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On the Value of Structural Health Monitoring Information for the Operation of Wind Parks

Sebastian Thöns^a, Michael H. Faber^b, Dimitri V. Val^c

^a Department of Civil Engineering, Technical University of Denmark, Denmark

^b Department of Civil Engineering, Aalborg University, Denmark

^c Institute for Infrastructure and Environment, Heriot-Watt University, UK

Abstract: In the present paper, an approach for the quantification of the Value of Structural Health Monitoring (SHM) Information building upon a framework for infrastructure system utility and decision analysis is developed and applied to the operation of wind parks. The quantification of the value of SHM facilitates a benefit and risk informed assessment and optimization of SHM strategies and encompasses models for the infrastructure functionality, the structural constituent and system risks and its management as well as the performance of SHM strategies. A wind park system model incorporating the structural wind turbine systems and its components is developed accounting for the wind park functionality, i.e. power production, its operation and its cascading damage and failure scenarios. This system model facilitates to quantify the expected benefits and risks throughout the service life accounting for the propagation of SHM information and uncertainties from components to the different system levels and vice versa. The decision to extend the service life and the operation of a wind park is investigated without SHM information and by quantifying the value of several SHM strategies.

1 Introduction

Wind parks combine uniquely sustainable, renewable, greenhouse gas free and low risk energy production and are becoming important parts of the energy mix throughout Europe and worldwide. The operation of offshore wind parks constitutes a very recent challenge as substantial investments lead to the installation of a larger number of offshore wind turbines. Energy production efficiency is highly important and prioritized in an industrial and EU energy policy context (see e.g. [1]). Energy efficiency of wind parks necessitates an optimal economic functionality in combination with low risks accounting for the environmental exposures, limited accessibility and the high number of identical wind turbine structures. For commissioned wind parks, two important and interrelated energy efficiency influencing parameters are the structural integrity management and the service life extension for the elongation of the power production. The ranking and consistent assessment of integrity management and service life extension strategies necessitate that the functionality of the wind park together with its performance and structural risks are quantified. This may be facilitated through the utilization of the Bayesian decision analysis and utility theory.

This paper introduces an approach for the quantification of value of Structural Health Monitoring (SHM) Information building upon a framework for infrastructure system utility and decision analysis introduced in [2]. A decision scenario for the service life extension of wind parks supported by SHM and a system model for the wind park structures encompassing the structural components and wind turbine structures under extreme loadings and accounting for fatigue

degradation are developed. Taking basis in the formulation of SHM strategies on component, constituent and system levels, it is demonstrated how SHM information and uncertainties propagate from components to the different system levels and vice versa. The optimal decision to extend the service life with and without additional SHM information is investigated based on the quantification of the Value of SHM Information as a utility gain. The paper closes with a summary of the main characteristics of the introduced approaches and with conclusions on how a service life extension of wind parks can be supported with SHM.

1.1 Framework for infrastructure system utility, decision analysis and Value of Information analysis

A framework for infrastructure system utility modelling and decision analysis has been recently introduced by [2], building upon the systems risk modelling framework by the Joint Committee on Structural Safety [3]. The system utilities are distinguished into expected benefits accounting for the system functionality and the consequences are classified into: (1) hazards and threats, i.e. the system exposures, (2) constituent damage states associated with the condition of the system and (3) system damage states associated with the system functionality.

The utility is quantified by aggregation of the decision attributes in regard to the monetary income and losses (economy), human health and the environment through an objective function. A decision is reached by: (1) identifying a feasible range of decisions having a utility above a specified limit such as e.g. zero, (2) limiting the decisions to acceptable decisions accounting for acceptability criteria e.g. in relation to human life safety and environmental impacts, and (3) choosing the optimal decision parameters to locally maximize the utility (Figure 1).

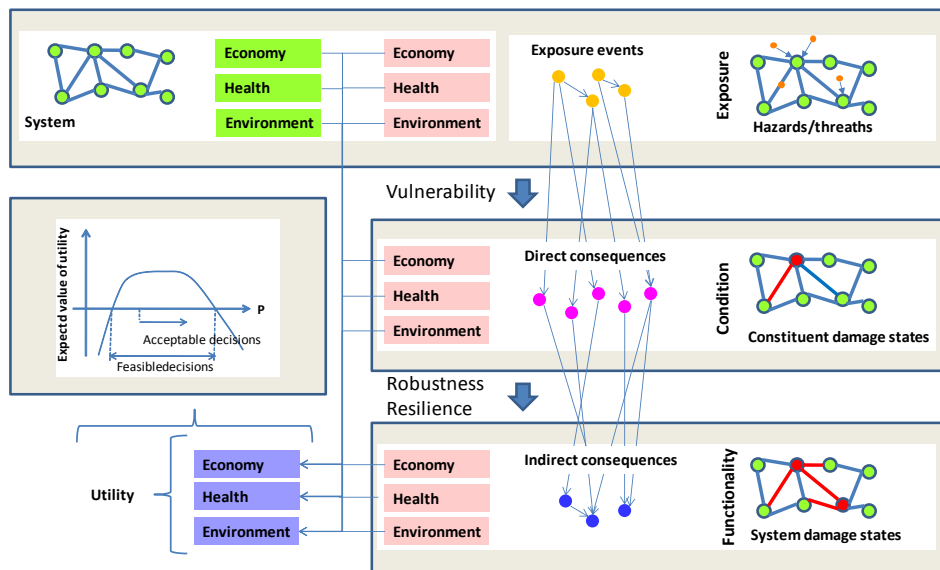


Figure 1: Generic framework for decision analysis of systems, see [2]

The Value of Information is defined as a utility gain caused by additional but not yet known information which may be modelled and quantified through a pre-posterior Bayesian decision analysis. More specifically, a Value of Information analysis is established by combining the choice of the information acquirement strategy $i_i \in \mathbf{i}$, its possible and uncertain outcomes $Z_j \in \mathbf{Z}$ with a choice of an action $a_k \in \mathbf{a}$ and the system states space $\Theta_i \in \Theta$. These elements are combined by means of a decision tree in conjunction with the underlying models to describe the performance of the information acquirement strategy, the actions and the system performance in terms of its functionality characteristics including costs, benefits and consequences to

health and environment. The Value of Information, VoI , may then defined as the difference between the maximum expected utility quantified with pre-posterior decision analyses considering SHM information, u_i^* , and the maximum expected utility without SHM information, u_0^* :

$$VoI_i = u_i^* - u_0^*, \quad (1)$$

The relative Value of Information, \overline{VoI} , as a measure of the significance of the acquired information, relates the Value of Information VoI to the maximum expected utility without SHM information:

$$\overline{VoI}_i = (u_i^* - u_0^*) / u_0^*. \quad (2)$$

The maximum expected utility is quantified by the identification of the optimal action for u_0^* or the optimal information acquirement strategy and optimal action for u_i^* , i.e.:

$$u_0^* = \max_{\mathbf{a}} E'_{\Theta} [u(\mathbf{a}, \Theta)] \text{ and } u_i^* = \max_i E_{Z_i} \left[\max_{\mathbf{a}} E''_{\Theta/Z} [u(\mathbf{i}, \mathbf{Z}, \mathbf{a}, \Theta)] \right]. \quad (3)$$

Both, the framework for infrastructure system utility modelling and decision analysis (Figure 1) and Value of Information analysis (Equations (1) to (3)) are connected by the constituent and system states encompassing the intact, the exposure, the constituent and the system damage and failure states. With this connection, it becomes evident that information about any of the constituent and system states can propagate from constituent to system level and vice versa and will influence the aggregated expected utilities. This puts Structural Health Monitoring, which is traditionally focused on acquiring information on loading (i.e. exposure) and mechanical characteristics of structural components (i.e. constituent condition), into a wider perspective. Monitoring information (1) may thus encompass any information of the constituent and system states, (2) monitoring is about the system performance and aggregated utilities and (3) the value of monitoring information is defined as an expected utility increase which itself may comprise an increase of the expected benefits for the system operation, the reduction of the expected consequences and an influence on the system characteristics such as e.g. the robustness and the vulnerability.

An information acquirement strategy may thus at least be characterized by (1) the information type describing the relation to the system state performance model, (2) the information precision accounting e.g. for measurement, operational, model and statistical uncertainties and (3) the expected costs of the information. Figure 2 illustrates the choice of information acquirement strategies (rectangular node) per system state accounting for their expected costs (diamond shaped nodes) and the precision of the information (circular nodes).

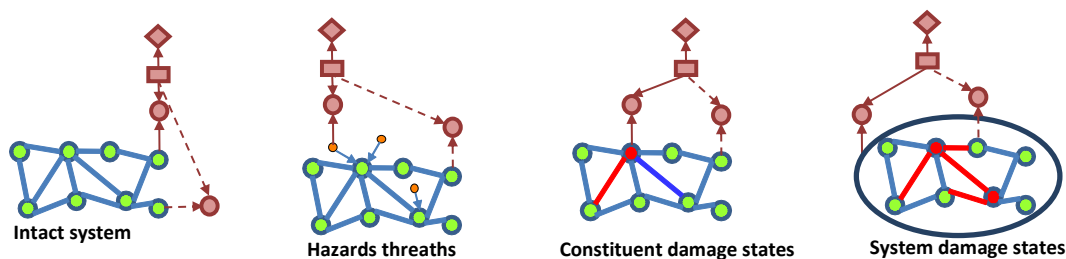


Figure 2: Principal illustration of decision analysis modeling for acquisition of additional information (rectangular decision node) for each of the system states characterized by type, precision (circular node), cost (diamond shaped node) for two measurement locations (dashed and continuous lines)

2 Functionality, operation and structural risk characteristics of offshore wind parks

With focus on wind energy production efficiency, this paper concentrates on the decision analysis for a service life extension of the wind turbine structures in a wind park based on the introduced approach for the quantification of value of Structural Health Monitoring (SHM). The decision context may be described through the decision maker, the time of the decision, the decision objective and the decision alternatives. The decision maker is constitutes an operator of an offshore wind park. The objective is to identify optimal (in terms of service life utility) decision alternatives concerning different SHM strategies as a means for extending the service life of the wind park structures. The decision is assumed to be taken in the commissioning phase of a wind park why utilities are discounted to their present values.

2.1 Functionality modeling

When the wind park is in an undamaged state, the expected benefits and costs are calculated according to the planned power production. The expenditures associated with energy production is covered by the feed-in-tariff and calculated taking into account both the turbine availability factor and the nominal capacity availability factor. The annual wind park operation is assumed to cost 2% of the total wind park investment. A generic discount rate of 5% is considered. The analysis parameters shown in Table 1 take basis in [4].

Table 1: Wind park cost benefit analysis parameters

Number of wind turbines n_{WT}	10	Feed-in-tariff	0.12 Euro
Nominal capacity	5.00 MW	Turbine investment	20.0 Million Euro
Turbine availability factor	0.95	Wind park operation	0.02 1/a
Nominal capacity availability factor	0.45	Discount rate	0.05

The cost-benefit analysis yields a return over investment of 15.1% for an operation of 20 years. Given the wind park can be operated for 25 years without any further costs, there would be a return over investment of 30.1%. This generic and simplistic costs-benefit-analysis can be adjusted to calculate the Levelized Costs of Electricity (LCOE), i.e. the net present value of the unit-cost of electricity over the service life of a power plant. Here, the development expenditures (DEVEX) and country dependent taxation schemes are considered in addition to the already accounted Capital, Operational and Abandonment Expenditures (CAPEX, OPEX and ABEX, respectively). It should be noted that OPEX includes the operation and maintenance costs of the wind turbines (which amount to about 50% [4]) of which the structural integrity management costs constitute a relatively small part.

From the viewpoint of a cost benefit analysis only, it seems to be straightforward to extend the service life to increase the return over investment. However, the structural risks are not considered which, however, are an important element of the reliable wind park operation.

2.2 System, constituent and component hazard, damage and failure modelling

The structural risks are calculated with consideration of the hazards, constituent damage states and the system damage states for a fatigue and extreme loading exposure leading to cascading damage and failure of the structural components, the wind turbine structures and the wind park structures. The probabilities of the component, constituent (wind turbine) and system (wind park) damage and failure are described by limit state functions. The fatigue deterioration at component level is modelled through a SN fatigue model assuming a fatigue design factor

(FDF) of 2.5 for a design life t_{DL} of 20 years. The SN limit state function for a component i out of n_c^D components subjected to fatigue damage is formulated as the difference of the fatigue capacity Δ and accumulated damage $D_i(t)$ at time t . The accumulated damage is calculated with the annual number of stress cycles ν , the stress ranges $\Delta\sigma_i$ and the SN curve constants m and K :

$$g_{i_c}^D(\mathbf{x}, t) = \Delta - D_{i_c}(t) = \Delta - \nu \cdot t \frac{E[\Delta\sigma_{i_c}^m]}{K} \text{ with } E[\Delta\sigma_{i_c}^m] = (Mk)^m \Gamma\left(1 + \frac{m}{\lambda}; \left(\frac{s_0}{k}\right)^\lambda\right). \quad (4)$$

The expected value of the stress ranges $E[\Delta\sigma_i^m]$ is calculated in terms of the model uncertainty M , the cut-off stress range s_0 , the Weibull scale parameter λ and the Weibull location parameter k . The model uncertainties for the fatigue stress range calculation include the model uncertainties for the fatigue loading M_L , the nominal stress M_σ , the hot spot stress M_{HS} and the weld quality M_Q .

The event of failure for each of the n_c^F representative components modelled through the limit state function:

$$g_{i_c}^F(\mathbf{x}) = M_{R_{i_c}} \cdot R_{i_c} \left(1 - f_D \cdot D_{i_c}(t)\right) - \frac{1}{n_c^F} \cdot M_S \cdot S. \quad (5)$$

as the difference between the component resistance taking the fatigue deterioration into account and the extreme wind turbine system loading. The model uncertainties for the resistance and loading model, M_{R_i} and M_{S_i} , are modelled according to [5]. The wind turbine system loading S_i is described by an extreme value distribution with a reference period of one year. The transfer function f_D models the influence of fatigue-induced damage on the ultimate resistance. For simplicity f_D is assumed here to 0.1. The mean of the component resistance R_i is calibrated to a probability of constituent failure of $5.0 \cdot 10^{-4}$ disregarding any damage, i.e. $f_D = 0.0$. The model parameters are summarized in Table 2.

Table 2: Random variables for the system state calculations

Var.	Dim.	Dist.	Exp. value	Std. dev.
M_R	-	LN	1.0	0.05
R_i	-	LN	Cal.	0.1
M_S	-	LN	1.0	0.1
S	1/y	WBL	3.5	0.1
Δ	-	LN	1.0	0.3
$\ln(K)$	-	N	28.995	0.572
m	-	Det.	3.0	
k	MPa	LN	Dep. on FDF	$0.2 \cdot \mu_k$
$1/\lambda$	-	Det.	1.2	
s_0	MPa	Det.	0.0	

Var.	Dim.	Dist.	Exp. value	Std. dev.
ν	yr ⁻¹	Det.	3.0×10^6	
t_{DL}	Yr	Det.	20.0	
M_L	-	LN	0.89	0.27
M_σ	-	LN	1.01	0.12
M_{HS}	-	LN	1.02	0.20
M_Q	-	LN	1.02	0.20
<i>FDF</i>	-	Det.	2.5	-
n_c^F	-	Det.	5	
n_c^D	-	Det.	10	

LN: Lognormal, N: Normal, EX: Exponential, Cal.: Calibrated, WBL: Weibull

The events of wind turbine damage and failure are modelled based on the component performances (Equ. (4) and (5)) modeling the dependent occurrence of constituent fatigue damages and failure with $n_C^D = n_C^F = 5$ contributing components (following e.g. [6]):

$$g_{i_{WT}}^D(\mathbf{x}) = \min(g_{i_{WT},1}^D(\mathbf{x}), \dots, g_{i_{WT},n_C^D}^D(\mathbf{x})) \text{ and } g_{i_{WT}}^F(\mathbf{x}) = \min(g_{i_{WT},1}^F(\mathbf{x}), \dots, g_{i_{WT},n_C^F}^F(\mathbf{x})). \quad (6)$$

The probabilities that one wind turbine in a wind park is damaged or fails ($P_{WT,D}$ and $P_{WT,F}$) is described with the limit state functions which are calculated with $n_{WT} = n_{WT} = 10$ contributing wind turbines (constituents):

$$g_{WP}^D(\mathbf{x}) = \min(g_1^D(\mathbf{x}), \dots, g_{n_{WT}}^D(\mathbf{x})) \text{ and } g_{WP}^F(\mathbf{x}) = \min(g_1^F(\mathbf{x}), \dots, g_{n_{WT}}^F(\mathbf{x})). \quad (7)$$

The cascading damage and failure formulations are chosen to model the probability of fatigue occurrences and subsequent the wind turbine and wind park damage and failure due to extreme loading. The occurrence of damage or failure at individual wind turbines does not necessarily mean a significant loss of the wind park functionality for higher numbers of constituents n_{WT} . The loss of functionality of the wind park, namely power production, may thus be modelled as the failure of a redundant system of which the components have no (production) capacity after failure, i.e. as a brittle Daniels system per definition:

$$g_{WP}^D = (n_{WT} - i_{WT}) \hat{\Delta}_{i_{WT}}(t) - D_{i_{WT}}(t) \cdot (n_{WT} - 1) \text{ and} \quad (8)$$

$$g_{WP}^F = (n_{WT} - i_{WT}) \hat{M}_{R,i_{WT}} \hat{R}_{i_{WT}}(t) - M_S \cdot S \cdot (n_{WT} - 1). \quad (9)$$

Note that $\hat{M}_{R,i_{WT}} \hat{R}_{i_{WT}}(t)$ and $\hat{\Delta}_{i_{WT}}(t)$ represent the ordered realizations (increasing in value) of the constituent resistances.

The dependencies of the fatigue and extreme performance of the individual components in a wind turbine system take basis in [7]. The modelling of the dependencies between the constituents in the wind park should account for a higher variability due to the spatial distribution of wind turbines and, e.g. larger variations in the construction. The correlation of the fatigue performance between components is thus set to 0.8 and between wind turbines to 0.7. A similar argument applies to the correlation of the ultimate resistance between the components and between the wind turbines, which are set to 0.9 and 0.8, respectively. The extreme loads across the wind park are assumed fully dependent, i.e. they are modelled with a correlation of 1.0.

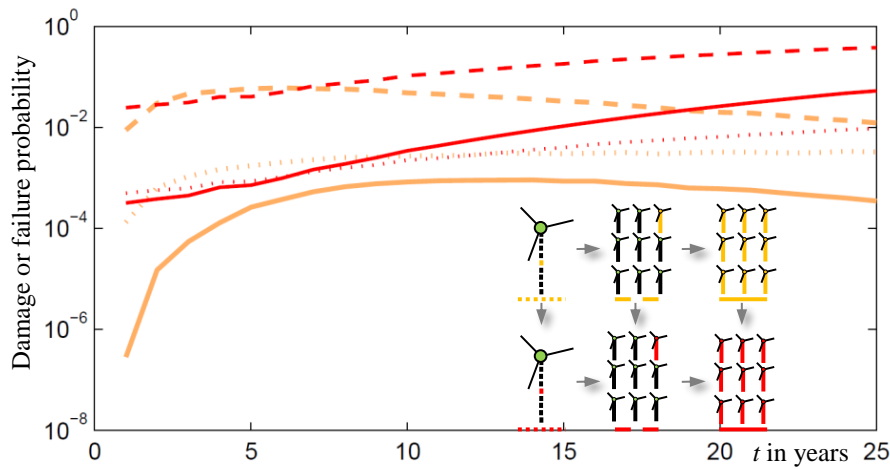


Figure 3: Annual probabilities of component (orange dotted), wind turbine (orange dashed) and wind park damage (orange continuous) and component (red dotted), wind turbine (red dashed) and wind park failure (red continuous)

Figure 3 shows the probabilities for the component, wind turbine and wind park damage and failure scenarios. The probabilities of fatigue damage and failure occurrence in a wind park (dashed lines) are significantly high despite the utilization of a typical fatigue design factor (2.5) and a typical design probability of failure ($5.0 \cdot 10^{-4}$). This is explained with the high number of the components, the series characteristic of the system, the limited correlation and the interaction of the limit states. The annual probability of wind park damage and failure (continuous lines) is then respectively lower due to the considered redundancy.

The probabilities of the different system states are related to benefits, costs and consequences as shown in Table 3. Any consequences regarding human health and the environment are assumed negligible as the wind turbines are unmanned and failure of wind turbines are associated with a relatively low environmental impact. The structural integrity management actions are not explicitly modeled but included in the functionality-modelling, see Section 2.1.

Table 3: Consequences according to system states

System state	Description	Benefits, costs and consequences
Intact	System operation	Power production and operation costs (Section 2.1)
Constituent damage	Component fatigue damage	1.0 % of component investment at time of damage
	Component failure	Component investment and corresponding part of SHM system investment at time of failure
	Wind turbine fatigue damage	1.0 % of wind turbine investment at time of damage
	Wind turbine failure	Wind turbine and corresponding part of SHM system investment at time of failure
System damage	Wind park fatigue damage	1.0 % of wind park investment at time of damage
	Wind park failure	Wind park and SHM system investment at time of failure and loss of power production for the time of failure to service life end (Section 2.1)

3 Pre-posterior modelling of SHM and integrity management actions

In the context of a pre-posterior decision analysis, the yet unknown SHM information may be modeled by the realization of the model uncertainty, which are not known unless SHM is performed on a built structure. The realization of the model uncertainty – which can both apply to the resistance and loading - can then be (1) close to their expected value, (2) lower than the expected value or (3) higher than the expected value. For a realization of the model uncertainty close to the expected value, an uncertainty reduction for the component performance is achieved given a sufficiently low SHM uncertainty. In this case, the risks and the required structural integrity management actions throughout the service life may be reduced. Realizations of the loading (resistance) model uncertainty higher (lower) than the expected value lead to inferiorly performing components which may be associated to high risks and additional repair or retrofitting actions. Components performing better may lead to significantly reduced costs and risks and increased benefits throughout the service life. In the further, it is thus assumed that an expected cost reduction and benefit increase due to better performing components equalize expected losses due to additional repair and retrofitting actions for inferiorly performing structures without explicit modelling. It follows that the utility can be described solely by considering the expected value of the model uncertainty.

Available SHM strategies focus on the loading and structural condition characteristics, i.e. on exposures and the component damage states. Due to the local characteristic of the fatigue deg-

radation, relevant SHM information may be obtained locally, by e.g. utilizing gauges to measure the strains which can then be transformed to stresses or the damage accumulation by Rain-flow counting (SHM strategies 1 and 2, Table 4). The utilization of wind and wave measurement equipment may lead to information about the extreme loading (SHM strategy 3).

Table 4: Modelled SHM strategies and system scenario states

No.	Strategy	Model	System state
1	Component loading monitoring	Pre-posterior model of component stress measurement	Exposure on component level
2	Hot spot monitoring	Pre-posterior model of hot spot damage accumulation measurement	Direct consequences on component level
3	Wind turbine loading monitoring	Pre-posterior model of wind turbine system extreme loading monitoring	Exposure on component, wind turbine and wind park level

SHM strategy 1 consists of monitoring the fatigue loading throughout the service life. The expected values of the far field stress ranges for the individual hot spots are modelled conditional on the realizations of the hot spot loading model uncertainty taking the SHM uncertainty U into account, i.e.:

$$E[\Delta\sigma_i / \hat{M}_L] = (\hat{M}_L M_\sigma M_{HS} M_Q U k)^m \Gamma\left(1 + \frac{m}{\lambda}; \left(\frac{s_0}{k}\right)^\lambda\right). \quad (10)$$

SHM strategy 2 (hot spot monitoring and damage accumulation) is modeled accordingly:

$$E[\Delta\sigma_i / \hat{M}_L, \hat{M}_\sigma, \hat{M}_{HS}] = (\hat{M}_L \hat{M}_\sigma \hat{M}_{HS} M_Q U k)^m \Gamma\left(1 + \frac{m}{\lambda}; \left(\frac{s_0}{k}\right)^\lambda\right). \quad (11)$$

SHM strategy 3 focusses on the extreme loading and is modeled with the realization of the loading model uncertainty accounting for the SHM uncertainty, i.e. with $\hat{M}_S \cdot U$. Information about the extreme wind turbine loading influences then the uncertainties at component level, at wind turbine level (Equ. (5)) and at wind park level (Equ. (9)).

The precision of the SHM strategies is modeled through a Normal distributed random variable, i.e. $U \sim N(\mu_u, 0.1)$ where μ_u is a random variable itself accounting for statistical uncertainties due to the limited number of yearly observations n_o , i.e. $\mu_u \sim N(1.0, 0.1/\sqrt{n_o})$. The SHM strategy cost modelling includes the SHM system investment (500,000.00 Euro), installation (500,000.00 Euro), operation (20,000.00 Euro/a) and replacement every 10 years. For simplicity, the costs and precision are equal for all considered strategies.

4 Utility and Value of Structural Monitoring Information

The Value of SHM Information is quantified as the difference between the optimal utility when no SHM is performed and the optimal utility when SHM is performed (see Section 1.1). It should be noted that when no SHM is utilized, the optimal action is a_0 , i.e. do nothing and keeping the planned service life of 20 years.

The Value of SHM Information for the three modelled SHM strategies is quantified and shown in Table 5. The relative Value of SHM Information lies between -0.9% and 33%. SHM strategy 1 (fatigue loading monitoring) and 2 (hot spot monitoring) have a high Value of SHM Information because they significantly reduce the uncertainties related to the fatigue performance of

the wind turbines and the wind park and consequently the direct and indirect risks. For SHM strategies 1 and 2, a service life extension is the optimal action.

Table 5: Value of SHM for the considered SHM strategies

No.	Strategy	Value of Information		Vulnerability	Robustness
		VoI_i	\overline{VoI}_i		
1	Component loading monitoring	$4.9 \cdot 10^7$	$2.7 \cdot 10^{-1}$	$8.9 \cdot 10^{-2}$	$6.5 \cdot 10^{-1}$
2	Hot spot monitoring	$6.1 \cdot 10^7$	$3.3 \cdot 10^{-1}$	$5.4 \cdot 10^{-2}$	$7.5 \cdot 10^{-1}$
3	Wind turbine loading monitoring	$-1.6 \cdot 10^6$	$-8.8 \cdot 10^{-3}$	$1.9 \cdot 10^{-1}$	$5.6 \cdot 10^{-1}$

To illustrate the utilities over time, Figure 4 is enclosed showing the yearly expected benefits, the direct and indirect risks throughout the service life associated to the optimal prior decision (black lines) and the optimal pre-posterior decision in relation to the three considered SHM strategies, i.e. SHM strategy 2 with the optimal action of a service life extension (green lines). The optimal pre-posterior utilities for SHM strategy 2 show a significant reduction of the direct and indirect risks due to the reduction of the (model) uncertainties.

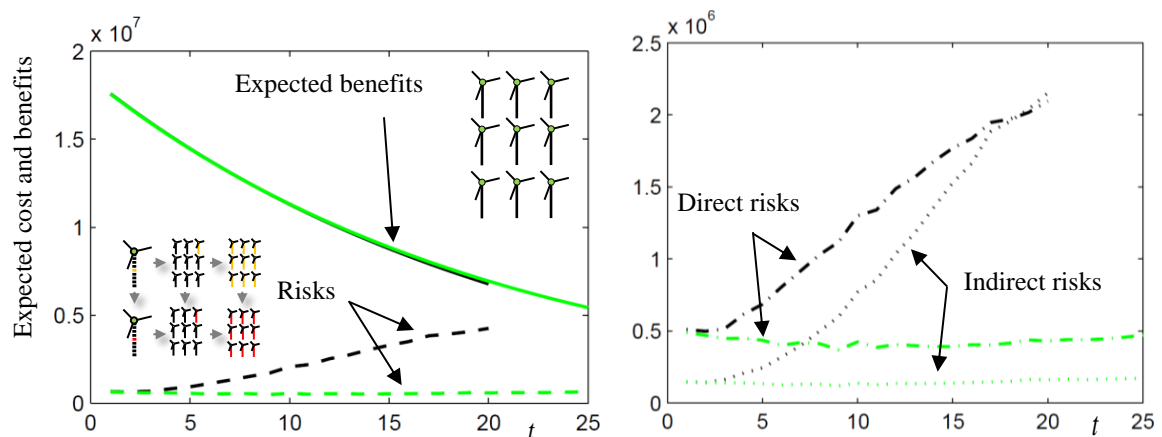


Figure 4: Yearly expected benefits due to power production (solid), aggregated risks (dashed), direct risks (dash-dotted) and indirect risks (dotted) for the optimal prior (black; no service life extension) and pre-posterior decision (green; service life extension)

For the optimal prior utilities, the expected benefits are decreasing mainly due to the discounting but also due to a slightly decreasing probability of the system survival. The considerable risks first increase with a high slope, which decreases towards the end of the service life. This behavior is explained by the interaction of increasing risks of wind park damage and failure in combination with decreasing risk caused by the production loss and the discounting.

For both scenarios, i.e. no SHM with the action of no service life extension and SHM strategy 2 with a service life extension, the expected benefits are approximately constant. Towards the end of the service life, the expected benefits are slightly lower for the no SHM strategy due to a slightly lower probability of survival.

The vulnerability as the ratio of the direct risks to monetary value of the system constituents has been calculated to $1.3 \cdot 10^{-1}$ for the extreme loading scenario taking fatigue degradation into account (see Figure 3). The index of robustness as the ratio of the direct risks to the total risk is $5.7 \cdot 10^{-1}$. It is noted that SHM strategy 2, which has the highest value of SHM, leads to highest increase of the robustness and the lowest vulnerability of the system.

5 Conclusions

An approach for the quantification of the Value of SHM Information has been introduced by the integration of the Value of Information theory and a framework for the infrastructure system utility and decision analysis. This puts Structural Health Monitoring in a wider perspective so that SHM information may encompass any information on the constituent and system states leading to an expected utility increase which itself may comprise an increase of the expected benefits for system operation, the reduction of the expected consequences and an influence on the system characteristics such as e.g. the robustness and the vulnerability.

A system model for the structures of an offshore wind park has been developed, which accounts for consistent and dependent functionality, damage and failure scenario modelling encompassing the components and the structural systems on wind turbine and wind park level. This in turn facilitates to account for the propagation of SHM information and its uncertainties from components to the different system levels and vice versa and to quantify the effect of SHM information on the utilities encompassing the expected benefits due to power production and the risks due to cascading damage and failure mechanisms.

From the case study, it can be concluded that a wind park service life extension is only optimal with additional SHM information of relatively high precision. Only then the required low ratio of the direct and indirect risks to the benefits in conjunction with an optimal robustness increase and vulnerability reduction may be achieved.

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