

# A MULTI-OBJECTIVE FRAMEWORK FOR THE OPTIMIZATION OF LIFE-CYCLE COSTS OF WIND TURBINES

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## ABSTRACT

Multi-objective optimization of the life-cycle costs and reliability of offshore wind turbines (WTs) is an area of immense interest due to the widespread increase in wind power generation across the world. Though there has been significant research done in this field for structures such as bridges and offshore oil and gas platforms, less research has been conducted for the costs and reliability optimization of offshore WTs. Most of the existing studies have addressed the conjunction of structural reliability and the Bayesian pre-posterior analysis for multi-objective optimization. This paper proposes an extension of the previous approaches as a novel framework for multi-objective probabilistic optimization of the total life-cycle costs and reliability of WTs by combining the elements of structural reliability analysis, Bayesian pre-posterior analysis with neuro-fuzzy and evolutionary algorithms. The output of this framework would determine the optimal inspection, monitoring and maintenance schedules to be conducted during the life span of the offshore WTs while maintaining a trade-off between the life-cycle costs and reliability of the structure.

## NOMENCLATURE

$\alpha$	Location parameter of monitoring method damage detection performance
$\beta$	Scale parameter of monitoring method damage detection performance
$\theta$	True state of structure
$\lambda$	Scale parameter of deterioration model
$\Phi(\cdot)$	Standard normal cumulative distribution function
$d^*$	Structure failure threshold
$t_0$	Initial damage occurrence time
$C_f$	Cost of failure
$C_{prior}$	Expected monetary cost under prior information
$C_r$	Cost of repair action
$D_0$	No damage occurrence
$D_1$	Damage occurrence
$De_0$	Damage not detected
$De_1$	Damage detected
$D_{min}$	Minimum detectable damage severity
$D_{th}$	Damage threshold
$F_0$	No failure
$F_1$	Failure
$M_0$	No monitoring adopted
$M_1$	Monitoring adopted
$P(D_1)$	Probability of damage occurrence
$R_0$	No repair action
$R_1$	Repair action

## 1. INTRODUCTION

The generation of renewable wind energy through development of offshore wind farms is increasing at a tremendous rate owing to its nature-friendly and green characteristics. However, the production of the wind energy entails high life-cycle costs. The deterioration of wind turbine (WT) structural condition is a critical issue and needs to be addressed through regular operation and maintenance (O&M) schedules. Appropriate inspections or the use of structural health monitoring (SHM) techniques can greatly assist O&M, but come at a cost. It is thus necessary to use optimal decision-making approaches to plan inspection/monitoring schedules in such a way that there is a favourable trade-off between the total life-cycle costs and reliability of the WTs.

There has been significant research performed in the field of life-cycle cost optimization of different structures such as bridges, and offshore oil and gas platforms. Generalized probabilistic frameworks were developed that included structural reliability analysis and multi-objective optimization, using evolutionary algorithms of several indicator functions such as the cost, reliability, service life, optimal inspection and maintenance schedules through construction of decision trees and event trees [1-7].

The Bayesian pre-posterior analysis for making decisions through the construction of decision tree, along with the inclusion of stochastic models for

deterioration and damage detection is a popular approach [8, 9]. The concept of Value of Information (VoI) of installing a monitoring system has been widely studied over the recent years [10-13]. The VoI provides a method to quantify the benefits of performing an experiment such as inspection or monitoring [14]. Several studies have been conducted for offshore WT that performed detailed reliability analysis and reliability-based optimization of WTs [15], proposed a framework of optimization of operation and maintenance schedules using Bayesian pre-posterior analysis [16] and Markov chain deterioration process [17, 18].

Adaptive network-based fuzzy inference system (ANFIS) is a type of neuro-fuzzy system that combines the best features of the fuzzy logic and artificial neural networks. ANFIS is gaining interest due to its versatility and computational efficiency. Petkovic et al. [19] recently used ANFIS for the optimization of wind power efficiency. Another recent application is an optimization of layout of a wind farm to obtain optimal net profit of the project [20]. However, it should be noted that, till date, no research has been conducted on life-cycle costs, reliability and O&M schedule optimization of WTs using ANFIS.

This paper proposes a novel framework for multi-objective probabilistic optimization of the total life-cycle costs and reliability of WTs by combining the elements of structural reliability analysis (SRA), Bayesian pre-posterior analysis with ANFIS and evolutionary algorithms such as genetic algorithm (GA). The output of such a framework would provide the optimal operation and maintenance schedules to be implemented over the design life of a WT. The novelty of the proposed framework is such that there is no current framework that integrates all the aforementioned elements for the optimization of life-cycle costs and reliability of WTs. The next section describes the detailed probabilistic optimization framework. A simplified model of the framework is illustrated in the subsequent sections, followed by conclusions.

## 2. O&M OPTIMIZATION FRAMEWORK

The detailed framework for optimization of the life-cycle costs and O&M schedules is outlined in this section. The proposed framework integrates a deterioration model, a damage detection model, a cost model through the construction of a decision tree using the Bayesian pre-posterior analysis and a hybrid optimization algorithm such as joint ANFIS-GA approach. The detailed methodology of the proposed framework is outlined in Figure 1.

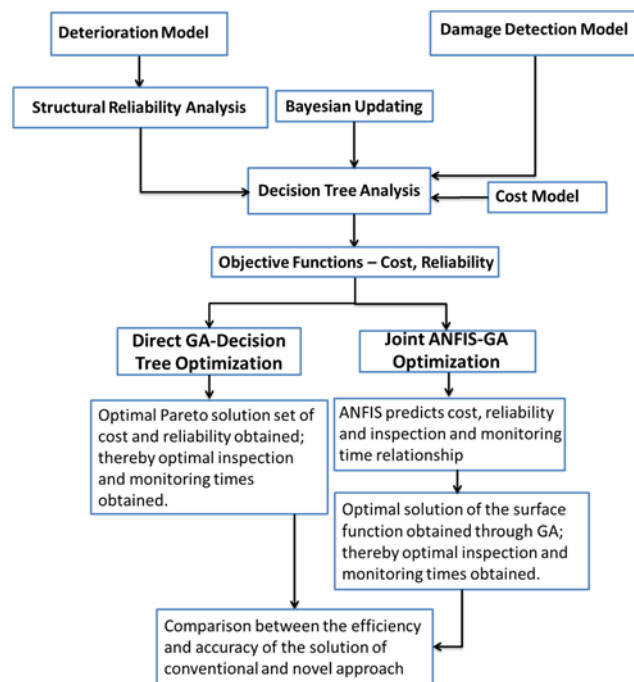


Figure 1 Detailed optimization framework

Detailed deterioration modelling is performed to include the main deterioration mechanism of fatigue. The different types of loads acting on a WT structure are considered. Deterioration and load model uncertainties are also included. A detailed monitoring or inspection method efficiency modelling is also necessary to incorporate errors associated with damage detection by the inspection/monitoring method. The SRA techniques are adopted to compute the probabilities of failure and damage occurrence associated with the deterioration model. The probabilities are used in the decision tree and are updated using Bayesian analysis.

Using a decision tree, it is possible to calculate objective functions such as cost and reliability. In the final stage, multi-objective optimization techniques are performed to obtain Pareto solutions of the objective functions. Two methods for the

optimization of conflicting objective functions are proposed in this research. The first approach, direct GA-decision tree optimization, uses the conventional method of optimization that encompasses GA performed directly on the decision tree, which has been used frequently in the literature as a preferred method of optimization for obtaining the optimal operation and maintenance schedules [6, 7, 21].

The second approach, referred to as joint ANFIS-GA optimization, proposes a novel method of introducing an ANFIS system prior to the optimization using a GA. ANFIS is proposed in the project since it is a hybrid intelligent system that could learn and adapt from the input data obtained through the decision tree analysis and is an alternative to performing GA directly on the decision tree which needs the decision tree to be run significantly more times.

## 2.1 DIRECT GA-DECISION TREE APPROACH

The steps involved in the conventional direct GA-decision tree optimization are outlined in this subsection. The first step involves the deterioration model that will calculate the time-dependent probabilities of damage occurrence and failure by using structural and material properties and the loads as inputs. The conditional probabilities of detecting or not detecting a damage given it actually occurred or not using the quality of the monitoring/inspection method is modelled in the damage detection model. The errors associated with a monitoring/inspection method are included within this model.

The time-dependent probabilities of damage occurrence and detection obtained from the first step are fed into the decision tree and updated using the Bayesian pre-posterior analysis. The objective functions for costs and reliability are calculated from the decision tree. The independent variables for the total cost are the discount rate of money, inspection/monitoring time intervals and individual costs of the initial installation of a WT, repair and failure, and for reliability, the independent variables are the loads, material parameters, inspection/monitoring time intervals, time of damage occurrence and failure.

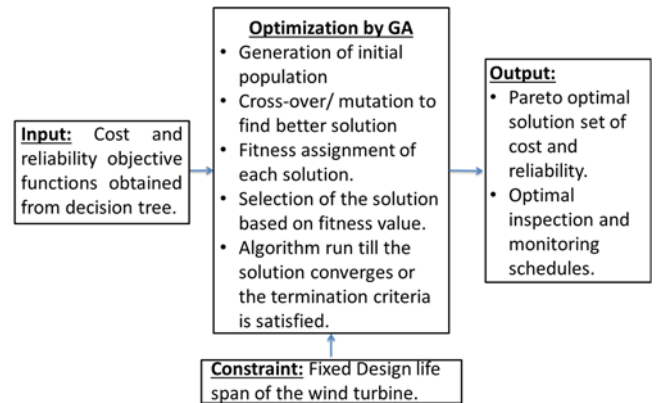


Figure 2 Direct GA-decision tree approach

The objective functions obtained from the previous steps are used as inputs to run a GA to obtain the Pareto optimal set of cost and reliability solutions to find the trade-off between the two conflicting objective functions as outlined in Figure 2. The fixed design life span of the WT structure will act as the termination criterion or the constraint for the optimization algorithm. The various steps involved in the optimization by GA are also provided in the flow chart. The solution of the conventional GA approach for optimization will give information regarding the inspection or monitoring time intervals to be carried out within the design life span.

## 2.2 JOINT ANFIS-GA APPROACH

The initial steps involved in the joint ANFIS-GA approach are similar to the direct GA-decision tree approach till the formulation of the objective functions for cost and reliability of WTs.

Using the inputs (inspection/monitoring time intervals and reliability) and the outputs (cost), an ANFIS system is trained which predicts the relationship between the inputs and output. An approximation of the target response function of cost, reliability and inspection/monitoring time intervals are obtained from the ANFIS. The structure of the ANFIS system is outlined in Figure 3.

The target surface function obtained in the previous step is minimized using a GA to find the optimal Pareto solution set of cost and reliability as outlined in Figure 3. The solution of both the conventional and novel approaches for optimization will give

information regarding the inspection or monitoring time intervals to be carried out within the design life span to achieve the optimal cost and reliability. The solution sets obtained from both approaches for optimization can be compared to verify the efficiency and accuracy of each method.

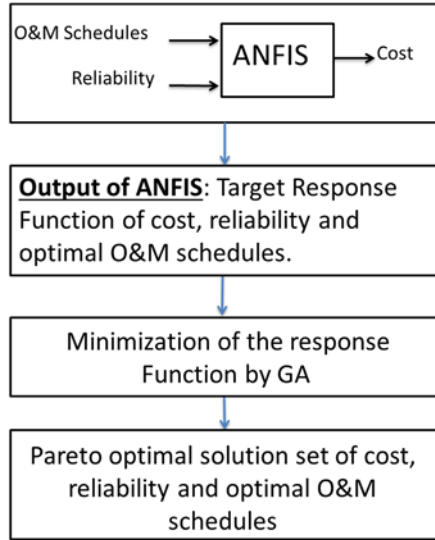


Figure 3 Joint ANFIS-GA optimization

### 3. DECISION-MAKING MODEL

The methodology explained in Section 2 is illustrated in this section with an example of quantifying the value of SHM. This example aims to quantify the benefits of installing or adopting a monitoring scheme for the design life of WTs and also aims to illustrate the use of a structural deterioration model, damage detection model and cost model in conjunction with the pre-posterior decision analysis where the decisions need to be made to adopt or not adopt a monitoring scheme, the outcome of monitoring is detection or non-detection of damage, the decision rule is used to perform repair actions or not based on the damage detection outcome, and the true state of the nature represents the state of the system. We refer in our discussions to ‘monitoring scheme’ but the same process can be applied easily to ‘inspection scheme’. The outcome of this process will determine the VoI from an SHM method.

A decision tree is formulated as presented in Figure 4. Let  $M_0$  and  $M_1$  represent the decision to not adopt a monitoring method and adopt it, respectively,  $De_0$  and  $De_1$  be the event of not detecting and detecting a damage (corresponding to an outcome of

monitoring),  $R_0$  and  $R_1$  represent the decision to not repair or repair (corresponding to a decision rule),  $D_0$  and  $D_1$  denote no occurrence or occurrence of damage, and  $F_0$  and  $F_1$  denote no failure or failure of the structure (corresponding to the true state of nature).

The random outcomes or states of nature are the occurrence of the damage and further consequences such as failure of the structure are represented in Nodes 12-15 of the decision tree. In the alternative top branch corresponding to installing a monitoring scheme ( $M_1$ ), the decision will lead to a monitoring detection outcome (Node 11) that may subsequently lead to performing repair actions (Node 5 and 10). The true states of nature (damage and failure) are represented in Nodes 1-4 and 6-9. The probabilities of damage being present given the detection outcome are updated using the Bayes theorem [22].

#### 3.1 DETERIORATION MODEL

While a detailed modelling of fatigue deterioration process is planned for further studies, a simple, generic model is adopted here from [6] as shown below:

$$D_1(t) = 0 \quad \text{for } t < t_0 \quad (1)$$

$$D_1(t) = e^{(t-t_0)/\lambda-1} \quad \text{for } t \geq t_0 \quad (2)$$

$D_1$  is the damage intensity,  $\lambda$  is the scale parameter and  $t_0$  is the initial damage occurrence time in years. Structural reliability methods such as FORM, SORM and simulation techniques are generally adopted to find the reliability profile of deteriorating structures based on the above equations. The FORM methods in STRUREL [23] software are used herein to calculate the damage occurrence due to deterioration. The probability of damage,  $P(D_1)$ , exceeding a certain damage threshold,  $D_{th}$ , can be defined as:

$$P(D_1) = P[D_1(t) \geq D_{th}] \quad (3)$$

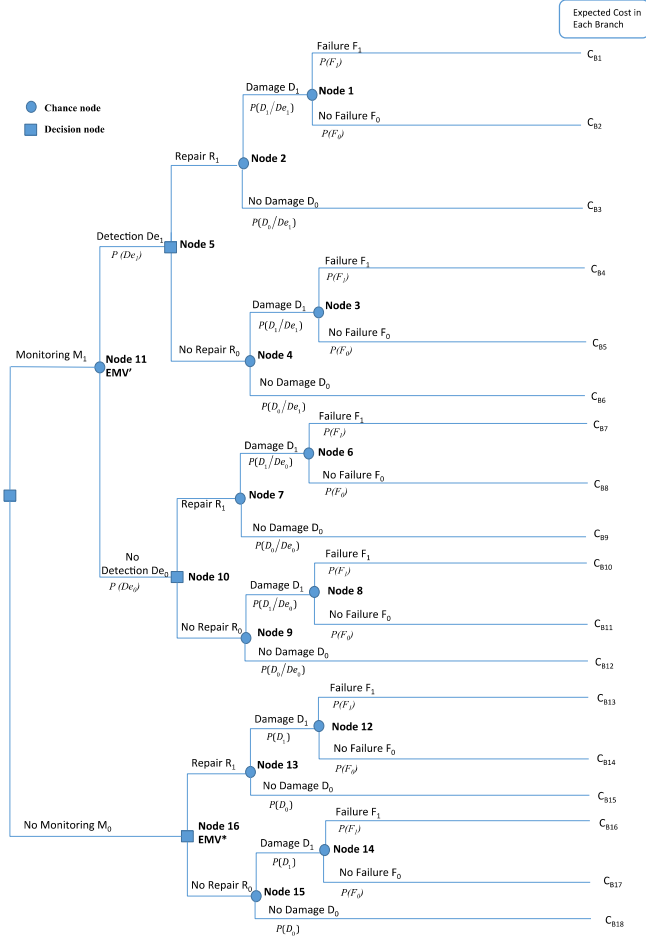


Figure 4 Decision tree for a monitoring scheme

To obtain a comprehensive probability of damage distribution, it is required to consider a range of threshold values for  $D_{th}$  from 0 to 1. The cumulative probability distribution function of the damage occurrence is calculated by solving Equation (3) for a range of threshold values for  $D_{th}$  from 0 to 1. By differentiating Equation (3), the probability distribution function of the damage occurrence can be estimated as

$$p(D_1) = \frac{dP[D_1(t) \geq D_{th}]}{dD_{th}} \quad (4)$$

where  $p(D_1)$  represents the probability density function of the damage occurrence. However, in the initial phase of this framework, a single value for  $D_{th}$  is considered.

### 3.2 DAMAGE DETECTION MODEL

The uncertainties associated with the ability of a monitoring technique to detect damage can be expressed using probabilistic approaches e.g. using

the probability of detection (POD) curves. An example of a POD curve of a monitoring method is presented in Figure 5. The POD curves represent the probability of damage being detected by a monitoring method conditional on its extent (e.g. crack length or defect depth). It is normally an ‘S-shaped’ curve that increases with the increase in damage intensity.

In this report, the conditional probability of damage detection given it actually occurred,  $P(De_1|D_1)$ , is modelled using a cumulative log-normal distribution function, which is widely used and can be expressed as [6]:

$$P = \begin{cases} 0 & \text{for } 0 \leq D_1 \leq D_{\min} \\ 1 - \Phi \left[ \frac{\ln(D_1) - \ln(\alpha)}{\beta} \right] & \text{for } D_{\min} < D_1 \end{cases} \quad (5)$$

where  $\Phi(\cdot)$  is the standard normal cumulative distribution function, and  $\alpha$  and  $\beta$  are the location and scale parameters, respectively, associated with the quality of the monitoring method. These parameters are the intercept and slope of the linear transformation of the POD function, which in turn signifies the ability of a monitoring method to detect damage [24]. A comparison between POD curves of different monitoring methods with different parameters of quality ( $\alpha=0.1, 0.3$  and  $0.5$ , and  $\beta=-0.21, -0.12$  and  $-0.07$ , respectively) is presented in Figure 5.

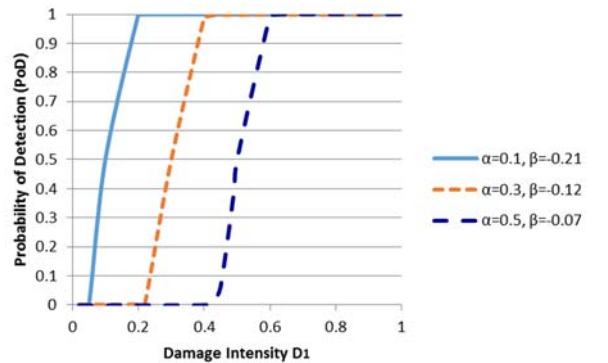


Figure 5 POD curves of different monitoring methods

As seen from the figure, monitoring methods with lower  $\alpha$  and  $\beta$  represent higher quality as they detect smaller damage extents. The minimum damage intensity,  $D_{\min}$ , which can be detected by a monitoring method, is assumed to be the damage intensity when the POD is 0.001 [6].

The incidents of false indications will arise for any monitoring method adopted. The conditional probabilities of not detecting or detecting damage given the absence or presence of damage are expressed as  $P(De_{0/1}/D_{0/1})$  (see Table 1). True positive values are the probability values of detecting damage when there exists actual damage. True negative values correspond to the probability of not detecting damage when there is no actual damage. False negative values correspond to Type 1 errors when damage detection is missed when there exists actual damage. False positive values are Type II errors, which arise from detection outcomes when there is no actual damage.

**Table 1 True and false indications of a monitoring method**

	<b>De<sub>0</sub> (No Detection)</b>	<b>De<sub>1</sub> (Detection)</b>
<b>D<sub>0</sub> (No Damage)</b>	True Negative: $P(De_0/D_0)$	False Positive: $P(De_1/D_0)$
<b>D<sub>1</sub> (Damage)</b>	False Negative: $P(De_0/D_1)$	True Positive: $P(De_1/D_1)$

A theoretical schematic representation of the different scenarios of damage detection by a monitoring method is represented in Figure 6. A decision threshold is shown that acts as an acceptance criterion for damage detection such that the values to the right/left of the threshold will produce Type I/II errors [25, 26]. However, in the initial phase of this project, it is assumed that both Type I/II errors have the same probabilities.

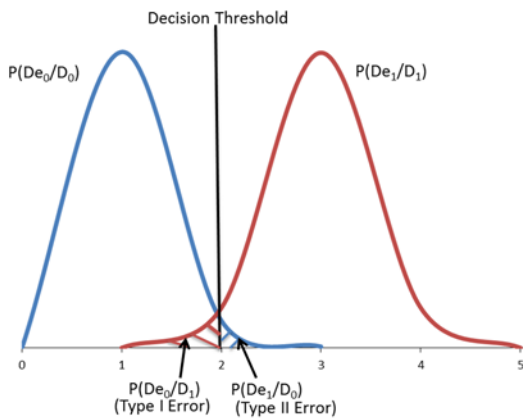


Figure 6 Theoretical representation of detection by a monitoring method [25, 26]

The posterior probabilities of damage occurrence are calculated using Bayes theorem [22]:

$$P(D_0/De_0) = \frac{P(De_0/D_0)P(D_0)}{P(De_0/D_0)P(D_0) + P(De_0/D_1)P(D_1)} \quad (6)$$

$$P(D_0/De_1) = \frac{P(De_1/D_0)P(D_0)}{P(De_1/D_0)P(D_0) + P(De_1/D_1)P(D_1)} \quad (7)$$

$$P(D_1/De_0) = \frac{P(De_0/D_1)P(D_1)}{P(De_0/D_0)P(D_0) + P(De_0/D_1)P(D_1)} \quad (8)$$

$$P(D_1/De_1) = \frac{P(De_1/D_1)P(D_1)}{P(De_1/D_0)P(D_0) + P(De_1/D_1)P(D_1)} \quad (9)$$

The updated probabilities are used to calculate the VoI of the adopted monitoring method as described in the next subsection.

### 3.3 ESTIMATION OF VALUE OF INFORMATION FROM SHM

The concept of VoI has been widely examined in the field of structural engineering [10, 13, 27, 28]. Pozzi and der Kiureghian [28] have outlined a procedure for the assessment of VoI, which is further explored in this paper. Under prior information, when there are no monitoring schemes adopted, the expected cost can be calculated as [28]:

$$C_{prior} = \min(C_r, P(D_1) \times C_f) \quad (10)$$

where  $C_r$  is the cost of repair and  $C_f$  is the cost of structural failure. Once a hypothetical perfect monitoring method is adopted (i.e. one that does not suffer from Type I or II errors), the expected cost of using the perfect monitoring method,  $C_{perfect}$ , will be:

$$C_{perfect} = P(D_1) \times C_r \quad (11)$$

Therefore, the VoI of the perfect monitoring method is calculated as:

$$VoI_{perfect} = C_{prior} - C_{perfect} \quad (12)$$

However, in reality, the monitoring methods are imperfect with errors associated with detection as discussed in Section 3.2. The probability of damage can be updated using Bayes theorem as outlined in equations (6)-(9). Given a specific monitoring

detection outcome, the expected costs are now calculated as:

$$C_{De_1} = \min(C_r, P(D_1/De_1) \times C_f) \quad (13)$$

$$C_{De_0} = \min(C_r, P(D_1/De_0) \times C_f) \quad (14)$$

The expected cost of using an imperfect monitoring method is calculated as:

$$C_{imperfect} = C_{De_1} \times P(De_1) + C_{De_0} \times P(De_0) \quad (15)$$

The VoI of the imperfect test is evaluated as:

$$VoI_{imperfect} = C_{prior} - C_{imperfect} \quad (16)$$

A numerical illustration for estimating the VoI using the deterioration and damage detection models described in Sections 3.1-3.2 are explained in the next section.

#### 4. NUMERICAL ILLUSTRATION

A general framework was developed that can be applied to any component of the WT as described in previous section but for illustrative purposes, this framework uses a generic deterioration model that can be applied on any structural component of a WT to find the VoI with an assumption of adopting monitoring or inspection only once over the entire design life.

The structure is assumed to be deteriorating with time as modelled in Equations (1)-(2). The stochastic deterioration data is assumed after literature [6] with  $\lambda$ , the scale parameter, following a lognormal distribution with a mean of 50 and standard deviation of 10, and  $t_0$ , the initial damage occurrence time, with a lognormal distribution with a mean and standard deviation of 3 years and 1 year, respectively. The probability density functions and the simulations of the random variables  $\lambda$  and  $t_0$  are shown in Figure 7 and Figure 8, respectively.

The input parameters for the POD function are  $\alpha=0.1$  which implies a high quality of the monitoring method such that it detects smaller damage intensities, and  $\beta$  is assumed to take the value of  $0.1\ln(\alpha)$  [6]. The minimum detectable

damage threshold,  $D_{min}$ , is defined as damage intensity at POD of 0.001 [6].

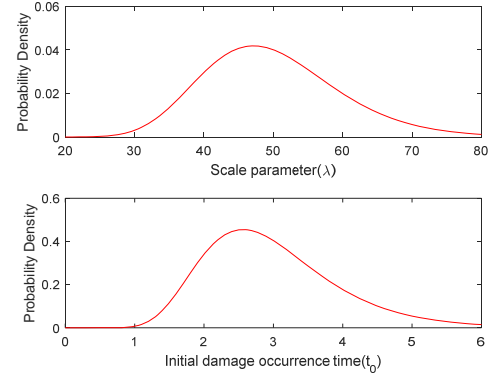


Figure 7 Probability density functions of the random variables  $\lambda$  and  $t_0$

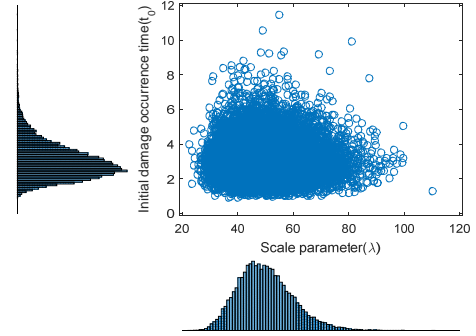


Figure 8 Monte Carlo simulations of the random variables  $\lambda$  and  $t_0$

From Figure 5, for  $\alpha=0.1$ , the minimum detectability value,  $D_{min}$ , is found to be 0.05. A value of  $D_I$  of 0.405 is assumed for the numerical illustration. Using Equation (5), the results are obtained as shown in Table 2.

**Table 2 Probabilities of true and false indications by adopted monitoring method ( $\alpha=0.1, \beta=0.1\ln(\alpha)$ )**

	De <sub>0</sub> (No Detection)	De <sub>1</sub> (Detection)
D <sub>0</sub> (No Damage)	$P(De_0/D_0)$ = 0.99999	$P(De_1/D_0)$ = $6.22 \times 10^{-10}$
D <sub>1</sub> (Damage)	$P(De_0/D_1)$ = $6.22 \times 10^{-10}$	$P(De_1/D_1)$ = 0.99999

The time-dependent probability of damage occurrence,  $P(D_I)$ , is calculated in STRUREL for different times by formulating the limit state function by considering the occurrence of damage greater than  $D_{th}$  of 0.1 as follows:

$$P(D_1) = P[1.1 - e^{(t-t_0)/\lambda} \leq 0] \quad (17)$$

The solution of the above equation is presented in Figure 9.

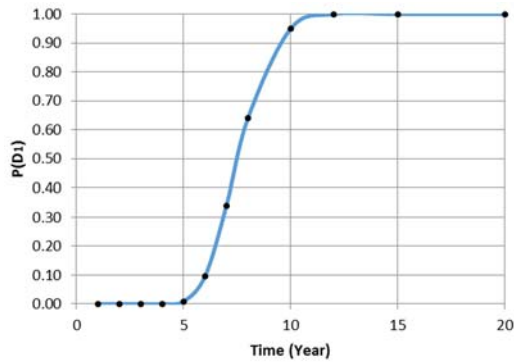


Figure 9 Probability of damage occurrence at different times (year)

As an illustration, the probabilities at the 6<sup>th</sup> year are demonstrated. It can be seen, from the above figure, that the probability of damage occurrence at  $t=6$  years is 0.0959. Using the Bayes' theorem as outlined in Equations (6)-(9), the posterior probabilities are computed in the Table 3.

Table 3 Posterior probabilities at 6<sup>th</sup> year

Posterior Probabilities	
$P(D_1 De_0)=$ 0.00011	$P(D_1 De_1)=$ 0.991

Using Equations (10)-(16), and the input values of  $C_f = \text{£}10,000$  and  $C_r = \text{£}1,000$ , the VoI of the imperfect and perfect monitoring method adopted once in the entire design life of the structure is outlined in Figure 10.

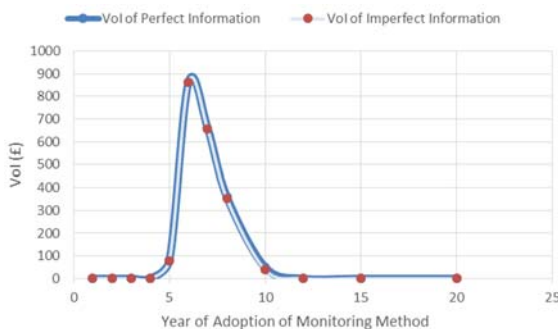


Figure 10 VoI of perfect and imperfect information

Different cases of the cost of failure are now considered to determine the VoI of the imperfect monitoring method. The cost of failure is varied to compute the VoI of imperfect monitoring method adopted at the 6<sup>th</sup> year as shown in Figure 11. Different monitoring methods with different qualities as described in Section 3.2 are also

considered. The different failure costs used in the calculations are given in Table 4. The results of VoI for different scenarios are displayed in Figure 11.

Table 4 Ranges for cost of failure [29]

Class	Cost of failure (£)
A	300,000
B	100,000
C	50,000
D	10,000
E	5,000
F	1,000
G	500
H	100

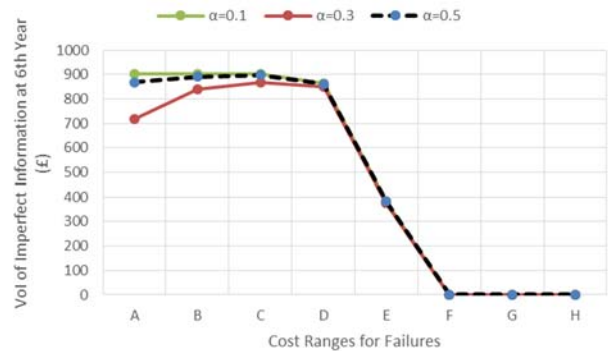


Figure 11 VoI estimated for different scenarios

It can be seen in Figure 11 that the VoI differs with the selection of different failure costs while the VoI varies only slightly for different monitoring methods. The VoI is higher for larger costs of failure. The estimation of VoI helps the decision maker to assess the benefits of installing a monitoring method and also the cost to be paid to obtain the information. VoI determines the maximum cost of inspection/monitoring that still delivers positive net value.

## 5. CONCLUSIONS

A framework for multi-objective optimization of life-cycle costs and reliability of offshore wind turbines has been developed. The framework uses structural reliability analysis of a deterioration model and a damage detection model along with Bayesian pre-posterior analysis. The decision tree is constructed to visualize the set of alternative actions and true states of nature. The framework introduces the novel use of joint ANFIS-GA approach for multi-objective optimization of the



cost and reliability of WTs, which can be computationally more efficient than the conventional direct GA-decision tree approach. A numerical illustration for estimating the VoI of adopting a monitoring method during the design life of a wind turbine has been outlined. Future research will involve the application of this framework in wind turbine support foundation structures.

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