Expert judgment is a key source of data especially in relation to the failure process and the quantification of epistemic uncertainties. For example, we need to specify and to determine the values of target variables, such as the baseline probability and risk reduction proportions, which we assume are fixed. The shock rate, wear-out parameters and onset of premature wear-out also require to be assessed. For the epistemically uncertain parameters, such as the onset of aging, we use the whole uncertainty distribution as assessed by experts.

To run our model we also need to specify farm features, such as the number of turbines, rated power, farm layout, time horizon, entry into service times. The details of the maintenance strategy, such as the restoration rates under different degrees of repair, the impact on virtual age, the times and durations of anticipated overhauls, the effect of de-rating on turbine energy output and the characteristics of the logistics operations such as waiting times. Historical experience data can be used, where appropriate, to provide estimates of repair rates and waiting times, conditional on weather. Sources of experience data include Reliawind.

The model has been coded in MATLAB and is implemented as a two-loop Monte Carlo simulation [Bier & Lin, 2013; Wu & Tsang, 2004]. The outer loop determines realizations of the epistemically uncertain parameters, whereas the inner loop is a nested loop that performs iterations given the parameters determined in the outer-loop. This code configuration allows us to distinguish between the epistemic and aleatory uncertainty: variation within the inner loop is linked to aleatory uncertainty whereas variation across the outer loop is a representation of epistemic uncertainty.

3 PROTOCOL FOR EXPERT JUDGEMENT

A formal expert judgment elicitation comprises of the stages of motivating (i.e. establishing rapport between the experts and the analyst), structuring (i.e. clarify the objects and events that are the subjects of the elicitation process), conditioning (i.e. explaining to the experts how to coherently assess their degree of belief), encoding (i.e. obtaining expert assessments) and verifying (i.e. ensuring that the assessments made by the experts reflect their true belief) [Morgan and Henrion, 1990; Merkhofer, 1987; Spetzler and von Holsteins, 1975].

In our protocol, motivating, structuring and conditioning are undertaken during a qualitative stage involving a workshop with the selected experts to identify key uncertainties and to prepare experts for encoding. Encoding of subjective probability assessments are conducted during a follow-up quantitative stage when experts are asked individually to complete questionnaires with questions associated with the parameters associated with epistemic uncertainties. Figure 3 summarizes our protocol.

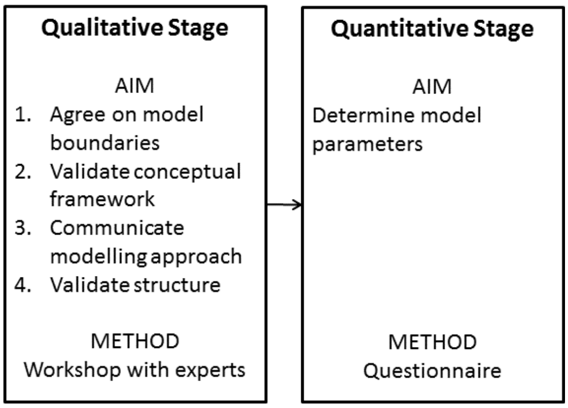

Figure 3. Two-stage expert judgment elicitation protocol.

3.1 *Qualitative Stage*

The aims of the qualitative stage are two-fold: to agree the structure the general model for the specific application; and to identify the key uncertainties relevant to the application. A facilitated, semi-structured workshop provides a suitable mechanism for achieving these aims because it allows experts to share their knowledge and reasons for articulating uncertainties and to be made aware of the issues to consider when expressing their later judgments probabilistically. For example, the potential for biases such as representativeness and anchoring [Tversky, 1974] can be explained to improve the quality of expert assessments. The qualitative stage is extremely important because the insights gained can be used to simplify the model complexity and reduce the requirements from the quantitative stage.

A key workshop activity will be the identification of key subassemblies whose reliability estimates are subject to large or moderate epistemic uncertainty for the farm under consideration. In other words, these are subassemblies that are exposed to triggers and can potentially have a worse than expected reliability. Thus we first identify the key subassemblies and secondly we identify for each key subassembly the relevant failure mechanisms in a typical situation, as expected, or when a trigger is present.

The selection of key subassemblies potentially subject to epistemic uncertainties is done both to reduce the quantitative elicitation burden on experts and to ensure that the computations will run faster. The cost of this is some loss of variance in the overall computed epistemic uncertainty in the model, but it is judged that this is relatively small. Furthermore, the kind of decisions that we wish to consider will be around the subassemblies with larger epistemic uncertainties.

3.2 *Quantitative Stage*

Prior to quantification, the analyst determines the model parameters on the basis of expert judgment gained at the qualitative stage. Typically we might expect to want to elicit probabilities related to the trigger probabilities and the reliability of subassemblies under different scenarios. We choose a questionnaire as the data collection method because it gives experts the time and freedom to consult other sources of information (e.g. past data, event reports, etc), in order to form a probability assessment with which they feel comfortable.

A number of techniques are reported that allow the analyst to associate expert assessments to target variables [Merkhofer, 1987; Meyer & Booker, 1991; Kadane & Wolfson, 1998]. We use the quantile method, according to which experts assess, for example, the 5%, 50% and the 95% quantiles of their uncertainty distribution on the target variable. We subsequently use the classical method with equal weights [Cooke, 1991] to aggregate the expert responses. For epistemically uncertain parameters the output of the elicitation exercise is an uncertainty distribution. For the remaining parameters, the output is a median value. Let us consider two examples in relation to the elicitation of the trigger probabilities and their reliability profiles.

3.2.1 *Eliciting trigger reliability profiles*

The trigger reliability profiles questionnaire supports elicitation of the uncertainty distributions on the parameters of the trigger-induced hazard functions h_j for each key subassembly. The hazard parameters are not directly observable quantities and so it is hard for experts to assess their values. To facilitate elicitation, experts are asked to assess the times by which a certain number of subassemblies in a group behave in a certain way (e.g. fail or exhibit premature wear-out). Responses are subsequently linked to the parameters based on the distributional assumptions made within the model framework (i.e. shocks occur according to an exponential distribution). Table 1 shows an example question relating to the assessment of the times of wear-out onset. Since these are epistemic uncertainties, we elicit three quantiles to determine an uncertainty distribution.

Table 1. Example question on quantile assessment of wear-out onset from trigger reliability profiles questionnaire.

Consider a turbine that operates under normal conditions. Assume that the turbine is affected by a design inadequacy in the gearbox but by no other triggers. The design inadequacy causes the gearbox to age prematurely (over early life).			
After how many months of operation (since installation) will initial signs of degradation be observed?	Lower Value (5%-ile)	Upper Value (95%-ile)	Central Value (50%-ile)

3.2.2 *Eliciting trigger probabilities*

The trigger probabilities questionnaire supports elicitation of the information necessary to determine the parameters of the model given in Equation (5). In effect we are assessing the relative weights of the influencing factors. To determine the parameters, experts are asked to state the median of their individual, internal uncertainty distribution on relative risk reductions. Table 2 provides an example of such a question. Assuming the validity of Equation (5), we can then restrict the number of questions we have to ask of experts, because the impact of a specific factor can be determined by holding the other factors constant. Hence the experts are asked to answer a set of questions in which one factor at a time is changed.

Table 2. Example question from the trigger probabilities questionnaire. *Central value corresponds to the 50% quantile of the expert's uncertainty distribution.*

Suppose that the subassembly has the worst possible configuration across Quality Control, Process Novelty and Manufacturer Status i.e. vector of attribute levels (1, 1, 1) , which means no existing process standards, new manufacturer, no quality control. This configuration results in the highest probability of a manufacturing fault.	
Please provide your assessments of this probability.	Central Value

4 ELICITATION WITH ENERGY EXPERTS

We have worked with a panel of eight experts with experience in wind farm engineering, technology and operations to conduct a formal elicitation following the protocol explained in Section 3. All experts were employed by the same renewable energy company and had many years of experience in the sector or in the relevant technologies. Experts were selected in collaboration with a lead technical specialist to ensure all were suitably qualified to provide probability assessments. The purpose of our study was primarily to trial our elicitation process and to challenge our modelling approach. Hence the wind farm under consideration was a typical UK Round III Offshore Wind Farm.

4.1 *Workshop Insights*

We found that it was very important to carefully explain the difference between state-of-knowledge uncertainty and the aleatory uncertainties associated to lifetimes of the subassemblies: our experience was that after some initial confusion the experts quickly understood. It was the explanations of epistemic uncertainties as arising through triggers that helped to create this understanding.

Figure 4 shows the set of key subassemblies and the triggers to which they are believed to be susceptible as elicited during the workshop. This diagram is particularly important because it illustrates where the experts believe there is no significant epistemic uncertainty arising from the triggers. This qualitative step therefore justifies a simplification in modelling.

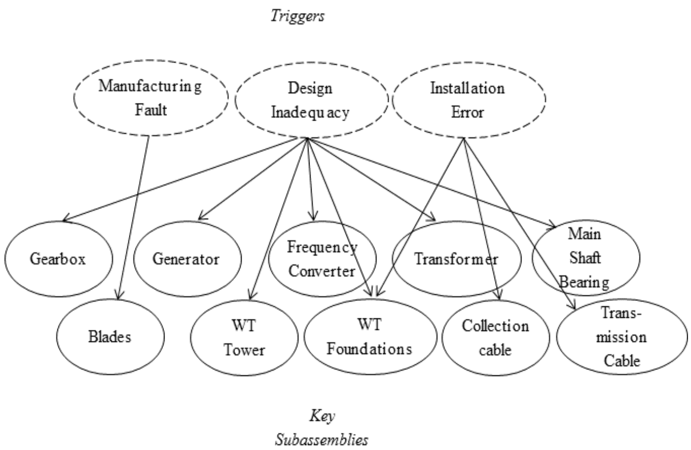

Figure 4. Illustrative output of qualitative elicitation stage.

subassemblies triggers susceptibility

4.2 *Quantitative Expert Subjective Assessments*

Quantitative elicitation used the two questionnaires on reliability profiles and trigger probabilities. The former was used to determine the form of the hazard when the trigger is present, and the latter was used to assess the weights in the trigger model.

For example, each expert in our panel provided their own subjective probability assessment of the number of months of operation, since installation, will initial signs of degradation be observed for a type of turbine affected by a design inadequacy in the gearbox but by no other triggers; the example question shown in Table 1. On analysis of the elicited judgmental data we found that a lognormal distribution gave the best fit on the distributions aggregated across experts.

Figure 5 shows the hazard rate, $h(v_t)$ computed from Equation (3), for the population of gearboxes affected by a design inadequacy, consistent with the questionnaire data collected. During the first months of operation, the hazard rate decreases due to infant mortality failures but then the hazard rate levels out. Since design inadequacy issues cause gearboxes to age prematurely, the first signs of ageing start as early as after 100 operating months.

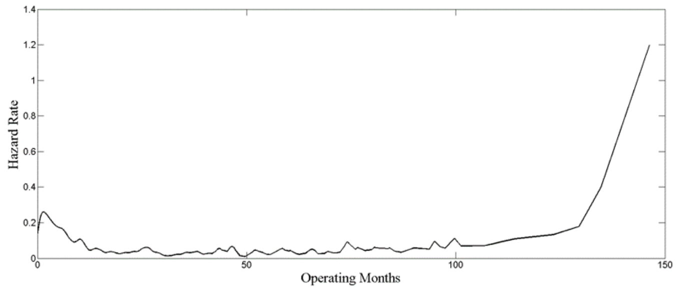

Figure 5. Hazard rate of gearboxes affected by a design inadequacy consistent with the elicited judgments of expert panel.

Our expert panel also provided individual probability judgments about the chance of each of the trigger probabilities such as a manufacturing fault for a subassembly produced by a new manufacturer who had not employed process standards and not used any form of quality control. That is, a worst case scenario as shown in Table 2.

By using the aggregated probability assessments of the expert panel for each trigger scenario within the model given in Equation (5), we can obtain the relative risk reduction of each attribute as illustrated in the bar chart in Figure 6. Interpreting the relative risks we find that improving the configuration of a subassembly across Manufacturer Status from new manufacturer (i.e. worst level) to established manufacturer (i.e. best level) will be reduced to 40% of its original value. The bar chart shows that Manufacturer Status is the most important attribute in terms of exposing the subassembly to the trigger and, in the context of our data for this application, Quality Control of the least important attribute.

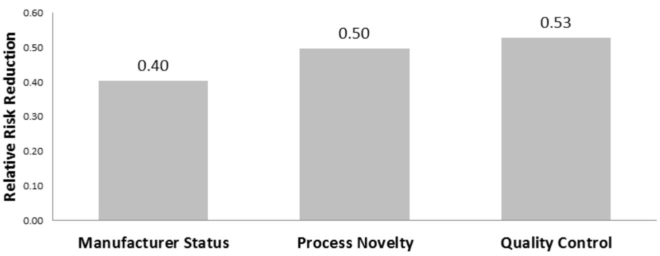

Figure 6. Relative risk reduction achieved by moving each attribute affecting the Manufacturing Fault trigger from the best to the worst level configuration, whilst the other attributes remain fixed to a mid-level.

5 EXAMPLE MODELLING OF EPISTEMIC UNCERTAINTY ON FARM AVAILABILITY

To illustrate how the expert judgment elicited from our panel of experts for a typical UK Round III wind farm might be used within our availability informed capability model depicted in Figure 1 and explained in Section 2, let us consider the following example situation.

Our interest lies in assessing the early-life technical performance of the large-scale offshore wind farm at a pre-construction stage. The farm comprises 100 5MW turbines of a new design and its target performance is 97% availability. The turbines will be subject to both corrective and preventive maintenance, and the effect of maintenance is expected to vary from perfect to imperfect, depending on the type of failure and maintenance action. The maintenance strategy setting is similar to the one considered in [Zitrou et al, 2013].

Each turbine has the key subassemblies shown in Figure 4 and these represent the subassemblies likely to have large or moderate epistemic uncertainties in their reliability estimates. We also create a further generic subassembly category that collectively represents the other non-key subassemblies for which it is anticipated to have small epistemic uncertainties in their reliability estimates. We assume that this generic subassembly will be subject to shock failures only over early life and will achieve target reliability.

Using Equation (5) we can determine the exposure of key subassemblies to triggers. Specifically, we assume that gearboxes are the main source of epistemic risk, with a design inadequacy probability as high as 0.8. The generator follows with a 0.5 probability of a design inadequacy, whereas blades have a 50% chance of having manufacturing faults.

As well as populating our availability model using the elicited expert judgment from our panel, we also used sources such as Reliawind (REF) to provide generic data for this example. We make additional assumptions about the timing of major interventions to address the realization of weaknesses that trigger a drop in reliability to illustrate their effect on availability estimates and their uncertainties. We have run the Matlab model as a simulation with 50 outer-loop (i.e. epistemic uncertainties) and 50 inner-loop iterations (i.e. aleatory uncertainties).

5.1 *Selected Results*

Figure 7 shows weekly farm availability-informed capability during early life when the simulation results across all 2500 iterations are combined. The output is summarized in terms of the median weekly capability, together with the 5% and 95% quantiles. These uncertainty bounds represent a mix of epistemic and aleatory uncertainties. Farm performance appears to deteriorate over the first two years dropping to near 85% in the worst case around year 2. Major innovations to replace the original gearboxes which possess a design inadequacy being in year 2 allow farm performance to gradually reach the target levels, close to 97%.

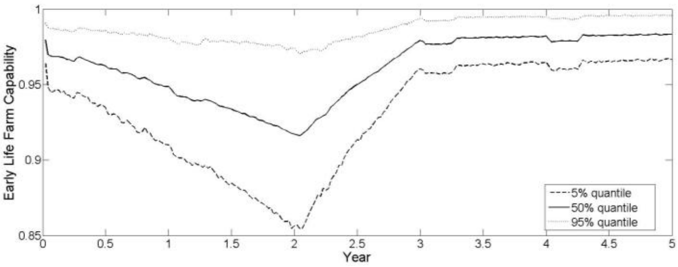

Figure 6. Estimated weekly farm availability-informed capability with 95% combined epistemic and aleatory uncertainties from simulation model of example scenario.

We can focus on the effect of epistemic uncertainty only by calculating the mean farm availability averaged over the whole early life from the inner-loop iterations of the model. Figure 7 shows the empirical probability distribution of this mean. The variance of this distribution is a representation of the effect of epistemic uncertainty.

Now, suppose that extensive testing can reduce the chance of design inadequacy in gearboxes to 15%. This value has been obtained by modulating the Field Testing attribute from the worst to the best level and is, thus, consistent with Equation (5). Our model can then provide insight into the impact of this decision on farm performance and, at the same time, on our ability to assess this at a pre-construction stage. Figure 8 compares the distributions of the mean early-life farm availability-informed capability under the two decision scenarios: with and without field testing. Our outputs suggest that, in the worst case scenario, the mean farm capability might drop to 95% if no field testing is undertaken. However, if field testing is undertaken, this capability will increase to 96%.

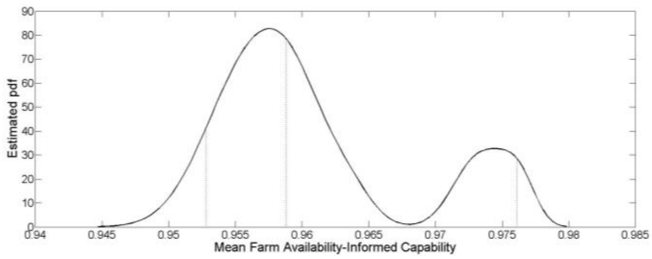

Figure 7. Epistemic probability distribution function on the mean farm availability-informed capability averaged over first 5 years of operation.

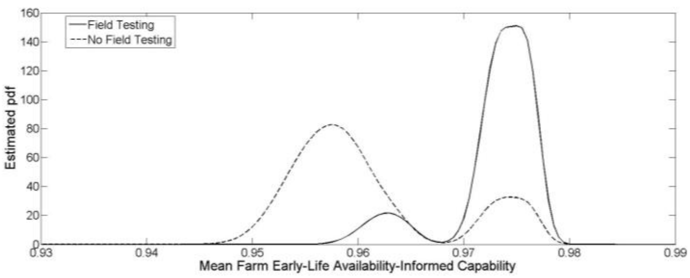

Figure 8. Epistemic probability distribution function on the mean farm capability averaged over first 5 years of operation under the two decision scenarios with and without field testing.

6 CONCLUSIONS

New offshore wind farms deploy novel large-scale and complex technology. Such high degree of innovation brings the potential for systemic weaknesses in, for example, design, manufacturing and operational processes. As farms accumulate experience such weaknesses should be resolved, although most likely at the cost of additional investment. Our goal is to support pre-construction stage modelling to capture our state-of-knowledge uncertainties so that we might better understand systemic technology risks and make good decisions to buy down these uncertainties in a timely manner.

Throughout our research we have worked with engineering experts with experience with the offshore wind technology, environment and business to ground our model in the real decision-making context. In this article we focus on the role played by a panel of experts from a particular company to provide judgments about their epistemic uncertainties on selected variables and parameters. Through their engagement our experts also played a role in validating our model structure and allowing us to test our expert judgment elicitation protocol.

In this paper we have presented elements of our mathematical model relevant to the representation of epistemic uncertainty and show how the model can be used with the expert judgment elicited from the panel of engineers from the company. We have sought to explain the rationale for our elicitation protocol and provide insight into elements of the judgmental data collected and its analysis.

Our model requires further validation study to mature our framework for practical implementation. Equally there are technical improvements required for the simulation model to speed computation, for which either parallelization of the code, or use of statistical code emulators, may provide useful approaches. Also, we have designed the modelling software in a modular manner so that the richness of the set of, for example, degradation models and so on, can be increased beyond those already reported.

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