14th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP14
Dublin, Ireland, July 9-13, 2023

Evaluating SHM/Inspection Benefits for an Innovative Offshore Substation

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ABSTRACT:

Offshore wind energy is crucial to reducing CO2 levels by 2050, but visual constraints require the use of Floating Offshore Sub-Stations (FOSS), a new concept in the sector. Due to the harsh environment, FOSS systems have higher failure rates and more uncertainty. Structural health monitoring (SHM) and inspections can reduce costs and uncertainty in decision-making. Choosing the best SHM/inspection strategy is vital, and the value of information (VoI) concept can help rank and confirm their usefulness. This paper proposes a time-dependent VoI approach to assess the benefits of SHM/inspections for innovative FOSS.

1. INTRODUCTION

Reducing greenhouse emissions, especially CO2, is a critical priority in addressing global warming and its consequences. To achieve this goal, there is a need to develop greener methods of energy harvesting, such as wind, tidal, and solar power. Of these, wind energy has been the most widely used source, given the technology's maturity and wind source availability. However, offshore winds are steadier and faster, and the development of offshore wind farms has gained significant attention in recent years (Tuy et al., 2022; Li et al., 2022).

A Floating Offshore Sub-Station (FOSS) is an essential component of offshore wind farms, which collects and exports power generated by wind turbines. The FOSS is made up of several electrical and mechanical subsystems and is placed in a crucial location within the power grid. Any failure in the substation can lead to a power outage, resulting in increased life cycle costs. FOSS is exposed to harsher conditions and uncertainties, resulting in a higher failure rate (Qvale et al., 2022; Jacob and Mehmanparast, 2021).

Structural health monitoring (SHM) and inspections can provide valuable information about the real environmental conditions and current state of the system. They can help reduce uncertainties in the decision-making process and make it easier to perform preventive maintenance operations and repairs (Zhang et al., 2021; Thöns, 2018; Agusta et al., 2020). Therefore, this study aims to identify the benefits of SHM and inspection strategies for an innovative FOSS. Using the concept of the value of information (VoI), this study evaluates the impact of several factors such as SHM/inspection quality, number of inspections, failure cost, among others, on VoI.

2. VOI ANALYSIS

The concept of Value of Information (VoI) in engineering risk analysis originates from Bayesian decision theory (Raiffa and Schlaifer, 1961). VoI measures the difference between the maximum utility gained from the pre-posterior analysis with SHM/inspection information U^* and the prior analysis without it U_{prior} (see Eq. 1). A positive VoI value indicates the positive impact of SHM/inspection on increasing the expected benefit of the structure (Zhang et al., 2021; Long et al., 2020).

$$VoI = U^* - U_{\text{prior}} \tag{1}$$

The SHM/inspection strategy e is selected from a group of strategies $\mathbf{e} = \{e_1, \ldots, e_{n_e}\}$, and its potential outcomes are grouped $\mathbf{z} = \{z_1, \ldots, z_{n_z}\}$. Depending on the outcome, maintenance actions are chosen from available options $\mathbf{a} = \{a_1, \ldots, a_{n_a}\}$, and a utility $u(e, z, a, \theta)$ is assigned to each scenario. A decision-making process involving the outcomes of SHM/inspection is illustrated in Figure 1. The total cost, including the cost of actions and consequences, is considered in the utility function.

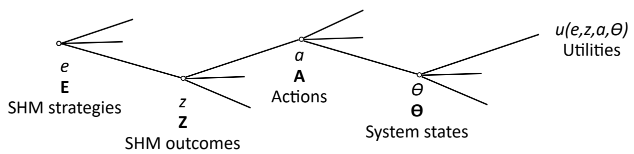


Figure 1: Classic form of a decision tree regarding SHM/inspection (Long et al., 2020)

In the absence of the SHM/inspection information, the expected utility u gained from action a_i can be calculated using the following equation:

$$E_\theta[u(a_i, \theta)] = \sum_{j=1}^{n_\theta} u(a_i, \theta_j) P(\theta_j) \tag{2}$$

where $P(\theta_j)$ is the prior probability of being at state θ_j, and n_θ is the total number of states. The optimal action a_{opt} among all actions $\mathbf{a}$ is the one that leads to the highest expected utility as follows:

$$U_{prior} = \max_{\mathbf{a}} E_\theta[u(\mathbf{a}, \boldsymbol{\theta})] = E_\theta[u(a_{opt}, \boldsymbol{\theta})] \tag{3}$$

To calculate U^*, sometimes, the SHM/inspection is planned, but the outcomes are still uncertain. In this case, the expected utility is calculated with forecast information based on prior models in which one need to assign the SHM/inspection methods and the probabilities of their outcomes. The expected utility must be computed for all possible actions. Eq. 4 is therefore used to calculate the maximum utility called pre-posterior utility.

$$U^* = \max_{\mathbf{e}} E_{z|e}[\max_{\mathbf{a}} E_{\theta|\mathbf{z}} u(\mathbf{e}, \mathbf{z}, \mathbf{a}, \boldsymbol{\theta})] \tag{4}$$

where for a given e_i:

$$U^*_{e_i} = E_{\mathbf{z}|e_i}[\max_{\mathbf{a}} E_{\boldsymbol{\theta}|\mathbf{z}}[u(e_i, \mathbf{z}, \mathbf{a}, \boldsymbol{\theta})]] = \max_{\mathbf{a}} \sum_{k=1}^{n_z} \sum_{j=1}^{n_\theta} u(e_i, z_k, \mathbf{a}, \theta_j) P(\theta_j|z_k) P(z_k, e_i) \tag{5}$$

$P(z_k, e_i)$ is the probability of the outcome z_k from the SHM/inspection e_i, and $P(\theta_j|z_k)P(z_k, e_i)$ is the pre-posterior probability. The optimal action a_{opt,e_i,z_k} for a given SHM/inspection outcome z_k of inspection e_i is the one that leads to the highest utility which can be formulated as:

$$a_{opt,e_i,z_k} = \operatorname{argmax}_{\mathbf{a}} \sum_{j=1}^{n_\theta} u(e_i, z_k, \mathbf{a}, \theta_j) P(\theta_j|z_k) \tag{6}$$

The VoI for a given SHM/inspection method e_i can therefore be formulated as $VoI_{e_i} = U^*_{e_i} - U_{prior}$ and it can be calculated by the following equation:

$$VoI_{e_i} = \sum_{k=1}^{n_z} \sum_{j=1}^{n_\theta} u(e_i, z_k, a_{opt,e_i,z_k}, \theta_j) P(\theta_j|z_k) P(z_k, e_i) - \sum_{j=1}^{n_\theta} u(a_{opt,\theta_j}) P(\theta_j) \tag{7}$$

The calculation of VoI can be expanded for cases with multiple inspections in time. Further information on this topic can be found in (Straub, 2014).

3. PRESENTING THE INNOVATIVE FOSS STUDY CASE

The FOSS study case comprises three main blocks of components from the reliability perspective: mooring & anchor system, floating platform & topside structure, and electro-technical subsystem. Under the availability assumption, these blocks (sub-systems) are connected in series. It is important to mention that the aim here is to perform the

VoI analysis for the main electrical subsystem since the FOSS is still in the research and development stage and, at this stage, we only have adequate information about the failure rates and the configuration of the main electrical components.

The system's main electrical components are the GIS switchgears, the transformer, and the dynamic power (umbilical) cables. The umbilical cables are used to collect the power generated by the floating wind farm and to export it to the hub connecting to the static export cable that goes to the shore station (collection point). Figure 2 shows an illustration of the FOSS and Figure 3 shows the alignment of components in the system. Components' failure rates are provided in Table 1.

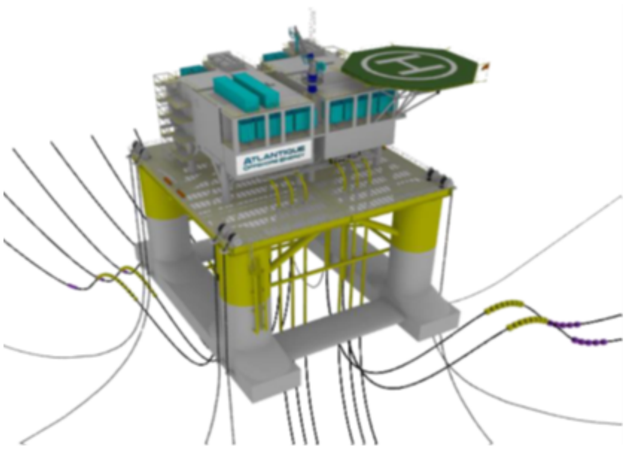


Figure 2: An illustration of a FOSS

Table 1: Failure rate of FOSS components

Component	Failure rate
GIS 66 kV	0.0125
GIS 225 kV	0.0125
Transformer	0.005
Umbilical 66 kV	0.036
Umbilical 225 kV	0.036

A primary failure mode and effect analysis was conducted to pinpoint the crucial components in the system, revealing that the GIS 225 kV, GIS 66 kV, and umbilical 225 kV are the most critical. However, as research on the umbilical cable is still ongoing, for the sake of simplicity, the VoI analysis

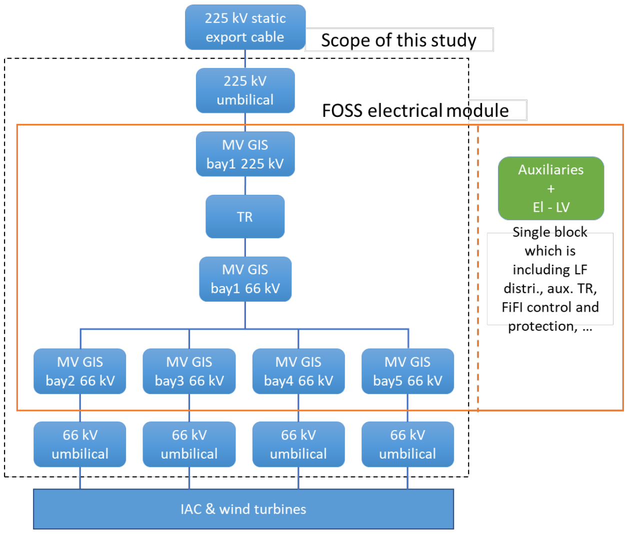


Figure 3: An illustration of FOSS main electrical configuration

will only focus on the GIS 225 kV component, assuming that its failure would result in a system failure.

4. Calculating time-dependent conditional probabilities

To better understand how to calculate the expected benefits for different conditions, assume a system at time t where decision-makers can decide to perform the planned actions (e.g. replacement a_1 or do nothing a_0). The decision can be made with the help of and SHM/inspection strategy e_1 or without it e_0. In the first case the SHM/inspection outcomes can help to improve the decisions. Figure 4 illustrates the decision tree based on the results of a punctual inspection.

Considering only two states (safe θ_0 and fail θ_1), the inspection quality is defined with false alarm probability $P_{FA} = P(z_1|\theta_0)$ and false silence probability $P_{FS} = P(z_0|\theta_1)$. where P_{FA} is the probability of detecting damage when there is none, and P_{FS} is the probability of detecting no damage when there is some. Eq. 8 calculates the probability of detection for a given inspection method that can be reformulated as Eq. 9 using the system's failure probability and false alarm/false silence probabilities.

$$P(z_1) = P(z_1|\theta_1)P(\theta_1) + P(z_1|\theta_0)P(\theta_0) \quad (8)$$

$$P(z_1) = (1 - P_{FS})P(\theta_1) + P_{FA}(1 - P(\theta_1)) \quad (9)$$

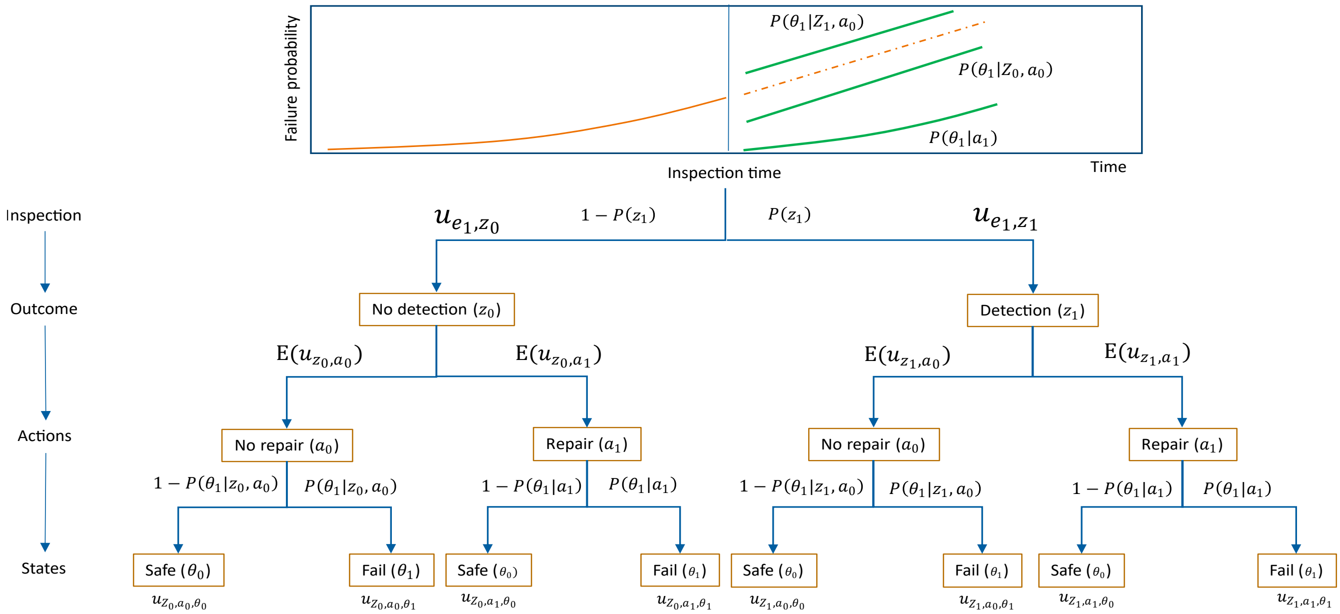


Figure 4: An illustration of the decision scenarios and associated probabilities and benefits for a case with a punctual inspection

No damage detection is the complementary event to the damage detection. Therefore, one can write: $P(z_0) = 1 - P(z_1)$.

After knowing the inspection's outcome, decision-makers can decide if further actions are required. They can choose, for instance, to do nothing a_0 or perform a replacement a_1 for both outcomes (z_0,z_1). Any action can lead to a different scenario (safe θ_0 or fail θ_1) with its associated probability (updated using the inspection outcome). Such probabilities can be calculated through Bayesian inference. With this respect, we have:

$$P(\theta_1|z_1) = \frac{P(z_1|\theta_1)P(\theta_1)}{P(z_1)} \tag{10}$$

$$P(\theta_1|z_0) = \frac{P(z_0|\theta_1)P(\theta_1)}{P(z_0)} \tag{11}$$

where $P(z_1|\theta_1) = 1 - P(z_1|\theta_0)$.

In order to calculate the time-dependent VoI, we need to calculate the time-dependent conditional probabilities for each action after the inspection, see Figure 5. If the decision after the inspection is replacement a_1, the curve of the failure probability will be the same for both cases of no damage detection and damage detection, see Eq. 12.

$$P(\theta_1|z_0,a_1) = P(\theta_1|z_1,a_1) = P(\theta_1|a_1) \tag{12}$$

However, if the decision is to do nothing a_0, assum-

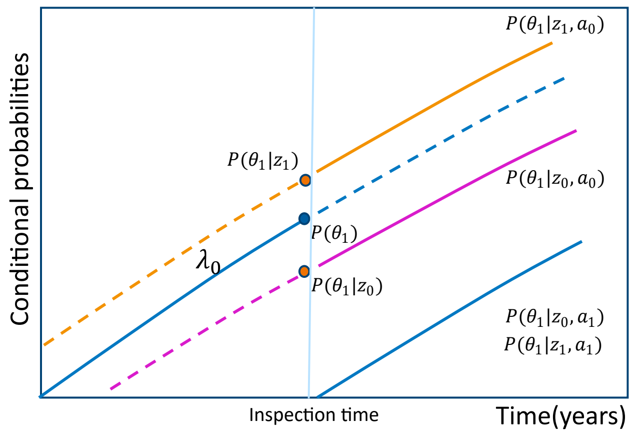


Figure 5: An illustration of time-dependent conditional probabilities after inspection

ing that the failure rate of the system remains the same, we can update the consumed service life of the system according to the calculated conditional failure probabilities. Since conditional failure probabilities are known, one can uses the failure probability function ($P_f(t) = 1 - e^{-\int_0^t \lambda(t)dt}$) to calculate the consumed service life. Then, by using the original failure rate $\lambda(t)$ we can construct the curves of failure probabilities. Accordingly for no damage detection z_0 and damage detection z_1 cases we have:

$$t_{consumed,z_0} = \frac{-ln(1-P(\theta_1|z_0))}{\lambda} \quad (13)$$

$$t_{consumed,z_1} = \frac{-ln(1-P(\theta_1|z_1))}{\lambda} \quad (14)$$

Therefore, time dependent failure probabilities for those cases can be calculated using the following equations:

$$P(\theta_1|z_0,a_0) = 1 - e^{\lambda(t+t_{consumed,z_0})} \quad (15)$$

$$P(\theta_1|z_1,a_0) = 1 - e^{\lambda(t+t_{consumed,z_1})} \quad (16)$$

5. EXPECTED COST/BENEFIT MODELS

To calculate the expected costs and benefits of the system, it is assumed that all blocks of the offshore wind farm except the FOSS are functioning without a failure. The system's theoretical revenue is equal to the revenue related to the amount of electricity that it can transfer to the distribution center when there is no failure. Accordingly, by knowing the cost of electricity C_{MWh} and the capacity of the substation, the revenue after t years can then be calculated as:

$$Revenue(t) = Revenue_{annual} \times t \quad (17)$$

where $Revenue_{annual} = C_{MWh} \times capacity \times \mu \times 24 \times 365$ in which μ is the load factor.

In the next step we need to calculate different costs during the service life of the system. Each cost is calculated by considering all possible subcosts using Eq.s 18-21 where C_{eq}, C_{mob}, C_{op}, C_{post}, C_{down} respectively stand for equipment, mobility, operation, post treatment, and downtime costs.

$$\begin{aligned} C_{SHMinsp} = C_{eq\_SHMinsp} + C_{mob\_SHMinsp} \\ +C_{op\_SHMinsp} + C_{post\_SHMinsp} \end{aligned} \quad (18)$$

$$\begin{aligned} C_{maintain} = C_{eq\_maintain} + C_{mob\_maintain} \\ +C_{op\_maintain} \end{aligned} \quad (19)$$

$$\begin{aligned} C_{repair} = C_{eq\_repair} + C_{mob\_repair} + C_{op\_repair} \\ +C_{down\_repair} \end{aligned} \quad (20)$$

$$C_{fail} = C_{down\_fail} + C_{repair} \quad (21)$$

It must be noted that $C_{maintain}(t)$, $C_{repair}(t)$, and $C_{SHMinsp}(t)$ must respectively include all maintenance, repair, and SHM/inspection costs until time t. Also, all indirect costs of failure except the downtime cost are ignored in $C_{fail}(t)$.

The benefit of the system under a given condition is then calculated by subtracting associated costs from the revenue. For example, for the case with an inspection where no damage has been detected, no action has been taken and the system is in the safe state (see Figure 4), the Benefit u_{e_1,z_0,a_0,θ_0} is calculated by Eq. 22. The benefits for other scenarios can be calculated in the same fashion.

$$\begin{aligned} u_{e_1,z_{0,1},a_0,\theta_0}(t) = Revenue(t) - C_{maintain}(t) \\ -C_{SHMinsp}(t) \end{aligned} \quad (22)$$

For the case involving SHM/inspection, decision makers choose the action that leads to highest expected utility either a damage is detected or not. With this respect, the utility for the damage detection case is found by:

$$U_{e_1,z_1} = \max(E(u_{z_1,a_0}), E(u_{z_1,a_1})) \quad (23)$$

where

$$\begin{aligned} E(u_{z_1,a_0}) = u_{e_1,z_1,a_0,\theta_0} \times (1-P(\theta_1|z_1,a_0)) \\ +u_{e_1,z_1,a_0,\theta_1} \times P(\theta_1|z_1,a_0) \end{aligned} \quad (24)$$

$$\begin{aligned} E(u_{z_1,a_1}) = u_{e_1,z_1,a_1,\theta_0} \times (1-P(\theta_1|z_1,a_1)) \\ +u_{e_1,z_1,a_1,\theta_1} \times P(\theta_1|z_1,a_1) \end{aligned} \quad (25)$$

Similarly, for no damage detection case we have:

$$U_{e_1,z_0} = \max(E(u_{z_0,a_0}), E(u_{z_0,a_1})) \quad (26)$$

where

$$\begin{aligned} E(u_{z_0,a_0}) = u_{e_1,z_0,a_0,\theta_0} \times (1-P(\theta_1|z_0,a_0)) \\ +u_{e_1,z_0,a_0,\theta_1} \times P(\theta_1|z_0,a_0) \end{aligned} \quad (27)$$

$$\begin{aligned} E(u_{z_0,a_1}) = u_{e_1,z_0,a_1,\theta_0} \times (1-P(\theta_1|z_0,a_1)) \\ +u_{e_1,z_0,a_1,\theta_1} \times P(\theta_1|z_0,a_1) \end{aligned} \quad (28)$$

The expected utility with inspections e_1 is then calculated as follows:

$$U^*_{e_1} = U_{e_1,z_0} \times P(z_0) + U_{e_1,z_1} \times P(z_1) \quad (29)$$

For the case with no inspection, however, the decision is simply in favor of the action that leads to a higher expected utility.

$$U_{e_0} = \max(E(u_{a_0}), E(u_{a_1})) \quad (30)$$

6. VoI ANALYSIS FOR THE INNOVATIVE FOSS

The aim of this section is to perform time-dependent VoI analyses on the FOSS, focusing on the critical component GIS 225 kV. To simplify the analysis and maintain confidentiality, costs are considered as a function of annual revenue (see Table 2). The maintenance cost covers all components and the wind farm, which must operate without failure.

Table 2: Revenue and different costs of FOSS

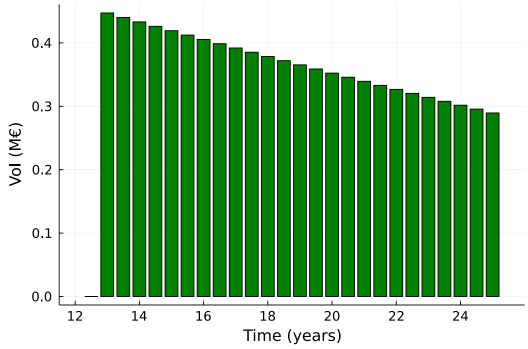
Annual revenue	71175 (k€)
Maintenance cost	0.1×Annual revenue
Replacement cost	0.05×Annual revenue
Inspection cost	0.001×Annual revenue
Failure cost	0.1×Annual revenue

A Julia programming algorithm has been developed to calculate the time-dependent VoI for various inspection scenarios, including single or multiple inspections. Additionally, the algorithm allows for analyzing the impact of different parameters such as the number of inspections, failure rate, inspection quality, among others, on the VoI.

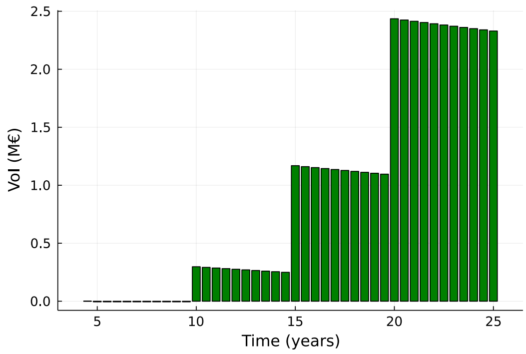
6.1. Evaluating the VoI for single and multiple inspection cases

The previous section provided the necessary input values for a VoI analysis, including revenue and costs. For the inspection quality, false alarm and false silence probabilities were arbitrarily set to $P_{FA} = 0.05$ and $P_{FS} = 0.05$ since no information was available on those parameters. The VoI analysis was performed for a single inspection at year 13 and four inspections at years [5, 10, 15, 20].

Figure 6 presents the time-dependent VoI values for both scenarios, indicating a constructive impact on increasing the system's benefit with positive VoI values. The results also show that the VoI values are higher for the multiple inspection case, suggesting that increasing the number of inspections can increase the VoI. Other parameters such as system's failure rate, inspection quality, failure cost, and inspection cost can also impact the VoI. In the following, only the impact of number of inspections, failure rate and inspection quality are investigated.



(a) Case with one inspection



(b) Case with 4 inspections

Figure 6: Time-dependent VoI analysis for cases with single and multiple inspections

6.2. Influencing parameters on VoI

Number of inspections

To investigate the impact of the number of inspections on the VoI, a VoI analysis was conducted with varying numbers of inspections, ranging from 1 to 10. The input values for the analysis were the same as in the previous section, with a failure rate of 0.0125, and inspection parameters set to $P_{FA} = 0.01$ and $P_{FS} = 0.01$.

The results, shown in Figure 7, demonstrate that performing inspections has a positive impact on the VoI, with all curves having positive values. Moreover, increasing the number of inspections leads to a direct increase in VoI, with the case of 10 inspections yielding a VoI of over 6 M€. However, it is important to note that this conclusion may not hold in all cases, as when inspections are prohibitively expensive, increasing their frequency may not be optimal. Thus, finding the optimal number of inspections is crucial.

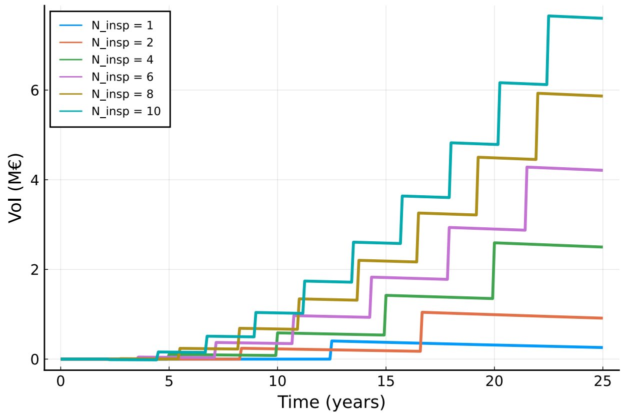


Figure 7: VoI for different number of inspections

Failure rate

The component's failure rate is an important parameter that can impact VoI. To investigate its influence, we performed 5 inspections on the system with the same inspection quality $P_{FA} = 0.15$ and $P_{FS} = 0.10$, and the same revenue and cost inputs as before, while varying the failure rate from 0.0001 to 0.01. Figure 8 shows the VoIs for different failure rates. Higher failure rates lead to greater benefits from inspections, as inspections can detect failures more frequently. When a system is highly reliable (low failure rate), inspections may not yield additional benefits, but increasing inspection quality can enhance VoI for reliable systems.

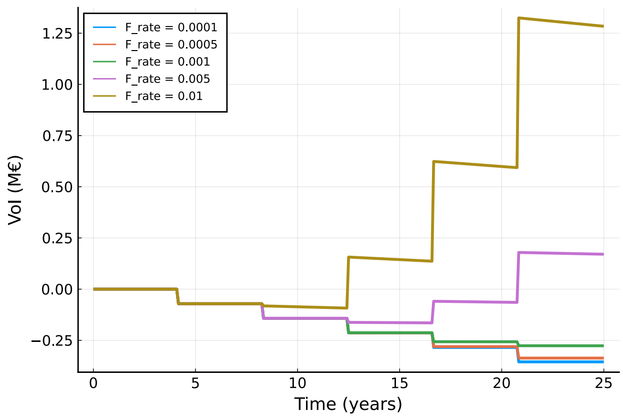


Figure 8: VoI for different failure rates

Inspection quality

The quality of inspections is a critical factor in detecting damage accurately. The inspection quality is determined by two parameters - false alarm and false silence probabilities, which require several experiments to define. The objective here is to understand the impact of these parameters on the value of VoI for a given inspection.

To calculate the VoI, we keep the inspection cost constant while varying the false alarm and false silence probabilities from 0.0 to 0.5. The calculations are performed for a case with five inspections, and the component's failure rate is 0.0125. For each pair of false alarm and false silence probabilities, we perform the VoI analysis to find the value of VoI at the end of the service life.

Inspections with lower levels of false alarm and false silence probabilities lead to more accurate results, which, in turn, improve the VoI. Figure 9 illustrates the heat-map graph of the VoI for different values of P_{FA} and P_{FS}. The highest VoI occurs when both parameters are minimum, and the lowest VoI occurs when they tend to 0.5. For inspections with high values of false alarm and false silence probabilities, the results are unreliable, and the decisions do not lead to extra benefits.

Figure 9 also demonstrates that P_{FA} and P_{FS} do not have the same impact on the VoI for the given example. The contours in this figure show that the VoI is more sensitive to P_{FA} and P_{FS} as increasing the former parameter leads to a faster decrease of VoI. It is important to note that the inspection cost remains the same regardless of the changes in inspection quality.

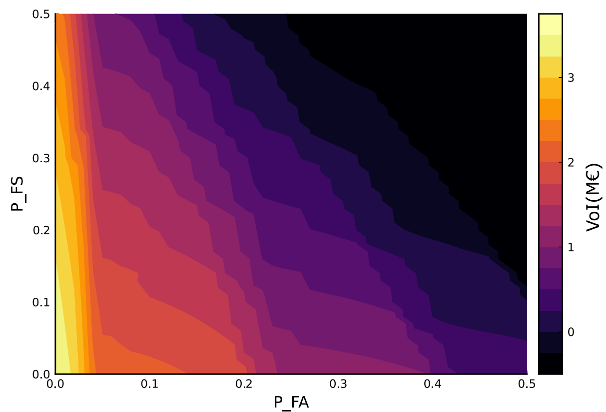


Figure 9: Impact of inspection quality on VoI

7. Conclusions

This study has tried to illustrate the importance of inspections during the service life of an innovative FOSS. For this reason, the concept of the value of information has been employed. In this way, one can quantitatively evaluate the effectiveness of inspection methods in reducing the life-cycle costs of a system.

The results of VoI analysis have shown the positive impact of inspections (single/multiple) on increasing the utility of the FOSS. In addition to that, the impact of several important parameters such as number of inspections, failure rate and inspection quality on VoI has been investigated. Knowing the impact of each parameter is very beneficial for an optimal SHM/inspection planning.

The study scheduled inspections at equal intervals for multiple cases. Optimal inspection planning for innovative FOSS can be achieved by optimizing the inspection times through an optimization process. Additionally, the study can perform VoI analysis at the system level. To improve the study, one can consider more SHM/inspection methods, actions, and condition states in the decision process.

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