Quantification of the value of monitoring information for deteriorated structures

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AALBORG UNIVERSITY
DENMARK

QUANTIFICATION OF THE VALUE OF MONITORING INFORMATION FOR DETERIORATED STRUCTURES

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PREFACE

This PhD project was carried out at the *Federal Institute for Materials Research and Testing (BAM), Berlin, Germany,* in collaboration with the *Department of Civil Engineering, Aalborg University, Denmark*. This research work was performed within the European project INFRASTAR (infrastar.eu), which has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska Curie grant agreement No 676139. The grant is gratefully acknowledged. Furthermore, the support of COST Action TU1402 on Quantifying the Value of Structural Health Monitoring is gratefully acknowledged.

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Finally, I want to say special thanks to my boyfriend, my parents, and my brother. It is all your love and encouragement that support me to get through the down times, keep me climbing the mountain and overcome the difficulties.

LIST OF PUBLISHED PAPERS

This Ph.D. thesis follows an article-based format. The thesis includes an extended summary of the study and published papers, which are listed below. Parts of the papers are used directly or indirectly in the extended summary of the thesis.

Papers included in the thesis:

1. Lijia Long, Sebastian Thöns, Michael Döhler. Determination of structural and damage detection system influencing parameters on the value of information, Structural Health Monitoring (2020), https://doi.org/10.1177/1475921719900918
2. Lijia Long, Isaac Farreras Alcover, Sebastian Thöns. Utility analysis for SHM durations and service life extension of welds on steel bridge deck. Structure & Infrastructure Engineering (2021 https://doi.org/10.1080/15732479.2020.1866026
3. Imane Bayane, Lijia Long, Sebastian Thöns, Eugen Brühwiler. Quantification of the value of SHM data for the fatigue safety evaluation of a road viaduct. ICASP13-13th International Conference on Applications of Statistics and Probability in Civil Engineering. May 26-30, 2019, Seoul, South Korea. https://doi.org/10.22725/ICASP13.275
4. Lijia Long, Quang Anh Mai, Pablo Gabriel Morato, John Dalsgaard Sørensen, Sebastian Thöns. Information value-based optimization of structural and environmental monitoring for offshore wind turbines support structures. Renewable Energy. 2020 Jun 12. https://doi.org/10.1016/j.renene.2020.06.038
5. Sima Rastayesh, Lijia Long, John Dalsgaard Sørensen, Sebastian Thöns. Risk Assessment and Value of Action Analysis for Icing Conditions of Wind Turbines Close to Highways, Energies Journal, Volume 12, Issue 14, 2019. https://doi.org/10.3390/en12142653

Other papers:

6. Lijia Long, Isaac Farreras Alcover, Sebastian Thöns. Quantification of the posterior utilities of SHM campaigns on an orthotropic steel bridge deck. IWSHM - 12th International Workshop on Structural Health Monitoring, Sep 2019, Stanford, United States.
7. Lijia Long, Sebastian Thöns, Michael Döhler. The effects of deterioration models on the value of damage detection information. IALCCE - The Sixth International symposium on Life-Cycle Civil Engineering 2018, Ghent, Belgium.
8. Lijia Long, Sebastian Thöns, Michael Döhler. The effects of SHM system and algorithm characteristics on the value of damage detection information.

The 9th European Workshop on Structural Health Monitoring Series Conference, Manchester, UK.

9. Sebastian Thöns, Michael Döhler, and Lijia Long. On damage detection system information for structural systems. Structural Engineering International 28.3 (2018): 255-268.
10. Lijia Long, Sebastian Thöns, Michael Döhler. Damage Detection and Deteriorating Structural Systems. IWSHM - 11th International Workshop on Structural Health Monitoring, Sep 2017, Stanford, United States.

This thesis has been submitted for assessment in partial fulfillment of the PhD degree. As part of the assessment, co-author statements have been included.

SUMMARY

At present, many infrastructures in the most developed countries will soon be at or may have already reached the end of their design service life. Infrastructure owners and operators are facing the severe challenges of operation and maintenance as well as service life extension towards those structures. Structural Health Monitoring (SHM), as a method of identifying and characterizing infrastructure damage, can be very effective in delivering structural safety knowledge to owners and operators. However, there is a gap to transfer the SHM information into the integrity management decision processes. Owners and operators may be hesitant to apply SHM because they have no comprehensive method to consistently answer these questions:

- What is the value of SHM?
- How to choose the proper SHM technique?
- How to design the SHM system, e.g., sensor location and numbers?
- How to use SHM information for maintenance planning and service-life extension?
- When should the monitoring be done and when should the maintenance be done?
- How long should the structure system be monitored and how often is maintenance necessary?

In the past, owners and operators solved these decision problems mainly based on either experience and/or their budget. This thesis develops a new framework for minimizing the expected structural integrity costs and operational risks by finding optimal employment scenarios to solve decision problems quantitatively, which is namely the quantification of the value of monitoring information for deteriorated structures. The new framework provides forefront of the in-depth development of value of information theory approaches in civil and structural engineering, which integrates the Bayesian decision analysis with SHM through detection theory, structural performance and utility modelling considering probabilistic analysis, cost, and benefit analysis as well as consequences analysis.

This framework provides a comprehensive basis to facilitate answering the above questions through comprising (1) a novel generic pre-posterior decision theoretical framework of implementing a damage detection system, (2) a comprehensive utility-based and information value-based optimization of lifecycle structural integrity management, (3) various probabilistic modelling approaches for the utilization of SHM data into knowledge related to decision-making and (4) a general parametric analysis of structural and damage detection system influencing parameters, the decision rules as well as the cost and benefit model parameters on the value of information. The innovation of the thesis is on the value of information determination on system level for both a structural health monitoring system and an engineering system.

With aim to develop monitoring strategies to plan the structural integrity management most efficiently throughout and prolonging the service life for deteriorated structures, the thesis starts with introducing an extended methodological summary in the SHM process and application, value of information modelling, decision analysis, Bayesian updating, detection theory, structural performance, reliability computation and lifecycle utility modelling.

Then the proposed approaches are applied into several case studies on system configurations of structural and building information systems for the efficient risk and integrity management of bridges and wind turbines, such as the design of a damage detection system on a Truss bridge girder regarding the sensor location, sensor numbers and monitoring year, whether or not to replace a 60-year-old Crêt de l'Anneau Viaduct in Switzerland, the implementation of short-term or long-term monitoring on the service life extension of the welds on the Great Belt bridge in Denmark, whether or not to install an ice heating system on an onshore wind turbine near a highway in the icing condition and the comparison of SCADA and strain gauges monitoring information on an offshore wind turbine.

With the proposed approaches and applied case studies, this thesis has shown that value of information-based pre-posterior decision analysis is an effective method for offering a concrete decision framework for optimal structural and building information system employment in industrial applications by risk reduction, expected cost saving and service life benefits for the value of industry and society.

RESUMÉ

Mange infrastrukturanlæg i de mest udviklede lande vil snart være ved eller har måske allerede nået slutningen af deres designlevetid. Infrastrukturejere og operatører står over for store udfordringer mht. drift og vedligeholdelse samt forlængelse af levetiden for disse konstruktioner. Structural Health Monitoring (SHM), der er en metode til at identificere og karakterisere infrastrukturskader, kan være meget effektiv til at levere information on strukturel sikkerhed til ejere og operatører. Der er dog et problem mht. at overføre SHM-informationen til beslutningsprocesserne for styring af integritet. Ejere og operatører kan være tøvende med at anvende SHM, fordi de ikke har nogen sammenfattende metode til konsistent at besvare følgende spørgsmål:

- Hvad er værdien af SHM?
- Hvordan vælger man den rigtige SHM-teknik?
- Hvordan designer man SHM-systemet, f.eks. sensorplacering og -antal?
- Hvordan bruges SHM-oplysninger til vedligeholdelsesplanlægning og forlængelse af levetiden?
- Hvornår skal overvågningen udføres, og hvornår skal vedligeholdelse udføres?
- Hvor længe skal struktursystemet overvåges, og hvor ofte er vedligeholdelse nødvendig?

Tidligere løste ejere og operatører disse beslutningsproblemer hovedsageligt baseret på enten erfaring og / eller deres budget. Denne afhandling udvikler en ny ramme til minimering af de forventede strukturelle integritetsomkostninger og operationelle risici ved at finde optimale scenarier til at løse beslutningsproblemerne kvantitativt, hvilket omfatter kvantificering af værdien af information fra overvågning for konstruktioner, der nedbrydes over tid. Den nye ramme giver basis for den grundlæggende udvikling af metoder til vurdering af værdien af information for konstruktioner inden for byggeri og anlæg, som integrerer Bayesiansk beslutningsanalyse med SHM gennem detektionsteori, strukturel ydeevne og brugsmodellering ved at anvende probabilistisk analyse, kost-benefit analyse samt konsekvensanalyse.

Denne ramme giver et godt grundlag til at besvare ovennævnte spørgsmål ved at benytte (1) en generisk pre-posterior beslutningsteoretisk ramme til implementering af et skadesregistreringssystem, (2) en omfattende brugsbaseret og informationsværdibaseret optimering af livscyklusbaseret integritetsstyring, (3) forskellige probabilistiske modelleringsmetoder til anvendelse af SHM-data til viden der kan benyttes til beslutningstagning og (4) en generel parametrisk analyse af et struktur- og skadesøgningssystem, og af de parametre der påvirker beslutningsregler og omkostninger og rangerer modelparametre på værdien af information. Afhandlingens innovation knytter sig til bestemmelse af værdien af information på

systemniveau for både et strukturelt skades overvågningssystem og for et strukturel system.

Med det formål at udvikle overvågningsstrategier til at planlægge den strukturelle integritetsstyring mest effektivt og forlænge levetiden for skadede konstruktioner, starter afhandlingen med at introducere en række metodologiske reviews og basis for SHM-processen og dens anvendelse, værdien af informationsmodellering, beslutning analyse, Bayesian opdatering, detektions teori, strukturel ydeevne, pålideligheds beregning og livscyklus benefitcost- modellering.

Derefter anvendes de foreslåede metoder i flere case-studier med systemkonfigurationer indenfor bygge- og anlægs informationssystemer til effektiv risiko- og integritetsstyring af broer og vindmøller, såsom design af et skadesdetekteringssystem på en bro med hensyn til sensor placering, sensorantal og overvågnings tidspunkter, uanset om de skal anvendes på en 60-årig Crêt de l'Anneau Viaduct i Schweiz, implementering af kortvarig eller langvarig overvågning af levetiden af svejsningerne på Storebæltsbroen i Danmark, og om der skal installeres et isvarmesystem på en vindmølle på land nær en motorvej under isdannelse og sammenligning af SCADA og strain gauge målinger, der indsamler oplysninger om en offshore vindmølle.

Med de foreslåede metoder og anvendte casestudier har denne afhandling vist, at værdien af informationsbaseret pre-posterior beslutningsanalyse er en effektiv metode til en konkret beslutningsramme for optimal struktur- og bygningsinformations system anvendelse i industrielle applikationer til risikoreduktion, reduktion af omkostninger og levetidsforlængelse og derved skabe værdi for både industri og samfundet.

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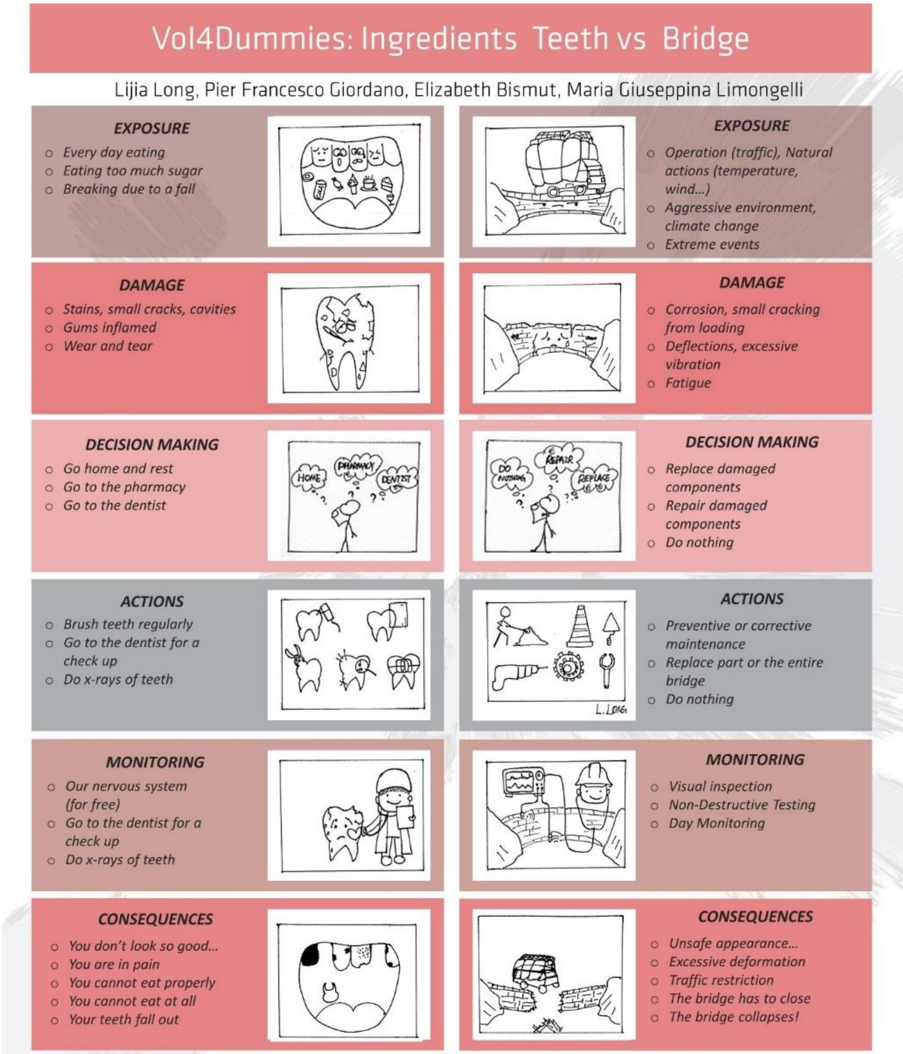
“The fundamentals for structure integrity management like bridges can be learned from looking at teeth care.”



CHAPTER 1. INTRODUCTION

All the structures deteriorate over time due to ageing of materials (e.g., concrete and steel), fatigue, corrosion, overloading, exposure to aggressive conditions etc. [1]. A significant number of worldwide deteriorated infrastructures are nearing the end of their designed service life.

In Europe, a substantial set of infrastructures is constructed after the Second World War in the 50s and 60s of the last centuries such as bridges with a common design lifetime of 50-100 years [2]. Some of such infrastructures are near to the end of designed life, or even beyond.

In the US more than 39% of the bridges have exceeded their 50 years of design life, and an additional 15% are between the ages of 40 and 49 according to the Federal Highway Administration (FHWA) [3]. The average age of bridge in the US is 43 years old [4]. Therefore, a growing number of bridges would have to be rehabilitated or replaced in the immediate future.

1.1. MOTIVATION

1.1.1. DRIVER OF SHM

It is essential that owners and operators have ideas on how severe the deterioration is and what effect on remaining service life, as failure of the structures may result in loss of lives and incur high costs. For example, the collapse of Miranda bridge in Genoa Italy 2018, which caused the death of 43 people and left 600 homeless after 50 years of usage [5].

Furthermore, due to design, poor construction, and other external factors such as the growing number of populations, number of cars, climate change and more often natural and manmade hazards, more infrastructure recently has shown a faster deterioration process than expected [6].

Therefore, proper actions needed to be made towards the sustainability, functionality, and reliability of the structures. Necessary maintenance and appropriate inspection methods are needed to maintain the safety of the deteriorated structures. Moreover, more and more stringent regulations have been released to support regular maintenance of public infrastructure, engineering structure as well as heritage structures world-widely, e.g., European Standard [7, 8], International Organization for Standardization [9-11], Germany [12], Canada [13], China [14], etc.

There are typically two strategies of maintenance for machinery systems where a failure can be corrected, which are corrective maintenance (repair after failure) and preventive maintenance (repair/maintenance before failure). For structures[1], it often uses preventive maintenance as to avoid catastrophic failures of the structures. To achieve preventive maintenance, operators can implement periodic scheduled maintenance or condition-based maintenance.

Periodic scheduled maintenance is based on experience. In terms of structure systems, there are two major disadvantages [15] related to an experience-driven approach, namely that (is) there are no applicable experiences to be drawn on for new structures and that (ii) new monitoring technologies may be applied prior to deployment with no referenced experience. This demands a comprehensive framework and coherent theoretical approaches beyond expertise to devise both the analysis and the enhancement of maintenance strategies.

Condition-based maintenance is more 'intelligent' compared to periodic scheduled maintenance, as the maintenance decisions are made using the present information on the actual health of the component, which can be accessed through Structural Health Monitoring (SHM).

SHM is a term composed of a large variety of methods, which are implemented to collect information for the evaluation of the structural performance during their service life. SHM applications are intended to provide managers with detail on the integrity (and forecasting of integrity) of a structure, as e.g., discussed in [16] and [17]. The general purpose is to monitor the performance of structures by applying diverse sensing technologies and data analysis algorithms [18] to utilize all relevant knowledge to model and to document the structure's health and damage detection, aiming at ensuring an appropriate level of safety for users, maintaining the environment sustainability, and reducing life-cycle costs for the asset.

Implementing SHM can bring superior benefits [19] like (a) code and standard calibration-decision support in the design phase, (ii) structure prototype creation and validation by testing in the design phase and (iii) utility management during the operational phase of an infrastructure system, e.g., integrity management preparation, service life extension, utilization adjustment, performance improvement, damage detection and early damage notification for risk mitigation measure. However improper SHM implementation may also result in big losses if the information is not relevant and causes a lot of data processing efforts.

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[1] In the Eurocodes EN1990, preventive maintenance is not included as a non-structural mean for buildings since it cannot be assured that the maintenance is actually performed.

1.1.2. CHALLENGES OF SHM

Due to the need to avoid catastrophic failure of deteriorated structures and achieve sustainability of structures, the field of SHM research has been boosted. To reduce the uncertainties in structural behavior, SHM strategies and measurement methods have been intensively studied.

However, only few SHM studies were undertaken considering the economic issues [18]. It is not clear that any private sector or government agency would be willing to invest on a SHM system if it is not shown that this SHM technology will have a more quantifiable, enhanced safety level and economic advantage compared to the existing employed maintenance strategy.

Common practice in SHM research starts with measurement, then feature extraction, and finally deviation of the damage index [18], mostly without a quantifiable consideration of the further maintenance decision processes, so that the relevance and value of the SHM information may not be clear. There is need to transform data from SHM into information that contributes to integrity management decision processes. For owners and operators of infrastructure it is often unclear whether it is worth undertaking an SHM project that takes into consideration the risk and economical aspect. The consequence of inadequate SHM strategies may be needless or improper remedial practices resulting in financial losses and wasted workforce due to unnecessary disruption to infrastructure network users or structures safety jeopardizing.

If the profit is not explicitly defined, the decision makers are hard to be persuaded to invest in SHM for complex systems. The benefits of SHM are mostly not clear up front, decision makers may prefer to incorporate practice experience to evaluate appropriate performance monitoring strategies. They may not account how to utilize the gathered information to contribute to optimizing lifecycle structural integrity management.

Therefore, the value of SHM needs to be more thoroughly understood before its deployment. It is important to establish a technically realistic framework to quantify the value of monitoring information. This would be of greatest importance regarding the problem of evaluating the value of SHM pre-posteriorly before implementing the monitoring strategy.

Another challenge is that it may be difficult to guarantee that the SHM is performed during the whole lifetime and that the associated decision rules are followed throughout the management of the structure. So, it cannot be assured that an acceptable level of structural reliability is obtained.

1.2. VALUE OF SHM INFORMATION

To quantify the value of SHM information, the Value of information (VoIP) theory can be utilized. It originates from the Bayesian decision analysis, which is firstly presented from Raiffa and Schlaifer [20] and Howard [21] with regards to business decisions. VoI analysis has been used in many technological and research fields, including oil and gas industry [22-24], earth science [25], environmental health risk management [26], nuclear waste storage assessment [27], but only few results are accessible on how to quantify and assess the value of SHM before its implementation regarding the structural lifecycle management.

1.2.1. STATE OF ART

Among the domain of quantifying the value of SHM information, Pozzi et.al. [28] and Thöns [29] did the early research in 2011. Pozzi established the methodology for evaluating the VoI as relevant to the rating of efficient long-term structural health monitoring systems on civil structures. The issue of non-linearity of the cost-to-utility mapping is discussed and the time-consuming predictive models are solved and estimated by a Monte Carlo approach. It concludes that if the expected expense of the experiment is below the VoI calculated prior to implementation, the experiment should then be performed.

Thöns extracted the posterior measurement uncertainty from Bayesian updating the statistical observations' uncertainty and the model uncertainty in his PhD thesis in 2011, which enables the measurement uncertainty quantification using all accessible measurement process data. Consecutively, an early approach for quantifying and optimising the service life cumulated expected of costs and risks has been introduced and applied to an offshore wind turbine. It has been seen that through utilisation and optimisation of local monitoring information in conjunction with comprehensive numerical mechanical models of the wind turbine fatigue, ultimate and serviceability limit states, the total risks and expected costs can be significantly reduced.

A more comprehensive description of the approach was presented in Thöns et al. [30] and Faber et al. [31] regarding the application of the value of information theory in the field of SHM. An expanded definition of decision analyses can be found in Thöns et al. [32], which offers an extended framework for determining the value of decisions namely the VoI, the value of actions and the value of actions and information.

Inspired by Pozzi, Zonta et al. [33] presented a framework for evaluating the impact of SHM on decision, which drawed on the principle of VoI and is illustrated on the Streicker Bridge case study. The methodology is focused on the hypothesis that the bridge manager must respond if the expected loss for taking no action is greater than the cost for acting, not unless the monitoring system suggests that the bridge is more probable to be damaged rather than being intact. Generalized models are built utilizing different damage scenarios and corresponding remedial actions. The case study is an example of how the monetary gain of an SHM system for certain observable events can be measured.

Based on the same case study from Zonta, Bolognani et al. [34] differentiated how the value of information can be varied by the different opinions of decision maker, e.g., the manager and the owner. It suggests that if manager and owner are separate persons, the benefit of monitoring is not equal compared to the case of a single decision maker.

Straub [35] also provided a method for modelling and estimating VoI with structural reliability methods based on importance sampling, which is applicable to fatigue monitoring. The difficulties in practical application of VoI are addressed, which includes how to set up a reasonable probabilistic modelling of the monitored process, how to model the action alternatives according to the monitoring results, and how to minimize computational efforts to determine the VoI. It is concluded that the VoI analysis is an effective method for offering valuable insights even when complicated decisions are needed to be made with significant uncertainty.

Konakli et al. [36] described an approach of VoI analysis in structural safety given inspections or structural health monitoring based on pre-posterior Bayesian theory, aiming to optimize different possible experimental schemes. An analysis is carried out on how the VoI is influenced by different factors, such as structural properties uncertainty, the inspection numbers, monitoring details and the component interdependencies. It concludes that the computational demand is the main limitation of VoI analysis.

Thöns et al. [37] introduced a continuous resistance deterioration model to calculate the value of SHM for fatigue deteriorating structural steel Daniel systems. The findings point to the significance of considering the structural system risks in quantifying the value of SHM.

Qin et al. [38] quantified the value of SHM in terms of lifecycle integrity management. A lifecycle cost analysis with generic structural performance model combining the observation of deterioration increments has been developed. The value of SHM is computed as the variation between the expected lifecycle structural integrity management costs with and without considering an optimal SHM system.

Due to the European project of COST Action TU1402: "Quantifying the Value of Structural Health Monitoring" from 2014 to 2019 (https://www.cost-tu1402.eu/), more and more researchers, scholars, experts, and engineers from other sectors participate in this research field and have contributed recently. Developments of the COST Action TU1402 can be found in [39].

Stepinac et al. [40, 41] explained how pre-posterior decision analysis can aid to quantify the VoI acquired by the condition evaluation of timber structures and further lead to choose suitable evaluation procedures and corresponding maintenance activities, which is investigated based on a timber exhibition hall in Zagreb, Croatia. Sykora et al. [42] [43] optimized in-site testing for historic masonry structures in Czechia through assessing the value of non-destructive and destructive techniques.

Honfi et al. [44] and Leander et al. [45, 46] provided potential evaluation criteria and a basis for decision on actions to prolong the designed service life of Söderström bridge in Sweden subjected to fatigue deterioration. Skokandić et al. [47, 48] and Mandić-Ivanković et al. [49] addressed decisions on bridge maintenance techniques and value of Bridge Weight-in-Motion data while analyzing road bridges in Croatia.

Limongelli et al. [50] adopted a methodology focused on the VoI definition and applies it to a two-span reinforced concrete bridge case study in Italy to quantify the value of visual inspections for bridges emergency management under seismic hazards.

Sousa et al. [51, 52] developed a constructive SHM method devoted to early damage identification on bridges from Portugal through the usages of VoI, which supports the infrastructure designer and operation managers to better (re)negotiate for the contract regards to civil structures assets management.

Thöns and Stewart [53, 54] utilized a decision theoretical process based on VoI theory to evaluate the cost-effectiveness of risk reduction measures for a historical bridge in case of terrorist attacks.

Mendoza et al. [55] suggested a decision process to identify an optimum design for a Norwegian offshore wind farm foundation with emphasis on identifying the expected consequences of failure utilizing risk indicators and discuss the value of obtaining site-specific soil characteristics data via a VoI study.

Thöns et al. [56] quantified the value of several SHM strategies for service life extension of a wind park. Nielsen et al. [57] quantify the value of SHM for blades of offshore wind turbines and evaluate three sensor configurations.

Maślak et al. [58] performed a case study on the maintenance of a tendon supported large span roof from Poland. In the study from Diamantidis et al. [59, 60], the enhancement of monitoring and decision requirements for the future use of structures is shown using the stadium roof located in northern Italy as an example.

Malings et al. [61, 62] explored optimum data acquisition in space and time for system integration and developed methodologies for effective VoI computation to optimize online and offline placement and scheduling of sensors. Li et al. [63] studied the connection between the VoI and measure accuracy and availability of measurements, degradation rates, predictability of damage, response time, maintenance expenses, and the financial discount rate.

The TU1402 Guide for scientists [19] represents a collection of models for structural health information (SHI) encompassing local (inspections) and global damage detection, monitoring, Nondestructive testing and evaluation (NDE, NDT) and load testing information. It is observed that the guideline excludes the Markov Decision Processes. It provides a consistent and comprehensive formulation of the value of SHI quantification encompassing the probabilistic modeling of SHI and a classification of SHI strategies.

1.2.2. SUMMARY

The quantification of the value of SHM information has been intensively under research in the aforementioned three areas throughout the past 10 years by:

1. Development of a theoretical framework on assessing and recompiling the mathematical framework of VoI analysis on the structural integrity management. The contribution references can be found in [30-32, 35, 36, 64].

2. Application of VoI on the selection of suitable SHM strategies and on the choice of life-cycle integrity management. The relevant illustrative examples for civil infrastructures include bridges [45, 50, 52, 53, 65], offshore wind turbine structures [55, 57, 66], dam structures [67], buildings [40, 41, 43] and roofs [59, 60].

3. Development of guidelines on the use of available methods and tools for the computation of the VoI, which can be found in TU1402 website[2] with the factsheet on tools. A complete VoI analysis tool called VoICalc [68] is currently in development. Existing decision and policy planning tools that may be used in a VoI study [40] are GeNiE[3], QGeNIe[4] Modeler based on

[2] https://www.cost-tu1402.eu/action/working-groups/methods-and-tools.

[3] GeNIe is a graphical user interface (GUI) from BAYES FUSION, which allows for immersive model building and learning.

[4] QGeNIe, from BAYES FUSION, is a rapid model development interface that allows for fast prototyping of decision models, useful especially in applications such as strategic planning.

Bayesian networks, Netica[5] based on Bayes nets, KUBA[6] based on Markov Decision processes, Perseus POMDP[7] based on Partially Observable Markov Decision Processes (POMDPs), and Precision Tree[8] based on the decision trees.

[5] Netica, from NORSYS Software Corp, works with influence diagrams to fidentify optimal decisions which maximize the expected values of specified variables.

[6] KUBA, from Infrastructure Management Consultants GmbH (IMC), facilitates management of engineering structures such as bridges, galleries, retaining walls and tunnels.

[7] Perseus POMDP, from Matthijs Spaan, TU DELFT, Frans Oliehoek. The toolbox is a free C++ software toolbox for decision theoretic planning and learning in multiagent systems (MASs). This addresses a limitless horizon decision making issues.

[8] PrecisionTree, from Palisade, visually maps out, organizes, and analyzes decisions using decision trees, in Microsoft Excel.

1.3. AIM OF THE THESIS

This PhD research was started two years after the launch of the European project of COST Action TU1402: "Quantifying the Value of Structural Health Monitoring" from end of 2016, which also contributes and is in alignment with the aim of COST Action TU1402. This PhD program was performed within the INFRASTAR (Innovation and Networking for Fatigue and Reliability Analysis of Structures - Training for Assessment of Risk) network (https://infrastar.eu/) with the goal of structure service lifetime extension, overall cost and risk reduction and development of value of information-based lifecycle approaches for future SHM designs.

The latest work accomplishments, focused on the pre-posterior Bayesian decision analysis, have provided a systematic and straightforward theoretical basis to quantify the value of SHM prior to its deployment and showed that the value of a SHM strategy can be quantified even before it is implemented. Furthermore, recent studies show a large industrial potential for substantially increased life cycle benefits utilizing a pre-designed and optimised SHM strategy. This PhD focusses on structures exposed to deterioration such as bridges and wind turbines aiming at:

- Further development of formulations, applications and extensions of approaches and methods for quantifying value of monitoring information based on utility theory, Bayesian decision theory, probabilistic approaches, risk, and reliability analysis as well as cost and benefit models.

- Development of a generic methodology of structural integrity management based on value of information theory with combination of structural performance by utilizing the monitoring data.

- Development of methods for coupling SHM information with structural reliability models during the lifecycle of the structure system.

- Establishment of cost-efficient and reliable operation and maintenance plans based on Bayesian statistics and optimization of maintenance scenarios.

- Identification of optimal monitoring strategies to efficiently manage and to prolong the service life of deteriorated structures.

- Establishment of intelligent sensor deployment and SHM design by studying the influence of the structural and damage detection model as well as cost and benefit model parameters on the value of information.

- Application of the theoretical basis on case studies for reliability analysis and value of information-based optimal life-cycle decision analysis.

- Improvement of knowledge and decision basis for optimizing the design of SHM systems and utilization of monitoring data for more reliable structural safety verification and more precise fatigue life prediction of the existing structures.

- Achievement of sustainable societal development through maintaining reliability, safety, serviceability, and productivity in the asset management of structures and infrastructures.

1.4. THESIS OUTLINE

To systematically achieve this aim, the thesis includes the extended methodological summary (Chapter 2) as well as the research issues (Chapter 3 to 7) and summary, conclusion, and outlook (Chapter 8), as shown in Figure 1.

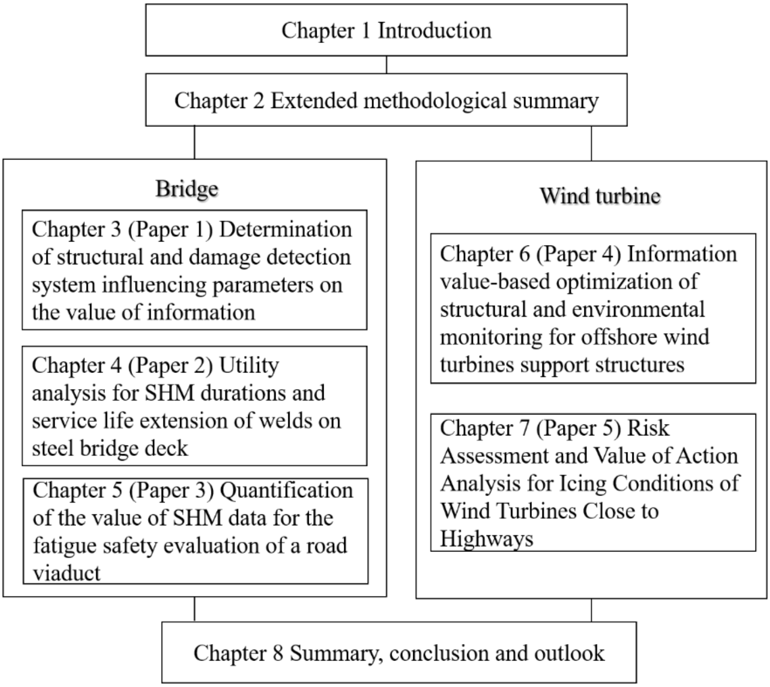


Figure 1 Outline of the thesis

This Ph.D. thesis is a paper-based thesis, consisting of an extended methodological summary (Chapter 1 and 2) and five published papers (Chapter 3 to 7). Chapter 1 is the Introduction, describing the motivation, aims, state of the art and thesis outline. Chapter 2 is the summary of methodological knowledge (shown in Figure 2) that is related to the quantification of the value of monitoring information for deteriorated structures. It also contains a short description of the results in the papers and how the papers are contributing to fulfilling the objectives of the work. Chapter 3 to 7 (Paper 1 to 5) are the collection of five papers as follows, in which three of them (Paper 1 to 3) are applied research case studies on bridges, the remaining two (Paper 4 and 5) are case studies on wind turbines. The summary of the papers is shown in Table 1.

Paper 1 Long L., Döhler M., Thöns S. *Determination of structural and damage detection system influencing parameters on the value of information*. Structural Health Monitoring Journal (2020), https://doi.org/10.1177/1475921719900918

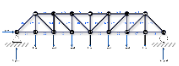
Paper 2 Long L., Alcover F. I., Thöns S. *Utility analysis for SHM durations and service life extension of welds on steel bridge deck.* Structure and Infrastructure Engineering (2021), DOI: 10.1080/15732479.2020.1866026

Paper 3 Bayane I., Long L., Thöns S., Brühwiler E. *Quantification of the value of SHM data for the fatigue safety evaluation of a road viaduct*. ICASP13-13th International Conference on Applications of Statistics and Probability in Civil Engineering. May 26-30, 2019, Seoul, South Korea.

Paper 4 Long L., Mai A. Quang., Morato G. P., Sørensen D. J., Thöns S. *Information value-based optimization of structural and environmental monitoring for offshore wind turbines support structures*. Renewable Energy. 2020 Jun 12. https://doi.org/10.1016/j.renene.2020.06.038

Paper 5 Rastayesh S., Long L., Sørensen D. J., Thöns S. *Risk Assessment and Value of Action Analysis for Icing Conditions of Wind Turbines Close to Highways*. Energies Journal, Volume 12, Issue 14, 2019.

Table 1 Summary of papers

Paper	**Object**	**SHM information**	**Decision scenario**
1	Theoretical truss bridge girder 	Damage Detection System (DDS)	-Whether to implement DDS? -How are sensors placed? -How many sensors to install? -In which year to implement DDS? -How to choose the proper sensors? -How will the structural deterioration state influence the choice?

2	Great Belt bridge in Denmark 	-Strain gauges -Pavement temperature -Traffic	-What is the optimal monitoring campaign regarding the monitoring duration and phase? -Service life extension of the monitored welds or not?
3	Crêt de l'Anneau Viaduct in Switzerland 	-Strain gauges -Thermocouples	-Whether to replace the viaduct after 60 years of usage?
4	Offshore wind turbine 	-Strain gauges -SCADA data	-What is the optimal monitoring strategy?
5	Onshore wind turbine 	-Ice detecting system	-Implementation of the ice heating system or not, given that ice detecting system is already installed?

Paper 1 is the core contribution of the thesis with a very comprehensive description, computation, and discussion of the pre-posterior decision on determination of all aspects of Damage Detection System (DDS) design on a truss bridge girder before its implementation. This offers complete answers to the following questions: Whether to implement DDS? Where to place the sensors? How many sensors are needed? In which year to deploy DDS? How to pick the proper sensors? How will the structural deterioration condition (deterioration type, rate and initialing year) impact the choice?

Paper 2 and 3 discuss the scenario when the SHM system is already applied, how to utilize the SHM data obtained to facilitate decision. Paper 2 is based on the monitoring data on an steel bridge deck in Denmark to investigate the optimal monitoring campaign regarding the monitoring duration and phase and determine whether the service life of the monitored welds should be extended or not. Paper 3 is based on the obtained monitoring data from Crêt de l'Anneau Viaduct in Switzerland to determine whether to replace the viaduct after 60 years of service.

Paper 4 and 5 are the applied research on wind turbines. Paper 4 investigates the optimal monitoring strategy for offshore wind turbines based on obtained monitoring information. Paper 5 addresses the issue of whether to place the ice heating system if the ice detecting system is already installed under freezing conditions for an onshore wind turbine near a highway.

Another five peer-reviewed papers are not included in the thesis (see the list below). The reasons for exclusion are that the content of Paper 6 is already described in part of Paper 2, the content of Paper 7, 8 and 9 are included and summarised in parts of Paper 1.

Paper 6 Long L., Farreras Alcover I., Thöns S. *Quantification of the posterior utilities of SHM campaigns on an orthotropic steel bridge deck*. IWSHM 2019, The 12th International Workshop on Structural Health Monitoring, Stanford, California, USA, 10-12 September 2019

Paper 7 Long L., Thöns S., Döhler M. *The effects of deterioration models on the value of damage detection information.* IALCCE 2018, The Sixth International Symposium on Life-Cycle Civil Engineering, Ghent, Belgium, 28-31 October 2018

Paper 8 Long L., Thöns S., Döhler M. *The effects of SHM system parameters on the value of damage detection information.* EWSHM 2018, The 9th European Workshop on Structural Health Monitoring Series, Manchester, UK, 10-13 July 2018

Paper 9 Long L., Thöns S., Döhler M. *Damage detection and deteriorating structural systems.* IWSHM 2017, The 11th International Workshop on Structural Health Monitoring, Stanford, California, USA, 12-14 September 2017

Paper 10 Thöns S., Döhler M, Long L. *On damage detection system information for structural systems.* Structural Engineering International 28.3 (2018): 255-268.

1.4.1. INTEGRATIONS AMONG CHAPTERS

The integrations among chapters are shown in Figure 2. Quantifying the value of SHM information is based on the VoI principle and the SHM methodology as introduced in Chapter 2.

Section 2.1 covers the general aspects of SHM and its applications on bridges and wind turbines. Section 2.2 describes the VoI theory with decision analysis and Bayesian updating. Then Section 2.3 presents the Detection theory, which is the fundamental knowledge basis of SHM and is needed to be integrated into VoI analysis. With the computation effort of probabilistic modelling and life-cycle utility modelling in Section 2.4, the value of SHM information can be finally quantified.

The chapters 3 to 7 (Paper 1 to 5) contain detailed mathematical/statistical methods and the applied methodology from Chapter 2, but with different emphasizing aspects of the examples of applications from the papers:

Chapter 3 (Paper 1) addresses the pre-posterior decision analysis with consideration of influence parameters to probability of damage and influence of structural performance parameters.

Chapter 4 (Paper 2) illustrates the posterior decision analysis taking into account the influence of utility modelling parameters.

Chapter 5 and 6 (Paper 3 and 4) both present the conditional value of sample information analysis, with chapter 5 emphasizing the Bayesian updating with observed events and chapter 6 Bayesian updating of observed stochastic variables.

Chapter 7 (Paper 5) addresses the value of action analysis.

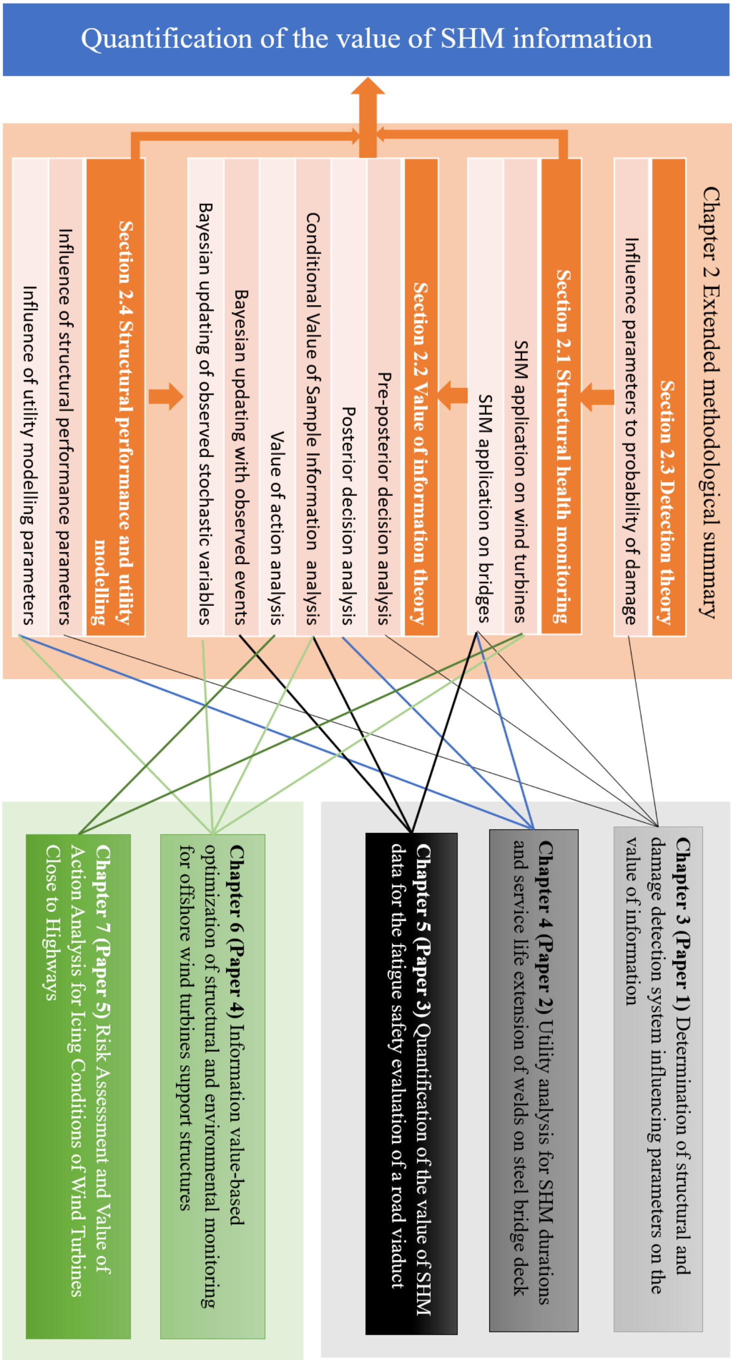


Figure 2 Flowchart of methodological summary and integration of chapters

CHAPTER 2. EXTENDED METHODOLOGICAL SUMMARY

This chapter provides a general overview of the topics of the thesis including an account for the current state of the art to the quantification of the value of monitoring information for deteriorated structures. It focusses on further reviewing the results of the papers included in the following chapters 3-7 and explains how the results are related to the current state of the art of the methodology.

2.1. STRUCTURAL HEALTH MONITORING

During the period of 1940-1960s, with the emerging of sophisticated measurement technologies, modern Non-destructive Evaluation (NDE) has seen rapid advancement in the development of penetrant test, eddy current and acoustic methods (composite tap testing, ultrasonic, acoustic emissions), as well as radiography and thermography [69]. However, these methods are primarily local which usually requires taking the system out of service for access, and they are somewhat qualitative. Due to the need for an online and automate damage detection method, the concept of SHM emerged from NDE in the 1980s and was developed at that time.

Numerous practical SHM researches have been conducted in the offshore industry during the 70's and 80's owing to the high risks and costs involved in subsea inspections [70]. In 1979 a first systematic overview of SHM technologies and procedures of inspection and testing was published [71]. However, due to immature development of data treatment capabilities at that time, SHM was not commonly applied in parallel with inspection technologies [72]. SHM development has been accelerated over the last decades due to development of electronic data processing, storage technologies and data analysis algorithms. Today SHM is applicable to different kinds of structures, e.g., bridges, nuclear plants, buildings, and pipelines, not only to assist inspection and maintenance in the offshore sector.

The aim of SHM is to establish methods for damage detection, evaluation, model recognition and feature extraction to tackle the functional and the environmental variation with the objective of damage diagnosis related to significant life-safety and economic benefits (see e.g., the most comprehensive review until 2001 [16], a recent review from 2011 [73] and [15]). Recently, SHM findings have been used for structural reliability evaluations to determine uncertainties in monitoring, update models and improve inspection planning (see e.g. [74], [75], [29], [76]) in various fields of engineering.

Now this field has broadened to transform monitoring information into decision making. Todd (e.g. [77], [78]) performs a method called Bayesian experimental model based on a risk and expected cost analysis to improve the sensor placement and performance for a monitored structure. Another approach is to use VoI theory to determine the value of SHM information as described in [28]. This implies that an experiment will be carried out if the expected expenses of performing the experiment for the particular case is smaller than the value of information. More detailed references on the quantifying value of SHM information have been stated in Chapter 1.2. The knowledge of VoI theory will be presented in section 2.2.

2.1.1. SHM PROCESS

SHM strategies and measurement techniques, containing various physical technologies (hardware) and a broad range of data analysis algorithms (software) have been well developed. The algorithms for data analysis constitute a broad area of research focusing on data normalisation, uncertainty elimination, damage detection, damage evaluation, model recognition and feature extraction. Wang [79], [80] and Farrar [72] summarize the most detailed overview of sensor technologies, implementations, and data processing procedures.

Around 2000, groups at Los Alamos and the University of Sheffield started to pose SHM as a problem in statistical pattern recognition [18], with realization that damage detection is not a deterministic problem. It opened the door to adopt technology from radar and sonar detection, speech pattern recognition, machine learning, econometrics, and statistical decision theory to the damage detection problem. Farrar and Worden [18] summarize the SHM process into the following four steps:

1. Operational evaluation
2. Data acquisition & network
3. Feature selection & extraction
4. Statistical model development

2.1.1.1 Operational evaluation

Operational evaluation defines the damage to be identified and address concerns regarding implementation issues for an SHM system, which can be considered as collecting a prior information to inform the SHM system design process.

The prior information should answer the following questions: Why perform the monitoring (financial and life-safety rationales)? What are the expected damages (type, size, location, and time scale for damage evolution) to look for? What are the requirements of operational and environmental conditions? What are the legal and economic constraints? What are the limitations of operational environment on data acquisition?

In order to gather prior information, inputs from different sources, e.g., designers, technicians, maintenance staff, financial analysts and regulatory officials are needed. However, there are not many references that address the operational evaluation step, there is no widely accepted procedure to demonstrate the rate of return on investment in an SHM system.

The newly recent development of quantifying the value of SHM information, which is also presented in this thesis aim to strengthen the operational evaluation by quantifying the benefit of an SHM system before its implementation.

2.1.1.2 Data acquisition& network

Once the assessment of the operation system is completed, the next step is to identify the sensing equipment and select the data for the feature extraction process, which is called Data acquisitions & network.

The definition of SHM derives from techniques used in NDE, commonly known as non-destructive testing (NDT). The key distinction between NDE and SHM is that NDE requires the item be withdrawn from operation for the inspection, whereas SHM does not [18]. Based on the commonly used NDE methods, the sensing technologies in SHM are summarised in Table 2 together with the sensor types and their principles.

Table 2 Summary of sensing technologies in SHM

Sensing technologies	**Sensors**	**Principle**
Conventional force/pressure sensing	Piezoelectric and piezoresistive force and pressure transducers	Deformation is proportional to the force applied to the material.
Conventional strain sensing	Strain gage	The structure is attached to a foil that holds a wire, which is stretched or compressed as the structure deforms.
Conventional acceleration sensing	Piezoelectric accelerometer	Base-excited spring mass system where the piezoelectric crystal is the stiffness element.
Acoustic Emission (AE) sensing [81]	Acoustic Emission Sensors	Passive sensor that "listens" for elastic waves generated when damage initiates or propagates.

Fiber optic sensing [82]	Fiber optic sensors	Light from a laser source is transmitted via an optical fiber, reaches a detector which measures these changes in its parameters in the optical fiber or fiber Bragg gratings.
Piezoelectric transducer based SHM methodologies [83]	Guided wave, Electro-mechanical impedance	An electric charge will be produced when the materials are mechanically stressed. If an electric field is applied to the material, the material will also deform (produce a mechanical strain).
Laser-based sensing techniques [84]	Scanning laser Doppler velocimetry (LDV)	Analysing reflected light using the principle of displacement.
Video-based non-contact measurement [85]	Photogrammetry using digital video cameras; Discrete-point tracking; Digital image correlation (DIC)	Obtaining 3D geometric information through stereoscopic image overlap of real objects.
Mobile wireless robotic sensing technologies [86]	UAV (Helicopter) Robotic for Visual Interrogation; Articulated Ultrasonic Robot Arm; Reinforced Concrete Toy Truck for Visual Inspection	A combination of sensors (such as accelerometers or strain gages) and artificial intelligence (AI) and physical robotic elements.
Microelectron-mechanical-system (MEMS) sensors [88]	MEMS Sensors (acceleration; gyro; strain sensing; ultrasonic inspection; temperature)	A “microfabrication” of mechanical elements within a silicon integrated circuit process.

Vision-based measurement techniques [87]	X-ray technology; Augmented Reality Tools for Enhanced Structural Inspection	A high-Resolution, photo-realistic 3D model of the infrastructure automatically generated during inspection.

After the sensing technologies are chosen and installed, the system's dynamic response will be measured, and the measurement data will be obtained. According to [18], the data acquisition process can be divided into six parts: 1) excitation; 2) sensing; 3) analogy to digital conversation; 4) initial signal conditioning; 5) data storage and transfer; 6) data cleaning, normalization, compression, and fusion. More recent development has integrated data acquisition components with feature extraction as SHM software.

2.1.1.3 Feature selection & extraction

Selection and extraction of features is the process of distinguishing details related to damage from the measured data. Normally an inverse modeling approach is applied to identify indications of damage from measured system responses. For instance, if stiffness changes are detected, there may be crack in a mechanical part; if boundary condition changes are detected, scour may exist on the bridge pier; and if connectivity changes are detected, the bolted joint may be loosening. The measured response has a certain feature that is well associated with the damage, i.e., an indicator giving indirect information about the size of a defect.

To recognize damages, it is intended to use the simplest feature possible to differentiate between the damaged and undamaged signals. There are three approaches to identify damage-sensitive features including experience and knowledge base, component and system testing and numerical analysis on how damage changes the system response.

The commonly used three damage sensitive features are: 1) waveform or image comparisons, 2) features derived from linear and nonlinear model parameters and 3) features derived from residual errors between measured and predicted response. Several references can be found in [88-92] with relevant models and methods for damage identification.

2.1.1.4 Statistical model development

After the features are extracted, the challenge is to make an objective evaluation of the state of damage to a specific structure based on the extracted features. Five levels of decision challenges arising via a five-step damage-related process, along the line of hierarchy from Rytter [93].

- Level 1: Damage detection. Does damage occur?
- Level 2: Damage localization. Where is probable position of the damage?
- Level 3: Damage classification. What kind of damage does it represent?
- Level 4: Damage assessment. How big is the damage size? How severe is the damage?
- Level 5: Damage prediction. How will the damage influence the residual life of the structure?

However, it is often challenging to describe the interactive connection between the selected features and the structural damage state depending on an engineering physics-based evaluation process. Farrar and Worden [16] suggested a machine learning-based method, more precisely, the pattern recognition dimensions of machine learning, utilizing mathematical models to transform features into real state performance-level decisions.

The algorithms used in mathematical models of machine learning fall into two groups, 1) supervised learning algorithms, utilizing training data accessible from both the undamaged and damaged structure, e.g., neural networks, classification and regression, support vector machines; 2) unsupervised learning algorithms, if only data from undamaged structures is accessible, e.g., outlier or novelty detection. However, the unsupervised learning nearly entirely addresses the level 1 problems and in certain instances level 2. Therefore, the only usage is the detection and determining the location of the damage. The detail theory of damage detection will be presented in Chapter 4.

2.1.2. APPLICATION OF SHM

2.1.2.1 SHM on bridges

A summary of the application of SHM on five main types of bridges can be found in Inaudi [94] including concrete beam bridges [94], steel beam bridges [95], concrete cantilever bridges [96], arch bridges [97], cable stayed bridges [98] and suspended bridges [99]. The key risks or uncertainties that are generally correlated with each kind of bridge are shown in Table 3 in different colors [94]. The priority risks or uncertainties that need to be addressed first are marked with red. The very often relevant risks are denoted in orange. The least significant risks, which can be added when the budget allows for it, are indicated with green.

Table 4 summarizes the usual predicted responses and the suggested sensors types to monitor each defined risk. The table can be viewed as a foundation step for the implementation of a bridge health monitoring system, which will be followed with detailed risk assessment for each single bridge component.

Table 3 Typical risks and uncertainties associated with different bridge types. Recreated based on [94]

Risk/uncertainty on the bridges	Concrete beam	Steel beam	Concrete cantilever	Arch	Cable stayed	Suspended
Correspondence between finite element model and real behavior	orange	orange	orange	orange	green	green
Dynamic strain due to traffic, wind, earthquake, explosion, etc.		red		green	red	red
Creep, relaxation of pre -stress	red		red	green		
Changes in cable forces					orange	orange
Correspondence between calculated vibration models and real behavior	green	green	green	green	green	green
Non-working bearings and expansion joints	orange	orange	orange		orange	green
Cracking of concrete or steel	green	green	green	green	green	green
Temperature changes and temperature gradients in load bearing elements	red	red	red	red	red	red
Different settlement between piers or foundations	green	green	orange	orange		
Change in water table or pore water table or pore water pressure around foundations	green	green	green	green	green	green
Stability of slopes around foundations and abutments	green	green	green	green		
Change in the concrete chemical environment: carbonation, alkali silica reaction, chlorine penetration	red	green	red	orange	orange	orange
Environmental conditions				green	red	red
Traffic and overloads	green	green	green	green		
Construction schedule and specific actions	orange	orange	orange	orange	orange	orange

Legend: green = sometimes relevant; orange = usually relevant; red = always relevant

Table 4 Risks, responses, and candidate sensor types from [94]

Risk/uncertainty on the bridges	**Response/consequences**	**Proposed sensors**
Correspondence between finite element model and real behavior	Strain distribution and magnitude different form model	Local strain sensors including strain gauges, vibration wire gauges and fiber optic sensors, tiltmeters.
Dynamic strain due to traffic, wind, earthquake, explosion, etc.	Large strains, fatigue, cracks	Local strain sensors, including strain gauges, vibration wire gauges and fiber optic sensors, with dynamic data acquisition systems. Distributed fiber optic sensors to detect ne crack. Crack-meters.
Creep, relaxation of pre-stress	Global deformations, bending	Long-gauge fiber optic strain sensors, settlement gauges, tiltmeters, laser distance meters, topography
Changes in cable forces	Force and strain redistribution	Local cells: vibration wires, resistive or fiber optics.
Correspondence between calculated vibration models and real behavior	Mode shapes and frequencies different from model	Accelerometers, long-gauge fiber optic strain sensors.
Non-working bearings and expansion joints	Reduced movement, movements occur at wrong location, strain redistribution	Joint meters: potentiometers, vibrating wire, or fiber optics
Cracking of concrete or steel	Crack opening	Crack-meters: potentiometers, vibrating wire, or fiber optics

Temperature changes and temperature gradients in load bearing elements	Strain redistribution, cracking	Temperature sensors: electrical, fiber optics point sensors or distributed sensors
Different settlement between piers or foundations	Global movements, tilting, strain redistribution	Laser distance meters, topography, settlement gauges, tiltmeters.
Change in water table or pore water table or pore water pressure around foundations	Change in pore water pressure	Piezometers: vibration wire or fiber optics
Stability of slopes around foundations and abutments	Slope sliding	Distributed fiber optic soil stability sensors, laser distance meters, inclinometers
Change in the concrete chemical environment: carbonation, alkali silica reaction, chlorine penetration	Corrosion of rebars	Concrete corrosion and humidity sensors
Environmental conditions	Actions on bridge	Weather station, wind speed measurement
Traffic and overloads	Actions on bridge	Weight-in-motion station, dynamic strain sensors
Construction schedule and specific actions	Difficulty in analyzing data	Webcam, image capture and archival

The application of SHM on bridges can be further found in case studies in Chapter 4 (Paper 2: The Great Belt bridge, a suspension bridge.) and in Chapter 5 (Paper 3: Crêt de l'Anneau Viaduct, a composite concrete-steel road-viaduct). The SHM systems on the Great Belt bridge including strain monitoring system, traffic monitoring system (used by the toll system) and pavement temperature monitoring system are further introduced. The obtained SHM information on the Crêt de l'Anneau Viaduct includes the strain and the temperature of the concrete, the steel, and the air, which are measured respectively by the strain gauges in steel reinforcement bars and thermocouples.

2.1.2.2 SHM on wind turbines

The overview of application of SHM on wind turbines depending on the monitoring components/objects, e.g., rotating drivetrain, rotor blades and onshore and offshore support structures can be found in [100], [101], [102] and [103] which is further summarized in Table 5. This includes monitoring components/objects, related risk, and uncertainty and proposed SHM. The application of SHM for electrical components, e.g., the main frequency converter, pitch and yaw systems are not covered as it is still under research and development.

Table 5 Summary of SHM on wind turbines

Monitoring component/objects	**Risk/uncertainty**	**Proposed SHM**	**Ref.**
Rotating drivetrain components (main bearing, gearbox, generator bearing, tower oscillation)	• Grid loss • Emergency stops • Grid faults • Generator short circuits • Crowbar events • Resonant vibration • Wind gusts • Control malfunctions • Curtailments • High wind shutdowns	•Vibration-based SHM • Oil-based SHM •Others: Acoustic Emission (AE), thermography, electromechanical parameters, holistic SHM	[104]
Rotor blade	• Lighting strike • Icing •Fatigue of the composite laminates, buckling in sandwich panels, bond line failure, root bolt connection • Rotor imbalance due to rain erosion, pitch control errors and mass differences from blade to blade • Overload due to pitch or yaw-control errors	•Vibration-based SHM • Acoustic Emission (AE) • Ultrasonic wave propagation •Strain measurement •Deflection-based methods	[105]
Onshore support-structure (Tubular steel tower/Lattice towers/Reinforced	Tower: •Strong wind, •Insufficient strength of bolts •Poor bolt quality control	•Strain gauges •Fiber optical sensors •Vibration and temperature sensors	[106]

concrete tower/Hybrid tower with concrete in the bottom and tubular steel in the top)	Foundation: •Cracks due to deficiencies in the design, poor workmanship, or inappropriate material selection	•Inclination sensors; displacement sensors •Photometry and laser interferometry	
Offshore support structure (Monopile foundations/Jacket foundations /Gravity base foundation /Floating foundations)	Foundation: •Storms or harsh environment •Fatigue of the Material •Scour at the seabed •Problems in grouted joints •Splash zone subjected to a highly corrosive environment •Corrosion	•Strain gauges •Temperature sensors •Displacement sensors •Accelerometers •Additional sensors: inclinometers, load cells, wind speed and direction and wave height sensors	[107]
Operation and environmental condition	•Storms or harsh environment	SCADA supervised control and data acquisition system in 10-minute interval: Wind speed, wind direction, active power, reactive power, ambient temperature, pitch angle, rotational speed (rotor and generator)	

The application of SHM on wind turbines can be further found in case studies in Chapter 6 (Paper 4) and Chapter 7 (Paper 5). In Chapter 6, the acquired SHM information for an offshore monopile wind turbine including meteo-oceanographic data from the SCADA system and stress ranges from strain gauges are introduced. In Chapter 7, for an onshore wind turbine under icing condition, an ice detection system and an ice heating system are introduced.

2.2. VALUE OF INFORMATION

Quantifying the value of SHM information utilizes the value of information theory (VoI) and the methodology of SHM. The general aspects of SHM have been discussed in Section 2.1. Section 2.2 will focus on describing how the VoI theory works. The following Section 2.3 will present the detection theory involved in SHM, which is needed to be integrated into VoI analysis.

2.2.1. GENERIC DECISION MODELLING

The VoI theory is developed by Raiffer and Schlaifer [20]. The research of VoI utilizes Bayesian updating and decision theory based on utility, providing a way to evaluate the changes in the utility of obtained and predicted information. The decision format (a decision tree) in regards of SHM is shown in Figure 3 by [108], which contains the following five dimensions.

- $\boldsymbol{E} = \{e_1, \dots, e_m\}$ SHM Strategy

SHM strategies are the options on how to implement SHM, e.g., selection or combination of sensing techniques, determination of monitoring duration and comparison of monitoring location, etc. Decision-makers are usually facing the choice of the optimal SHM Strategies, as different SHM strategies will result in different investment costs and monitoring costs, which lead to different lifecycle costs in maintaining structural integrity. Therefore, the SHM Strategies are presented by a 'square' decision node in the decision tree.

- $\boldsymbol{Z} = \{z_1, \dots, z_m\}$ SHM outcomes

SHM outcomes are information to determine the actual state of the structures, e.g., detection of damage or no detection of damage. However due to the uncertainty of the sensing technologies and the physical (and model) uncertainty of modelling a damage process, it is hard to find an absolute SHM outcome. Therefore, a probability $P(\boldsymbol{Z})$ is used to describe the frequency of appearing SHM outcomes. The SHM outcomes in the decision tree are presented with a chance node 'circle'.

- $\boldsymbol{A} = \{a_1, \dots, a_m\}$ Actions

Actions are the methods that could be taken to affect (improve or maintain) the physical states of the structure, e.g., do nothing, repair, rehabilitation and replace etc. As the choice of actions will influence the structure system performance, decision-makers need to make decisions on the optimal actions depending on the SHM outcome. Therefore, the actions in the decision tree will be presented by the 'square' decision node.

- $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_m\}$ System states

System states describe the physical status of the structure, e.g., safe, minor damaged, major damaged and failed. However, there is uncertainty towards the true state of the system structure. Therefore, a probability $P(\boldsymbol{\theta})$ can be assigned to describe the knowledge of belief on the system states. The system states in the decision tree are presented with a chance node 'circle'.

- $u(e, z, a, \theta)$ Utility Evaluation

With a certain SHM strategy performed, SHM outcome obtained, action implemented, and system state predicted, it leads to a value or utility $u(e, z, a, \theta)$. The utility function u contains all the costs and benefits as well as the consequences involving the decisions on the structure integrity management, which will be presented in Section 2.4 in detail. The utility is presented with a 'diamond' node in the decision tree.

Usually, a structural system may be under a set of structural states $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_m\}$ representing different health status. A probabilistic structural system reliability model will be used to compute the probabilities of the structural states $P(\boldsymbol{\theta})$. A set of possible actions $\boldsymbol{A} = \{a_1, \dots, a_m\}$ are needed to be chosen to deal with the uncertain system states. To obtain more information related to the choice of a proper action, decision makers may have various options to carry out certain SHM strategies $\boldsymbol{E} = \{e_1, \dots, e_m\}$, like different types of sensing technologies. The set of SHM strategies will have a set of potential outcomes $\boldsymbol{Z} = \{z_1, \dots, z_m\}$ with a probability of detecting outcomes $P(\boldsymbol{Z})$ which provide information on the actual structural state, which will be further described in Chapter 4. The decisions of actions and SHM strategies are determined by the order of the expected values of the utility $u(e, z, a, \theta)$. Examples of decision trees can be found in case studies from Chapter 3 to 7 (Paper 1 to 5).

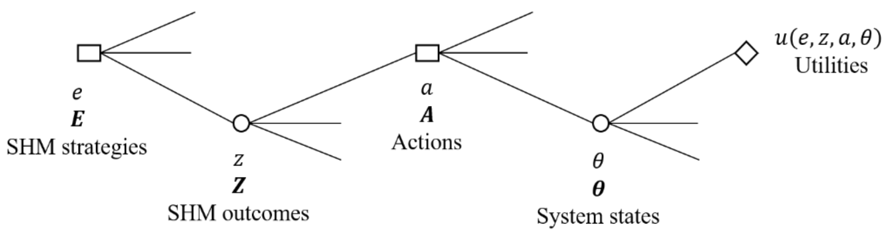


Figure 3 Decision format in the context of SHM

2.2.2. DECISION ANALYSIS

There are three different decision analysis types relying on the status of knowledge at the point of the assessment, namely prior decision analysis, posterior decision analysis and pre-posterior decision analysis.

2.2.2.1 Prior decision analysis

Prior decision analysis applies to a circumstance where the utility function is known and the probabilities of the particular system state leading to various consequences have been predicted, which means that $P(\theta)$ is given after a certain action a is chosen. The action a in the prior decision analysis is determined by initial design based on prior knowledge of uncertainties. Assume there are m system states in total, $\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_m\}$. The expected utility of an action a is calculated by Eq. 1.

$$E'_\theta[u(a,\theta)] = \sum_{j=1}^{m} u(a,\theta_j)\, P'(\theta_j) \qquad \textit{Eq. 1}$$

To make a differentiation, $P'(\theta_j)$ is used to represent the assigned probability at state θ_j , which is called prior probability. After the calculation of all the expected utilities of different actions, the decision analysis consisting of choosing the best action will lead to the highest expected utility U', shown in Eq. 2.

$$U' = \max_a E'_\theta[u(a,\theta)] \qquad \textit{Eq. 2}$$

U' is called prior expected utility.

2.2.2.2 Posterior decision analysis

Posterior decision analysis refers to a case where empirical evidence is available, indicating that a certain SHM experiment e has been applied and the experiment findings z are understood. The probability of the structure system state in the decision problem can be updated as $P''(\theta_j)$ by use of the Bayes' rule illustrated by Eq. 3.

$$P''(\theta_j) = P(\theta_j|z) = \frac{P(z|\theta_j)P'(\theta_j)}{\sum_{j=1}^{m} P(z|\theta_j)P'(\theta_j)} \qquad \textit{Eq. 3}$$

Where $P(z|\theta_j)$ is the likelihood function of the experiment outcome z. Once the posterior probabilities $P''(\theta_j)$ are determined, the decision procedure is similar to that explained before, the probability $P'(\theta_j)$ is simply replaced by $P''(\theta_j)$ in the Eq. 1.

$$E''_{\theta|z}[u(z,a,\theta)] = \sum_{j=1}^{m} u(z,a,\theta_j)\, P''(\theta_j) \qquad \textit{Eq. 4}$$

The maximum expected utility can be selected by

$$U'' = \max_a E''_{\theta|z}[u(z,a,\theta)] \qquad \textit{Eq. 5}$$

U'' is called posterior expected utility.

2.2.2.3 Pre-posterior decision analysis

In this situation, the SHM technique or the trial is prepared but the result remains uncertain, which involves decisions on which exact SHM strategy e to choose and what action a to take. The pre-posterior analysis is based on assumptions and knowledge of belief.

It is assumed that an SHM experiment e is chosen and the probability of the outcome of experiment z can be assigned. Knowing that the decision e is yet to be done its outcome z is a random variable. The maximum utility $U''(e,\boldsymbol{z})$ needs to be calculated for each outcome (e,z). Assuming $\boldsymbol{Z} = \{z_1, \dots, z_l\}$, there are a total of l outcomes. $P(z_k, e)$ represents the probability of detecting outcome z_k with the SHM experiment e. The expected values of the utility for every potential action can be found through Eq. 6. The maximum utility U''' can be selected by Eq. 7.

$$\begin{aligned} E_{z|e}[U''(e,z)] &= \max_a \sum_{k=1}^{l} U''(e,z_k)\, P(z_k,e) \qquad \textit{Eq. 6} \\ &= \max_a \sum_{j=1}^{m} \sum_{k=1}^{l} u(e,z,a,\theta)\, P(z_k,e)\, P(\theta_j|z_k) \\ &= \max_a \sum_{j=1}^{m} u(e,z,a,\theta) P'''(\theta_j) \end{aligned}$$

$$U''' = \max_e E_{z|e}\left[\max_a E''_{\theta|z}[u(e,z,a,\theta)]\right] \qquad \textit{Eq. 7}$$

U''' is called the pre-posterior expected utility. $P'''(\theta_j) = P(z_k, e)\, P(\theta_j|z_k)$ is the predictive probability, which can be computed as $P(z_k \cap \theta_j)$. The computation details can be found in Section 2.4.1.

Therefore, the pre-posterior Bayesian decision analysis will then be used to determine the benefit of the information that has not yet been obtained on the basis of models describing predictions for this yet uncertain information, with the latest relevant facts at the moment of the decision.

An application of pre-posterior Bayesian decision analysis is further developed in Chapter 3 (Paper 1) with focus on whether to install the Damage Detection System (DDS), when, where and how to install the DDS, are analyzed before the monitoring data of the DDS is obtained in chapter 3. The applications of posterior Bayesian decision analysis are further presented in case studies in Chapter 4, 5 and 6 (Paper 2, 3, 4). The monitoring data of welds on a steel bridge deck (Paper 2), the SHM data for the road viaduct (Paper 3) and the structural and meteo-oceanographic monitoring data for offshore wind turbines support structures (Paper 4) have already been obtained at the time of the decision analysis. Chapters 4 to 6 utilize the monitoring data to support lifecycle maintenance planning and service life extension.

2.2.3. VALUE OF INFORMATION ANALYSIS

The expected VoI can be defined as the discrepancy between the maximum utility from the pre-posterior analysis and the maximum utility using only prior knowledge without extra information, which is shown in Eq. 8. $\overline{VoI_e}$ in Eq. 9 is called the relative VoI.

$$VoI_e = U''' - U' = \max_{\boldsymbol{e}} E_{\boldsymbol{z}|\boldsymbol{e}}\left[\max_{\boldsymbol{a}} E''_{\boldsymbol{\theta}|\boldsymbol{z}}[u(\boldsymbol{e},\boldsymbol{z},\boldsymbol{a},\boldsymbol{\theta})]\right] - \max_{\boldsymbol{a}} E'_{\boldsymbol{\theta}}[u(\boldsymbol{a},\boldsymbol{\theta})] \qquad \text{Eq. 8}$$

$$\overline{VoI_e} = \frac{VoI_e}{|U'|} \qquad \text{Eq. 9}$$

If the expense of obtaining information is small relative to the potential gain, the experiment will be carried out. When various kinds of monitoring techniques are feasible, the technique resulting in the overall maximum expected utility should be selected [109].

2.2.3.1 Two forms of analysis

There are two forms of analysis: the extensive form and the normal form. Even if the two forms are mathematically equal and contribute to similar results, each has technical advantages in certain cases. In both forms, the prior decision analysis is analyzed in the same manner without supplementary information.

The extensive form of analysis starts from the end of the decision tree (the right side of Figure 2) to the original starting point by working backwards. First, it specifies an optimal action a corresponding to the potential result z of each SHM strategy, therefore indirectly defining the optimal decision rule for any e. The Bayesian updating is required in the process of computation. The equations of the extensive form have been described in Section 2.2.2.

The normal form of analysis proceeds by operating from the left side to the right side of the decision tree. The decision tree is described with the decision rules $\boldsymbol{d}(\boldsymbol{z}) = \boldsymbol{a}$ connecting the adaptive action with the knowledge acquirement strategy e and the strategy outcomes z. It starts by specifically evaluating every feasible decision rule d for a given e and then choosing the optimal decision rule of action a for each outcome of e. After this has been done for all e in $\boldsymbol{E}$, the optimal combination (e^*, d^*) of decision rule d^* for action a^* of strategy e^* is selected to compute each performance state the same way as done in the extensive form.

$$U'''(e^*, d^*) = E_\theta \left[E''_{z|\theta}[u(e^*, z, d^*, \theta)] \right] \qquad \textit{Eq. 10}$$

Compared to the extensive form, normal form analysis is more efficient on computation, as there are no necessary operations and only the optimal branches needed to be considered, which may be known before.

2.2.3.2 Types of VoI analysis

The VoI in most cases is referring to the expected VoI, which equals the maximum utility from pre-posterior analysis minus the maximum utility using only prior information. However, if the money has been already spent to obtain additional information and the evaluation is conditional on the SHM outcomes, it is called the conditional VoI, which equals to the maximum utility from posterior analysis minus the maximum utility from only prior knowledge.

Depending on the uncertain level of the information, it can be sample information or perfect information. Sample information refers to information with uncertainty and a finite precision, which is applied in most of the cases. Perfect information refers to information without uncertainty, which is quite rare.

So that the VoI can be distinguished into four types: conditional value of perfect information (CVPI), expected value of perfect information (EVPI), conditional value of sample information (CVSI) and expected value of sample information (EVSI). The illustration of a case study on CVSI can be found in Chapter 5 (Paper 3) and Chapter 6 (Paper 4). Chapter 5 quantified the utilities difference of the obtained SHM information on a road viaduct with the prior information. Chapter 6 quantified the utilities difference of the collected three-year SCADA information and additional one-year strain monitoring information with the prior information.

Recently, Thöns and Medha [32] established an expanded framework for describing the VoI and introduced the modern definition of the value of actions and the value of actions and information analysis. The extended classification of decision analysis is shown in Figure 4. The strategy, outcome, action, and state indexes (e, z, a, θ) are presented with (s, z, a, X). The index i is added to assign structural management strategy related actions and information, the random variable Y accounts for the uncertainty of action implementation. Depending on the acquisition condition of information and the operation state of actions (the continuous lines present the not yet implemented decisions and the dashed lines present the already implemented decision), the types of decision analysis are defined as:

- Predictive Analysis (PA), which only addresses the action prediction without information and is analogous to a prior decision analysis.
- Predictive Information (PI) analysis, which refers to decision analysis with only predictive information and without action.
- Predictive Information and Implemented Action (PIIA) analysis, which refers to decision analysis with predictive information and implemented action.
- Obtained Information and Predictive Action (OIPA) analysis, which is analogue to a posterior decision analysis.
- Predictive Information and Predictive Action decision analysis (PIPA), which is analogue to a pre-posterior decision analysis.
- System State Analysis (SSA), which is used to addresses the basic decision whether to incorporate any information acquisition and action execution strategies.

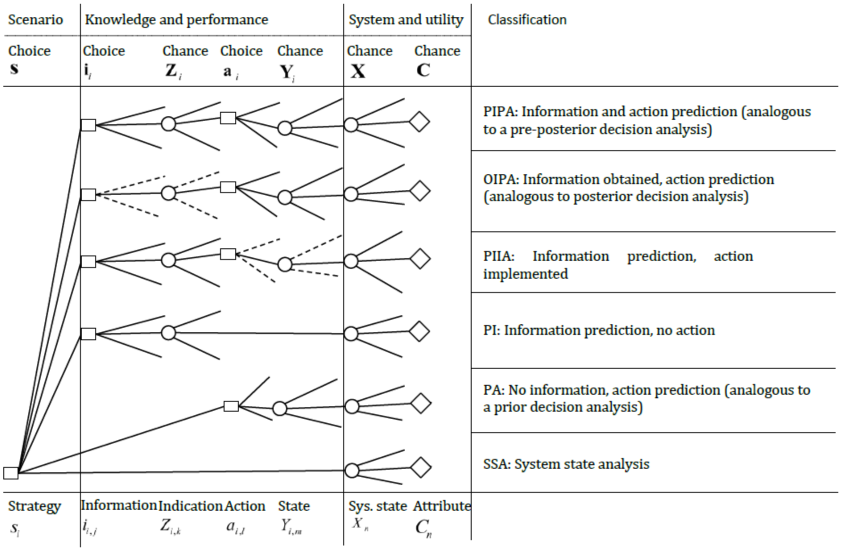


Figure 4 Illustration of the extended classification of decision analyses with decision trees from Thöns and Medha [32]

According to Thöns and Medha [32], 20 kinds of decision related value analysis applications can be obtained by rearranging all combinations of the decision analysis classification as shown in Figure 5. It extends the VoI analysis into value of action analysis and value of information and actions analysis. The new definitions are:

1) Value of information analysis, in which the anticipated increase of utility is purely due to information predicted or already obtained.
2) Value of actions analysis, in which the decision is entirely due to predicted or already applied actions.
3) Value of information and action analysis, in which an expected utility gain is achieved by both information and actions – independent of their deployment status.

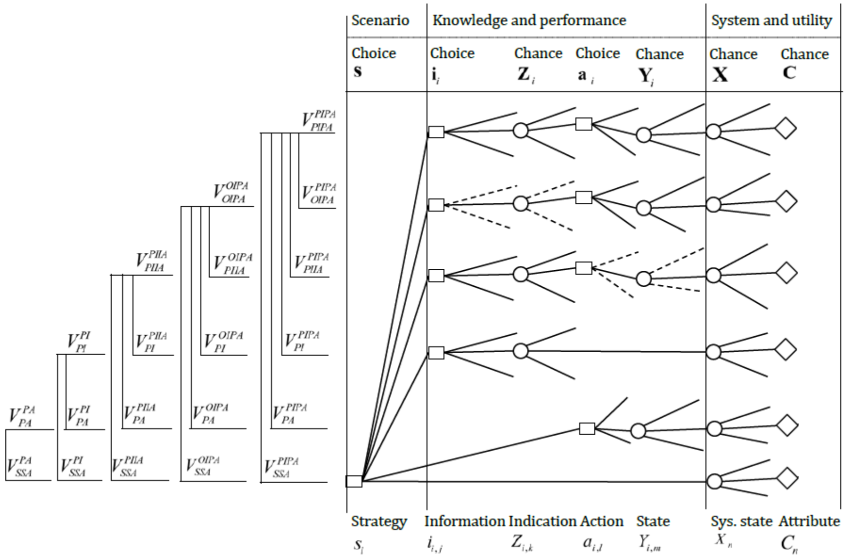


Figure 5 Decision value analyses by combining different types of decision analyses from Thöns and Medha [32]

An application of value of action analysis is implemented in Chapter 7 (Paper 5). It presents the different choices of decision actions scenarios for wind turbines along the highway under icing condition. The expected utility is gained according to predicted actions, which provides a decision basis on whether to implement an action.

2.2.3.3 Decision scenario modeling

The application of VoI analysis can be summarized into four steps:

- Derivation of the decision problem

The description of the decision problem should involve the recognition of the decision maker, decision alternatives and illustration of the decision scenario with e.g., a decision tree. An example of formulation of the decision scenario can be found in Table 6 from case study classification of COST Action TU1402 [110].

- Identification and assessment of potential consequences and their utility (cost/benefit)

When a decision problem is formulated, the potential consequences and their cost and benefits analysis related to the utility function $u(e, z, a, \theta)$ should be assessed. The expanded consideration of utility analysis can be found in Section 2.4.2.

Table 6 Formula of decision problem from COST Action TU1402 [110]

		Description	Pre-description
Structure	Type		Bridge, wind Turbine, Building, …
	Life cycle Phase		Which phases are considered in the decision analysis: design, construction, operation, decommissioning …
	Performance		Extreme loading, deterioration, fatigue, corrosion…
Decision scenario	Decision maker		Manager, Operator, owner, engineer
	Decision point in time		Design phase, operation and maintenance phase or decommission phase…
	Objective		Aim of the decision analysis
Decision variables	Actions		E.g., Repair, maintenance, replace
	Action parameters		Which parameters of the actions are varied?
	Information acquirement strategies		E.g., strain gauge measurements, accelerometer sensor, damage detection etc.
	Strategy parameters		Which parameters of the information acquirement strategies are varied?
Results	Value of Information		
	Decision rules		What is the relation between action and the information outcome?
	Readiness level		Based on Horizon2020 Technology readiness levels (TRLs)

- Calculation of the probabilities of the scenario branches

The probability of detecting outcomes $P[\boldsymbol{Z}]$ can be obtained through detection theory from section 2.3. The methods to calculate the probabilities of the structural states $P[\boldsymbol{\theta}]$ can be found in Section 2.4.1.

- Decision making through comparing the different decision alternatives depending on their expected utilities.

After all the expected utilities are calculated, the decision can be made through ranking the expected utilities of different decision alternatives. It is to be noted that all the underlying assumptions and limitations should be documented together with the decision alternatives.

2.2.4. BAYESIAN UPDATING

When new information is available, the estimation of probability of failure needs to be updated. The updating method which can be used is called Bayesian updating.

2.2.4.1 Bayesian updating of observed events

When the new information is the observation of events, the updating can be performed by modelling the observation as an event margin. The failure event can be modelled as a safety margin. This kind of observed events can be:

- Monitoring outcome, e.g., indication of damage when the signal is over a certain threshold.
- Inspection event, e.g., measurement of crack size in steel structures.
- Repair event, e.g., a structure gets repaired and behaves like a new one.
- Proof loading event where a determined load is added before a level of damage is detected.

Let H represent the observed events, h is the limit state function. The actual measurements can be interpreted as realizations of the stochastic variable.

$$H = h(X) \qquad \textit{Eq. 11}$$

The updated failure probability can be computed by:

$$P(F|H) = P(g(X) \leq 0|h(X) \leq 0) = \frac{P(g(X) \leq 0 \cap h(X) \leq 0)}{P(h(X) \leq 0)} \qquad \textit{Eq. 12}$$

The probability of failure event given an observed event $P(F|H)$ is equal to $\frac{P(F\cap H)}{P(H)}$. $P(g(X) \leq 0 \cap h(X) \leq 0)$ can be expressed as the probability of a two-component parallel system, which can be easily evaluated using methods mentioned in Section 2.4.1.6.

One of the examples of Bayesian updating with observed events is developed in Chapter 3 (Paper 1), where the monitoring outcome (probability of damage indication) is updated to the failure event (probability of failure).

2.2.4.2 Bayesian updating of stochastic variables

If the new information is samples or measurements of a stochastic variable, the updating can be carried out using Bayesian statistics. This type of information could be temperature, wave height, wind speed, etc.

As defined, X is the stochastic variables vector, $f_X(x)$ is the PDF of X. Let q denote a vector of parameters that describes the distribution of X, e.g., mean and standard deviation, which are realizations of Q. The original density function for the parameters Q is seen as a prior density function denoted by $f'_Q(\mathrm{q})$.

$\hat{\mathrm{x}}$ is the sample of the stochastic variable X. If $\hat{\mathrm{x}} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$ is containing n realizations and they are available, this information can be updated into $f'_Q(\mathrm{q})$. $f''_Q(\mathrm{q}|\hat{\mathrm{x}})$ is the updated density function of the uncertain parameters Q given the realizations and is often called as posterior density function.

$$f''_Q(\mathrm{q}|\hat{\mathrm{x}}) = \frac{f_N(\hat{\mathrm{x}}|\mathrm{q}) f'_Q(\mathrm{q})}{\int f_N(\hat{\mathrm{x}}|\mathrm{q}) f'_Q(\mathrm{q}) d\mathrm{q}} \qquad \textit{Eq. 13}$$

$$f_N(\hat{\mathrm{x}}|\mathrm{q}) = \prod_{i=1}^{N} f_X(\hat{x}_i|\mathrm{q}) \qquad \textit{Eq. 14}$$

$f_N(\hat{\mathrm{x}}|\mathrm{q})$ is the PDF given observations of distribution parameters that are assumed to be q. $f_X(\hat{x}_i|\mathrm{q})$ is the conditional PDF of $f_X(x)$. The density function of the stochastic variable X given the realization $\hat{\mathrm{x}}$ is predicted by:

$$f_X(x|\hat{\mathrm{x}}) = \int f_X(x|\mathrm{q}) f''_Q(\mathrm{q}|\hat{\mathrm{x}}) d\mathrm{q} \qquad \textit{Eq. 15}$$

An example of Bayesian updating of observed stochastic variables is presented in Chapter 6 (Paper 4), where the continuous wind speed from the SCADA system is updated using Bayesian statistics.

2.3. DETECTION THEORY

The fundamental problem in the SHM field is the identification of the damage. To answer the question “Is it damage?”, the detection theory has been developed. The detection theory emerged in the first half of this century from the growth of communications and radar equipment [111], which adopted mathematical development from theories of statistical inference. Peterson, Birdsall and Fox introduced the basic principle in 1954 [112] as a basis for measuring the efficiency of statistical tests and classifiers. Later in 1966, it was applied in psychophysics, see e.g., Swets & Green [113]. The detection theory follows directly from the theory of hypothesis testing [114].

2.3.1. HYPOTHESIS TEST

A hypothesis testing is done by expressing the problem as an assertion that some hypothesis is true. Then a numerical test will be constructed and applied to the data, and the hypothesis is accepted or rejected depending on the result of the test. There are three steps for the process of hypothesis testing. First, a null hypothesis H_0 needs to be formulated, then an alternate hypothesis H_1 needs to be proposed which is the alternative to the null hypothesis. Finally, a criterion (threshold) needs to be established to either accept or deny the null hypothesis H_0 since rejecting the null hypothesis means supporting the alternate hypothesis.

However, during the hypotheses testing two kinds of errors may occur, namely, rejecting H_0 when it is true or acknowledging H_0 when it is wrong. These two types of errors are known as Type I error and Type II error respectively (Table 7). Type I error is also called False Alarm or False Positive. Type II error can also be called False Negative.

Table 7 Hypothesis testing

	H_0 is right	H_1 is right
Acceptance of H_1	Type I error (False alarm, False positive)	True positive
Acceptance of H_0	True negative	Type II error (False negative)

2.3.1.1 Type I and Type II errors in damage detection

To differentiate between the damaged and undamaged system and recognize the damage, H_0 is used to represent the hypothesis of the undamaged state. When the healthy state of the structure with SHM is measured, only the noise will be recorded. H_1 is used to represent the hypothesis of damaged states. When the structure is damaged, the SHM system will record both the noise and the damage signal.

If the measurement signal of a healthy (undamaged) structure is plotted in a histogram, it can be described with a PDF $f_s(\mu_0, \sigma_0)$ with mean value μ_0 and standard deviation σ_0, a function of test results/signal s. If the measurement signal of a damaged structure is plotted in a histogram, it can be described with a PDF $f_s(\mu_1, \sigma_1)$ with mean value μ_1 and standard deviation σ_1, which will be different from $f_s(\mu_0, \sigma_0)$. Then a threshold S_t is set to differentiate these signals, e.g., it detects no damage if the measurement is below the threshold, then the damaged and undamaged signal will be differentiated. Figure 6Figure 6 describes the measurement signals distribution between damaged states and undamaged states.

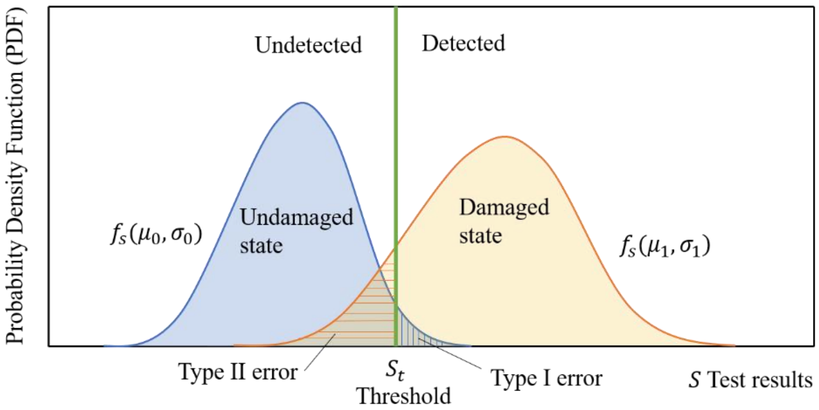


Figure 6 Schematic illustration of signal distribution between a damaged and undamaged structure

Follow the definition from the decision problem in Section 2.2, the hypothesis can be written directly as system state $\boldsymbol{\theta}$ with damaged state D and undamaged state $\overline{D}$, the SHM outcomes $\boldsymbol{Z}$ will be damage detected I or damage undetected $\overline{I}$. Therefore, the Type I error is detecting damage when there is no damage and Type II error is detecting no damage when damage exists, which are described in Table 8.

Table 8 Type I and Type II error in SHM

SHM outcomes $\boldsymbol{Z}$	System state $\boldsymbol{\theta}$	
	Damaged D	Undamaged $\bar{D}$
Detected I	Probability of detecting damage $PoD(D) = P(I\|D)$	Type I error rate, probability of false alarm $PFA = P(I\|\bar{D})$
Undetected $\bar{I}$	Type II error rate $P(\bar{I}\|D)$	$P(\bar{I}\|\bar{D})$

Then the probability of detecting damage (PoD) can be written as $P(I|D)$, which is calculated by Eq. 16 and shown in Figure 7. The probability of false alarm (PFA), also known as Type I error rate, is written as $P(I|\bar{D})$, which is calculated by Eq. 17 and shown in Figure 7. The Type II error rate is $P(\bar{I}|D)$, which is calculated by Eq. 18. From the Eq. 16 and Eq. 17, it is seen that the value of PoD and PFA will be largely influenced by the threshold value S_t.

$$PoD = P(I|D) = \int_{S_t}^{\infty} f_s(\mu_1, \sigma_1) ds \qquad \textit{Eq. 16}$$

$$PFA = P(Type\ I\ error) = P(I|\bar{D}) = \int_{S_t}^{\infty} f_s(\mu_0, \sigma_0) ds \qquad \textit{Eq. 17}$$

$$P(Type\ II\ error) = P(\bar{I}|D) = \int_{-\infty}^{S_t} f_s(\mu_1, \sigma_1) ds = 1 - PoD \qquad \textit{Eq. 18}$$

$$P(\bar{I}|\bar{D}) = \int_{-\infty}^{S_t} f_s(\mu_0, \sigma_0) ds = 1 - PFA \qquad \textit{Eq. 19}$$

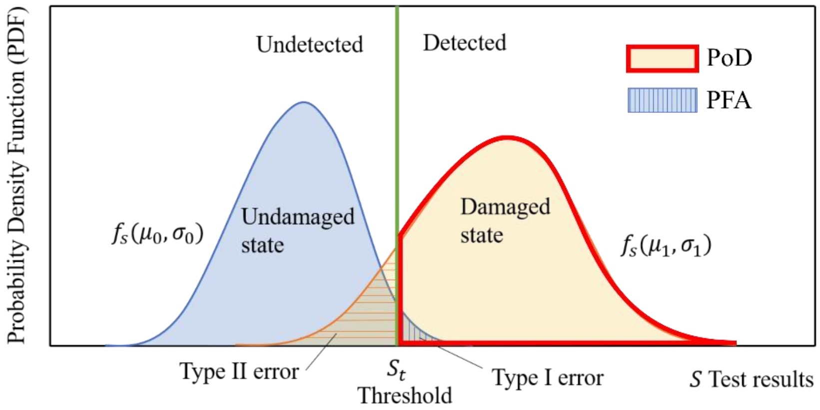


Figure 7 Schematic illustration of Probability of detecting damage (PoD) and probability of false alarm (PFA)

2.3.1.2 Effects of threshold

Supposing that an SHM implementer chose a low threshold (Figure 8, top), so that the monitoring device will respond "Damage detected" to almost every measurement, then they will never miss any damage when it is present, and they will therefore have a high PoD. On the other hand, responding "Damage detected" to almost everything will greatly increase the number of false alarms (potentially triggering unnecessary remedies actions), which will in turn result in high maintenance costs.

If the SHM implementer chose a high threshold (Figure 8, bottom), then the monitoring device will respond "No damage detected" to almost each measurement. Then a false alarm will rarely occur, but existing damage may be neglected, which may cause potential risk to the structure and lead to dramatic loss due to not taking remedies actions promptly. The choice of threshold thus implies that there is a trade-off between PoD and PFA.

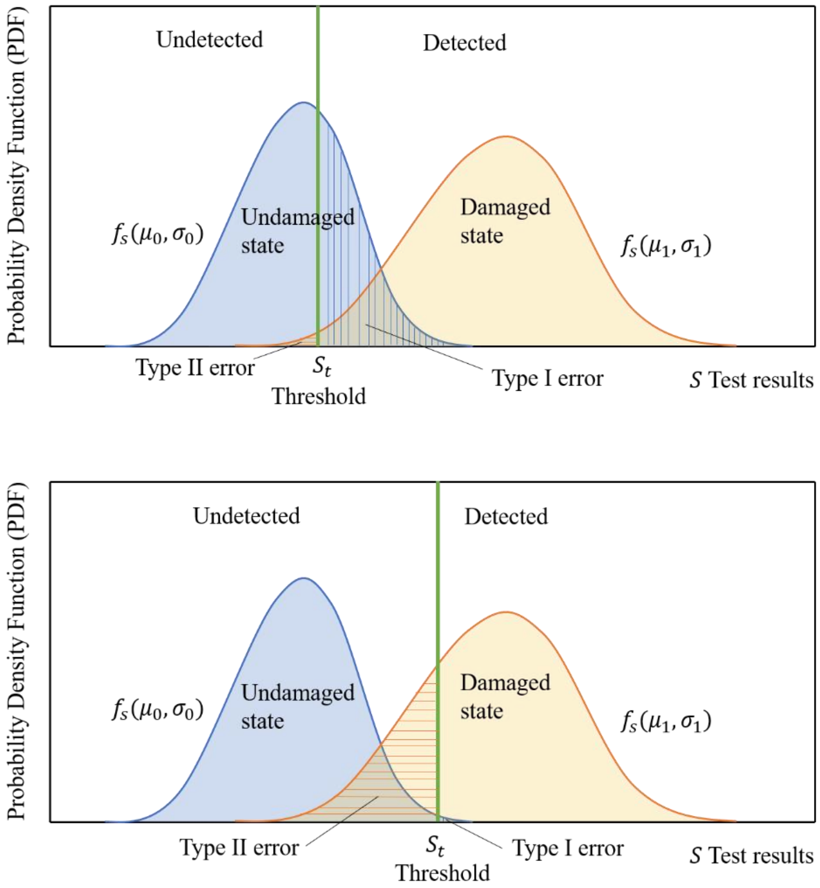


Figure 8 Effects of shifting the threshold

2.3.1.3 Probability of damage

The probability of damage (PoD) is not only influenced by the threshold but will also be influenced by the properties of the measurement system and stochastic system properties, which are further discussed in Chapter 3 (Paper 1). In chapter 3, the performance of the Damage Detection System (DDS) is investigated according to different scenarios, including changes of sensor numbers, sensor node locations, measurement noise, Type I error, and deterioration rate.

According to the computed results of the PoD on a truss system in each monitoring year in Figure 9 (here $P(I|\boldsymbol{D}(t_m)) = PoD$), it is more probable to detect the damage with more sensors, proper sensor locations, less measurement noise, and less Type I error.

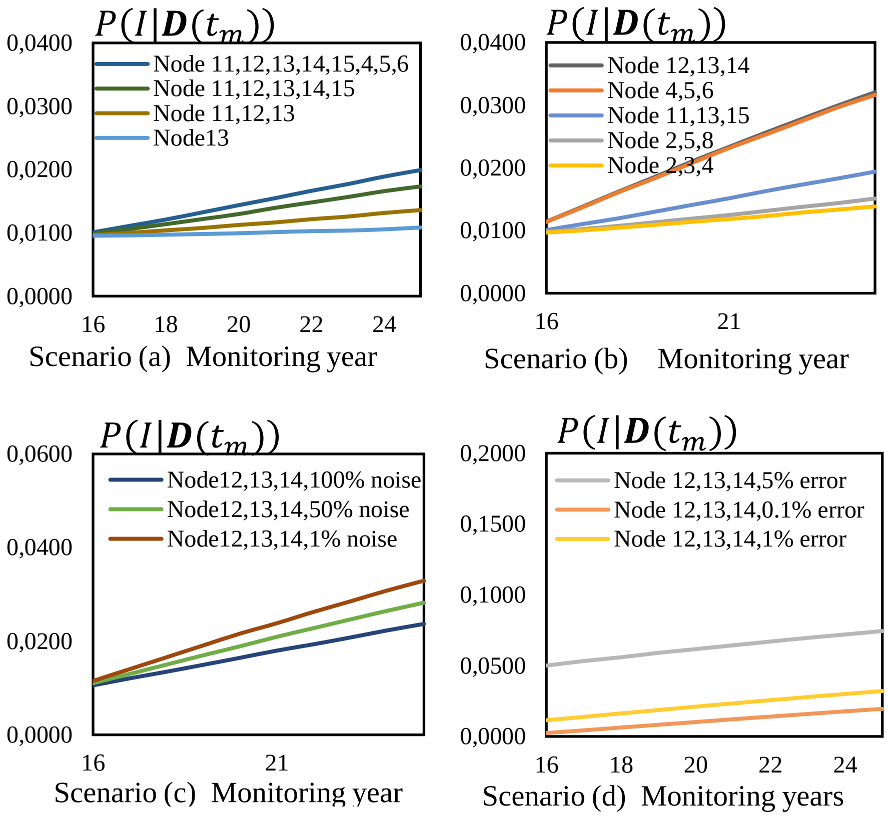


Figure 9 PoD with changes of number of sensors, sensor locations, measurement noise and Type I error. Adapted from [148].

2.3.2. RECEIVER OPERATING CHARACTERISTIC

These two values: PoD and PFA can be mapped against each other as a function of threshold using a Receiver Operating Characteristic (ROC) curve. The ROC curve is aimed to measure the quality of the test. The impact of adjusting the threshold point along with the ROC curve is illustrated in Figure 10 which describes the general performance of a hypothesis test [115].

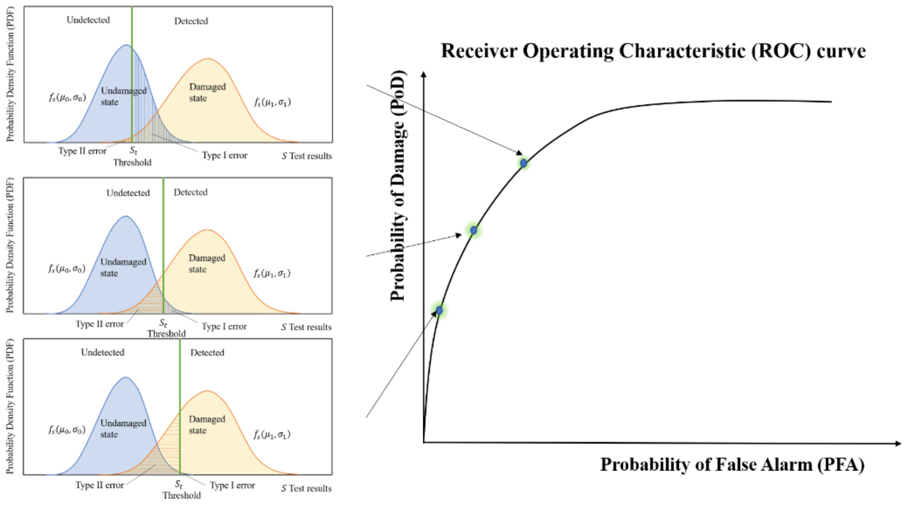


Figure 10 ROC curves with different values of Threshold [115]

Another measure of how well a hypotheses test performs as a comparative performance metric is the Area Under the ROC curve (AUC) or c-statistic [116]. The ROC curve can also be used to locate the value where the overall misclassification (Type I error plus Type II error) is at its minimum to determine the optimal cut-off value for a test [115].

2.3.2.1 Discriminability index

When the threshold value is fixed, the ROC curve is varied with the degree of separation provided by the discriminability index d' between two distributions $f_s(\mu_0, \sigma_0)$ and $f_s(\mu_1, \sigma_1)$. This is the disparity between the mean value of the two distributions divided by sum of their standard deviation [117]:

$$d' = \frac{\mu_1 - \mu_0}{\sigma_1 + \sigma_0} \qquad \textit{Eq. 20}$$

According to Figure 11 from [115], it is indicated that the discriminability index increases with rising distinction (decreased overlap) between the distributions, (Figure 11, right side) and the middle of the ROC curve goes up to the top left corner of the curve (Figure 11, left side). So that it is needed to choose a damage detection test in which its performance is approaching the upper left of the ROC curve. However, to achieve a reliable discriminability index, the distributions must have a normal distribution with identical standard deviations, which is challenging to satisfy in reality.

From Figure 11, it is visible that a narrower test distribution with less overlap will contribute to easily distinguish the damage signal and health signal. As it is known that the measured signal of the damaged state contains both the noise and damage signal, if the noise in the measurement variable can be reduced as much as possible, the performance of damage detection tests may be improved [115].

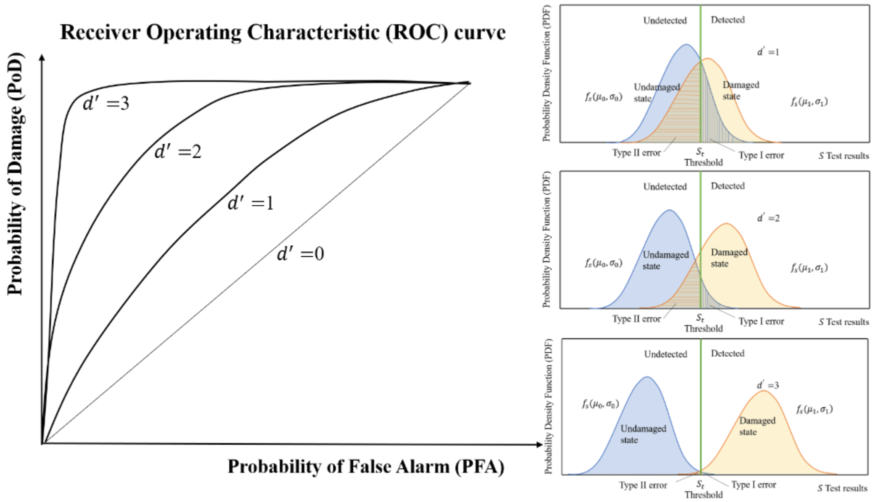


Figure 11 ROC curves [115] with different values of discriminability index

2.3.3. BAYES RISK APPROACH

Apart from the value of information-based decision approach building upon the decision theory in Raiffa and Schlaifer [18] described in Section 2.2, an alternative is the Bayes risk approach [114] which minimize the probability of making an error (i.e., a wrong decision). The distinction between Bayes risk approach and the value of information-based decision theoretical approach is that the Bayes risk approach aims to minimize the expected loss in case of a wrong decision while the value of information-based decision theoretical approach aims to maximize the expected benefits/utilities through optimizing decisions.

As described in Section 2.2, based on the SHM outcomes, decision makers need to take proper actions depending on the detection results, e.g., inspect / halt operation / repair if detecting damage; do nothing if not detecting damage. However, due to the existence of the Type I and Type II error, there are four types of consequences when taking the actions as seen in Table 9.

$C_{D|I}$ the consequences of taking a necessary inspection / halting operation /repair action when detecting damage I and the structure is damaged D, which is linked to the probability of detecting damage (PoD).

$C_{\bar{D}|\bar{I}}$ the consequences of doing nothing and continuing operation when detecting no damage $\bar{I}$ and the structure is undamaged $\bar{D}$, which normally costs nothing.

$C_{\bar{D}|I}$ the consequences of taking an unnecessary inspection / halting operation /repair action when detecting damage I but the structure is undamaged $\bar{D}$, which is the consequence of Type I error (False alarm).

$C_{D|\bar{I}}$ the consequences of doing nothing and continuing operation when detecting no damage $\bar{I}$ but the structure is damaged D, which is the consequence of Type II error.

Table 9 Consequences of actions based on SHM outcomes

Actions $\boldsymbol{a}$ based on SHM outcomes $\boldsymbol{Z}$	System state $\boldsymbol{\theta}$	
	Damaged D	Undamaged $\bar{D}$
Inspect/halt operation/repair if detected I	Necessary Inspect / halt operation/ repair costs $C_{D|I}$	Type I error consequences, unnecessary inspect/halt operation/ repair costs $C_{\bar{D}|I}$
Do nothing if undetected $\bar{I}$	Type II error consequences, potential loss without timely remedies $C_{D|\bar{I}}$	No consequences $C_{\bar{D}|\bar{I}} = 0$

The total Bayes risk is the sum of the expected value of the four kinds of consequences, which is also called as expected loss. So that the Bayes risk $E^{(L)}(e)$ for a SHM strategy e can be written as [118]:

$$E^{(L)}(e) = C_{D|I}(e) \cdot P(D|I) \cdot P(I) + C_{\bar{D}|\bar{I}}(e) \cdot P(\bar{D}|\bar{I}) \cdot P(\bar{I}) + C_{\bar{D}|I}(e) \cdot P(\bar{D}|I) \cdot P(I) + C_{D|\bar{I}}(e) \cdot P(D|\bar{I}) \cdot P(\bar{I}) + C_m(e) \qquad \textit{Eq. 21}$$

$C_m(e)$ is the intrinsic design cost of the SHM strategy e. $P(\bar{D}|\bar{I})$ is the probability of an undamaged structure giving no indication of damage, $P(\bar{D}|I)$ is the probability of an undamaged structure giving indication of damage, $P(D|I)$ is the probability of a damaged structure giving indication of damage, $P(D|\bar{I})$ is the probability of a damaged structure giving no indication of damage. Based on Bayes' rule, $P(\bar{D}|\bar{I}) = \frac{P(\bar{I}|\bar{D})\cdot P(\bar{D})}{P(\bar{I})}$, the $E^{(L)}(e)$ can be written as:

$$E^{(L)}(e) = C_{D|I}(e) \cdot P(I|D) \cdot P(D) + C_{\bar{D}|\bar{I}}(e) \cdot P(\bar{I}|\bar{D}) \cdot P(\bar{D}) + C_{\bar{D}|I}(e) \cdot P(I|\bar{D}) \cdot P(\bar{D}) + C_{D|\bar{I}}(e) \cdot P(\bar{I}|D) \cdot P(D) + C_m(e) \qquad \textit{Eq. 22}$$

As known from Section 2.3.1.1, $P(I|\bar{D})$ is also known as the probability of false alarm (PFA), $P(I|D)$ is the probability of detecting damage (PoD), $P(D)$ is the prior probability of the damage state, $E^{(L)}(e)$ can also be written as:

$$E^{(L)}(e) = C_{D|I}(e) \cdot PoD \cdot P(D) + C_{\bar{D}|\bar{I}}(e) \cdot (1 - PFA) \cdot (1 - P(D)) + C_{\bar{D}|I}(e) \cdot PFA \cdot (1 - P(D)) + C_{D|\bar{I}}(e) \cdot (1 - PoD) \cdot P(D) + C_m(e) \qquad \textit{Eq. 23}$$

The optimal Bayes risk for choosing the SHM strategy is to minimize $E^{(L)}(e)$. If the value of $C_{D|I}$ and $C_{\bar{D}|\bar{I}}$ are set to zero and $C_{\bar{D}|I}$ and $C_{D|\bar{I}}$ are set to 1.0, the value of $E^{(L)}$ will be minimized by minimizing PFA [119].

2.4. STRUCTURAL PERFORMANCE AND UTILITY MODELLING

As described in Section 2.2, in the process of calculating VoI, when a decision problem is formulated, the potential consequences and their cost and benefits analysis related to utility function $u(e, z, a, \theta)$ should be assessed and the probability of system states needs to be calculated. In Section 2.4, the details of structural performance and utility modelling will be described.

2.4.1. STRUCTURAL SYSTEM RELIABILITY ANLAYSIS

The probabilities of the structural states $P[\boldsymbol{\theta}]$ can be calculated through Structural Reliability Analysis (SRA), which is built upon the reliability theory through the concepts of the limit state function and safety margin to compute the probability of failure or reliability index (see e.g. [120, 121]).

It depends on two classes of factors whether a failure occurs in a structural model. These two classes are the external factor s and the internal factor r, with s describing loads and actions on the structure, r on the other hand encompassing e.g., material properties and geometrical characteristics of components, corresponding structure resistances. Failure occurs when the load s is greater than the resistance r. Considering uncertainties, the load and resistance variables are both not deterministic, which is described with the random variables S and R. The probability of failure $P(F)$ can be defined as:

$$P(F) = P(R \leq S) = P(R - S \leq 0) = \iint_{\Omega_{FS}} f_{RS}(r, s)\, drds \qquad \textit{Eq. 24}$$

Where $f_{RS}(r, s)$ is the joint PDF of the random variables R and S. The failure domain is denoted Ω_{FS}. However, both load and resistance are functions of a number of random variables, which are further grouped into a random vector X for simplification. Thus, the load and resistance become $S(X)$ and $R(X)$.

2.4.1.1 Limit state function

For computation convenience, the structure performance is defined using a limit state function $g(X)$ or a safety margin M in terms of load $S(X)$ and a resistance $R(X)$.

$$g(X) = R(X) - S(X) \qquad \textit{Eq. 25}$$

Then the limit state function can be divided into two regions depending on $g(X)$: failure domain, if $g(X) \leq 0$ and safe region, if $g(X) > 0$. Consequently, the probability of failure is determined on the failure domain $\Omega_{FS} = g(X) \leq 0$ as:

$$P(F) = P(g(X) \leq 0) = P(R(X) - S(X) \leq 0) \qquad \textit{Eq. 26}$$

$$= \int_{\Omega_{FS}} f_X\,(X)\, dx_1 \dots dx_n$$

Where $f_X(X)$ is the joint PDF for all the random variables. Depending on the status of the structural behavior, the failure modes (limit states) include [122]:

- Ultimate Limit States (ULS)

ULS refers to the optimum potential of bearing load and consider the collapse of the whole structure, e.g., excessive plasticity, fatigue rupture and buckling.

- Serviceability Limit States (SLS)

SLS are linked to regular use of the structure. When the structure approaches the SLS, it may not fulfill technological criteria for usage even though it might be robust enough to stay standing due to e.g., excessive deflections and local damage.

2.4.1.2 Resistance and load distribution

Normally the probabilistic models for loads and resistances are formulated based on a scientific mathematical and physical description or an empirical description based on observation. First, the uncertainties in the loading and resistance should be defined with random variables. Then a distribution type should be selected, and distribution parameters need to be determined. Finally, the validation of the distribution should be done.

Choices of the distribution functions for extreme loads are e.g., the Gumbel distribution, which is recommended in JCSS [123], DS410 [124], EN1990 [125], ISO2394 [126] for extreme snow load and annual maximum wind pressure; Weibull distribution for significant wave heights for offshore structures design and analysis; and Generalized Pareto distribution for significant wave height on shallow water [127]. The widely used load distributions for fatigue analysis are Normal distribution, Lognormal distribution, and Weibull distribution, which are approximating the central part of the load variations distribution (stress ranges) well.

The choice of distribution functions for material strengths (resistance) are e.g. Normal distribution for ductile materials; Lognormal distribution, which is recommended in DS410 [124], Eurocodes [125] and ISO 2394 [126]; Weibull distribution for material strength which are significantly affected by the defect size in Eurocodes [125] and ISO 2394 [126].

The estimation of the statistical parameters in the load and resistance distribution functions can be obtained through the Maximum Likelihood method, the Moment method, the Least square method, or Bayesian statistics, etc. [122].

2.4.1.3 Deterioration model

The resistance will decrease with the increase of deterioration. A generic time variant deterioration model $D(t)$ can be presented in terms of three parameters [149]:

$$D(t) = \alpha(t - T_i)^{\beta} \qquad \textit{Eq. 27}$$

α is annual deterioration rate, β is the deterioration type, T_i is the deterioration initiating time at time i. If a structure is under corrosion or under fatigue with a stationary stress process, it can be modeled as $\beta = 1$; if a structure is under diffusion-controlled deterioration, then it can be modeled as $\beta = 0.5$; if a concrete structure is deteriorated due to sulfate attack, it can be modeled as $\beta = 2$.

2.4.1.4 Uncertainty

The system load S is randomly varied in space and time and highly uncertainty. The resistance R is decreasing in dependence of time due to deterioration, e.g., fatigue, cracking, aging, corrosion, mechanical properties, which is also uncertain. The uncertainties modeled by stochastic variables are allocated to four classes [122] (Noted that gross errors and human errors are not covered):

- Physical uncertainty

Physical uncertainty is associated with a number of the natural randomness, e.g., uncertainty due to variation in production variability.

- Measurement uncertainty

Measurement uncertainty is the uncertainty induced by inaccurate measurements, e.g., attributable to geometrical quantity.

- Statistical uncertainty

Statistical uncertainty is caused by the small sample size of the number of measurements.

- Model uncertainty

Model uncertainty is the uncertainty of choosing mathematical models due to imperfect knowledge, e.g., opting for stochastic variables for probability distribution types.

2.4.1.5 Structural system reliability

In practice system structures are formed from a combination of components. Utilizing the combination of individual failure modes of each failure element, the overall system reliability can be estimated. Depending on the type of logical systems, the structure can be modelled as series system (Figure 12 a), parallel system (Figure 12 b) and mixed system (Figure 12 c). Each block diagram stands for one failure mode or component.

A series system refers to a non-redundant system. If one component in a series system fails, the whole system will fail, e.g., a statically determinate (non-redundant) truss structure. Thus, the probability of failure of the series system with m components is:

$$P(F_S) = P\left(\bigcup_{i=1}^{m}\{g_i(X) \le 0\}\right) = P\left(\min_{i=1:m}\{g_i(X) \le 0\}\right) \qquad \textit{Eq. 28}$$

On the contrary, a parallel system is a redundant system. If all the components in the system fail, the parallel system will fail. Thus, the failure probability of a parallel system with n components is:

$$P(F_S) = P\left(\bigcap_{j=1}^{n}\{g_j(X) \le 0\}\right) = P\left(\max_{j=1:n}\{g_j(X) \le 0\}\right) \qquad \textit{Eq. 29}$$

The failure probability of a mixed system of m series system with sub parallel system of n components is:

$$P(F_S) = P\left(\bigcup_{i=1}^{m}\bigcap_{j=1}^{n}\{g_{i,j}(X) \le 0\}\right) \qquad \textit{Eq. 30}$$

Moreover, the system reliability is not only dependent on the system types and the components' reliability but also the number of components and their interdependencies. The system behaves as one component for full correlation of the component failures. In general, a parallel system's reliability decreases with increased correlation. Conversely, a series system's reliability increases as correlations increase.

According to [128], increasing the number of components leads to a decreasing system reliability for an ideal series system but an increasing system reliability for an ideal parallel system and a ductile Daniels [9] system. The system reliability is approximately constant for a brittle Daniels system when increasing the number of components.

The influence of structural performance parameters on the structural system reliability including correlation, deterioration rate, deterioration type and deterioration initial time have been further discussed in Chapter 3 (Paper 1). The computation results of system failure probability with varied deterioration types, varied deterioration rate and initial year as well as a repair plan with varied deterioration types have been presented.

[9] A Daniels system can be understood as logical parallel system considering the mechanical behavior.

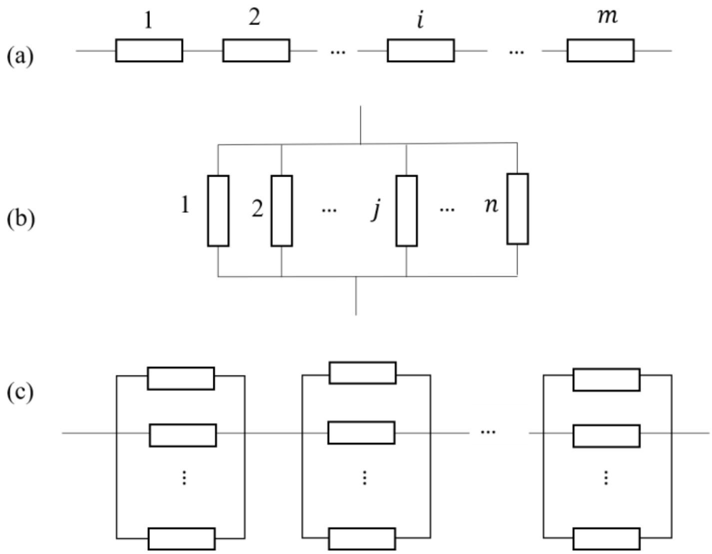


Figure 12 Logical systems: (a) series system (b) parallel system (c) mixed system

2.4.1.6 Computation methods

The computation methods of calculating the failure probability include analytical methods, approximation methods and numerical methods. The analytical method is utilized when the limit state function $g(X)$ is a linear function or safety margin M is normally distributed with mean μ_M and the standard deviation σ_M by introducing the reliability index $\beta = \frac{\mu_M}{\sigma_M}$ from Cornell [129]. The probability of failure is $P(F) = \Phi(-\beta)$, the variable Φ represents the function of the standardized normal distribution.

The approximation methods are applied when the limit state function is non-linear or the safety margin is not normally distributed, e.g., the First Order Reliability Method (FORM) by Hasofer & Lind [130] and Second Order Reliability Method (SORM). The difference between the FORM and SORM is that FORM deals with linearization of the safety margin, while SORM provides a second order (quadratic) approximation to the failure limit state function [122]. The estimation of the reliability index will start with the transformation of X into a normalized stochastic variable U. The shortest distance from the origin in the u space to the failure surface is called Hasofer & Lind reliability index β_{HL}, and the solution point for u is denoted u*.

Figure 13 below shows the first and second order approximations of the failure surface from [122].

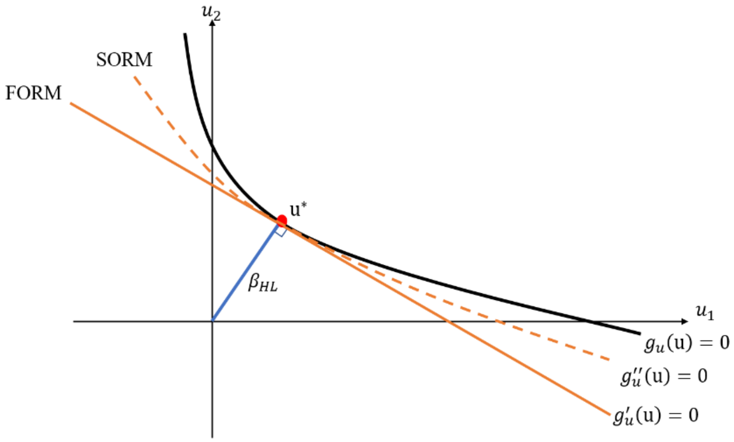


Figure 13 First and second order approximations of the failure surface [122]

The numerical methods are simulation techniques, which is especially useful because there are many possible probable failure regions. Realizations $\hat{x}$ of the stochastic variables X are produced for each sample in simulation methods. For each realization $\hat{x}$, the failure function is determined and if the realization is in the failure zone, then a connection to the probability of failure is derived [122].

2.4.1.7 Monte Carlo simulation

Monte Carlo Simulation (MSC) is one of the most widely used simulation techniques. It first generates a total number of N realizations of the random variable X, for each realization $\hat{x}$ the value of the limit state function $g(\hat{x})$ is evaluated, the realizations of the limit state function that are zero or negative $g(\hat{x}) \leq 0$ are counted, then the failure probability is calculated as:

$$P(F) = \frac{\sum_{j=1}^{N} I\left[g(\hat{x}_j)\right]}{N} \qquad \textit{Eq. 31}$$

$$I[g(\hat{x})] = \begin{cases} 0, if\ g(\hat{x}) > 0 \\ 1, if\ g(\hat{x}) \leq 0 \end{cases} \qquad \textit{Eq. 32}$$

The standard deviation of the MCS error equals the square root of the probability of failure divided by the sample size. Therefore, the precision of MCS is highly dependent on the number of samples.

$$\sigma_{MCS} \approx \sqrt{\frac{P(F)}{N}}$$ *Eq. 33*

If it is only focused on the sampling in the overall sample space region having the highest impact on the probability of failure by introducing sample vectors $\hat{y}_i$ generated from the sampling density function $f_s(y)$, it is called Monte Carlo importance sampling. The advantage of the Monte Carlo importance sampling is that the standard error of estimate $P(F)$ can be greatly reduced.

.

$$P(F) = \frac{\sum_{i=1}^{N} I[g(\hat{y}_i)]}{N} \cdot \frac{f_x(\hat{y}_i)}{f_s(\hat{y}_i)}$$ *Eq. 34*

Besides, there are many more methods: Response Surfaces, Importance Sampling Methods for Monte Carlo Simulations, Asymptotic Sampling, Subspace Sampling, Adaptive Sampling [122].

2.4.1.8 Software packages

Due to the computation challenges to get very small probabilities of failure for complex systems containing various components/limit states, different software packages are built to help reliability analysis, e.g. FERUM (Finite Element Reliability Using MATLAB) [10] developed by University of California, Berkeley, STRUREL (Structural Reliability Analysis Program System), which is windows based and contains Statrel [11], Comrel [12] and Sysrel [13], UQLab [14] (Uncertainty Quantification framework) developed by ETH Zurich and SARA (Structural Analysis and Reliability

[10]FERUM: https://www.sigma-clermont.fr/en/ferum

[11]Comrel: http://www.strurel.de/.

[12]Statrel: http://www.strurel.de/strurel.html#collapseFive.

[13] Sysrel: http://www.strurel.de/strurel.html#collapseFour.

[14]UQLab: https://www.uqlab.com/.

Assessment) by Cervenka Consulting which contains ATENA[15] and FReET[16] and et al.

2.4.2. UTILITY MODELLING

The utility modelling for a lifecycle integrity management analysis is similar to the lifecycle costs analysis [140] which considers both lifetime benefits and costs, while the lifecycle costs analysis only considers the total costs during service life. The lifecycle of an infrastructure project includes the production of raw materials; refining, assembling, and manufacturing (construction); usage and operation; and recycling or recovery after end of life. The lifecycle cost is the total discounted cost over the whole service life, from the planning stage to the end of the lifetime of a structure. This includes construction, operation, maintenance, decommission and recycling costs.

2.4.2.1 Generic formulation

The lifecycle utility formulation U_{SL} is derived from utility theory and Bayesian decision analysis, which follows the lifecycle integrity management decision process as shown in Figure 14, encompassing the following groups:

- Expected benefit U_B
- Design and construction expenses related initial costs C_o
- Expected running costs like expected operations and maintenance costs, e.g., expected inspections costs U_I, expected monitoring costs U_M, expected repair costs U_R and expected failure costs U_F
- End-of-life costs C_E, e.g., disposal, recycle costs.

[15]ATENA: https://www.cervenka.cz/products/atena/.

[16]FReET: https://www.cervenka.cz/products/sara/.

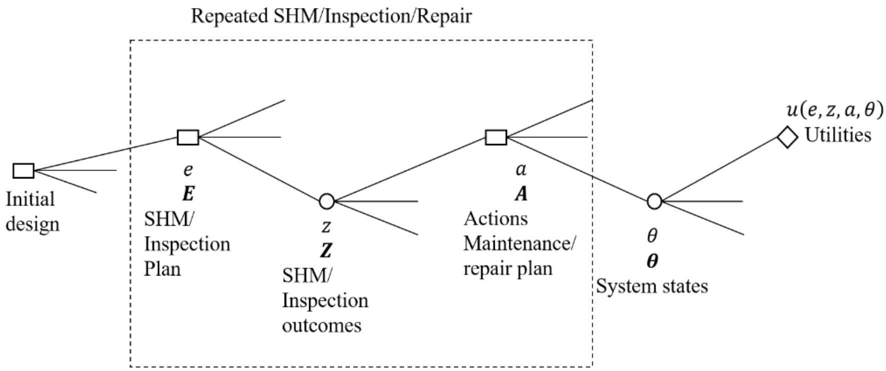


Figure 14 Lifecycle integrity management decision process based on [131]

The decisions on the operation and maintenance are determined by the physical performance of the system. A discounting rate of money γ is considered owing to the changing time value of capital. So that the life-cycle utility U_{SL} can be modelled as:

$$U_{SL} = U_B - U_F - U_R - U_I - U_M - C_o - C_E \quad \textit{Eq. 35}$$

$$U_B = \sum_{t=1}^{T_{SL}} B(t) \cdot \left(1 - P(F_t)\right) \cdot \frac{1}{(1+\gamma)^t} \quad \textit{Eq. 36}$$

$B(t)$ is the annual benefit at year t, $P(F_t)$ is the probability of failure at year t. The expected benefit U_B is the sum of discounted annual benefit conditioned on survival during service life T_{SL}. The expected failure cost U_F is calculated as:

$$U_F = \sum_{t=1}^{T_{SL}} C_F(t) \cdot \left(P(F_t) - P(F_{t-1})\right) \cdot \frac{1}{(1+\gamma)^t} \quad \textit{Eq. 37}$$

$C_F(t)$ is the cost of failure at year t considering the direct and indirect losses, e.g. loss of life, economic, social and environmental impact. $P(F_t) - P(F_{t-1})$ is the annual probability of failure. The expected failure cost U_F is the sum of discounted annual probability of failure times the cost of failure. The expected repair costs U_R follows:

$$U_R = \sum_{i=1}^{N_R} C_R(T_i) \cdot P\left(R_{T_i}\right) \cdot \left(1 - P\left(F_{T_i}\right)\right) \cdot \frac{1}{(1+\gamma)^{T_i}} \quad \textit{Eq. 38}$$

$C_R(T_i)$ is the cost of repair at repair year T_i, $P\left(R_{T_i}\right)$ is the probability of repair at repair year T_i, i is the number of repair times, N_R is the total number of repairs. The expected repair cost U_R is the sum of repair costs times the probability of repair conditioned on survival and discounted on the year of repair. The expected inspection costs U_I and expected monitoring costs U_M are:

$$U_I = \sum_{j=1}^{N_I} C_I(T_j) \cdot \left(1 - P\left(F_{T_j}\right)\right) \cdot \frac{1}{(1+\gamma)^{T_j}} \qquad \textit{Eq. 39}$$

$$U_M = \sum_{m=1}^{N_M} C_M(T_m) \cdot \left(1 - P\left(F_{T_m}\right)\right) \cdot \frac{1}{(1+\gamma)^{T_m}} \qquad \textit{Eq. 40}$$

$C_I\ (T_j)$ is the cost of inspection at inspection year T_j, j is number of inspection times and N_I is the total number of inspections. $C_M\ (T_m)$ is the cost of monitoring at monitoring year T_m, m is the number of monitoring times and N_M is the total number of monitoring. The expected inspection cost U_I or expected monitoring cost U_M is the sum of inspection/monitoring costs times the probability of survival discounted on the year of inspection/monitoring, respectively.

The influence of the parameters mentioned above on utility modelling can be further found in chapter 4 (Paper 2) and chapter 6 (Paper 4). Chapter 4 implemented a parametric analysis of the utilities on different monitoring durations and and choices of service life extension on welds of a steel bridge deck, considering the changes of the target probability P_{Target}, benefit B, failure cost C_F, reahbilitation cost C_R, monitoring cost C_M and discount rate γ. Chapter 6 performed a parametric analysis on CVSI of strain and meteo-oceanographic monitoring for offshore wind turbines support structures with respect to cost of failure C_F, inspection cost C_I, repair cost C_R and discounting rate r.

It is noted that the probability of failure of the structure needs to be updated after inspection, monitoring, and repair with obtained information so that the lifecycle utility should be computed carefully. The optimization of operation and maintenance planning is to maximize the lifecycle utility U_{SL} through optimizing the year and total number of monitoring, inspections, and repairs to minimize the risk and costs.

2.4.2.2 Discounting rate

The discount rate is often related to the interest rate or the social discount rate (SDR), which represents the current value of costs and benefits that will be obtained in the future. The main approaches for evaluation of the discount rate are:

- Social Rate of Time Preference (SRTP)

The SRTP is a measure of the willingness of a society to save the present consumption for more future consumption. It builds the discounting rate taking pure time consumption and economic growth into account [132].

$$\gamma = \rho + \theta\eta \qquad \textit{Eq. 41}$$

ρ is the factor related to the pure time preference considering individuals' impatience or myopia as well as the risk of death or human race extinction, θ is a constant considering the consumption elasticity of marginal utility, η is the annual growth rate per capita real consumption.

- Social Opportunity Cost of capital (SOC)

The SOC solution is derived from the premise that resources are still limited, government and private sector have equal right to compete for the same funds with same return rate on the investment. The SOC is suggested to be similar to the marginal pretax return rate on private investments with no risk [133].

- Weighted average approach

The SRTP approach of discounting future potential costs and benefits is controversial because it does not recognize the effects of public projects on available funds for private investment assets. The SOC approach implies that public investment just replaces private investment rather than private consumption, which is not necessarily valid. To align the SRTP approach with SOC, Harberger et al. [134] suggest the weighted average approach:

$$\gamma = \alpha SOC + (1 - \alpha - \beta)i_f + \beta SRTP \qquad \textit{Eq. 42}$$

i_f is the actual long-term foreign borrowing rate from the government, α is ratio of funds for the public investment received at the costs of private investment, β is the ratio of founds collected at the expense of present consumption, and $(1 - \alpha - \beta)$ is the ratio of funds from foreign loans. SOC and $SRTP$ are measured discounting rates from the SOC and SRTP approach, respectively.

The selection of the discount rate varies across the world depending on the development level of different countries. Normally in developed countries the rates are lower (3%-7%) than in the developing countries (8%-15%). However, there is no specific rule to select a fixed value of discount rate.

The social discount rate in some selected countries is shown in Table 10. Countries vary in economic structure resource shortage, financial growth level, financial intermediation performance, impediments to entry into the foreign capital market, and social time choice, resulting in a specific social discount rate factor. A wider debate on the strategies of selecting discounting rates can be found in [135].

Table 10 Social discount rates in selected countries from [135]

Country	**Discount rate**	**Theoretical Basis**
Australia	Annually reviewed; 8% (1991)	SOC approach
Canada	10%	SOC approach
People's Republic of China	8% for short- and medium-term projects; <8% for long-term projects	Weighted average approach
France	8% (1985); 4% (2005)	1985: to keep a balance between public and private sector investment. 2005: SRTP approach
Germany	4% (1999), 3% (2004)	Based on federal refinancing rate
India	12%	SOC approach
Italy	5%	SRTP approach
New Zealand	10%	SOC approach
Norway	7% (1978);3.5% (1998)	Government borrowing rate in real terms
Pakistan	12%	SOC approach
Philippines	15%	SOC approach
Spain	6% (transport sector); 4% (water sector)	SRTP approach
United Kingdom	8% (1967);10% (1969); 5% (1978); 6% (1989); 3.5% (2003); < 3.5% for long-term projects over 30 years	Soc approach until early 1980s; thereafter SRTP approach

US	10% (before 1992); 7% (after 1992) from Office of management and budget	SOC approach
	2-3% for environmental projects from Environmental protection Agency	SRTP approach

The influence of the discounting rate on the utility modelling can be further found in Chapter 4 (Paper 2). With increasing discounting rate, the utilities will decrease, as shown in Figure 15. The discounting rate represents the economic situation of the country. When the discounting rate is high, money will lose its value fast with time. So, for a long-term investment project it is important to consider the discounting rate for the whole duration of the investment. Because the utilities may be negative when the discounting rate is high if it changes over time.

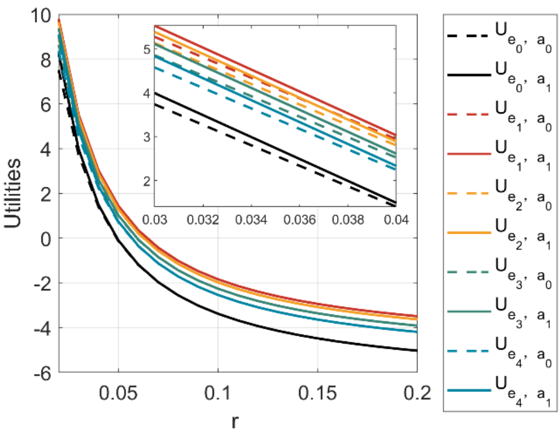


Figure 15 The influence of discounting rate on the utilities modelling. Adapt from [150].

2.4.2.3 Cost of Loss human lives

The failure consequences of civil infrastructures may lead to fatality, injury, economic loss, social and environmental impact, e.g., collapses of a highway bridge. Three methods to find the economic effects of loss of life are:

- Life Quality Index (LQI)

The LQI is a composite socioeconomic indicator of human welfare established by Nathwani et al. [136] as a supportive framework to enhance the decision basis for events that have impact on public health and safety. The LQI may be viewed as a utility function composed of: $e(a)$ life expectancy at age a, g the real gross domestic product per person and q trade off factor regards the expected healthy life span to enjoy the available resources [137].

$$L(a) = g^q e(a) \qquad \textit{Eq. 43}$$

- Societal Willingness to Pay (SWTP)

The SWTP can be interpreted as the societies willingness to invest, e.g., to reduce risk, which is developed by Rackwitz [138]. The way to measure $SWTP$ is to differentiate $L(a)$ to offset the shift in life expectancy and the resulting expenditure to keep the LQI constant.

$$SWTP = dg = -\mathrm{E}\left[\frac{g}{q}\frac{de_d(a)}{e_d(a)}\right] \approx G_x dm \qquad \textit{Eq. 44}$$

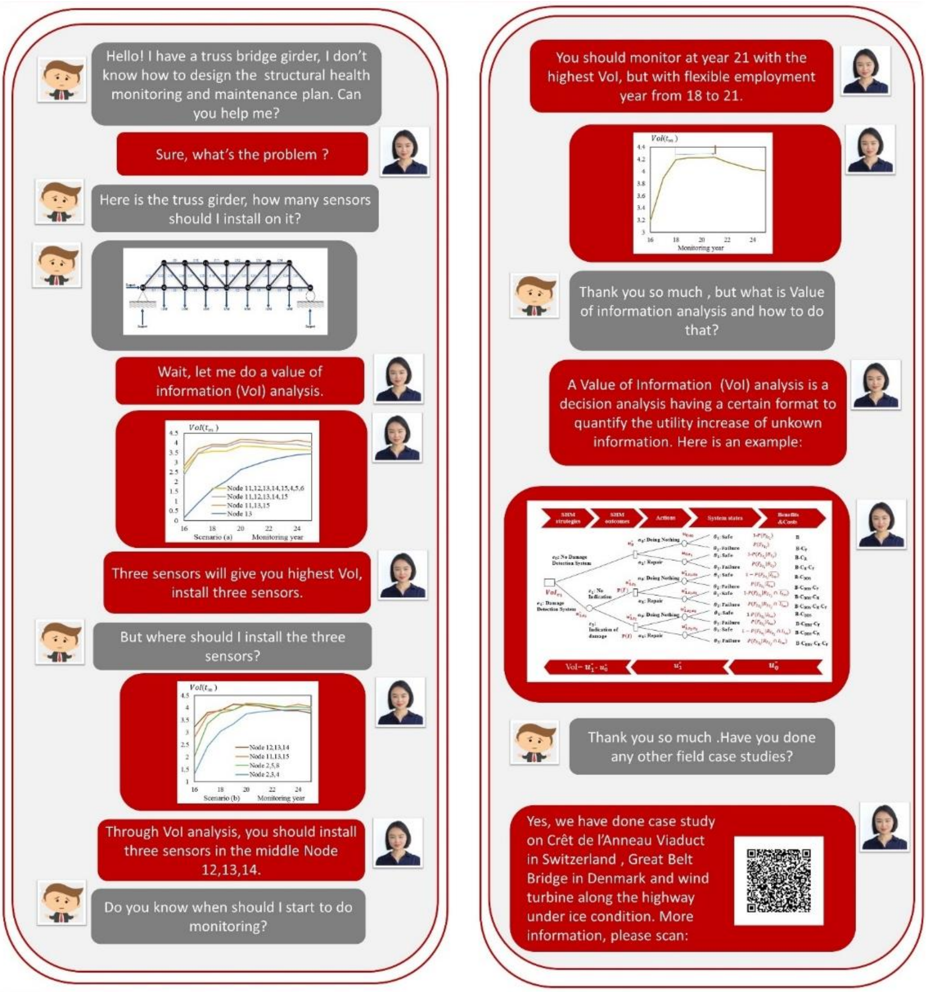
For a particular intervention, the constant G_x is depending on the mortality reduction scheme x. $dm = \frac{de(a)}{e(a)}$ is the mortality elimination. In [139] the authors show an overlook of different mortality regimes. The SWTP for countries having different socioeconomical conditions has been compiled by [140].

- Social Value of Statistical Life (SVSL)

According to Pandey and Nathwani [141], the SWTP can be supplemented by the statistical value of societal life (SVSL). The difference between SVSL and SWTP is that the SVSL refers to the amount to be paid to compensate for each fatality, independent of the age, while the SWTP is the amount that the government is willing to allocate towards the mortality reduction even if the change in life expectancy caused by the safety measures is very low.

$$SVSL = -\mathrm{E}\left[\frac{g}{q}\frac{de_d(a)}{e_d(a)}\right] \approx -\frac{g}{q}\bar{e}_d \qquad \textit{Eq. 45}$$

$\bar{e}_d$ is the discounted life expectancy. The SVSL can be interpreted as the amount of money which the society is willing to spend to ensure the safety of an anonymous citizen [142], especially when it is exposed to problems caused by environmental risks. The SVSL for a number of countries having different discount rates can be found in [140].


Hello! I have a truss bridge girder, I don't know how to design the structural health monitoring and maintenance plan. Can you help me?
Sure, what's the problem ?
Here is the truss girder, how many sensors should I install on it?
Wait, let me do a value of information (VoI) analysis.
Three sensors will give you highest VoI, install three sensors.
But where should I install the three sensors?
Through VoI analysis, you should install three sensors in the middle Node 12,13,14.
Do you know when should I start to do monitoring?
You should monitor at year 21 with the highest VoI, but with flexible employment year from 18 to 21.
Thank you so much , but what is Value of information analysis and how to do that?
A Value of Information (VoI) analysis is a decision analysis having a certain format to quantify the utility increase of unkown information. Here is an example:
Thank you so much .Have you done any other field case studies?
Yes, we have done case study on Crêt de l'Anneau Viaduct in Switzerland , Great Belt Bridge in Denmark and wind turbine along the highway under ice condition. More information, please scan:

CHAPTER 3. DETERMINATION OF STRUCTURAL AND DAMAGE DETECTION SYSTEM INFLUENCING PARAMETERS ON THE VALUE OF INFORMATION (PAPER 1)

Lijia Long, Sebastian Thöns, Michael Döhler.

Structural Health Monitoring

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Scientific contribution of the PhD student:

Lijia Long

- proposed the extended idea of structural and damage detection system influencing parameters on the value of information based on Sebastian Thöns's initial idea.
- wrote code and implemented all value of information quantification simulations in Matlab.
- formulated the structural and damage detection system influencing parameters.
- wrote the entire draft version of the paper and revised it according to co-authors' comments.

Scientific contribution of co-authors:

Michael Döhler

- assisted in defining the damage detection system influencing parameters.
- provided the Matlab code of probability of damage indication based on damage detection system.
- assisted in interpretation of the damage detection system influencing parameters on the value of information.
- carefully reviewed the manuscript and provided critical comments.

Sebastian Thöns

- proposed the initial idea of quantification the value of damage detection system information for a truss bridge girder.
- assisted in defining the decision problems.
- assisted in value of information analysis formulation.
- carefully reviewed the manuscript and provided critical comments.
- assisted in shaping the manuscript and improved the scientific language.

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Determination of structural and damage detection system influencing parameters on the value of information

Lijia Long[1,2], Michael Döhler[3] and Sebastian Thöns[1,4]

Abstract

A method to determine the influencing parameters of a structural and damage detection system is proposed based on the value of information analysis. The value of information analysis utilizes the Bayesian pre-posterior decision theory to quantify the value of damage detection system for the structural integrity management during service life. First, the influencing parameters of the structural system, such as deterioration type and rate are introduced for the performance of the prior probabilistic system model. Then the influencing parameters on the damage detection system performance, including number of sensors, sensor locations, measurement noise, and the Type-I error are investigated. The pre-posterior probabilistic model is computed utilizing the Bayes' theorem to update the prior system model with the damage indication information. Finally, the value of damage detection system is quantified as the difference between the maximum utility obtained in pre-posterior and prior analysis based on the decision tree analysis, comprising structural probabilistic models, consequences, as well as benefit and costs analysis associated with and without monitoring. With the developed approach, a case study on a statically determinate Pratt truss bridge girder is carried out to validate the method. The analysis shows that the deterioration rate is the most sensitive parameter on the effect of relative value of information over the whole service life. Furthermore, it shows that more sensors do not necessarily lead to a higher relative value of information; only specific sensor locations near the highest utilized components lead to a high relative value of information; measurement noise and the Type-I error should be controlled and be as small as possible. An optimal sensor employment with highest relative value of information is found. Moreover, it is found that the proposed method can be a powerful tool to develop optimal service life maintenance strategies—before implementation—for similar bridges and to optimize the damage detection system settings and sensor configuration for minimum expected costs and risks.

Keywords

Damage detection systems, value of information, deteriorating structures, probability of damage indication, decision theory

Introduction

It is well known that structural health monitoring (SHM) can be beneficial for structural performance assessment over time.[1] Substantial research has been devoted to the development of SHM strategies and measurement techniques to reduce the various uncertainties associated with structural characteristics and performances. SHM results have been utilized for structural reliability assessments in various fields of engineering,[2–5] which comprise the utilization of monitoring data for reliability-based inspection planning, updating models, and the assessment of the monitoring uncertainty. However, only very recently, it is acknowledged that the benefits of SHM in a life-cycle perspective prior to its implementation can be properly quantified by using the value of information (VoI) theory.[6]

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Decision-makers, such as infrastructure owners and operators, are often bothered with questions[7,8] like whether it is beneficial to perform an SHM experiment considering the economical aspect, and if so, when the SHM experiment should be implemented? How to design a monitoring and maintenance plan accordingly with different deterioration types and rates in different environment? How many sensors should be chosen? Where to install the sensors? When the benefit is not clearly specified, it is usually hard to convince the decision-makers to invest in SHM of large systems, since inappropriate SHM strategies may trigger unnecessary or inappropriate remedial activities, which may lead to a loss of economical and human resources. Most often, the value of SHM is only implicitly assumed. Decision-makers would like to utilize experience as a basis for identifying efficient strategies for performance monitoring without considering how the information shall be utilized for improving the decision basis for optimal life-cycle management of the structures.

To overcome this issue, there is a need to establish a better understanding of the quantification of the value of SHM before its implementation. Early approaches for the assessment of the value of SHM information have been developed from 2011 onwards.[4,9–11] Further focused research efforts of many authors, also within the European Union–funded COST Action TU1402 (www.cost-tu1402.eu), resulted in comprehensive studies of many aspects for the quantification of the value of SHM.[6,12–24] These aspects include the quantification of the value of deterioration monitoring[18,25,26] and the quantification of the value of multiple SHM information.[26,27]

This article addresses the quantification of the value of damage detection system (DDS) information constituting an important part of the SHM research field. The quantification of the value of DDS information is parameterized to identify the optimal DDS configuration, the optimal DDS employment on a structural system, and the structural system characteristics for which DDS information provides the highest value. In this way, the authors aim at decision support for the employment of DDS by jointly analyzing the DDS system performance, the structural system performance and the associated benefits, costs, and consequences. The paper documents a 3-year research progress within the European Union–funded Marie Skłodowska–Curie Innovative Training Network project INFRASTAR (www.infrastar.eu) in conjunction with the findings of the COST Action TU1402. The novelty of this article encompasses:

1. A comprehensive and consistent formulation and elaboration of the Bayesian pre-posterior decision scenario model and its analysis.
2. A comprehensive and consistent analysis and parametric study of the value of DDS information in dependency of the DDS characteristics and structural system deterioration characteristics throughout the service life.
3. A detailed and comprehensive analysis of DDS characteristics.

This article starts with introducing the VoI theory in section "VoI theory." Then the influencing parameters of the structural system such as deterioration type, deterioration rate, and deterioration initialing year for the performance of a prior probabilistic system model are discussed in section "Structural probabilistic system performance." The DDS performance influencing parameters including number of sensors, sensor locations, measurement noise, and the Type-I error are presented in section "DDS information." The integrity management actions are discussed in section "Integrity management actions." The pre-posterior probabilistic model which is computed utilizing Bayes' theorem to update the prior system model with the damage indication information is described in section "Pre-posterior updating with DDS information." The utility modeling method is presented in section "Utility modelling and analysis." With the developed approach, a case study on a statically determinate Pratt truss bridge girder is investigated to validate the method in section "Generic parametric analysis of the value of DDS information." The results are discussed in section "Discussion." This article ends with conclusion in section "Conclusion."

Methodology

VoI theory

The VoI theory has been developed by Raiffa and Schlaifer.[28] The VoI analysis is rooted in the Bayesian definition of probability and utility-based decision theory to quantify the expected value of the utility increase related to yet unknown information.

The decision problems in the context of SHM for the life-cycle management of structures are illustrated in Figure 1. The essential decisions relate to whether implement SHM or not, when, at which locations and for which structural conditions to perform SHM. For different structures, different life-cycle phases may be considered in the decision analysis. For new structures, engineers need to think whether to integrate SHM into design or construction phases. While for existing structures, decisions about implementing SHM will be considered during the operation and maintenance phase and toward the end-of-service life. To figure out the decision of implementing SHM, further questions arise like: When should the SHM system been installed?

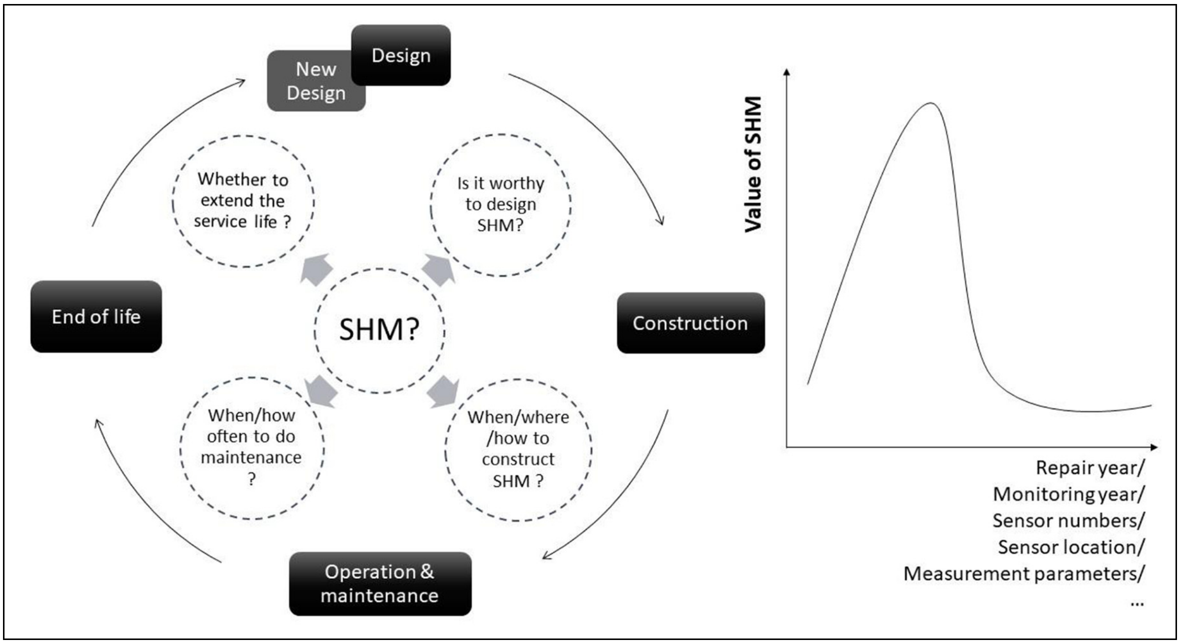

Figure 1. Decision problems in the context of SHM through life-cycle management of structures.

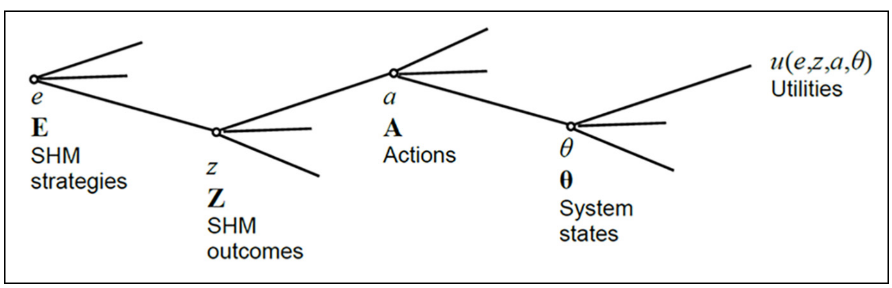

Figure 2. The classic format of decision tree[23] regards SHM.

Where to install the sensors? How many sensors to install? How to set measurement parameters? and Whether to extend service life? These questions can be answered with the utilization of the Bayesian decision and VoI analyses and an optimization of the expected benefits, the risk and the expected costs. By performing SHM, information about the states of the structural system are obtained, which will improve the state models. Actions such as repair and maintenance for example, based on the information acquired by SHM strategies like damage detection, change the physical properties and performance of the structural system. Both, the parameters of the SHM and the repair and maintenance strategies influence the expected benefits, costs, and the risk and in this way lead to different VoI.

The classic format of a decision analysis relating to experiments—or SHM—is shown in Figure 2, building upon the framework of Bayesian decision theory.[28] The decision-maker wishes to select a single action a from the domain $\mathbf{A} = \{a_1, \ldots, a_m\}$ of potential actions; the consequences of adopting the terminal action a depend on the state of the system, which cannot be predicted with certainty. Each potential state will be labeled by a θ with the domain $\boldsymbol{\theta} = \{\theta_1, \ldots, \theta_m\}$. To obtain further information on the importance of each state θ, a single experiment or SHM strategy e from a family $\mathbf{E} = \{e_1, \ldots, e_m\}$ of potential SHM strategies should be selected. Each potential outcome of an SHM experiment e will be labeled by a z with domain $\mathbf{Z} = \{z_1, \ldots, z_m\}$. The decision-maker assigns a utility $u(e, z, a, \theta)$ to perform a particular e, observing a particular z, taking a particular action a, and then obtaining a particular θ. The evaluation u takes into account of the costs (monetary and other) of SHM and the consequences (monetary and other) of the terminal action as well as the system states.

The VoI can be found as the difference between the maximum expected value of the utility obtained in preposterior analysis and the maximum value of the utility obtained using only prior information, shown in equation (1). This means that a value to information is assigned as expected utility gain caused by the optimal decisions regarding information acquirement and actions with and without that information relative to the costs of collecting the information

$$\mathrm{VoI}_e = \max_{\mathbf{e}} E_{\mathbf{Z}|\mathbf{e}}\left[\max_{\mathbf{a}} E_{\boldsymbol{\theta}|\mathbf{Z}}[u(\mathbf{e}, Z, \mathbf{a}, \boldsymbol{\theta})]\right] - \max_{\mathbf{a}} E_{\boldsymbol{\theta}}[u(\mathbf{a}, \boldsymbol{\theta})] \quad (1)$$

The VoI can be normalized in relation to the prior utility resulting in the relative VoI ($\overline{\mathrm{VoI}_e}$)

$$\overline{\mathrm{VoI}_e} = \frac{\mathrm{VoI}_e}{\left|\max_{\mathbf{a}} E_{\boldsymbol{\theta}}[u(\mathbf{a}, \boldsymbol{\theta})]\right|} \quad (2)$$

In this way, the identification of optimal SHM strategies is facilitated for both new and existing structures under a range of operating conditions and constraints. If the cost of this information is small in comparison to the potential benefit of the information, the experiment should be performed. If several different types of experiments are possible, the decision-maker must choose the experiment resulting the overall largest expected value of utility.[29] The pre-posterior Bayesian decision analysis is utilized to model and to assess the expected value of the utility relating to yet unknown information, which can be modeled and forecasted using the prior system-state models.

Structural probabilistic system performance

For any structural model, failure occurs when the external load S exceeds the internal resistance (material strength) R due to increase of damage and degradation. Considering the resistance model uncertainty M_R and the loading model uncertainty M_s, the failure probability $P(F_S)$ of a series system with n_j parallel subsystems consisting of n_i components can be written as equation (3)

$$P(F_S) = P\left(\bigcup_{j=1}^{n_j}\bigcap_{i=1}^{n_i}\left(M_{R,i,j}R_{i,j}(t) - M_{S,i,j}S_{i,j}\right) \leq 0\right) \quad (3)$$

$R_{i,j}(t)$ is the time-variant resistance for a component, and $S_{i,j}$ is the external loading on the component. The resistance (strength) will be degraded due to the increase of damage with time

$$R_{i,j}(t) = R_{i,j,0}\left(\Delta_{i,j} - D_{i,j}(t)\right) \quad (4)$$

$R_{i,j,0}$ is the initial resistance, and $\Delta_{i,j}$ is the damage limit of the component. $D_{i,j}(t)$ is the damage on a component, which will be increasing with time. A general damage model is introduced by Mori and Ellingwood[30]

$$D_{i,j}(t) = \alpha(t - T_0)^{\beta} \quad (5)$$

where α is the annual deterioration rate of a component, β is the deterioration type, and T_0 is the deterioration initiating time. For $\beta = 1$, this corresponds to the most applied corrosion models and to the Palmgren–Miner fatigue model with a stationary stress process; for $\beta = 0.5$, the model is representative of diffusion-controlled deterioration; and for $\beta = 2$, the model approximates concrete deterioration caused by sulfate attack.

To calculate the probability of failure, a limit state function is introduced, when $g_{i,j} \leq 0$ represents the component failure due to deterioration

$$g_{i,j} = M_{R,i,j}R_{i,j,0}\left(\Delta_{i,j} - \alpha(t - T_0)^{\beta}\right) - M_{S,i,j}S_{i,j}(t) \quad (6)$$

It is noted that for many structural systems, deterioration states of structural components are correlated.[31] Therefore, the correlation of the deterioration states should be accounted for. The deterioration process follows equation (4). Stochastic dependence can then be modeled[32] by introducing a correlation among the damage limit state, or among the parameters of the models describing the damage limit, for example, deterioration rate α. The component failures caused by deterioration are likely to occur at different times depending on the nature of the deterioration process, which will show a lower statistical dependence than the failure events caused by overloading as all components normally fail during the same load event. The correlation coefficient for limit states of overloading failure is thus close to 1.0,[31] and the correlation coefficient of deterioration states among components is normally estimated less than 1.0.

DDS information

SHM consists of a very wide range of activities, which should provide information of relevance for the management of existing and new structures for their life-cycle performance. SHM systems are designed to provide owners and operators with information about the health of a structure. A main issue of SHM is to develop approaches for damage diagnosis, involving for example, signal processing methods for model identification and feature extraction.[33–35]

An approach encompassing DDS and algorithms, which is used to evaluate the structural system performance with DDS information has been developed by Thöns.[36] The employed damage detection method, which is the stochastic subspace damage detection (SSDD) method,[37] detects changes in the dynamic properties of a structure, for example, due to stiffness loss, from output-only ambient vibration measurements in a (healthy) reference state and in the current state. From these measurements, a test statistic is computed that compares both states. This results in a chi-square–distributed damage indicator, having a central chi-square distribution in the reference state and a non-central chi-square distribution in the damaged state. A threshold is set up for a desired Type-I error for a decision between both states.

The non-centrality parameter of the distribution in the damaged state can be obtained easily from measurements of the structure in the reference state and from model-based information on the damage within the theoretical framework of the method.[38] This allows in particular an efficient model-based computation of the probability of indication for any damage, without the need of recording or simulating data from the damaged structure.[39]

In general, the performance of the DDS depends on the following properties:

1. Properties of the measurement system, like number and positions of sensors, type of sensors, sampling frequency f_s, and measurement duration. These properties are typically set up by the user.
2. Stochastic system properties, like ambient excitation properties and the measurement noise level. These properties are not or only partially controlled by the user.

Besides these properties, the performance of the DDS strongly depends on the chosen damage detection method and its setup. This includes in particular the desired Type-I error for the indication threshold between healthy and damaged states, which also needs to be set for the SSDD method.

Note that the considered damage detection method is used as an example in this study, and any damage detection method can be used in our VoI framework if it can provide the probability of indication for the damages included in the employed deterioration model.

Integrity management actions

Integrity management actions are the possible actions that the decision-maker can take during the service life of a structure to ensure safety and functionality, for example, maintenance, inspection, repair, and replace. The decision of theoretical optimal choice of integrity management actions can be derived in the form of decision rules, which relate an experimental outcome to an action. Decision rules can—once they are derived—enhance significantly the computational efficiency. Examples of decision rules are:[40]

- If the monitoring outcome is above the threshold value, an inspection is made.
- If the inspection outcome is above a threshold value, a repair is made.
- If the expected value of damage size is above a threshold value, an inspection or repair is made.

Pre-posterior updating with DDS information

Let $\mathbf{D}$ denote the damage size of a structural system or component, which is the vector of degradation consisting of random variables of $D_{i,j}$ from equation (5). $f_D(\mathbf{D})$ denotes the probability density function of $\mathbf{D}$. Considering that a DDS is used to inspect a structure or structural component, the quality of the measurement can be represented by the probability density function for indication, given a damage size $\rho(I|\mathbf{D})$. It can then be used to calculate the probability of indicating the damage with size $\mathbf{D}$. The probability of indication of detecting damage is then given as

$$P(I) = \int_{\Omega_D} \rho(I|\mathbf{D}) f_D(\mathbf{D}) d\mathbf{D} \quad (7)$$

as referenced by Hong.[41] Ω_D represents the domain of $\mathbf{D}$. Since the value of $\rho(I|\mathbf{D})$ ranges from 0 to 1, to compute equation (7), a uniformly distributed random variable μ can be introduced to form a limit-state function. The probability of no indication of detecting damage $P(\bar{I})$ can be calculated by integrating in the region which is defined using the limit-state function $g_U \leqslant 0$. The limit-state function g_U is defined as the difference between the probability of indication given damage $P(I|\mathbf{D})$ and μ

$$P(\bar{I}) = 1 - P(I) = \int_{\Omega_D} (1 - \rho(I|\mathbf{D})) f_D(\mathbf{D}) \mathrm{d}\mathbf{D} \quad (8)$$

$$g_U = P(I|\mathbf{D}) - \mu \quad (9)$$

The pre-posterior probability of failure if no damage is detected $P(F_s|\mathbf{D} \cap \bar{I})$ can be written as equation (10) and solved by two joint limit-state functions of g_S and g_U

$$P(F_s|\mathbf{D} \cap \bar{I}) = P(F_s|\mathbf{D}, \bar{I}) P(\bar{I}) = P(g_S \leqslant 0 \cap g_U \leqslant 0) \quad (10)$$

where $P(\bar{I})$ is the probability of no indication, $P(\bar{I}|F_s, \mathbf{D})$ is the probability of no indication given damage and failure. The limit-state function $g_S \leqslant 0$ can refer to equation (6).

Utility modeling and analysis

Let u be the utility function considering the costs and benefits. The total costs are the sum of individual costs, for example, cost of consequences like failure, cost of actions like inspection, repair, and replacement, costs of monitoring. The failure costs should include both direct and indirect costs regarding fatalities, economic, environmental, and social impact. The monitoring costs include investment, installation, operation, and monitoring system replacement costs. While some individual costs like monitoring costs can be estimated referencing similar cases from literatures and standards, repair costs should be modeled carefully considering the damage status of the structure.

Data from damaged buildings suggest that the repair costs are dependent on the overall damage state,[42–44] the more overall damage is present in a structure, the higher are the repair costs for restoring the structure to the original state. The repair costs dependency on the damage state is modeled in most case, either as a linear function with a limit of repairable damage,[42,43] or as a non-linearly increasing function of damage.[45] In the article, the cost of repair is modeled as a non-linearly increasing function of damage, dependent on the initial investment cost of the bridge C_I, the service life T_{SL} and the repair year t_j following Higuchi,[46] yielding

$$C_R = \frac{C_I}{T_{SL} + 2 - t_j} \tag{11}$$

The repair action is performed when the probability of failure exceeds the target probability P_{Target}, which serves as a boundary to the decision analysis. The utility analysis will be formulated following the decision tree analysis.

The utility can be analyzed depending on the state of information acquirement at the time of the analysis. There are two types of analysis[28] named extensive form and normal form to compute the utility. In this article, the extensive form analysis is applied. If the probabilities of the various system states corresponding to different consequences of action have been estimated, which means that information on action $\mathbf{a}$ and state $\boldsymbol{\theta}$ are given. Assume $\boldsymbol{\theta}$ in total has m states, the expected utility of action a_i can be calculated by

$$E_{\boldsymbol{\theta}}[u(a_i, \boldsymbol{\theta})] = \sum_{j=1}^{m} u(a_i, \theta_j) P(\theta_j) \tag{12}$$

$P(\theta_j)$ is the assigned prior probability at state θ_j. After calculating all the expected utilities corresponding to the different actions, the optimal action will result in the one with highest expected utility, which is called prior utility U

$$U = \max_{\mathbf{a}} E_{\boldsymbol{\theta}}[u(\mathbf{a}, \boldsymbol{\theta})] \tag{13}$$

If additional information becomes available, which means that a specific SHM experiment e has been implemented and a specific outcome of the experiment z is known. The expected utility is modeling by

$$E_{\boldsymbol{\theta}|z}[u(z, a_i, \boldsymbol{\theta})] = \sum_{j=1}^{m} u(z, a_i, \theta_j) P(\theta_j|z) \tag{14}$$

$P(\theta_j|z)$ is the posterior probability, given the outcome of z, which is updated by Bayles's rule. The maximum utility in this case is called posterior utility. When the SHM strategy or the experiment is planned but the result is still unknown, then the expected utility is modeled with forecasted information based on the prior models. The SHM experiment $\mathbf{e}$ and the probability of each of the l outcomes of the experiment z will be assigned. The expected values of the utility should be found for each possible action a for a specific experiment e and outcome z. The maximum utility is called pre-posterior utility U^*, which is calculated by

$$U^* = \max_{\mathbf{e}} E_{\mathbf{Z}|\mathbf{e}} \left[\max_{\mathbf{a}} E_{\boldsymbol{\theta}|\mathbf{Z}}[u(\mathbf{e}, \mathbf{Z}, \mathbf{a}, \boldsymbol{\theta})] \right] \tag{15}$$

$$\begin{aligned} & E_{\mathbf{Z}|\mathbf{e}} \left[\max_{\mathbf{a}} E_{\boldsymbol{\theta}|\mathbf{Z}}[u(\mathbf{e}, \mathbf{Z}, \mathbf{a}, \boldsymbol{\theta})] \right] \\ & = \max_{\mathbf{a}} \sum_{k=1}^{l} \sum_{j=1}^{m} u(e, z, \mathbf{a}, \theta_j) P(\theta_j|z_k) P(z_k, e_i) \end{aligned} \tag{16}$$

$P(z_k, e_i)$ is the probability of outcome z_k from experiment of e_i. $P(\theta_j|z_k)P(z_k, e_i)$ is the pre-posterior probability, which can be modeled as $P(\theta_j \cap z_k)$.

Generic parametric analysis of the value of DDS information

The parametric analysis of the value of DDS information takes basis in a generic structural system under degradation. The generic and representative structural system constitutes a series system accounting for the dependence in the component failure modes and in the deterioration of the individual structural components. Such system is representative, as it takes basis in common assumptions for target reliability determination and code calibration.[47,48] The complete decision scenario encompassing the decision-maker, the decision point time, the temporal framing of the decision analysis, the specific structural system and component failure and deterioration models and their dependencies, the specific DDS information, and the utility models are introduced in the following sections.

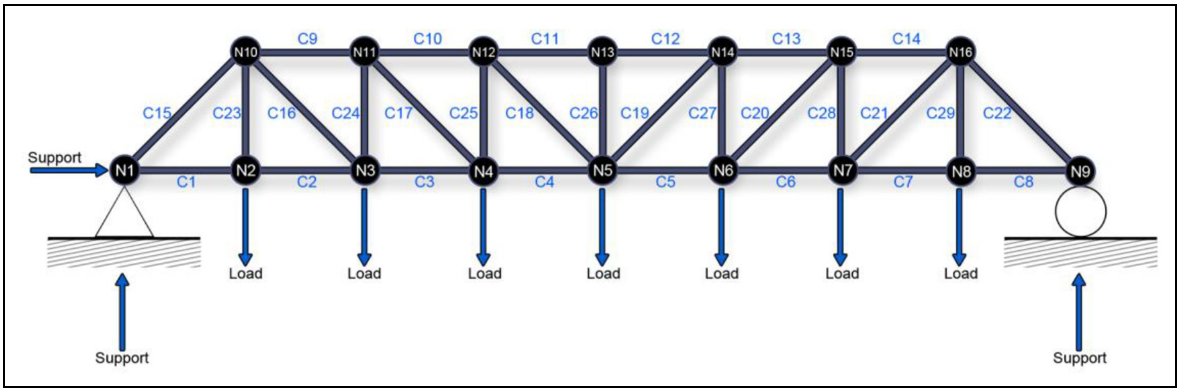

Figure 3. Illustration of truss bridge girder.

Decision scenario

A Pratt truss girder as shown in Figure 3 is considered under operation and maintenance phase. It is assumed to experience an unusually high deterioration in the first 15 years of operation. For the remaining 35 years of the service life, a bridge manager wants to design a maintenance plan. The manager considers whether the bridge should be repaired regularly after certain times without SHM or is it worthwhile to do SHM before repairing directly to minimize the risk and expected costs. Therefore, a VoI analysis is performed to provide the decision basis. The basic decision problem is whether to choose e_0, that is, no SHM or e_1, that is, DDS. If implementing DDS, there will be a cost of monitoring C_M with outcome of chances z_1 indication of damage or z_2 no indication of damage. The outcome of DDS will be influenced by the deterioration type β, deterioration rate α, point in time employment year t_m, number of sensors, sensor location, measurement noise, and Type-I error for indication threshold. So, the decision-maker is wondering how to design a monitoring and maintenance plan accordingly with different deterioration rates and environment? If choosing DDS, at which point in time during service life to implement it? How many sensors should be installed? Where to place the sensors? How does measurement noise affect the result? and How to set the Type-I error for the indication threshold for the DDS? Based on the varied information acquired by the DDS system outcome, the manager has two options of actions, either a_0 do nothing or a_1 repair the truss girder. When performing a repair action, there will be a repair cost C_R. Based on the choice of actions, the truss bridge girder could be either θ_1 safe or θ_2 failure state within the designed service life T_{SL} of 50 years. The failure of the truss will lead to the cost C_F, which account for the direct and indirect consequences. The respective decision tree is shown in Figure 4. With different combination of deterioration rate α, point in time employment year t_m, number of sensors, sensor location, measurement noise, Type-I error for indication threshold, and the decision tree branches will be expanded.

The costs model is shown in Table 1, considering the discount rate r in general for long-term regulations ranged between 0.01 to 0.05 per year;[49] here we adopt for our calculation a constant discount rate of $r = 0.02$ per year. The initial investment cost is chosen for convenience as $C_I = 100$ monetary units. The failure cost C_F and DDS cost C_M are set in relation to the initial investment costs. The normalized failure cost is set to $C_F/C_I = 10$ and $C_M/C_I = 0.001$ per sensor is assumed.

VoI analysis

The value of DDS information when monitoring at year t_m is written as $\mathrm{VoI}(t_m)$

$$\mathrm{VoI}(t_m) = U^*_{SL}(t_m) - U_{SL} \tag{17}$$

where U_{SL} is the expected service life utilities without monitoring. $U^*_{SL}(t_m)$ is the expected service life utilities with monitoring at year t_m. Then the relative VoI will be: $\overline{\mathrm{VoI}}(t_m) = \mathrm{VoI}(t_m)/|U_{SL}|$. The expected service life utilities without monitoring U_{SL} is

$$U_{SL} = \max[U_F; U_{F,R}] \tag{18}$$

where U_F is the utility of doing nothing and fail, $U_{F,R}$ is the utility of doing repair and fail. The utility of doing nothing and fail U_F is calculated as

$$U_F = -\sum_{t=1}^{T_{SL}} P(F_{S_t}) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \tag{19}$$

$$P(F_{S_t}) = P(g_S(t) \leqslant 0) \tag{20}$$

where $P(F_{S_t})$ is the prior probability of system failure at year t. The utility of doing repair and fail $U_{F,R}$ is

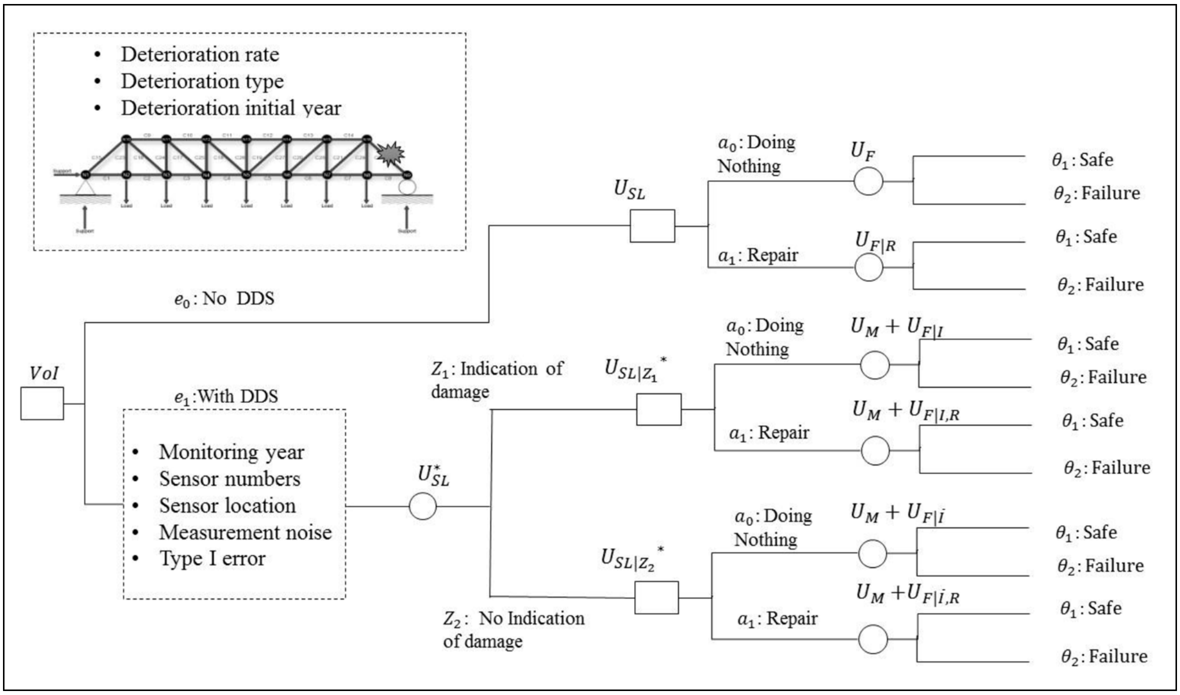

Figure 4. Illustration of decision tree.

Table 1. Costs model.

Discount rate r	Failure cost C_F	DDS cost (per sensor) C_M	Investment cost C_I
0.02	1000	0.1	100

DDS: damage detection system.

$$U_{F,R} = -\sum_{t=1}^{T_{SL}} P\left(F_{S_t}, R_{S_{t_j}}\right) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} - \sum_{n=1}^{n_R} C_R \cdot \frac{1}{(1+\gamma)^{t_j}} \tag{21}$$

$$P\left(F_{S_t}, R_{S_{t_j}}\right) = \begin{cases} P(F_{S_t}), t < t_j = arg\left(P\left(F_{S_{t_j}}\right) = P_{\text{Target}}\right) \\ P\left(F_{S_{(t-t_j)}}\right), t \geq t_j = arg\left(P\left(F_{S_{t_j}}\right) = P_{\text{Target}}\right) \end{cases} \tag{22}$$

where $P(F_{S_t}, R_{S_{t_j}})$ is the probability of system failure at year t, after repair event $R_{S_{t_j}}$ at year t_j. t_j is the repair year when the prior probability of system failure $P(F_{S_t})$ equals to the target probability P_{Target}. The system will behave like a new system after repair with same probabilistic characteristics as originally. n_R is the number of repair times during the service life. The expected service life utilities with monitoring $U_{SL}^*(t_m)$ at t_m can be written as

$$U_{SL}^*(t_m) = U_M + \max\left[U_{F|I}; U_{F|I,R}\right] + \max\left[U_{F|\bar{I}}; U_{F|\bar{I},R}\right] \tag{23}$$

where U_M is the utility of monitoring, $U_{F|I}$ is the utility of failure given indication of damage, $U_{F|\bar{I}}$ is the utility of failure given no indication of damage, $U_{F|I,R}$ is the utility of failure, given indication of damage and repair, $U_{F|\bar{I},R}$ is the utility of failure given no indication of damage and repair. The utility of monitoring U_M is

$$U_M = -\left(1 - P\left(F_{S_{t_m}}\right)\right) \cdot C_M \cdot \frac{1}{(1+\gamma)^{t_m}} \tag{24}$$

The utility of failure given indication of damage $U_{F|I}$ is calculated as

$$U_{F|I} = -\sum_{t=1}^{T_{SL}} P(F_{S_t} \cap I_{t_m}) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \tag{25}$$

$$P(F_{S_t} \cap I_{t_m}) = \begin{cases} P(F_{S_t}), t < t_m \\ P(g_S(t) \leq 0 \cap g_U(t_m) \geq 0), t \geq t_m \end{cases} \tag{26}$$

$P(F_{S_t} \cap I_{t_m})$ is the pre-posterior probability of system failure at year t if doing monitoring and giving indication of damage at year t_m and doing nothing. The utility of failure given no indication of damage $U_{F|\bar{I}}$ is calculated as

$$U_{F|\bar{I}} = -\sum_{t=1}^{T_{SL}} P(F_{St} \cap \bar{I}_{t_m}) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \tag{27}$$

$$P(F_{St} \cap \bar{I}_{t_m}) = \begin{cases} P(F_{St}), t<t_m \\ P(g_S(t) \leqslant 0 \cap g_U(t_m) \leqslant 0), t \geqslant t_m \end{cases} \tag{28}$$

where $P(F_{St} \cap \bar{I}_{t_m})$ is pre-posterior probability of system failure at year t if doing monitoring and giving no indication of damage at year t_m and doing nothing.

The utility of failure given indication of damage and repair $U_{F|I,R}$ is

$$\begin{aligned} U_{F|I,R} = &-\sum_{t=1}^{T_{SL}} P\Big((F_{St} \cap I_{t_m}), R_{St_j}\Big) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \\ &-\sum_{n=1}^{n_{I,R}} C_R \cdot \frac{1}{(1+\gamma)^{t_j}} \end{aligned} \tag{29}$$

$$P\Big((F_{St} \cap I_{t_m}), R_{St_j}\Big) = \begin{cases} P(F_{St}), t<t_m \\ P(F_{St} \cap I_{t_m}), t_m \leqslant t < t_j = arg\Big(P\Big(F_{St_j} \cap I_{t_m}\Big) = P_{\text{Target}}\Big) \\ P\Big(F_{S(t-t_j)}\Big), t \geqslant t_j = arg\Big(P\Big(F_{St_j} \cap I_{t_m}\Big) = P_{\text{Target}}\Big) \end{cases} \tag{30}$$

where $P((F_{St} \cap I_{t_m}), R_{St_j})$ is pre-posterior probability of system failure at year t and giving indication of damage at year t_m and repairing at year t_j. Here, t_j is the year when the $P(F_{St} \cap I_{t_m})$ equals to the P_{Target}. $n_{I,R}$ is the number of repair times during the service life after implementing DDS for 1 year at t_m and giving indication of damage.

The utility of failure given no indication of damage and repair $U_{F|\bar{I},R}$ is

$$\begin{aligned} U_{F|\bar{I},R} = &-\sum_{t=1}^{T_{SL}} P\Big((F_{St} \cap \bar{I}_{t_m}), R_{St_j}\Big) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \\ &-\sum_{n=1}^{n_{\bar{I},R}} C_R \cdot \frac{1}{(1+\gamma)^{t_j}} \end{aligned} \tag{31}$$

$$P\Big((F_{St} \cap \bar{I}_{t_m}), R_{St_j}\Big) = \begin{cases} P(F_{St}), t<t_m \\ P(F_{St} \cap \bar{I}_{t_m}), t_m \leqslant t < t_j = arg\Big(P\Big(F_{St_j} \cap^{\bar{I}_{t_m}}\Big) = P_{\text{Target}}\Big) \\ P\Big(F_{S(t-t_j)}\Big), t \geqslant t_j = arg\Big(P\Big(F_{St_j} \cap \bar{I}_{t_m}\Big) = P_{\text{Target}}\Big) \end{cases} \tag{32}$$

where $P((F_{St} \cap \bar{I}_{t_m}), R_{St_j})$ is pre-posterior probability of system failure at year t if doing monitoring and giving no indication of damage at year t_m and repairing at year t_j. Here, t_j is year when the $P(F_{St} \cap \bar{I}_{t_m})$ equals to the P_{Target}. $n_{\bar{I},R}$ is the number of repair times during the service life after implementing DDS for 1 year at t_m and giving no indication of damage.

Structural probabilistic performance

The truss bridge girder has 29 components with 16 joint nodes. Assume a probabilistic extreme loading S, which is Weibull distributed with mean of 3.5 and standard deviation of 0.1, applied vertically on the truss and evenly distributed on the lower nodes 2, 3, 4, 5, 6, 7, 8 with $1/7\ S$. Thus, the axial force on each beam element are calculated by the equilibrium equations. The truss's beams have similar geometrical and probabilistic properties.

The failure of a truss component can be the failure by yielding when it is under tension as well as failure by buckling when it is under compression. If the component is under tension, the critical strength is the yield strength σ_y, the corresponding tension resistance is R_y, which is related to the properties of materials. R_y is modeled as lognormal distributed with 0.1 coefficient of variation and the mean value is calibrated to a probability of system failure of 10^{-6} disregarding any damage, considering the consequence of failure is large and the relative cost of safety measure is small.[34] If the component is under bucking, the critical strength is the buckling strength, which follows the Euler buckling formula

$$\sigma_b = \frac{\pi^2 EI}{AL^2} \tag{33}$$

where σ_b is the buckling strength, L is the column length, A is the cross-section area, which is (10/144) m^2 in this case, I is the cross-sectional moment of inertia, E is the Young's modulus, which is 14,400 MPa for calculation. The corresponding buckling resistance R_b is also modeled as lognormal distribution with mean of $R_b = \sigma_b \cdot A$ and 0.07 standard deviation. The limit-state functions of 29 components can be formulated as follows. Due to the absence of redundancy, a series-system formulation is chosen for the truss bridge girder; the system limit-state function is the minimum of the n_i components limit-state function

$$g_S = \min_{i=1\ to\ n_i} (M_{R,i} R_{i,0}(\Delta_i - D_i(t)) - M_{S,i} S_i) \tag{34}$$

Then the probability of system failure $P(F_S)$, which is coupled with time-variant damage models describing continuously the deterioration process and structural resistance degradation throughout the service life can be written as

$$P(F_S) = P\left(\bigcup_{i=1}^{n_i}\left(M_{R,i}\ R_{i,0}\left(\Delta_i - \alpha(t - T_0)^{\beta}\right) - M_{S,i}S_i\right) \leqslant 0\right) \tag{35}$$

According to JCSS (Joint Committee on Structural Safety),[50] the resistance model uncertainty $M_{R,i}$ is modeled as lognormal distributed with mean of 1 and standard deviation of 0.05; the loading model uncertainty $M_{S,i}$ is lognormal distributed with mean of 1 and standard deviation of 0.1; and the damage limit of component Δ_i is modeled as lognormal distributed with mean of 1 and standard deviation of 0.3. The annual deterioration rate α, the deterioration type β, and the deterioration initiating time T_0 are modeled accordingly to Long et al.[51]

According to literature[52] with general corrosion, damage is equated to the total amount of metal lost. This may be expressed in terms of thickness lost, for example an expression in mm per year, or mass lost, such as grams per square meter per year. Corrosion rate on a carbon steel surface,[53] in atmospheric environment for example, industrial environment is 0.025–0.050 mm per year and in marine environment is 0.125–1 mm per year. So that three different deterioration rates are selected in this article to present three different deteriorating conditions. It is assumed that the system is required to take repair actions when the probability of failure exceeds 10^{-4} according to the same target reliability class with high costs of safety measures.[50]

As previously stated in section "Structural probabilistic system performance," the correlation among deterioration states of structural components should be accounted for. For computation convenience, the stochastic dependence is modeled by introducing a correlation among the parameters of the models describing deterioration. The damage limit is fully correlated. Thus, the correlation of the initial resistances $R_{i,0}$ and the deterioration rate α among 29 components, $\rho_{R_{i,0}}$ and ρ_{α} is assumed to 0.5. It should be noted that due to the non-redundancy of the truss structure, the dependency among the deterioration process of different components will not strongly influence the system reliability as, for example, shown by Thöns et al.[36]

The probability of component/system failure is calculated by Monte Carlo simulations based on Table 2. The prior probability of system failure will increase with time. The failure probabilities with a low deterioration rate and same initial year but varied deterioration types are shown in Figure 5(a). The failure probability of the diffusion-controlled type of deterioration will always be below the target probability during the entire service life requiring no repair. However, if the system is under corrosion and fatigue, it is required to do the first repair at year 25 and in total need to be repaired three times during service life. If it is the type of sulfate attack concrete deterioration, it needs to do the first repair at year 18 and in total to be repaired nine times, which is shown in Figure 5(b). The computation results of failure probabilities with same deterioration type of corrosion and fatigue but varied deterioration rate and initial year are shown in Figure 5(c).

Properties of DDS

The DDS can detect stiffness loss in the elements of the structure. A connection to the damage states is made in this regard as follows. A stiffness loss $\mathrm{d}k_i$ is expressed as the relative change of ratio of the initial axial stiffness $k_{i,0}$ for element i

$$\mathrm{d}k_i = 1 - \frac{k_i}{k_{i,0}} \tag{36}$$

Table 2. Summary of the prior probabilistic model parameters.

Variable	Description	Dim.	Dist.	Exp.value	SD
R_y	Yield resistance	MPa	LN	Cali.	CoV = 0.1
R_b	Buckling resistance	MPa	LN	Equation (33)	0.07
$M_{R,i}$	Resistance uncertainty	MPa	LN	1.0	0.05
S_i	Loading	MPa	WBL	3.5	0.1
$M_{S,i}$	Loading uncertainty	MPa	LN	1.0	0.1
Δ_i	Damage limit	–	LN	1.00	0.3
T_0	Deterioration initial time	Year	Det.	15/10/5	–
β	Deterioration type	Diffusion-controlled deterioration	Det.	0.5	–
		Corrosion and fatigue		1	
		Sulfate attack concrete deterioration		2	
α	Deterioration rate (/year)	Low $T_0 = 15$	LN	1.3E–5	0.001
		Medium $T_0 = 10$	LN	7.6E–5	
		High $T_0 = 5$	LN	2.54E–4	

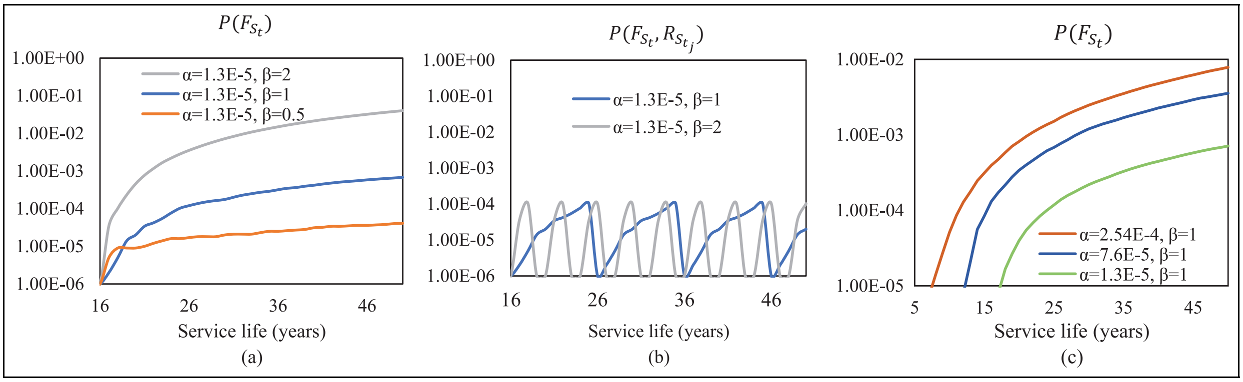

Figure 5. (a) Prior probability of system failure with varied deterioration types, (b) prior repair plan with varied deterioration types, and (c) prior probability of system failure with varied deterioration rate and initial year.

The element stiffness k_i has a relation with cross-section area A_i, length L and Young's modulus E, $k_i = E*A_i(t)/L$. The cross-section A_i is reduced due to the increase of damage states D_i

$$A_i(t) = A_{i,0} - h(D_i(t)) \tag{37}$$

$A_{i,0}$ is the initial cross-sectional area, $A_i(t)$ is the cross-sectional area at time t, h is the function between damage state and the cross-section area. Then, the relation between damage state and stiffness loss can be expressed as

$$\mathrm{d}k_i = 1 - \frac{A_{i,0} - h(D_i(t))}{A_{i,0}} \tag{38}$$

$$\mathrm{d}k_i = \gamma \cdot \ h(D_i(t)) \tag{39}$$

γ is the correction factor, in which $\gamma = 1/A_{i,0}$. There is small uncertainty about the cross-section area, length, and Young's modulus, so that the stiffness loss uncertainty will be very small, which is neglected. To simplify computation, we adopt $\mathrm{d}k_i = D_i(t)$. The probability of damage indication is calculated for the SSDD method based on the described damage states.[30] Hereby, the following parameters of the detection system are considered.

The number of sensors, their location, and their noise properties influence the structural information content that is contained in the measurement data. In particular, it is well known that the number and locations of sensors can be optimized to obtain more precise information about the dynamic properties of structures.[54] An explicit link of the sensor placement to the performance of the considered damage detection method has been made by Döhler et al.[55] Thus, the number and location of sensors have a direct influence on the damage detection probabilities, and hence on the VoI that is examined in this article. Measurement noise (as a property of the used sensors) affects the signal-to-noise ratio and thus the information content in the signals[56] and is therefore also an important factor for the examination of the VoI. The Type-I error rate is a user-defined value for the trade-off between a low false-alarm rate and a high probability of detection. It is a design parameter for any damage detection method, reflecting the applied reliability concept[57] and has therefore a direct influence on the decisions taken based on the outcome of the damage detection method. Hence, its influence on the VoI should also be examined.

Following the above argumentation, five scenarios of DDS settings are investigated. Within all the scenarios, the structural system is under deterioration type $\beta = 1$ corresponding to corrosion or fatigue, which is reasonable for the deterioration of a steel truss bridge girder. For the reference scenario, the bridge is under low deterioration, the DDS is modeled with the acceleration sensors located in nodes 12, 13, 14 of the truss in Y-direction recording the vibration response and using the DDS algorithm. Based on the dynamic structural system model, a reference data set of length $N = 10{,}000$ at a sampling frequency of 50 Hz is simulated in the undamaged state. Ambient excitation (white noise) is assumed at all degrees of freedom, whose covariance is the identity matrix. Measurement noise is added on the resulting accelerations with standard deviation at each sensor of 5% of the standard deviation of the signal. The Type-I error for the indication threshold is set as 1%.

Based on the reference scenario, scenario (a) varies the number of sensors between 1, 3, 5, and 8. Scenario (b) varies the sensor positions when the number of sensors is fixed with three sensors. Scenario (c) changes the measurement noise from 5% to 1%, 50% and 100%. Scenario (d) changes the Type-I error for indication threshold from 1% to 0.1% and 5%. Scenario (e) varies the deterioration rate α from low to medium and high. A summary of the DDS parameters and deterioration scenarios is shown in Table 3.

Table 3. Summary of the sensor configuration and deterioration scenarios.

Scenario	Sensor number	Sensor node location	Measurement noise	Type-I error	Deterioration rate α		
					Initial year	Mean	SD
Base	3	12, 13, 14	5%	1%	$T_0 = 15$	1.3E-5	0.001
(a)	1	13					
	3	11, 12, 13					
	5	11, 12, 13, 14, 15					
	8	11, 12, 13, 14, 15, 4, 5, 6					
(b)	3	4, 5, 6					
		2, 5, 8					
		2, 3, 4					
		11, 13, 15					
(c)		12, 13, 14	1%				
			50%				
			100%				
(d)			5%	0.1%			
				5%			
				1%			
(e)	3	12, 13, 14	5%	1%	$T_0 = 15$	1.3E–5	
					$T_0 = 10$	7.6E–5	
					$T_0 = 5$	2.54E–4	

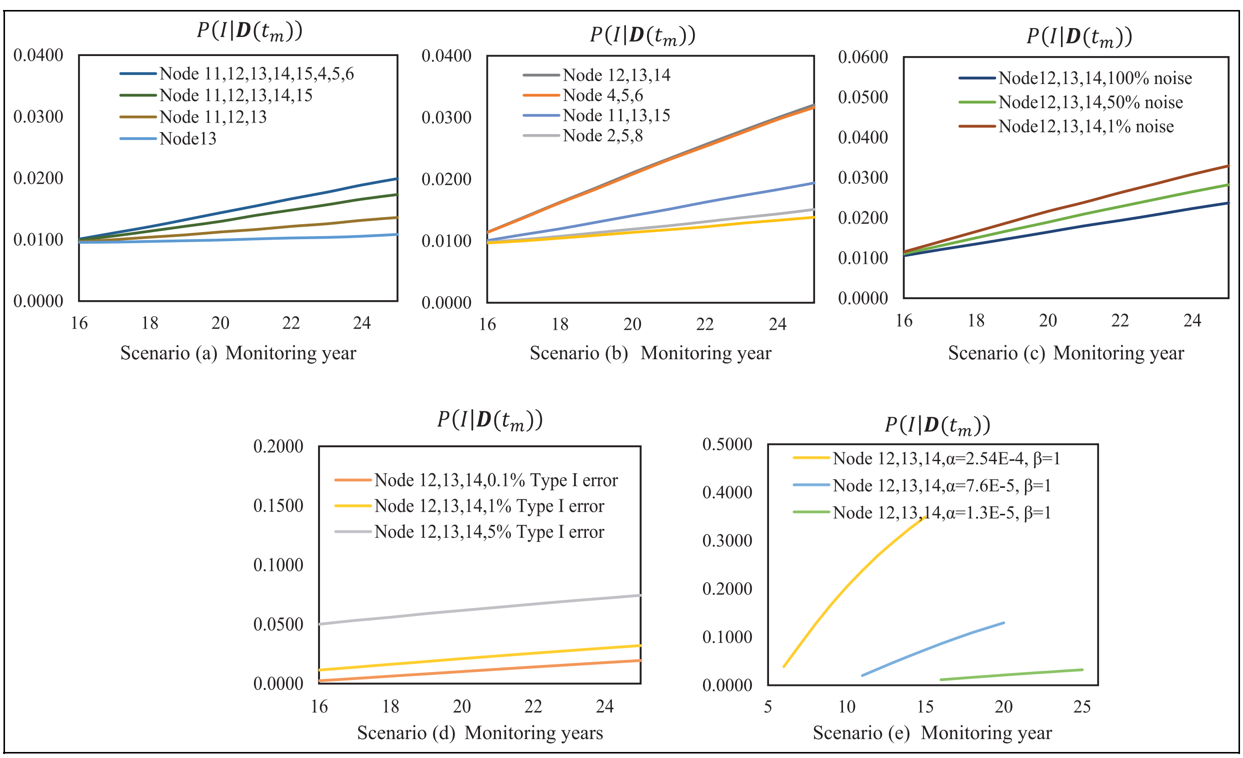

Figure 6. Probability of damage indication with varied scenarios (a) to (e).

The probability of damage indication in each monitoring year is computed and shown in Figure 6. The investigation of monitoring year is focused on the period from the initial deterioration year to the first scheduled repair year without monitoring from prior analysis as shown in Figure 5(b), in order to plan monitoring before directly repair. Figure 6(a) shows that the probability of damage indication $P(I|\mathbf{D}(t_m))$ increases with the increasing number of sensors from 1, 3, 5 to 8 accordingly, which indicates that it is more probable to

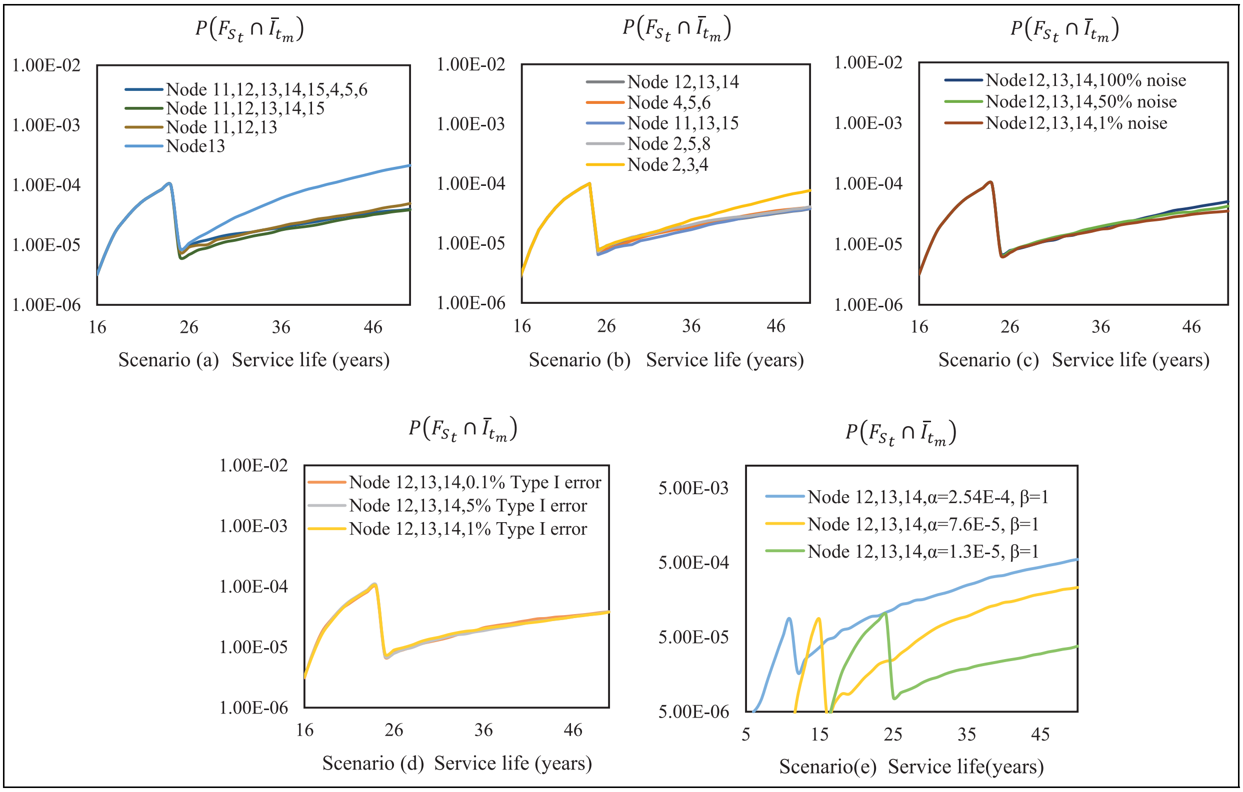

Figure 7. Pre-posterior probability of system failure during service life with varied scenarios (a) to (e) when monitoring and detecting no damage at a certain year.

detect the damage with more sensors. When installing three sensors, it is observed in (b) that the closer the sensor location is to the weakest components 11 and 12 which have the largest axial force from calculation, the larger the probability of damage indication will be. The maximum $P(I|\mathbf{D}(t_m))$ during the service life will be the case when the sensors are located in nodes 12, 13, and 14 (components 11 and 12). It is noted that due to the symmetry of the truss bridge girder, the sensor positions in node 4, 5, and 6 will lead to the same curve as for the sensor locations in 12, 13, and 14. When increasing the measurement noise in scenario (c), the probability of damage indication $P(I|\mathbf{D}(t_m))$ decreases, which means that it will be more difficult to detect damage when there is more noise. The probability of damage indication $P(I|\mathbf{D}(t_m))$ increases when the Type-I error for indication threshold is increased shown in Figure 6(d). For the same setting of the DDS, the probability of damage indication $P(I|\mathbf{D}(t_m))$ increases with higher deterioration rate, which is shown in Figure 6(e).

Pre-posterior updating

The pre-posterior probability of system failure given damage detection information is computed following section “Pre-posterior updating with DDS information” taking basis in the Bayesian updating methods. The results are shown in Figure 7 when a DDS is monitoring at a specific year with detecting no damage. When increasing the number of sensors (a), the updated probability of failure is much lower than in the case with only one sensor. However, it can be seen that the pre-posterior probability of system failure will not be lower if installing more than three sensors. Instead, the curve of the pre-posterior probability is similar if more than one sensor is installed, which can be explained that only sensor in a specific position provides sufficient information. When installing three sensors (b), if the sensor positions are far away from the weakest components 11 and 12 (nodes 12, 13, and 14), such as in node 2, 3, or 4, the updated probability of failure will be larger toward the end of the service life. Changes in the measurement noise (c) only have a small influence on the updated curve of the pre-posterior probability, which result in larger values toward to the end of the service life when the measurement noise is large. When increasing the Type-I error threshold (d), the updated pre-posterior probability of failure during service life shows only minor differences. When increasing the deterioration rate (e), the relative reduction of

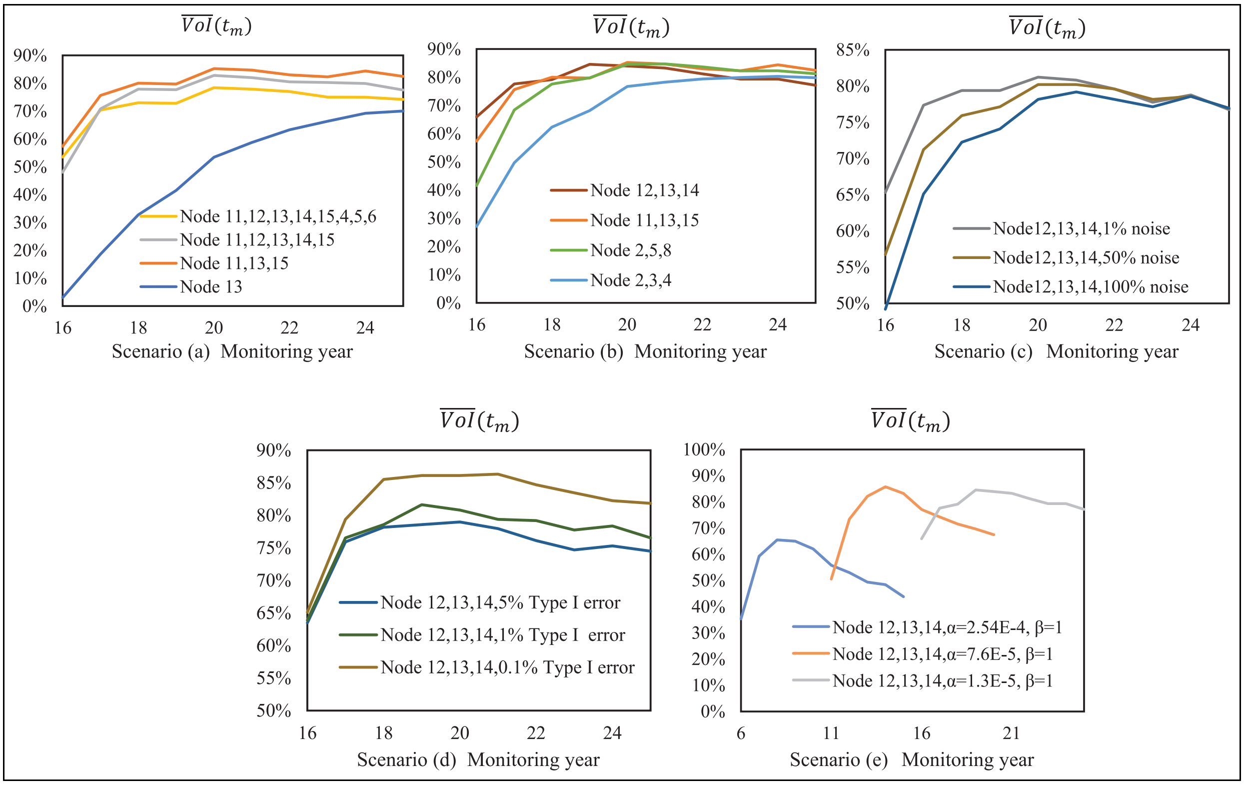

Figure 8. Relative value of information with varied scenarios (a) to (e) and different DDS monitoring year.

pre-posterior probability of failure given no damage indication is smaller.

VoI analysis results

The VoI depending on the DDS monitoring year are computed following section "VoI analysis." The relative VoI ($\overline{\mathrm{VoI}}$) for the considered DDS and structural system parameters is shown in Figure 8. When the deterioration rate is low, the $\overline{\mathrm{VoI}}$ is increasing fast from year 16 in the beginning and slowly decreases when reaching year 25. From Figure 8(a), the $\overline{\mathrm{VoI}}$ is increasing when increasing the number of sensors from 1 to 3, but when increasing the number from 3 to 5 to 8, the $\overline{\mathrm{VoI}}$ is decreasing. When there is more than one sensor, more sensors lead to a higher probability of damage indication, but it does not lead to higher $\overline{\mathrm{VoI}}$ because some sensors did not provide additional valuable information. In contrast, it will lead a lower $\overline{\mathrm{VoI}}$ because of higher sensor costs. The beneficial number of sensors is three sensors.

Figure 8(b) gives an indication of $\overline{\mathrm{VoI}}$ with changes of the sensor layout when only three sensors are selected. When the number of sensors is constant, the sensors which are located near the weakest components 11 and 12 will yield a higher probability of damage indication, which results in a higher $\overline{\mathrm{VoI}}$. The recommended sensor locations are subsequently in node 12, 13, and 14.

Figure 8(c) investigates the relationship between $\overline{\mathrm{VoI}}$ and DDS measurement noise. If the sensor number, positions are constant, then higher measurement noise leads to a lower probability of damage indication, because it will be harder to detect the damage. Hence, the $\overline{\mathrm{VoI}}$ will be lower.

Figure 8(d) describes how the $\overline{\mathrm{VoI}}$ behaves with the Type-I error threshold. The $\overline{\mathrm{VoI}}$ decreases when increasing the Type-I error threshold. Indeed, a higher Type-I error threshold results in more false alarms, and the system will detect more of the small damages. Then, the repair cost per time will be lower due to the early stage of damage, but more repairs may be needed during the whole service life, which results in higher total repair costs and a lower $\overline{\mathrm{VoI}}$.

When increasing the deterioration rate from low to medium and high based on the reference scenario in Figure 8(e), the change of the $\overline{\mathrm{VoI}}$ is stronger with time when the deterioration is medium and high. This is because, the damage size will grow faster and larger with time than in low deterioration, which will lead to higher risk and repair costs. So that the choice of the right monitoring time will be important to help reduce the risk and repair costs, resulting a strong influence on $\overline{\mathrm{VoI}}$. The highest $\overline{\mathrm{VoI}}$ will appear when the deterioration rate is medium, which can be explained by avoiding high risks of structure failure when the damage is too high and unnecessary repair when the damage is too small. The optimized year to implement DDS will be year 19 when under low deterioration, year 14 under medium deterioration, and year 8 under high deterioration.

From Figure 8(a) to (c), the impact of the three measurement parameters: sensor number, sensor location, and measurement noise, is decreasing with monitoring time. They show a similar behavior since they all influence the structural information content and are directly related to the structural condition. For the sensor numbers, it is important to have a minimum number of sensors. However, increasing the number of sensors beyond the minimum number leads to a moderate decrease of the $\overline{\mathrm{VoI}}$. Having sensor locations close to the weakest component increases the $\overline{\mathrm{VoI}}$, but if the sensors are in the vicinity of the weak point, the influence on the $\overline{\mathrm{VoI}}$ is not strong. The effect of the measurement noise on $\overline{\mathrm{VoI}}$ can be neglected toward the end of the service life. This is due to the increase of damage size resulting in a more pronounced measurement signal, which is influenced less by the noise. However, in Figure 8(d), the effect of the Type-I error on the $\overline{\mathrm{VoI}}$ increases with monitoring time. This is because the system will barely have damage in the beginning, the probability of damage indication will be very small no matter what the Type-I error is. With increasing service life, the damage is growing to a more detectable size, the probability of damage indication will be affected more by the Type-I error. As shown in Figure 8(e), the most sensitive parameter over the entire service life of the system is the deterioration rate because it directly influences the risk of the structural failure and costs for repair.

With Figure 8(a) to (e), the optimal DDS and structural system can be identified as: three sensors in nodes 12, 13 and 14 with 1% measurement noise and 0.1% Type-I error threshold to be employed at year 14 of the service life on a truss girder with a medium deterioration rate.

Discussion

The primary purpose of this study is to determine the structural and DDS influencing parameters on the value of DDS. Earlier research suggests that the value of SHM can be quantified,[6] previous application study focusses on methods of quantifying the VoI.[58] Our analysis provides a new insight into the relationship between VoI-based decision-making and DDS before its implementation. The results indicate that the VoI-based decision support facilitates that optimal SHM and structural system parameters can be identified leading to the maximum expected value of the utility gain. The utility gain may encompass, for example, an increased benefit generation, reduced costs for the structural integrity management and reduced risk of structural failure. These results clearly support some of the earlier research[53] that the quantification of the value of the DDS information may serve as a basis for DDS design and employment optimization.

Within the scope of this article, DDS information and structural system parameters have been identified leading to the highest expected risk and cost reduction for the structural integrity management of a representative engineering structure. The VoI-based decision-support beyond the scope of this article may encompass various other decision scenarios such as the combination of different monitoring/measurement strategies and techniques to determine the optimal maintenance planning as well as service life extension.[18,59]

From the viewpoint of structural integrity management, there is no necessity for continuous monitoring with a DDS, as a single application in the service yields a significant risk and cost reduction, through achieving a significant value of DDS information. It should be noted that multiple DDS information may incorporate a high dependency and thus may prevent an increase of the VoI. However, multiple and continuous structural health information and their dependencies require further research.

The application of VoI-based decision on the truss girder has demonstrated its ability to support the design and employment of a DDS before implementation. The parametric analysis of the value of DDS information takes basis in a generic and representative structural system accounting for the dependence in the component failure modes and in the deterioration of the individual structural components. The choice of the structural system and a comprehensive generic deterioration model is representative for many—but not all—structural systems according to codes and standards. Besides, due to the complexity of the decision scenario and the decision analysis, assumptions focusing on fatigue and corrosion degradation in conjunction with well-justified repair and normalized cost models are applied. However, there are still many challenges ahead. Clearly, for a specific application, it is required to adjust the decision scenario including the calibration of the generic and normalized models, for example, with a more specific degradation modeling approach.

Conclusion

This article introduces the VoI-based method to determine the structural system influencing parameters with deterioration type and deterioration rate as well as DDS-influencing parameters including the number of sensors, sensor location, measurement noise, and Type-I error for indication threshold. Through quantification of the value of DDS, it is shown that the design of the DDS system (i.e. the number of sensors, sensor positions, noise, and indication threshold) can be optimized as well as its deployment time to achieve maximum expected life-cycle benefits.

This article facilitates comprehensive guidance for (a) designing DDS by sensor number, sensor location, (b) decision support for DDS employment by degradation mechanisms, and (c) for the DDS utilization by determining the optimal time of information acquirement.

The example of the deteriorating truss bridge girder under fatigue or corrosion illustrates that

1. It is cost and risk reduction efficient to implement DDS compared to the scenario when directly repairing without monitoring.
2. The structural deterioration rate is the most sensitive parameter effecting of relative VoI of DDS over the entire service life.
3. The optimal DDS employment year varies depending on the DDS and structural system properties.
4. The employment of only one DDS measurement in the service yields a high relative VoI.
5. The number of sensors should be chosen with optimization as more sensors do not lead to a higher relative VoI.
6. The sensor locations should be chosen with thorough consideration of the damage and failure scenarios of the structural system.
7. The measurement noise and the Type-I error for indication threshold should be controlled as small as possible in order to achieve the highest relative VoI.
8. The value of DDS information quantification can be a powerful tool to determine optimal settings and sensor employment.

It should be noted that only a finite set out of many possible sensor configurations have been analyzed in this study, and there might be other configurations which may lead to a slightly higher relative VoI. Nevertheless, the results can be used as an example to develop optimal lifetime maintenance strategies for similar bridges to optimize the DDS settings and sensor configuration for maximum expected utilities before implementation of the DDS.

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CHAPTER 4. UTILITY ANALYSIS FOR SHM DURATIONS AND SERVICE LIFE EXTENSION OF WELDS ON STEEL BRIDGE DECK (PAPER 2)

Lijia Long, Isaac Farreras Alcover, Sebastian Thöns.

Structure and Infrastructure Engineering

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Scientific contribution of the PhD student:

Lijia Long

- proposed the idea of decision-making analysis on optimal monitoring duration and service life extension.
- implemented the utility calculations.
- implemented the parametric analysis.
- wrote the entire draft version of the paper and revised it according to co-authors' comments.

Scientific contribution of co-authors:

Isaac Farreras Alcover

- assisted in defining the case study in real practice.
- provided the fatigue reliability prediction model based on monitoring data.
- assisted in interpretation of the results of the parametric analysis.
- carefully reviewed the manuscript and provided critical comments.

Sebastian Thöns

- assisted in defining the decision scenario.
- carefully reviewed the manuscript and provided critical comments.

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Utility analysis for SHM durations and service life extension of welds on steel bridge deck

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ABSTRACT

Optimization of the duration of Structural Health Monitoring (SHM) campaigns is rarely performed. This article provides a utility-based solution to posteriorly determine: i) optimal monitoring durations and ii) the extension of the service life of the welds on a steel bridge deck. The approach is illustrated with a case study focusing on remaining fatigue life estimation of the welds on the orthotropic steel deck of the Great Belt Bridge, in Denmark. The identification of the optimal monitoring duration and the decision about extending the service life of the welds are modelled by maximizing the expected benefits and minimizing the structural risks. The results are a parametric analysis, mainly on the effect of the target probability, benefit, cost of failure, cost of rehabilitation, cost of monitoring and discount rate on the posterior utilities of monitoring strategies and the choice of service life considering the risk variability and the costs and benefits models. The results show that the decision on short-term monitoring, i.e., 1 week every six months, is overall the most valued SHM strategy. In addition, it is found that the target probability is the most sensitive parameter affecting the optimal SHM durations and service life extension of the welds.

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1. Introduction

Many studies on Structural Health Monitoring (SHM) have been made available in recent decades (e.g., Balageas, Fritzen, & Güemes, 2010; Farrar & Worden, 2007; Sohn et al., 2003). These studies focus mainly on data acquisition, normalization, cleaning, feature extraction and information condensation (Farrar et al., 2003; Farrar & Worden, 2012; Sohn et al., 2003). In the past decade, one of the main research topics in SHM was using monitoring for the management of structures (Okasha & Frangopol, 2012; Orcesi & Frangopol, 2011; Pozzi, Zonta, Wang, & Chen, 2010). Among these works, Vanik et al. presented a Bayesian probabilistic approach to SHM (Vanik, Beck, & Au, 2000). Wenzel et al. related the life cycle management for civil structures to SHM (Wenzel, Veit-Egerer, Widmann, & To, 2011). Flynn and Todd (2010) developed an approach for optimising sensor placement of a SHM system.

Herein, the optimal SHM system is the one leading to the lowest Bayes risk (expected loss) in the context of the operational modelling of the SHM (Flynn & Todd, 2010; Todd, Haynes, & Flynn, 2011). In continuation of research progress, it has been gradually acknowledged that without a decision analytical framework including the structural system performance, the SHM information cannot be optimally utilized for the structural integrity management. Pozzi & Der Kiureghian, Faber & Thöns, and Straub proposed and worked on utilizing Value of Information (VoI) theory to quantify the SHM performance (Faber & Thöns, 2013; Pozzi, Der Kiureghian, & Kundu, 2011; Straub, 2014). Based on this approach, the ideal SHM strategy is the one found with highest VoI (expected utility gain) identified with a decision analysis.

The quantified value of SHM information has been utilized to assess the impact of the SHM on decision-making (Zonta, Glisic, & Adriaenssens, 2014) to optimise the structural integrity management (Qin, Thöns, & Faber, 2015) to evaluate a road viaduct fatigue safety (Bayane, Long, Thöns, & Brühwiler, 2019) and to optimize the sensor configuration for damage detection systems (Long, Döhler, & Thöns, 2020; Long, Thöns, & Döhler, 2018). Moreover, in the framework of European project of COST Action TU1402 (Diamantidis, Sykora, & Sousa, 2019; Sousa, Wenzel, & Thöns, 2019; Thöns, 2019): "Quantifying the Value of Structural Health Monitoring" (https://www.cost-tu1402.eu/) detailed guidelines have been developed for operators, engineers and scientists on quantifying the value of Structural Health Information (SHI) for Decision Support.

However, in the field of SHM supported structural integrity management, there are still open questions. One of the issues is permanent versus short-term/periodic monitoring (del Grosso, 2013). Permanent monitoring is relatively expensive and may produce a very large amount of data

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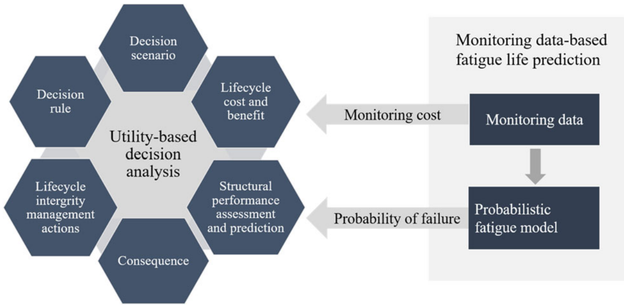

Figure 1. Road map of the proposed methodology.

requiring complex data transmission and management resources. Periodic monitoring is performed with temporary SHM installations on structures collecting data for a short time in defined intervals facilitating instrumentation use for multiple structures. Moreover, portable units may be deployed to maximize the spatial coverage of structures.

The focus of the article aims thus to provide new insights to strengthen the understanding of permanent versus periodic monitoring in the case of long-term deterioration assessment (fatigue) and to explore novel methodologies to rationalize the use of monitoring (permanent versus periodic) through utility-based decision analysis. For this, a methodology is illustrated with strain and temperature data used to assess a long-term deterioration mechanism as fatigue. Although the monitoring system was permanently installed, one could think of scenarios where sensors have been installed but not the acquisition units via Unmanned Aerial Vehicles. This would allow for monitoring a number of structures by having a limited number of data acquisition units (expensive equipment). For other mechanisms (e.g., to assess movement of bearings or articulations), one could reason similarly: use short-term monitoring strategies and then move the equipment to other structures.

This article posteriorly compares the SHM strategies in regard to monitoring durations based on a reference continuous monitoring dataset through utility-based decision analysis. The utility-based decision analysis is the basis of VoI analysis, in which the VoI is defined as the expected utility gain between (pre)-posterior decision analysis and prior decision analysis (Raiffa & Schlaifer, 1961). In this paper, a utility-based posterior decision analysis is implemented based on the obtained monitoring information to optimize SHM strategies posteriorly in terms of monitoring durations, in the case that the prior information of the structure is not available. With this study, it is envisaged to provide:

1. a methodology to extend the fatigue service life of the welds based on periodic monitoring,
2. a quantification on the duration of those periodic monitoring, and
3. a comprehensive understanding of the main parameters influencing the optimal decisions on the monitoring strategies.

The article starts by introducing the methodology employed for selecting optimal monitoring strategies and deciding to extend the service lives of welded joints. This includes utility theory and posterior decision analysis as well as specific data-driven probabilistic models employed to estimate remaining fatigue lives building upon the previous article by the authors (Long, Alcover, & Thöns, 2019). The proposed theoretical approach is then illustrated with a case study from the Great Belt Bridge. The monitoring data has been split between four options to simulate the case of periodic monitoring for the purpose of the article. The posterior expected utilities of different monitoring strategies are quantified and the optimal monitoring strategy and decision on service life extension of the instrumented welds are determined.

2. Methodology

The methodology section introduces the principles of both utility-based decision analysis and monitoring data-based fatigue life predictions, which is shown in Figure 1. The utility-based decision analysis solves the lifecycle integrity management problems considering structural performance assessment and prediction, consequences and lifecycle cost and benefit, with establishment of the decision scenarios and decision rules. The monitoring data-based fatigue life prediction provides input information for the utility-based decision analysis, such as monitoring costs and probability of fatigue failure based on a probabilistic fatigue model.

2.1. Utility-based decision analysis

The utility theory dates back to 1738 when Bernoulli defined that the value of an object must not be determined on the basis of the price or cost, but instead on the utility it yields (Bernoulli, 1738). Inspired by Bernoulli's hypothesis, Von Neumann et al. used it as a foundation to build their game theory in 1944, which is applicable to various contexts (Von Neumann, Morgenstern, & Kuhn, 2007). Furthermore, in 1961 Raiffa and Schlaifer formulated the decision theory (Raiffa & Schlaifer, 1961). This is now applied to the field of SHM and used for quantifying the value of monitoring information.

The decision process can be illustrated in a decision tree, as shown in Figure 2. According to Raiffa and Schlaifer, a utility (monetary) function $u(e, z, a, \theta)$ is assigned to a decision maker to describe the decision consequences when performing an experiment e, e.g., a SHM strategy according to (Faber & Thöns, 2013; Pozzi & Der Kiureghian, 2011); observing a particular outcome z, e.g., detecting damage or not; taking a particular action a, e.g., repair, replace or do-nothing; and then obtaining a particular state of a structure θ, e.g., safe, damaged or failed. The utility function should contain the total cost and benefits throughout the decision process. The total cost will be the sum of the costs of consequences (failure costs considering fatalities, economic, environmental and social impacts); the cost of actions (e.g., repair cost); and the cost of monitoring (strain gauges investment, installation, operation and replacement costs, etc.). The benefits are related to the socio-economic effects for the state and company e.g., from toll charges and for the users, e.g., time saving and for the environment, e.g., from reduction of CO_2 emissions.

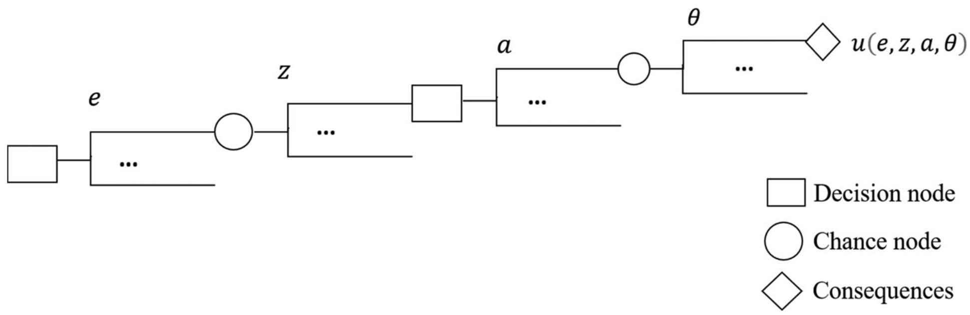

Figure 2. Illustration of a decision tree.

However, the state of the structure is subjected to uncertainties. Therefore, a probability $P(e,z,a,\theta)$ needs to be assigned to represent the belief of knowledge of the decision maker regarding the state of the structure θ after implementing a strategy e, obtaining the outcome z and taking an action a. There may be m states in total for the structure, e.g., damaged, undamaged, slightly damaged or failed, etc. So that the expected utility $U(e,z,a,\theta)$ can be written as:

$$U(e,z,a,\theta) = \sum_{j=1}^{m} u\left(e,z,\mathrm{a},\theta_j\right) \cdot P\left(e,z,\mathrm{a},\theta_j\right) \tag{1}$$

Depending on how much information is available at the time of decision making, the probabilities of the system states $P(e,z,a,\theta)$ can be differentiated as prior probability when only the design information of the structure is known, posterior probability when additional SHM information is obtained and pre-posterior probability when SHM information is modelled and predicted but not yet implemented. The expected utility $U(e,z,a,\theta)$ will be termed accordingly as prior utility, posterior utility and pre-posterior utility (Faber, 2012).

When considering SHM, inspection and repair planning within the lifecycle integrity management, the expected utility during service life U_{SL} can be formulated as:

$$U_{SL} = U_B - U_F - U_R - U_I - U_M \tag{2}$$

where:

$$U_B = \sum_{t=1}^{T_{SL}} B(t) \cdot (1 - P(F_t)) \cdot \frac{1}{(1+\gamma)^t}$$

$$U_F = \sum_{t=1}^{T_{SL}} C_F(t) \cdot \Delta P(F_t) \cdot \frac{1}{(1+\gamma)^t}$$

$$U_R = \sum_{i=1}^{N_R} C_R(T_i) \cdot P(R_{T_i}) \cdot (1 - P(F_{T_i})) \cdot \frac{1}{(1+\gamma)^{T_i}}$$

$$U_I = \sum_{j=1}^{N_I} C_I\left(T_j\right) \cdot \left(1 - P\left(F_{T_j}\right)\right) \cdot \frac{1}{(1+\gamma)^{T_j}}$$

$$U_M = \sum_{m=1}^{N_M} C_M(T_m) \cdot (1 - P(F_{T_m})) \cdot \frac{1}{(1+\gamma)^{T_m}}$$

where, U_B is the expected total lifecylce benifits, U_F is the expected total cost of failure during service life, U_R is the expected total lifecycle repair costs, U_I is the expected total inspection costs during service life, U_M is the expected total monitoring costs. In addition, $B(t)$ is the annual benefit at year t, $C_{\mathrm{F}}(t)$ is the cost of failure at year $t, C_R(T_i)$ is the cost of repair at repair year T_i, C_I (T_j) is the cost of inspection at inspection year T_j, C_M (T_m) is the cost of monitoring at monitoring year T_m, N_R is the total number of repair, N_I is the total number of inspection, N_M is the total number of monitoring; $P(F_t)$ is the probability of failure at year t; $\Delta P(F_t)$ is the annual probability of failure at year t. $P(R_{T_i})$ is the probability of repair at repair year T_i; T_{SL} is the service life; γ is the discounting rate. It is noted that a decision rule will normally be introduced to simplify the decision process, e.g. an action is required if the reliability reaches a specified target probability P_{Target}.

The integrity management of a structure usually involves multiple choices of actions and SHM strategies. The optimal choice of action and SHM strategies is found through maximizing the expected utilities of different actions and SHM strategies during service life. The optimal action and strategy will result in the highest expected utility. In order to systematically analyse the expected utility influencing parameters beyond the probabilistic engineering models, the target probability P_{Target}, benefit B, failure cost C_F, inspection costs C_I, repair cost C_R, monitoring cost C_M and discount rate γ will be parametrically analysed in the frame of a posterior decision analysis in Section 4. The posterior probability of failure will be calculated using probabilistic data-based models described in Section 2.2.

2.2. Monitoring data-based fatigue life prediction

The monitoring data-based probabilistic model is built on three types of data as show in Table 1: pavement temperatures acquired from temperature sensors, vehicle traffic counts obtained from a toll system and strain data obtained from strain gauges. The following is a brief summary of the monitoring data-based probabilistic model as shown in Figure 3, for a detailed and comprehensive model description it can be referred to (Farreras-Alcover, Chryssanthopoulos, & Andersen, 2017) .

Fluctuations of the average of the pavement temperatures $\overline{T}_t$ are modelled by a generic sinusoidal function with parameters α_1, α_2, α_3 and m_T:

$$\overline{T}_t = \alpha_1 \cdot \sin\ (\alpha_2 \cdot t + \alpha_3)\ + m_T \tag{3}$$

Daily-averaged pavement temperatures $T_{\Delta t}$ is de-seasonalized by deducting the daily mean value $\overline{T}_t$ and then differentiated by the monthly standard deviation $\sigma_{T,t}$ of the time series:

Table 1. Summary of the monitoring data from the monitoring system.

Monitoring system	Monitoring data
Temperature sensor	Pavement temperature
Toll system	Vehicle traffic counts
Strain gauges	Strain data

$$T_t^* = \frac{T_{\Delta t} - \overline{T}_t}{\sigma_{T,t}} \tag{4}$$

The de-seasonalized daily-averaged pavement temperature T_t^* is further fitted to an autoregressive (AR) model, where $\varphi_{T,1}$ is the coefficient of AR model and $\epsilon_{T,t}$ is a random normal error parameter at time t:

$$T_t^* = \varphi_{T,1} \cdot \overline{T}_{\mathrm{T},t-1} + \epsilon_{T,t} \tag{5}$$

Similarly, the heavy daily-aggregated traffic count $B_{\Delta t}$ is firstly de-seasonalized to $B_{\Delta t}^*$ by subtracting the daily average $\mu_{B,t}$ and divided by the weekly standard deviation $\sigma_{B,t}$ of the time series:

$$B_{\Delta t}^*(t) = \frac{B_{\Delta t} - \mu_{B,t}}{\sigma_{B,t}} \tag{6}$$

A regression model is applied to identify the day-of-the-week effect on the de-seasonalized time series $B_{\Delta t}^*$ with the parameters λ_i (ith regression coefficient), $X_{i,t}$ (ith dummy descriptive variable) and $\epsilon_{B,t}$ (random error process parameter at time t):

$$B_{\Delta t}^*(t) = \sum \lambda_i \cdot X_{i,t} + \epsilon_{B,t} \tag{7}$$

The traffic regression model's residuals are modelled by an AR model where $\epsilon_{B,t}$ is the regression error at time t, $\varphi_{B,i}$ is the parameter of the AR model, p is the order of the AR model and υ_t is a normal random error parameter:

$$\epsilon_{B,t} = \sum_{i=1}^{p} \varphi_{B,i} \cdot \epsilon_{B,t-1} + \upsilon_t \tag{8}$$

The daily-aggregated fatigue loading at a given welded joint, $D_{\Delta t}$, is conservatively calculated from Equation (9), where $\Delta\sigma_i$ is the stress range out of the total amount of stress cycles N_C within the time step Δt (1 day) and m is the SN endurance curve slope:

$$D_{\Delta t}(t) = \sum_{i=1}^{N_C} \Delta\sigma_i^m \tag{9}$$

In orthotropic steel decks, the key causes of fatigue damage are pavement temperatures and heavy traffic intensities. Hence, a regression model among daily-averaged pavement temperatures $T_{\Delta t}$, daily-aggregated heavy traffic counts $B_{\Delta t}$ and daily-aggregated SN fatigue loading $D_{\Delta t}$ is introduced by (Alcover, 2014). The left term in Equation (10) can be regarded as normalized fatigue loading per heavy vehicle when considering SN curve with fatigue parameter $m = 3$, which is for simplification conservatively considered as single-slopped with no cut-off limit:

$$\frac{D_{\Delta t}}{B_{\Delta t}}(T_0) = \theta_w \cdot T_0 \pm t_{n-p-1} \cdot s_{tot} \tag{10}$$

where $T_0 = \left[1 \; T_0^1 \; \ldots \; T_0^p\right]^T$ is a specified temperature of the pavement for which the forecast band is computed, θ are the parameters of the regression model, n the number of data points corresponding to the training dataset associated used to approximate the regression parameters, p the order of the regression model, t_{n-p-1} a t-distribution with $n-p-1$ degrees of freedom and s_{tot} the estimate of the overall regression model variance at a given $T_{\Delta t}(t)$.

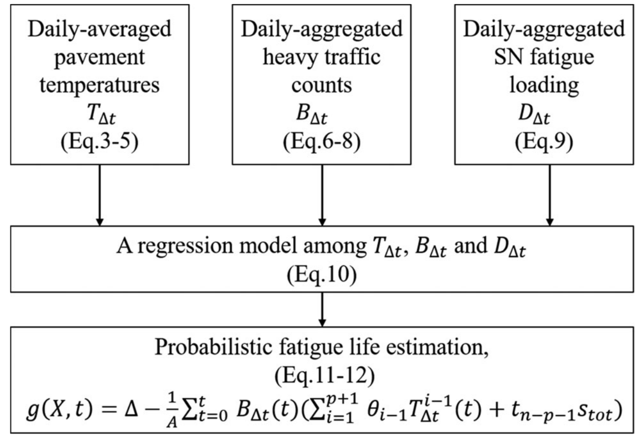

Figure 3. Flow chart of monitoring data-based probabilistic model.

The fatigue limit state function can be described on the basis of the SN curves to measure fatigue damage and with Miner's accumulation law:

$$g(X,t) = \Delta - \frac{1}{A} \cdot \sum_{t=1}^{t} D_{\Delta t}(t) \tag{11}$$

where X is the random variables vector, Δ is Miner's sum at failure (Miners Rule is one of the most used cumulative damage equations for failures caused by fatigue. When the sum of damage fractions is greater than 1.0, it will lead to failure), A is the material parameter defining the SN fatigue curve. Considering the above succession of regression and time-series models considering daily-averaged pavement temperatures and daily-aggregated heavy traffic, the limit state function of fatigue is:

$$g(X,t) = \Delta - \frac{1}{A}\sum_{t=0}^{t} B_{\Delta t}(t)\left(\sum_{i=1}^{p+1} \theta_{i-1} T_{\Delta t}^{i-1}(t) + t_{n-p-1}s_{tot}\right) \tag{12}$$

The sensor measurement error could be further included in the probabilistic model define in Equation (12). However, the measurement error has been found to be insignificant due to the quality of the installed equipment and its calibration in comparison to the other uncertainties (e.g., fatigue damage parameter A, Miner's sum at failure, etc.).

The weld will fail when the accumulated fatigue damage is larger than Miner's sum at failure. So that the probability of failure $P(F_t)$ can be estimated via Monte Carlo Simulation method as follows:

$$P(F_t) = P(g(X,t) \le 0) \tag{13}$$

The uncertainties of the monitoring-based model are considered through modeling the SN fatigue parameter and Miner's sum at failure as random variables not linked with SHM data. The uncertainties of the SHM data are treated on the process of deriving three different models for fatigue

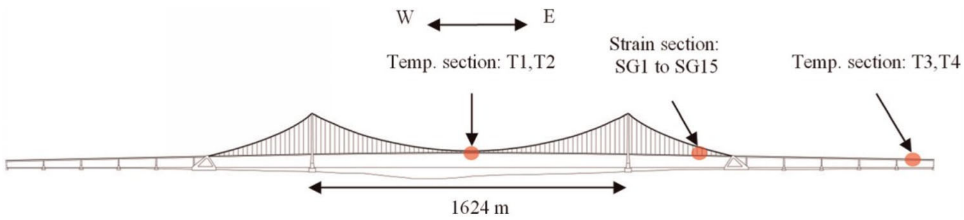

Figure 4. Illustration of Great Belt Bridge. (Temp. = Temperature, SG = Strain Gauge).

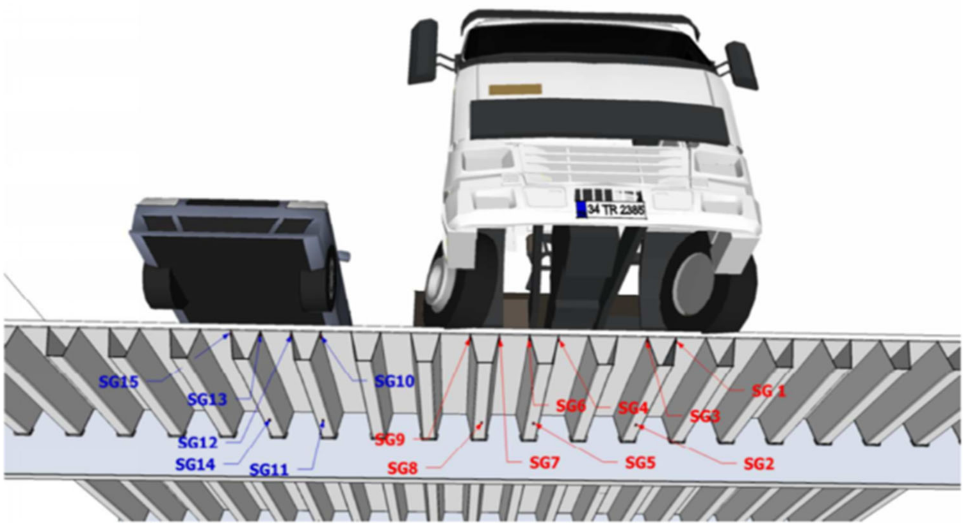

Figure 5. Illustration of strain monitoring system.

damage simulation: i) regression models for SN fatigue damage prediction (here the uncertainties are captured by the prediction bands of the models presenting described by $t_{n-p-1}s_{tot}$ in Equation (10), ii) time-series models for temperature prediction and iii) time-series models for traffic prediction. The uncertainties of the time-series models are captured by the random error process associated to each model and characterized via SHM data.

The pavement temperatures impact stress ranges on orthotropic steel decks and thereby influence fatigue life due to pavement-steel composite action. The model presented in Equation (10) predicts the fatigue damage at a given detail per unit of heavy vehicle and at a given pavement temperature. Then, Equation (12) uses independent models for predicting heavy traffic counts and pavement temperatures. These models are eventually used to calculate fatigue damages. The results presented in the article correspond to a case with no increase of average pavement temperatures nor traffic levels than the ones used to derive the different data-based models. The probabilistic model for data-based fatigue life prediction used in Equation (12) can consider different scenarios in terms of future average temperatures and traffic levels. This makes it possible to simulate unexpected events such as COVID-19 as they will have an impact on the daily number of heavy traffic vehicles used in the probabilistic model for fatigue prediction. In effect, vehicle counts and vehicle categories are monitored at the toll system of the bridge on an hourly basis; they have been used to characterize the traffic model $B_{\Delta t}$ in Equation (12). More details can be found in (Farreras-Alcover et al., 2017).

3. Case study

The above approach is illustrated with a case study from the Great Belt Bridge, which is a suspension bridge with main span of 1624 m and maximum hanger length of 177 m in Denmark as shown in Figure 4. The cross-section of the orthotropic steel bridge deck (OSD) is formed with a closed steel box girder. Longitudinal troughs and crossbeams are located about 4 m apart on the OSD. The fatigue of through to deck weld and trough splice weld is considered with designed fatigue life of 100 years with certain fixed inspection intervals. Its operation started in 1998.

3.1. sHM system

In 2007, after approximately 10 years of operation, a comprehensive SHM system for design verification and condition monitoring was installed. The SHM system on the Great Belt bridge consists of, among others, a pavement temperature monitoring system, traffic monitoring system (used by the toll system) and strain monitoring system (Figure 5). The location of the fatigue prone details to be assessed was determined prior to the writing of the article to perform a fatigue assessment task on the two critical details for the orthotropic steel deck under consideration: a trough-to-deck weld (detail category 50

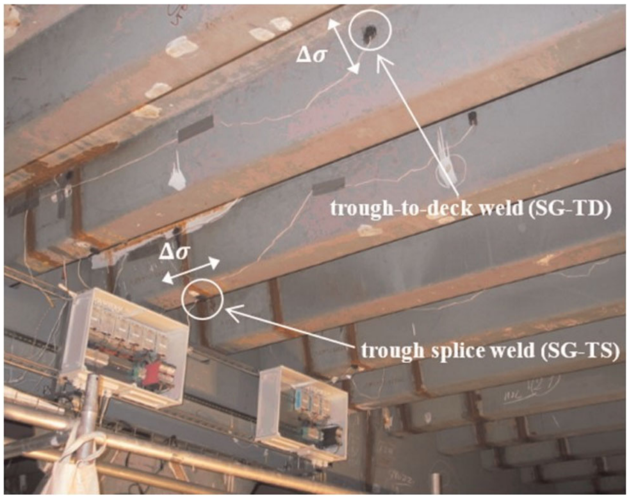

Figure 6. Strains gauges at welds (SG-TS = Strain Gauge Trough Splice, SG-TD: Strain Gauge Trough-to-deck).

according to EN1993-1-9-Part1-9) and a trough-splice weld (detail category 71 according to EN1993-1-9-Part1-9), as shown in Figure 6. Details on the fatigue prediction methodology can be found in (Farreras-Alcover, Andersen, & McFadyen, 2016).

A cross-sectional strain monitoring system instrumented consists of 15 uniaxial strain gauges (Figure 5), of which 10 gauges (i.e. 1,3,4,6,7,9,10,12,13,15) monitor the transverse nominal strains at the trough to deck weld, and 5 gauges (i.e. 2,5,8,11,14) monitor the longitudinal nominal strains at trough splice welds (Figure 6). Strain gauges 1 to 9 are positioned under the slow traffic lane, which is passed by the heavy vehicles, while the others are positioned under the fast traffic lane. Four temperature monitoring sensors are embedded into two different cross-sections of the pavement and record the temperature every 5 minutes. At the tollgate, the crossing vehicles are immediately recorded on an hourly basis according to their measurements.

3.2. SHM strategies

Farreras-Alcover et al. concluded that the measurement from SG8 (measured the trough splice weld) were associated with the highest fatigue loading (Farreras-Alcover et al., 2016). This weld is under the slow traffic lane where heavy vehicles run inducing higher stress cycles than at the fast lane. For convenience of demonstration, the modelling of SHM strategies is based on the training data sets from SG8 between February 2012 to July 2012, which is assumed to capture the entire temperature spectrum within a normal year owing to the regular repeatability of the temperature spread on the pavement (Farreras-Alcover et al., 2016).

According to the different monitoring phases and the time duration, four different monitoring strategies in terms of time durations are discussed as presented in Table 2. The reference monitoring option e_0 represents continuous monitoring for 168 days, option e_1 to option e_4 represent periodical monitoring with two phases of separate monitoring and 7, 14, 28, 42 monitoring days per phase respectively. The time windows associated with 4 options are selected based

Table 2. SHM strategies.

SHM strategies	Total days	Data used: %
e_1	14	8.3
e_2	28	16.6
e_3	56	33.3
e_4	84	50
e_0	168	100
February March April May June July		

on i) data availability and ii) consideration of representative 'extreme' weather conditions, i.e. data from February to July. In general, temperature variations are lower during cold conditions; hence this effect is accounted for in the calculated reliability profiles.

3.3. Fatigue life prediction

The faituge life prediction is calculated following the probabilistic fatigue model from Section 2.2 and the variables in the probabilistic model are simulated following the model described in Table 3. The posterior probability of failure based on monitoring data $P(F_{t,e_i})$ for monitoring straetgy e_i is calculated with Equation (13) and is shown in Figure 7(a), which increases with time. For the purposes of this study, it is assumed that when reliability profiles reach a certain target probability, it is required to take a certain action. The target probability is set as 10^{-4} (reliability index $\beta = 3.7$) according to the Joint Committee on Structural Safety (JCSS, 2001) considering normal relative costs of safety measures and minor consequences of failure. The weld is assumed to get rehabilitation after reaching the target probability. The probability of repair at the repair year is equal to the target probability. After the rehabilitation, the welds are assumed to behave as new and the posterior failure probability is assumed to be the failure probability in the year zero. The total number of rehabilitations depends on how many times it will reach the target probability during the whole service life.

Let $P(F_{t,e_i}|R_{t_R})$ be the posterior probability of failure after the rehabilitation event R_{t_R} implemented at year t_R with SHM strategy e_i; t_R is the year in which the resulting posterior probability of failure $P(F_{t,e_i})$ dependent on monitoring data from strategy e_i is equivalent to the target probability P_{Target}. The posterior probability of failure after rehabilitation $P(F_{t,e_i}|R_{t_R})$ is calculated by:

$$P(F_{t,e_i}|R_{t_R}) = \begin{cases} P(F_{t,e_i}), & t < t_R = arg(P(F_{t_R,e_i}) = P_{Target}) \\ P(F_{(t-t_R),e_i}), & t \geq t_R = arg(P(F_{t_R,e_i}) = P_{Target}) \end{cases} \tag{14}$$

The posterior probability of failure after rehabilitation $P(F_{t,e_i}|R_{t_R})$ given reference SHM data is shown in Figure 7(b). It is worth noting that the fatigue reliability profiles are rather conservative considering single-slopped SN curves with no cut-off limit. The probabilistic models for the SN resistance are given in Table 3 for the two details considered. A slope of

Table 3. Variables of the probabilistic model.

		Distribution/Expression			
Parameter	Symbol	Function	Mean	Standard deviation	Reference
Trough-to-deck weld fatigue parameter	A	Lognormal	7.30E11	4.23E11	(Eurocode, 2005), (Jcss, 2001)
Trough-splice weld fatigue parameter	A	Lognormal	2.09E12	1.21E12	(Eurocode, 2005), (Jcss, 2001)
Miner's damage at failure	Δ	Lognormal	1.0	0.3	(Wirsching, 1995)
Daily heavy traffic counts	$B_{\Delta t}(t)$		Equations (6) – (8)		
Daily averaged pavement temperatures	$T_{\Delta t}(t)$		Equations (3) – (5)		

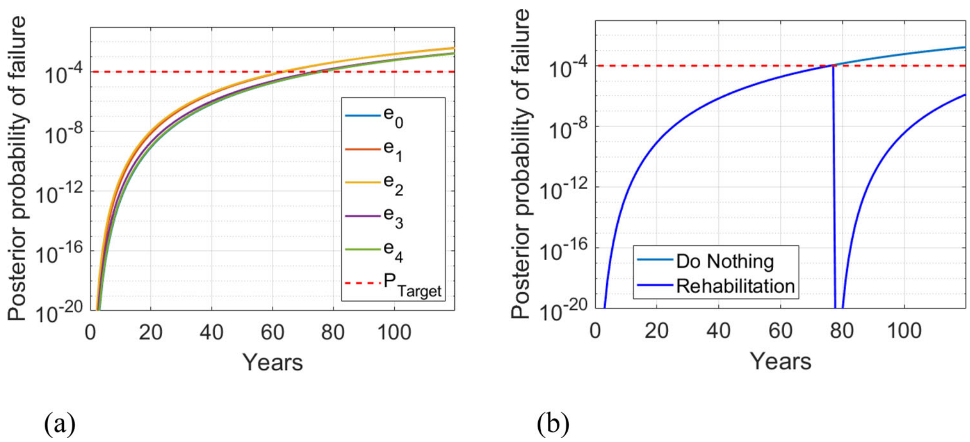

Figure 7. Prediction of probability of fatigue failure: (a) during service life of 120 years and with target probability (b) if doing nothing or rehabilitation given reference SHM data.

m = 3 is considered for the SN curve in log-scale (number of cycles to failure versus stress range). The above assumptions highlight that the results presented in the article shall be read as an illustration of the presented methodology for assessing optimal monitoring strategies, and not as representative of the actual fatigue life of the instrumented details.

3.4. Decision scenario

As mentionend before the welds are designed with a fatigue life of 100 years. After obtaining the predictions for fatigue life based on monitoring data, for the purpose of the investigation presented in this article, it aims to explore whether to extend the service life of the welds to 120 years. Given that different monitoring strategies provide different predictions of fatigue reliability profiles, it aims to figure out which monitoring strategy can achieve maximum utilities/benefits for the lifecycle integrity management to rationalize the use of SHM techniques for fatigue assessment.

A utility-based decision analysis is introduced in section 2.1 to solve the problem. The decision process is visualised in Figure 8 with a decision tree where a_i denoting the option of the actions, e.g., a_0 corresponding to a service life of 100 years and a_1 to an extended service life of 120 years. For different choices of the service life, the integrity of the welds needs to be managed, which involves planned rehabilitation costs C_R. The states of the welds θ_i are defined as safe state θ_1 and failure state θ_2, which is effectively characterized by the fatigue reliability profiles. Welds will fail when the accumulated fatigue damage is larger than Miner's damage at failure. If the weld stays safe, the bridge will be operated normally with annual benefits B. If the weld fails, unscheduled rehabilitation events will be required, so that there will be a fatigue failure cost C_F which will be the unscheduled rehabilitation cost. e_i represents the different monitoring strategies from Section 3.2. Given the different monitoring phases and monitoring durations, there will be different costs of monitoring C_M.

3.5. Utility calculation

U_{e_i} is to denote the expected maximum utilities regarding various actions with SHM strategy information e_i:

$$U_{e_i} = \max[U_{e_i,a_0}, U_{e_i,a_1}] \tag{15}$$

in which, U_{e_i,a_0} is the expected utility when the service life T_{SL} is kept at 100 years (a_0) with monitoring option e_i, U_{e_i,a_1} is the expected utility when the service life T_{SL} is extended to 120 years (a_1) with monitoring option e_i.

Let a_j represent a_0 and a_1 ($j = 0, 1$), then the expected utility U_{e_i,a_j} of the SHM strategy information e_i for taking action a_j is calculated by:

$$\begin{aligned} U_{e_i,a_j} = & \sum_{t=1}^{T_{SL,a_j}} \left(1 - P\left(F_{t,e_i} | R_{t_R}\right)\right) \cdot B \cdot \frac{1}{(1+\gamma)^t} \\ & - \sum_{t=1}^{T_{SL,a_j}} \Delta P\left(F_{t,e_i} | R_{t_R}\right) \cdot C_F \cdot \frac{1}{(1+\gamma)^t} \\ & - \sum_{n=1}^{N_{m,e_i}} C_M \cdot \left(1 - P\left(F_{t_m,e_i} | R_{t_R}\right)\right) \cdot \frac{1}{(1+\gamma)^{t_m}} \\ & - \sum_{n=1}^{N_{R,a_j}} C_R \cdot \left(1 - P\left(F_{t_R,e_i} | R_{t_R}\right)\right) \cdot \frac{1}{(1+\gamma)^{t_R}} \end{aligned} \tag{16}$$

It has to be noted that in Equation (16), there is either a_0 or a_1, but not both in the same time; B is the annual

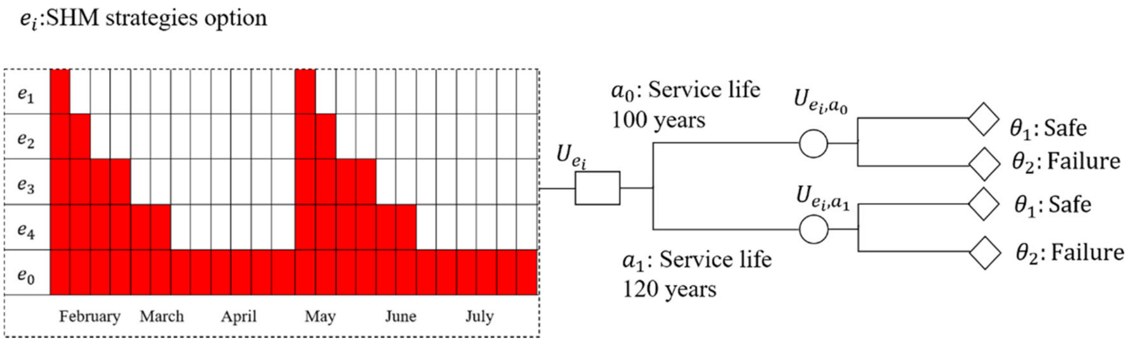

Figure 8. Decision tree of posterior decision analysis.

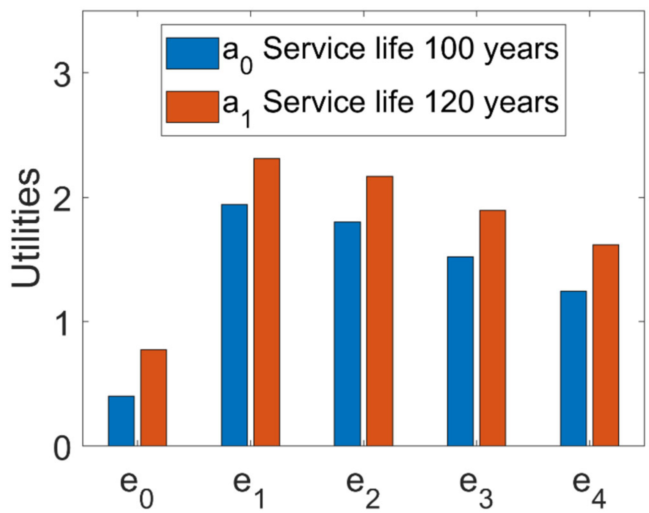

Figure 9. Identification on the most valuable SHM strategies during the bridge service life.

benefit, C_F is the failure cost and C_R is the planned rehabilitation cost (in relation to Equation (2), repair costs C_R and inspection costs C_I are taken together in the case study and presented as rehabilitation cost C_R) ; t_R is the year of rehabilitation; C_M is the cost of monitoring per day; N_{m,e_i} is the total monitoring days from strategy e_i; N_{R,a_j} is the total number of repair times with action a_j; t_m is the year of monitoring. γ is the discounting rate.

From the literature (Sund & Baelt, 2014), it is known that the Great Belt bridge and the connected tunnel, roads and railways together are called the Storebaelt link, which was built between 1988 and 1998, with the total construction costs amounting to EUR 3.56 billion in 1988 prices. The construction costs are financed through the state guarantee model and the loans are repaid by the users of the facilities. It is found that the Great Belt Company had loans guaranteed by the government and lent capital at an interest rate of 1.5-2% (Mouter, 2015). According to the report released by the Ministry of Transport and Sund & Baelt (2014), it is revealed that the Storebaelt link would bring a gain of EUR 50.87 billion over 50 years to Danish society, equivalent to EUR 1.21billion annually, while the construction and operation of the link over a 50 year period costs just EUR 18.66 billion.

Based on the information above, to illustrate the case study, it is assumed that half of the gain from the Storebaelt link comes from the Great Belt bridge, so that the normalized annual benefit B for the Great Belt bridge is 0.17 (0.5*1.21/3.56) per year, the normalized cost of rehabilitation C_R is 5 (18.66/3.56), the normalized cost of failure C_F is assumed to be 100, the the normalized cost of monitoring C_M is assumed to be 0.01 per day, the discounting rate γ is 0.02 (equavalent to interest rate) per year. It is noted that due to the confidentiality, the data shall be read as an illustration of the input paramenters of the presented methodology, and not as representative of the actual cost and benefits of the Great Belt bridge.

3.6. Results

The utility calculation follows Section 3.5 and the results are shown in Figure 9. The findings in Figure 9 indicate that for all SHM strategies it is recommended to extend service life to 120 years. The utilities in Figure 9 show that option e_1 will be recommended due to the highest utility. It is found that in the case study a long monitoring duration will reduce the risk but increase the cost of monitoring, which leads to an overall reduction in utility. The additional cost of longer monitoring is not justified here because the reduction of risk does not compensate for the increase of the cost. The optimal SHM strategy is thus short-term monitoring. However, the results may be sensitive to the variation of cost and benefit models, which is investigated in Section 4.

4. Parametric analysis

Further to the results presented in Figure 9, due to the uncertainties related to the input parameters, a parametric analysis of the utilities associated with different monitoring durations and and choices of actions is performed considering the variability of the model parameters: (a) target probability P_{Target}, (b) benefit B, (c) failure cost C_F, (d) reahbilitation cost C_R, (e) monitoring cost C_M and (f) discount rate γ.

4.1. Target probability P_{Target}

The target probability P_{Target} is the acceptable optimum failure probability which is known as an adaptive control parameter based on the degree of failure impact and the relative expense of protection measures (JCSS, 2001). It varies from 10^{-6} (large consequences of failure, small

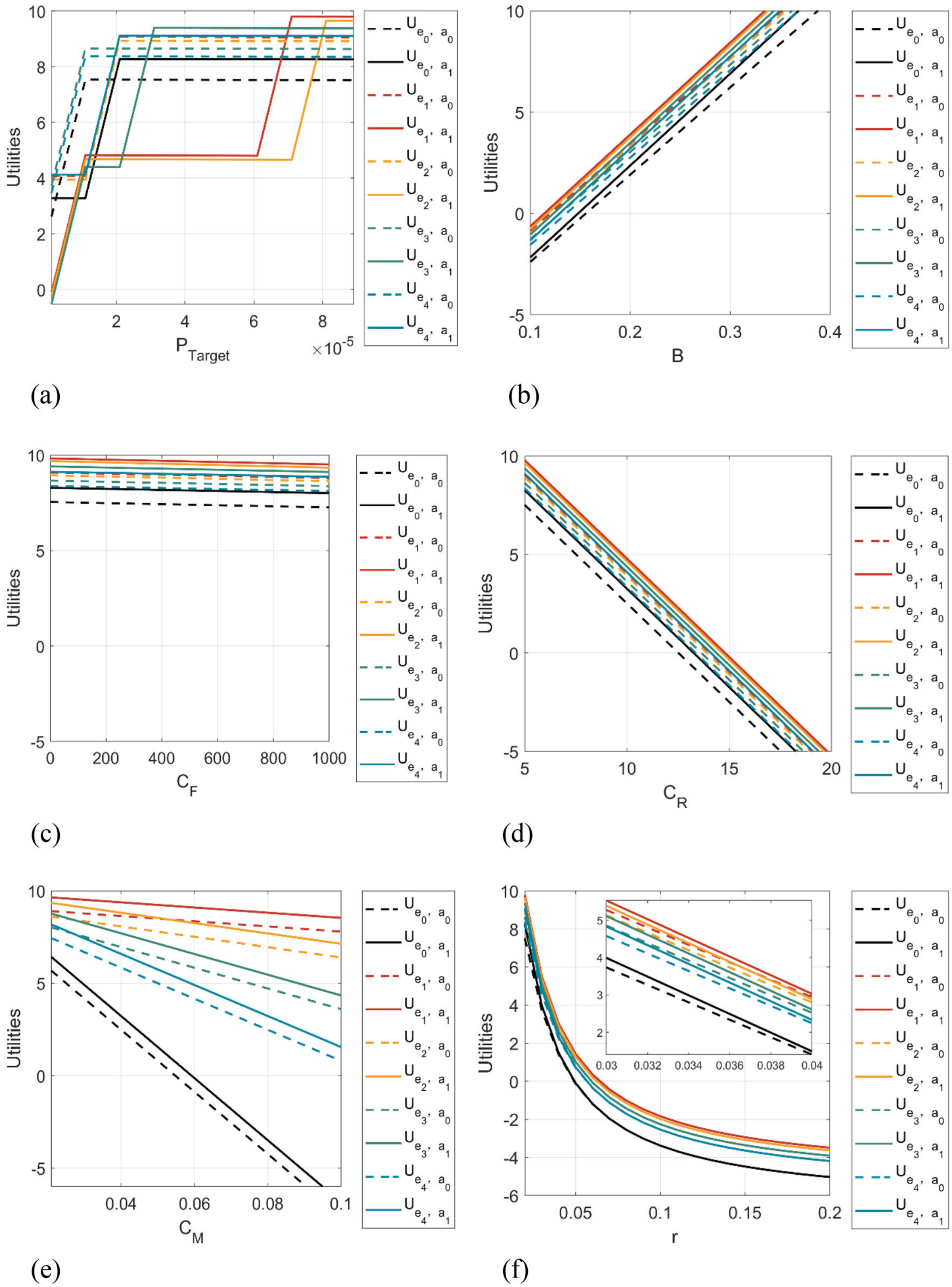

Figure 10. utilities associated with different monitoring durations and choices of actions considering the variability of the model parameters: (a) target probability P_{Target}, (b) benefit B, (c) failure cost C_F, (d) inspection and rehabilitation cost C_R, (e) monitoring cost C_M and (f) discount rate γ.

relative cost of safety meausres) to 10^{-3} (minor consequences of failure and large relative cost safety meaure) according to (JCSS, 2001). The target probability P_{Target} was previously chosen as 10^{-4} considering minor consequences of failure and a normal relative cost of safety measures. For assessing its effect, it is reduced from 10^{-4} to 10^{-5} and the outcomes are shown in Figure 10(a). Reducing the target probability means that decision-makers are more conservative with lower tolerance of risk leading to the welds being rehabilitated more often during service life.

Figure 10(a) presents the utilities with the abovementioned change. The uitilies are all increasing with the increase of the target probability. It increases linearly in some ranges but stays constant in other ranges. The utilities

Table 4. Summary of the most valued decisions about the SHM strategy to adopt, regarding the critical parameters.

Critical parameter	Most valued decision
Target probability, P_{Target}	For $P_{Target} < 2 \cdot 10^{-5}$, monitoring for 4 consecutive weeks every 6 months, given the service lifetime is kept to 100 years (e_3, a_0) For $2 \cdot 10^{-5} \leq P_{Target} < 3 \cdot 10^{-5}$, monitoring for 6 consecutive weeks every 6 months, given the service lifetime is extended to 120 years (e_4, a_1) For $3 \cdot 10^{-5} \leq P_{Target} < 7 \cdot 10^{-5}$, monitoring for 4 consecutive weeks every 6 months, given the service lifetime is extended to 120 years (e_3, a_1) For $P_{Target} \geq 7 \cdot 10^{-5}$, monitoring for 1 week every 6 months, given the service lifetime is extended to 120 years (e_1, a_1)
Benefit, B Cost of failure, C_F Cost of rehabilitation, C_R Cost of monitoring, C_M Discounting rate, γ	Monitoring for 1 week every 6 months, given the service lifetime is extended to 120 years (e_1, a_1)

curves of options e_1 and e_2 with action a_1 behave differently from the other curves. They start at the lowest value but end the highest values at the highest target probabilities. That's because options e_1 and e_2 provide higher probability of failure than others. Hence, when P_{Target} is high, options e_1 and e_2 will reach the target probability ealier, thus resulting in more times of rehabilitation when reaching 100 years (a_0). To compansate the increase of the rehabilitation costs, it will be suggested to continue operation to 120 years (a_1). Their flat plateau is however significantly lower than the plateaus of the other curves. The a_0 action is more consistent with longer constant flat plateau over almost all of the observed range. For a low value of P_{Target}, all options except e_1 and e_2 have very similar utility values.

There are certain thresholds for P_{Target} where sudden increases of the utilities occur. When $P_{Target} < 2 \cdot 10^{-5}$, option e_3 with action a_0 has the highest utility. When

$2 \cdot 10^{-5} \leq P_{Target} < 3 \cdot 10^{-5}$, utility with option e_4 and action a_1 is the highest. When

$3 \cdot 10^{-5} \leq P_{Target} < 7 \cdot 10^{-5}$, utility with option e_3 and action a_1 is the highest. When $P_{Target} < 2 \cdot 10^{-5}$, option e_1 with action a_1 will be recommended. A summary of most valued decisions with changed of P_{Target} can be found in Table 4. The summary of utilities in Figure 10(a) shows that the change of the target probability actively affect the decision of optimal SHM durations and service life extension of the welds. The tolerant- to- risk decision maker (high value of P_{Target}) will get more benefit with the change on the P_{Target}.

4.2. Benefit B

The annual benefit is subjective to change due to the growth of population, change of urban planning etc. Therefore, the annual benefit rate B is increased and the results are shown in Figure 10(b). It is found that e_1 has the highest utilities and the utilities associated with a_1 extending service life to 120 years are always higher than those with a_0. This is because of a higher profit-drive leading to a longer operation period. Figure 10(b) shows that the utilities increase linearly with the increase of benefit, but the difference between the slop of cures of the varied monitoring durations is very small.

4.3. Cost of failure C_F

When increasing the cost of failure C_F from 100 to 1000, the computation results in Figure 10(c) display the same trend as in Figure 9 leading to the extension to 120 years (a_1) with option e_1. The utilities are slightly decreasing with the increase of C_F. The choice of the service life extension and choice of monitoring duration are not influenced much by the change of cost of failure. It is because the difference between the utilities for 120 years and 100 years is the same. It is also due to the very small annual probability of failure, the accumulated risk of failure is comparably small as well.

4.4. Cost of rehabilitation C_R

The cost of rehabilitation may be subject to change due to the choice of rehabilitation methods. When increasing the cost of rehabilitation C_R from 5 to 50, the utilities in Figure 10(d) strongly decrease and become negative for both keeping the service life at 100 years a_0 and extending it to 120 years a_1. That is because the accumulated benefits and reduction of risk of failure cannot compensate the increase of cost of rehabilitations when the rehabilitation cost is too high. The variations between the maximum utilities of all the options in Figure 10(d) are very small. It can be interpreted that when the cost of rehabilitation is very high, it is no longer worthwhile to investigate the SHM strategies, which is not competitive, but the focus should be on finding solutions to reduce the cost of rehabilitations.

4.5. Cost of monitoring C_M

The cost of monitoring may differ based on the choice of monitoring techniques. When increasing the cost of monitoring C_M from 0.01 to 0.1 per day, Figure 10(e) shows that it is not beneficial to do monitoring with reference SHM option e_0 due to high monitoring costs. As expected, the utility decreases with increasing monitoring durations, but the decreasing gradient is different. The curve of option e_1 has the lowest gradient. Therefore, it is recommended to do monitoring with option e_1 and extend the service life to 120 years. A decision-maker could learn that the sparser and shorter the SHM campagins, the better is the payback of monitoring and lesser its sensitive to the SHM cost.

4.6. Discounting rate γ

The discount rate is also connected with the so-called social discount rate, which represents the value that society assigns to its existing situation compared to potential future states. It has significant variations in practice around the world (Zhuang, Liang, Lin, & De Guzman, 2007), with lower levels introduced by developed countries (3%-7%) than the developing countries (8-15%). The value of discount rate also changes with time depending on public policies, e.g., the Danish Ministry of Finance in May 2013 reduced its social consumption discount rate from 5% per year to 4% per year for the first 35 years for the investment of long-term projects, 3% for the years in the interval 36 to 69 years, and 2% for the rest of years (Finansministeriet, 2013).

The discounting rate γ is increased from 0.02 to 0.2 and the results in Figure 10(f) illustrate that the utilities are exponentially decreasing and option e_1 has the highest utilities. The utilities of keeping 100 years a_0 or extending to 120 years a_1 have almost the same value. When the discounting rate γ is larger than 0.05, the utilities become negative. That's because a higher discount rate means greater uncertainty and the cash flow in the future will have a lower value. Since money loses value fast with time, it is not beneficial to invest on long-term return projects. Thus it may be recommend not to invest in monitoring at all when the discounting rate γ is high. A decision-maker could learn that the longer is the implementation of the SHM strategy, the higher the importance of the economic situation of the country.

5. Conclusions

Many studies focus on SHM data gathering, processing and probabilistic model developing. Building upon these studies, this article contains methodology to utilize the obtained monitoring information for the determination of i) optimal monitoring durations and ii) service life extension of the welds on a steel bridge deck. Through a posterior utility-based decision analysis of the welds on an orthotropic steel bridge deck case study, it is shown that a short-term SHM strategy has a higher expected utility and is thereby preferred. In contrast, long-term monitoring duration reduces the risks but leads to an increase of the monitoring costs, which in turn leads to an overall reduction in the expected utility.

Through a parametric analysis, this article shows how the target probability P_{Target}, benefit B, failure cost C_F, rehabilitation cost C_R, monitoring cost C_M and discounting rate γ influence the expected value of the utility and thus the decisions:

- It is found that the target probability P_{Target} is the most sensitive parameter as the change of P_{Target} will directly change the number of rehabilitation times and the posterior probability of failure, thus change the total expected rehabilitation costs and the accumulated risk of failure, resulting in different choices of monitoring options and service life extension. However, P_{Target} may be subjected to optimization in conjunction witht the risk attitude of the decision makers. The tolerant- to-risk decision maker (high value of P_{Target}) will get more benefit with the change on the P_{Target}.
- An increase of annual benefit B will lead to service life extension. A higher profit-drive will lead to a longer operation period.
- SHM strategies become not competitive (i.e., not worthwhile) when the cost of rehabilitation is too high. The rehablitation methods should be chosen carefully as a high rehabilitation cost C_R results in negative utilities.
- An increase of monitoring cost C_M will result in a short-term monitoring option. The sparser and shorter the SHM durations, the better is the payback of monitoring and lesser its sensitive to the SHM cost.
- For the investment in monitoring, the discounting rate γ should be thoroughly considered, as a high discounting rate γ will lead to significantly declining utilities. In such a case, investing in long-term ventures is not advantageous and short-term returning investment is more beneficial. The longer is the implementation of the SHM strategy, the higher the importance of the economic situation of the country.

The presented research work considers solely the fatigue reliability and service life management of selected welds on an orthotropic steel bridge deck. Future research is needed to investigate the problem on a system level. Moreover, due to the methodology specificities, several assumptions on fatigue life prediction have been made and normalized cost and benefits models used. This highlights that the results presented in the article shall be read as an illustration of the presented methodology for assessing optimal monitoring strategies, and not necessarily as the actual fatigue life of the instrumented details and not as representative of the actual cost and benefits of the Great Belt bridge. Future research is envisaged to explore comprehensive probabilistic formulations of cost and benefit function and fatigue life prediction model considering not only a single slopped SN curve.

Notations list

$u(e,z,a,\theta)$	Utility function
e	The SHM strategy/experiment
z	The SHM /experiment outcome
a	Action
θ	System state
$P(e,z,a,\theta)$	Probability of the state of the structure θ after implementing a strategy e, obtaining the outcome z and taking an action a.
$U(e,z,a,\theta)$	Expected utility function
U_{SL}	Expected utility during service life
U_B	Expected benefit
U_F	Expected cost of failure
U_R	Expected cost of repair
U_I	Expected cost of inspection
U_M	Expected cost of monitoring
$B(t)$	The annual benefit at year t
$C_F(t)$	The cost of failure at year t
$C_R(T_i)$	The cost of repair at repair year T_i
$C_I\ (T_j)$	The cost of inspection at inspection year T_j

$C_M\ (T_m)$	The cost of monitoring at monitoring year T_m
T_i	The repair year
T_j	The inspection year
T_m	The monitoring year
N_R	The total number of repair
N_I	The total number of inspections
N_M	The total number of monitoring
$P(F_t)$	The probability of failure at year t.
$\Delta P(F_t)$	The annual probability of failure at year t
$P(R_{T_i})$	The probability of repair at repair year T_i
T_{SL}	The service life
γ	The discounting rate
P_{Target}	The target probability
$D_{\Delta t}$	S-N fatigue loading aggregated during a time interval Δt
$B_{\Delta t}$	Daily aggregated counts of daily vehicles
$T_{\Delta t}$	Daily averaged pavement temperature
s_{tot}	Estimator of the total variance of a regressing model
T_0	Given pavement temperature
n	Number of available datapoints
p	Order of a polynomial regression model
t_{n-p-1}	t-probability distribution with n-p-1 degrees of freedom
Δ	Miner's sum at failure
A	Material parameter defining the SN fatigue curve.

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CHAPTER 5. QUANTIFICATION OF THE VALUE OF SHM DATA FOR THE FATIGUE SAFETY EVALUATION OF A ROAD VIADUCT (PAPER 3)

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Scientific contribution of the PhD student:

Lijia Long

- proposed the idea of quantification of the conditional value of SHM data of a road viaduct.
- implemented the conditional value of sample information analysis.
- developed the prior and posterior damage model together with Imane Bayane.
- wrote the entire draft version of the paper with Imane Bayane and revised it according to co-authors' comments.

Scientific contribution of co-authors:

Imane Bayane

- provided the monitoring data of a road viaduct.
- performed fatigue safety evaluation of a road viaduct.
- developed the prior and posterior damage model together with Lijia Long.
- implemented the failure probability of the system simulation.
- wrote the entire draft version of the paper with Lijia Long and revised it according to co-authors' comments.

Sebastian Thönn

- assisted in defining the prior and posterior damage model.
- assisted in computing the failure probability of the system.
- carefully reviewed the manuscript and provided critical comments.

Eugen Brühwiler

- assisted in defining the problem of fatigue safety verification of existing bridges that uses ‘‘re-calculation’’ based on codes.
- carefully reviewed the manuscript and provided critical comments.

Quantification of the conditional value of SHM data for the fatigue safety evaluation of a road viaduct

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ABSTRACT:

Fatigue safety verification of existing bridges that uses ‘‘re-calculation’’ based on codes, usually results in insufficient fatigue safety, triggering invasive interventions. Instead of “re-calculation”, Structural Health Monitoring (SHM) should be used for the assessment of the existing bridges. Monitoring systems provide data that can reduce uncertainties associated with the fatigue loading process and the structural resistance. The objective of this paper is to quantify the value of the SHM system implemented in a 60-years-old road viaduct to investigate its fatigue safety, through modeling of the fundamental decisions of performing monitoring in conjunction with its expected utility. The quantification of the conditional value of information is based on the decision tree analysis that considers the structural reliability, various decision scenarios as well as the cost-benefit assessments. This leads to a quantitative decision basis for the owner about how much time and money can be saved while the viaduct fulfills its function reliably and respects the safety requirements. The originality of this paper stands in the application of the value of information theory to an existing viaduct considering the fatigue failure of the system based on the monitoring data and the cost-benefit of monitoring method.

INTRODUCTION

The fatigue assessment of existing bridges is important for sustainable use from both technical and economical point of view. To achieve this, bridge managers should understand existing bridges and use tools to take accountable decisions about their current and future fatigue safety. Bridge assessment based on re-calculations using design code provisions usually results in insufficient fatigue safety that requires strengthening or replacing the structure. This finding is often a problem on paper only and does not reflect the real performance of existing bridges. Subsequently, and in order to make the best decisions during the assessment, structural health monitoring (SHM) system is used, and the value of SHM data is quantified based on the decision tree that considers the structural reliability, various decision scenarios as well as the cost-benefit assessments. This methodology is illustrated with a case study, Crêt de l'Anneau Viaduct.

The structure is a 60-year-old composite concrete-steel road-viaduct (Figure 1) located in Switzerland, as part of a cantonal road leading from Switzerland to the French border. It has seven typical spans of 25.6m length and an approach span of 15.8m. The reinforced-concrete (RC) slab of variable thickness ranging from 17 to 24cm is fixed on two steel girders of 1.3m height. The girder is composed of a series of single span beams linked by hinges. The total length of the viaduct is 195m.

Because of a "re-calculation" based on design code provisions, the viaduct was suspected to present fatigue problems after 60 years of service. To take the best decision about doing nothing or replacing the structure, SHM system was implemented in the viaduct in June 2016 to investigate its effective fatigue behavior. For such a situation, a value of information analysis can be utilized to quantify the value of performing SHM and to derive the optimal decision about doing nothing or replacing the structure.

The Value of Information (VoI) theory has been developed by Raiffa and Schlaifer (1961) and is rooted in Bayesian updating and utility-based decision theory with a specific format to quantify the utility increase due to additional information. The utility increase of additional and already obtained information is termed as the Conditional Value of Sample Information (CSVI).

Monitoring system

A Structural Health Monitoring (SHM) system is implemented for one year to investigate the fatigue behavior of the viaduct. More details about the monitoring system can be found in (Bayane and Brühwiler 2018).Two techniques are used including strain gauges to measure the strain in steel reinforcement bars and thermocouples to measure the temperature of the concrete, the steel, and the air. Two slabs are instrumented, and for each slab, strain gauges are implemented in two transverse rebars and two longitudinal rebars at the mid-span, which is the most loaded part of the RC slab.

Figure 1: View of the Crêt de l'Anneau Viaduct

Monitoring data

The most critical part of the viaduct for fatigue is the RC slab since the recorded strains in the steel girder are smaller than the endurance limit. As such, the fatigue verification of the viaduct for the case study is focused on the RC slab in which the fatigue failure is determined by the failure of the steel rebars.

Stress cycles are calculated from the annual measured strain in the most loaded rebars. Temporal variation of stresses is first deduced from the recorded strain by a multiplication with the steel elastic modulus of 210GPa. The Rainflow counting method is then used to provide a set of stress cycles from stress variations. Table 1 presents the stress cycles $n_{i,1}$ over one year for each stress range i of the instrumented transverse rebar 1 at the mid-span, for the recorded stresses $\Delta\sigma_{i,1}$.

Table 1. Stress spectra

$\Delta\sigma_{i,1}$ [MPa]	$n_{i,1}$
5	67051
10	18180
15	6391
20	2744
25	1091
30	392
35	181
40	75
45	24
50	12
55	5
60	2
65	3
70	1
85	1

PROBABILISTIC MODEL FOR THE STRUCTURAL SYSTEM

The probability of fatigue failure of the viaduct is evaluated before the monitoring, using code provision criteria, which is given in the Swiss Standard, and after the monitoring, using the recorded data. Therefore, two probabilistic models are developed, the prior model corresponding to code provisions and the posterior model corresponding to monitoring data. The formulation of the fatigue limit state for the prior and posterior models will be based on the S-N curve approach.

Fatigue safety is verified according to two levels; the first level requires that the fatigue action effect is below the endurance limit. The second level is performed when the first level is not fulfilled. It requires the calculation of damage accumulation according to Miner's rule where the total fatigue damage must be less than 1.

To perform fatigue damage accumulation, the S-N curve parameters are taken from the Swiss standard SIA269. The straight reinforcement bars of the viaduct have a fatigue resistance $\Delta\sigma_{sd,fat}$ equal to 150 MPa, and an endurance limit $\Delta\sigma_{s,D}$ of 120 MPa. The slope m of the S-N curve is equal to 4 (SIA269).

Prior damage model

Based on the S-N curve, with Miner's accumulation rule, the fatigue limit of rebar j in the concrete can be expressed by $g_j(t)$ (Thöns, 2018):

$$g_j(t) = \Delta - D_{prior_j}(t) \tag{1}$$

$$D_{prior_j}(t) = n_D t \frac{E[\Delta\sigma_D{}^m]}{K} \tag{2}$$

$$E[\Delta\sigma_D{}^m] = (M_L M_\sigma M_D M_K k)^m \Gamma(1 + \frac{m}{\lambda}) \tag{3}$$

Γ is the gamma function, $\Delta\sigma_D$ is the design value of stresses that has a Weibull distribution (Thöns et al. (2015)) with the parameters λ and k, which are the scale and the location parameters. K is the material parameter from the S-N curve, m is the slope value, n_D is the annual cycle. M_L is the model uncertainty of traffic load. M_σ is the model uncertainty of stress ranges. M_D is the model uncertainty of accumulated damage. M_K is the model uncertainty of S-N curve. The parameters λ and k of the stress distribution are adjusted to reach both the mean value of $\Delta\sigma_D$ which is equal to $E(\Delta\sigma_D)$ and an accumulated fatigue damage of 1.0 after the service life t_{SL}, i.e.120 years.

$$\lambda * \left(\Gamma\left(1 + \frac{1}{k}\right)\right) = E(\Delta\sigma_D) \tag{4}$$

$$\frac{n_D t_{SL}\, (M_L M_\sigma M_D M_K k)^m \Gamma\left(1+\frac{m}{\lambda}\right)}{K} = 1 \tag{5}$$

Table 2 includes the random variables, their distributions and their parameters used to perform the prior study. Monte Carlo simulation is used to find the cumulative probability of component failure throughout the service duration.

Table 2. Probabilistic model for the random variables, prior study

Var.	Des.	Dist.	Mean	Std.	Ref.
$\Delta\sigma_D$	*Design value of stresses [MPa]*	*WB*	*200*	-	*FEM SIA 261*
Δ	*Miner's sum at failure*	*LN*	*1.0*	*0.3*	*JCSS*
n_D	*Annual cycles [/year]*	*Det.*	*7.10⁵*	-	*SIA 261*
m	*Slope value*	*Det.*	*4*	-	*SIA 269*
K	*Material parameter from SN curve [MPa]*	*LN*	*10¹⁵*	*0.58*	*SIA 269 & JCSS*
k	*Location parameter*	*Det.*	*Cali.*	-	*Eq. 4,5*
λ	*Scale parameter*	*Det.*	*Cali.*	-	*Eq. 4,5*
M_L	*Uncertainties related to traffic load calculation*	*LN*	*0.68*	*0.102*	*Folsø et.al. (2002)*
M_σ	*Uncertainties related to stress calculation*	*LN*	*1.00*	*0.05*	*Folsø et.al. (2002)*
M_D	*Uncertainties related to accumulated damage*	*LN*	*1.00*	*0.05*	*JCSS, for rebar*
M_K	*Uncertainties related to S-N curve*	*LN*	*1.00*	*0.05*	*Assumed*

The annual cycles of heavy trucks for principal roads is equal to 350'000 cycles per direction. This value was taken from the European traffic and was reduced by 30% to consider the volume of traffic in Switzerland (SIA261).

The recalculation value of stresses $\Delta\sigma_D$ was obtained using the load model 1 presented in the Swiss Standards (SIA261). The load model was applied to a 3D Finite Element Model (FEM) of the viaduct, considering the initial properties of materials and boundary conditions. The maximum stress at the mid transverse span of the slab was calculated and multiplied by a load factor of 1.50 to determine the re-calculation value of stress of 200 MPa (SIA261).

The prior fatigue damage of the instrumented rebar was calculated according to Eq. 1-5. A normal distribution $f_{D_{prior}}$ was fitted to the prior damage, and the corresponding mean and standard deviation were identified. The prior damage distribution is plotted in Figure 3.

Posterior damage model

Monitoring data provides the stress range and the corresponding cycles. The fatigue safety is then evaluated according to the level one of verification. Since the highest recorded stress range of 85 MPa is significantly smaller than the endurance limit (120MPa), the level one of fatigue verification is fulfilled as illustrated in Figure 2. Therefore, to perform a Miner's damage calculation, an arbitrarily chosen amplification factor of 4 is applied such that the stress ranges exceed the endurance limit and the fatigue damage can be calculated.

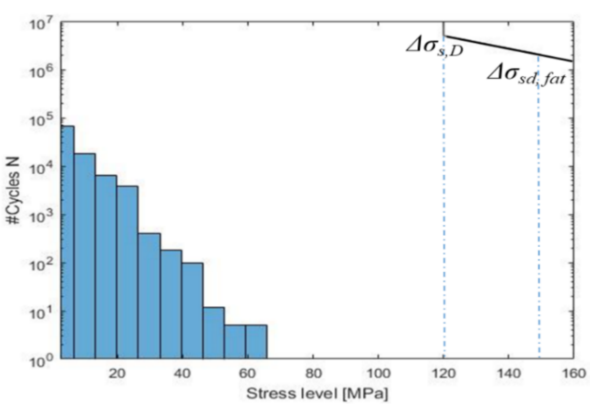

Figure 2. Annual stress ranges and cycles of the most loaded rebar

A likelihood damage model is developed based on the recommendations of JCSS (2006). Like for the prior study the model uses the S-N approach that can be expressed in the form of:

$$N\Delta\sigma^m = k \tag{6}$$

where N is the number of stress cycles to failure at a constant amplitude stress range $\Delta\sigma$, and k and m are material parameters.

In order to deal with variable amplitude loading in the S-N approach, fatigue damage is quantified in terms of Miner's damage summation. According to this rule, all stress cycles cause proportional fatigue damage, which is linearly additive. The scatter in the stress history may be neglected, and the damage D_{like_j} of the rebar j is equal to:

$$D_{like_j} = \sum_i \frac{n_{i,j}}{N_{i,j}} \tag{7}$$

where $N_{i,j}$ is the number of stress cycles to failure at a constant amplitude stress range $\Delta\sigma_{i,j}$
and $n_{i,j}$ is the number of actual stress cycles for the stress range $\Delta\sigma_{i,j}$
with $\quad logN_{i,j} = logk - mlog\Delta\sigma_{i,j} + \varepsilon \quad (8)$

where ε is the statistical error in the SN curve

and $\quad \Delta\sigma_{i,j} = E(\Delta\varepsilon_{i,j} + M_\varepsilon) \quad (9)$

where E is the young modulus of steel rebars
$\Delta\varepsilon_{i,j}$ is the strain range i for the rebar j
M_ε is the measurement error

The likelihood of damage can then be written as follow:

$$D_{like_j} = \sum_{\Delta\sigma_{i,j} > \Delta\sigma s,D} \frac{n_{i,j}t\left(E(\Delta\varepsilon_{i,j}+M_\varepsilon)\right)^m}{10^{\varepsilon+logk}} \tag{10}$$

Table 3 includes the definition of the random variables, their distributions and their parameters used to calculate the likelihood damage. Monte Carlo simulation is used to find the cumulative probability of component failure throughout the service duration.

Table 3. Probabilistic model for the random variables, likelihood study

Var.	Des.	Dist.	Mean	Std.	Ref.
Δ	*Miner's sum at failure*	*LN*	*1.0*	*0.3*	*JCSS*
ε	*Statistical error in SN curve*	*N*	*0*	*0.5*	*JCSS*
E	*Young modulus of steel (MPa)*	*LN*	*2.1 10^5*	*0.05*	*JCSS*
M_ε	*Monitoring error*	*N*	*0*	10^{-6}	*Monitoring*
Log k1	*Normal (MPa)*	*N*	*16. 2862*	*0.4*	*(Rastayest, et al., 2018)*
m	*Slope value*	*Det.*	*4*	*-*	*SIA 269 (Swiss standard)*

A normal distribution $f_{D_{like}}$ was fitted to the likelihood damage and the resultant mean, and the standard deviation is calculated.

The likelihood damage distribution for the instrumented rebar is plotted in Figure 3.

Based on Bayesian updating theory, the posterior damage distribution $f_{D_{post}}$ can be updated as:

$$f_{D_{post}}\left(d_{post}\right) = \frac{f_{D_{prior}}\left(d_{prior}\right) \cdot f_{D_{like}}\left(d_{like}\right)}{c} \quad (11)$$

where c is a constant ensuring the integral of the posterior density function equals 1.0, and d is the realization of (prior, likelihood or posterior) damage.

The posterior damage also has a normal distribution. The mean and standard deviation of the posterior model are identified accordingly. The normalized probability density function of the prior and the posterior damages and the likelihood are presented in Figure 3. The posterior damage follows the same shape of the likelihood, and it is far away from the prior damage. Therefore, the information provided by the likelihood is considered in the rest of the study as being the posterior information.

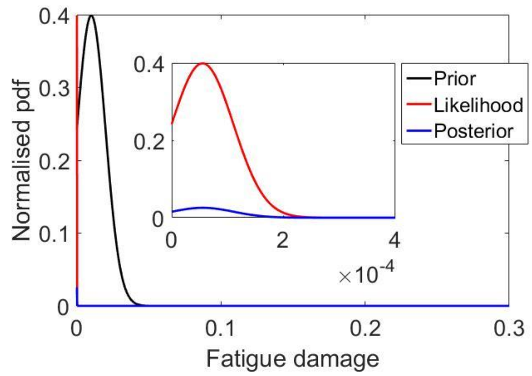

Figure 3. Fatigue damage distribution (prior, likelihood, and posterior)

The limit state function for the posterior model of a component j is written as:

$$g_j(t) = \Delta - \sum_{\Delta\sigma_{i,j} > \Delta\sigma_{s,D}} \frac{n_{i,j} t\left(E(\Delta\varepsilon_{i,j} + M_\varepsilon)\right)^m}{10^{\varepsilon + logk}} \quad (12)$$

Probability of failure of the system

The system fatigue failure of the viaduct is modeled. The viaduct system is of series type with different subsystems. The system failure is dominated by the weakest subsystem, which is the slender slab of 17cm thickness. From monitoring data, the cyclic stresses recorded in the transverse cross section were two times higher than in the longitudinal section. Therefore, the fatigue failure of the viaduct is assumed equal to the fatigue failure of the cross-section of the reinforced-concrete slab.

Herwig (2008), Johanssor (2004), and Schläfli and Brühwiler (1997) have shown that the fatigue failure of the reinforced concrete slabs is due to the failure of the rebars. The fracture of an isolated rebar (inside the concrete) may be considered as brittle; however, with the distributed reinforcement (254 rebars for the case of study), the failure of the cross-section has the potential for fatigue ductile behavior (Herwig, 2008). Consequently, the slab is modelled as a ductile Daniels system consisting of 254 components. The limit state function for the system is then presented in Eq. 13:

$$g_{sys}(\mathrm{t}) = \sum_{j=1}^{254} \left(\Delta - D_j(t)\right) \quad (13)$$

Monitoring data is available for the most loaded rebar located at mid-span. The distribution of the strain in all the rebars is taken from the finite element model of the structure. Fatigue stresses decrease linearly with a factor of 0.0008/rebar when moving from mid-span toward the box girders. The stress of each rebar j is then calculated according to Eq. 14:

$$\Delta\sigma_{i,j} = (1-(j-1)*0.0008)*\Delta\sigma_{i,1} \qquad (14)$$

where $\Delta\sigma_{i,j}$ is the stress range i of the rebar j, and $\Delta\sigma_{i,1}$ corresponds to the stress range i of the instrumented rebar 1. The cumulative probability of failure of the system is equal to:

$$P(F_S(t)) = P(g_{sys}(t) \le 0) \qquad (15)$$

It is calculated using both the prior and posterior models. The prior and posterior cumulative probabilities of the system failure are shown as:

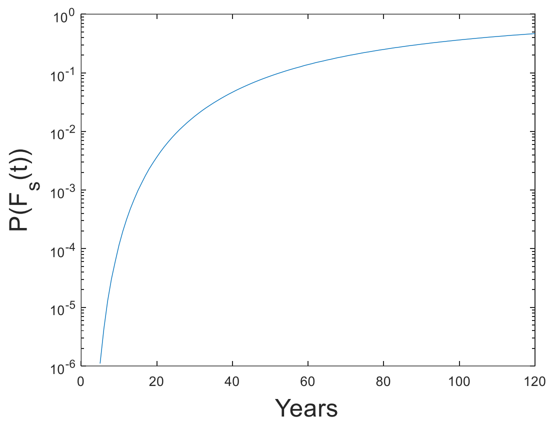

Figure 4. Prior cumulative probability of system failure

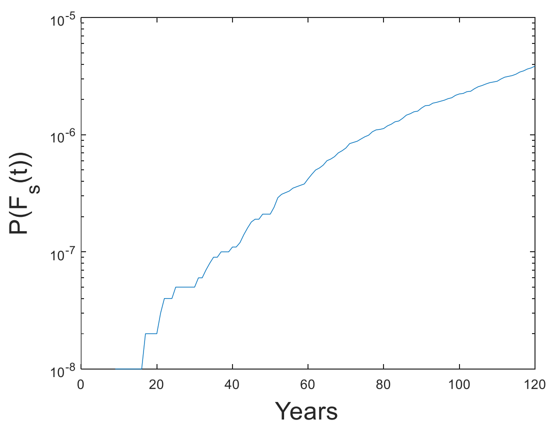

Figure 5. Posterior cumulative probability of system failure

The probability of failure calculated based on monitoring data is small, even after amplifying the loads by a factor of four, and assuming that the past traffic was similar to the present traffic. The heavy trucks are not frequent on the viaduct, and the slab is well reinforced, which explains the low-recorded strain values and the small probability of failure.

After 60 years of service, the prior probability failure is 0.172. According to the JCSS (2006), the target probability of failure is chosen as 5×10^{-4} for the existing bridge as the relative costs for safety measures are large and the consequences of failure are moderate. For the case study, the target probability of failure is exceeded according to the prior model but not reached for the posterior model.

CONDITIONAL VALUE OF SAMPLE INFORMATION ANALYSIS

The viaduct manager has to make decision about which action to take depending on the states of the viaduct namely to do nothing or to replace. The viaduct manager can reach the decision based on the minimum expected costs without additional information, which is modelled with a prior decision analysis or by considering the already obtained additional information. The latter decision can be modeled with a posterior decision analysis. With the difference of minimum expected costs for both cases (with and without additional information) and with the consideration uncertainties related to the additional information, a conditional value of sample information can be calculated (CSVI according Raiffa and Schlaifer (1961)).

The decision process can be described as shown in Figure 6 with a_i denoting the choice of the actions. θ_i is the viaduct states which can be safe or failure. e_i represent the different information of strategies. z_i is the outcome of the strategies. In this case, the information of z_1, no fatigue problem, is obtained after monitoring. We use u_i to present the expected utilities regards different actions under different strategy information, which is calculated by multiplying the probabilities and the consequences. Here we only consider the cost, so that the choice of action is performed based on the minimized expected costs.

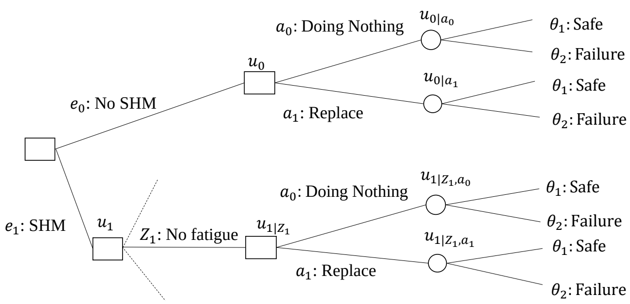

Figure 6. Illustration of decision tree

The conditional value of sample information is calculated as:

$$CVSI = u_0 - u_{1|z_1} \tag{16}$$

$$u_{1|z_1} = min\left[u_{1|z_1,a_0}; u_{1|z_1,a_1}\right] \tag{17}$$

$$u_0 = min\left[u_{0|a_0}; u_{0|a_1}\right] \tag{18}$$

$$r(F_S(t)) = \frac{dP(F_S(t))/dt}{1-P(F_S(t))} \tag{19}$$

$$u_{1|z_1,a_0} = \sum_{t=1}^{T_{SL}} r\left(F_S(t)|Z_{1_{t_m}}\right) C_F \frac{1}{(1+\gamma)^t} + C_M \tag{20}$$

$$u_{1|z_1,a_1} = \sum_{t=1}^{T_{SL}} r\left(F_S(t)|R_{t_m}, Z_{1_{t_m}}\right) C_F \frac{1}{(1+\gamma)^t} + C_M + C_R \tag{21}$$

$$u_{0|a_0} = \sum_{t=1}^{T_{SL}} r(F_S(t)\,) C_F \frac{1}{(1+\gamma)^t} \tag{22}$$

$$u_{0|a_1} = \sum_{t=1}^{T_{SL}} r\left(F_S(t)|R_{t_m}\right) C_F \frac{1}{(1+\gamma)^t} + C_R \tag{23}$$

$r(F_S(t))$ is the prior annual probability of failure. $r\left(F_S(t)|Z_{1_{t_m}}\right)$ is the posterior annual probability of failure given indication of no fatigue after monitoring. $r\left(F_S(t)|R_{t_m}\right)$ is the annual probability of failure after replacing the viaduct at year t_m based on prior knowledge. $r\left(F_S(t)|R_{t_m}, Z_{1_{t_m}}\right)$ is the annual probability of failure after obtaining the indication of no fatigue information and replacing the viaduct at year t_m. In this case $t_m = 60$ year and service life $T_{SL} = 120$ years. The replacement would result in a new viaduct.

The cost model is shown in Table 4. Since the height of the viaduct is from 2 to 7 meters, it can lead rarely to death in the case of failure. Considering the extreme case, the cost of failure is assumed to be equal to the cost of one person's life due to the collapse of the viaduct given in the Swiss Standards.

Table 4. Cost model

Cost	*Categories*	*Value*	*Reference*
C_R	*New structure (Replace)*	*5.5 MCHF*	*Assumed*
C_M	*Monitoring (for one year)*	*40 kCHF*	*Real case study*
C_F	*Cost of failure*	*10 MCHF*	*SIA 269*
γ	*Discounting factor*	*0.02*	*Higuchi(2008)*

Based on Eq. 16-23 and Table 4, the calculation of utilities results is shown as:

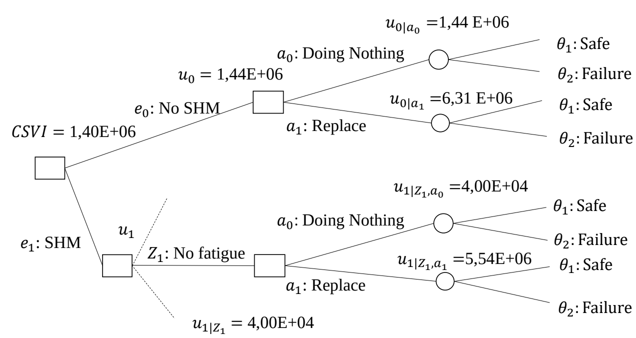

Figure 7. Decision tree with expected utilities

In Figure 7 it is shown that, without the structural health monitoring data, i.e. only with information provided by re-calculations based on codes, the viaduct has a very high probability of fatigue failure. Due to the associated high and unacceptable risks, the viaduct would be required to be replaced (action a_1). With monitoring data, action a_0 (do nothing) would be preferable due to the lower expected utilities. Thus, the Conditional Value of Sample Information is 1.4 MCHF, which means that by spending 40 kCHF money for monitoring, 1.4 million CHF of the cost is saved while keeping the viaduct in service.

CONCLUSIONS

The presented case study shows that the monitoring approach is found to give valuable information about the evaluation of the fatigue safety of the viaduct. The results show that there is no fatigue problem in the viaduct even by amplifying the monitored fatigue stresses arbitrarily by a factor of 4.

Through quantifying the conditional value of SHM information for this viaduct, by modeling the fatigue failure of the cross reinforced-concrete slab as a system failure, it is found that the money has been saved, the risk can be reduced and that the viaduct can operate much longer. It is demonstrated how SHM information can be utilized to support the optimal decision for a continuous monitoring, by integrating sound scientific structural models, SHM engineering models and cost and consequence models.

The SHM results indicate a significant bias of the model uncertainty in the design models. This indication may be used to derive models for value of information analyses with not yet obtained SHM information in order to predict for which bridges a SHM analysis may be valuable. This would support a quantitative decision basis for the owner based on an optimization of the time and money for keeping bridges reliably fulfilling their functions and being safe for users.

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CHAPTER 6. INFORMATION VALUE-BASED OPTIMIZATION OF STRUCTURAL AND ENVIRONMENTAL MONITORING FOR OFFSHORE WIND TURBINES SUPPORT STRUCTURES (PAPER 4)

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Scientific contribution of the PhD student:

Lijia Long

- developed the decision tree description.
- formulated the conditional value of sample information calculation.
- implemented the value of information simulations.
- implemented the parametric analysis.
- wrote section 1,2,5,6,7, and revised it according to co-authors' comments.

Scientific contribution of co-authors:

Quang Anh Mai

- provided the probabilistic fatigue model based on monitoring data.
- assisted in defining the decision problems.
- wrote section 3 and revised it according to co-authors' comments.

Pablo Gabriel Morato

- implemented the inspection updating based on Dynamic Bayesian networks.
- calibrated the fracture mechanic's model.
- wrote section 4 and revised it according to co-authors' comments.

John Dalsgaard Sørensen

- proposed the cooperation idea between Lijia Long and Quang Anh Mai.
- carefully reviewed the manuscript and provided critical comments.

Sebastian Thöns

- assisted in defining the decision scenario.
- carefully reviewed the manuscript and provided critical comments.

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Information value-based optimization of structural and environmental monitoring for offshore wind turbines support structures

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ABSTRACT

The use of load and structural performance measurement information is vital for efficient structural integrity management and for the cost of energy production with Offshore Wind Turbines (OWTs). OWTs are dynamically sensitive structures subject to an interaction with a control unit exposed to repeated cyclic wind and wave loads causing deterioration and fatigue. This study focuses on the quantification of the value of structural and environmental information on the integrity management of OWT structures, with the focus on fatigue of welded joints. By utilizing decision analysis, structural reliability methods, measurement data, as well as the cost-benefit models, a Value of Information (VoI) analysis can be performed to quantify the most beneficial measurement strategy. The VoI assessment is demonstrated for the integrity management of a butt welded joint of a monopile support structure for a 3 MW OWT with a hub height of approximately 71m. The conditional value of three-year measured oceanographic information and one-year strain monitoring information is quantified posteriori in conjunction with an inspection and repair planning. This paper provides insights on how much benefits can be achieved through structural and environmental information, with practical relevance on reliability-based maintenance of OWT structures.

1. Introduction

Offshore wind is a rapidly growing industry and to achieve reduction of operational costs of Offshore Wind Turbines (OWTs), it is important to choose optimal maintenance strategies to be implemented on the turbine components [1]. Applications of Structural Health Monitoring (SHM) for the design and maintenance of OWT structures have gained much attention within the past few years to detect and diagnose abnormalities of windturbine components, see e.g. Ref. [2–5]. Being exposed to repeated cyclic wind and wave loads, OWTs are dynamically sensitive structures and can benefit from monitoring systems. Implementing SHM in offshore wind energy support structures can help to investigate uncertainties in design, provide input for the verification of operational conditions and possible future design optimization, predict time-dependent deterioration for maintenance planning with the aim of reducing operations and maintenance costs and possible lifetime extension to achieve longer energy generation in the future while fulfilling the requirement of reliability, functionality and sustainability [6].

An OWT includes the Rotor and Nacelle Assembly (RNA), tower, substructure and foundations which e.g. can be a jacket/tripod with piles or bukets, monopiles, mono buckets, gravity bases or moored floaters. Up to now, the most commonly used OWT foundations are monopiles [7]. For the different components of the wind turbine different SHM techniques can be applied, see Ref. [8,9]. For example

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for monitoring the condition of the drivetrain, oil condition monitoring, acoustic emission, theomography, electromagnetical-parameter based monitoring and holistic or global condition monitoring are under research. For monitoring the rotor blades, vibration-based SHM, acoustic emissions, strain measurement and deflection based methods are under development. Sensor types for monitoring offshore support structures includes strain gauges, optical fibre sensors, temperature sensors, displacement sensors, accelerometers, inclinometers, photometers and laser interferometers. However, the techniques for blades and sub-structures are still under development, they are not industry practice yet. The operating and environmental conditions of virtually all wind turbines in operation today are recorded by the Supervisory Control And Data Acquisition (SCADA) system in 10-min intervals [8]. The minimum data set typically includes 10 min-average values of: wind speed, wind direction, active power, reactive power, ambient temperature, pitch angle and rotational speed (rotor and/or generator).

In particular the research on SHM of offshore wind energy support structures has been considerably intensified during recent years. Among the key drivers for this is the requirement in the standard from Bundesamt für Seeschifffahrt und Hydrographie (BSH) in Germany that at least 1 out of 10 OWT support structures must be equipped with a SHM system [8]. In this paper the focus is on SHM of offshore wind energy monopile support structures.

Most SHM research focuses on obtaining measurement data, extracting damage features, and deriving the damage indices e.g. miners sum of fatigue damage, without an explicit further consideration of the integrity management decision and action, see e.g. Ref. [5,10]. The scope of this paper aims to fill the gap of transforming the SHM data into knowledge that contributes to decisions of structural integrity management. Besides, among all the research related to SHM of OWTs, only few studies [11–14] focus on quantification the value of SHM in offshore wind energy support structures. The design of the SHM system is typically based on experience and limited by the budget. When improper SHM strategies are implemented, it may lead to big losses by obtaining an enormous amount of irrelevant information with high data processing costs that may trigger inappropriate remedial activities. Thus, there is a need to quantify the value of SHM in offshore wind energy support structures to improve the decision basis for implementing SHM and provide insight on how to choose the most beneficial measurement strategy. The information value-based decision analysis can be a very useful tool for the decision makers. Therefore, this paper focuses on the quantification of the conditional value of strain and wind monitoring information for maintenance of OWT monopile support structures, with emphasis on fatigue of welded joints.

To identify and quantify the most beneficial measurement strategy, a Value of Information (VoI) analysis is used, which is based on the Bayesian pre-posterior decision theory presented in Raiffa and Schlaifer (1961) [15] and Bayesian updating and utility-based decision theory to quantify the utility increase due to additional information. The expected value of SHM information can be found as the difference between the maximum utility obtained in analysis with SHM information and the maximum utility obtained without SHM information, considering the structural fatigue reliability, inspection and repair planning as well as the cost-benefit assessments. The utility increase, if additional information is already obtained at the time of decision-making, is denoted as Conditional Value of Sample Information (CSVI).

A similar proposed approach is used with great success for decision making on inspection planning for fatigue critical details in offshore structures [11,12] and the work presented in this paper is an extension to application for offshore wind energy support structures and is extended to include SHM in general. Through quantifying the value of different SHM system information, the optimal lifecycle maintenance planning can be determined, which facilitates the reliability and safety in the assets management for offshore wind energy support structures and in turn ensures a cost-efficient energy generation for sustainable societal developments.

This paper starts describing the VoI methodology and the process of quantification of the CSVI in Section 2, then Section 3 introduces a probabilistic model based on monitoring data to calculate the annual probability of failure, Section 4 describes the method of updating the annual probability failure with the inspection event, and finally Section 5 introduces a cost model and calculates the results of the conditional value of three monitoring strategies. Furthermore a parametric analysis regards the cost model is discussed in Section 6. The paper ends in Section 7 with the conclusion.

2. Value of information analysis

As described in the introduction, since the strain and wind monitoring information are already obtained at the time of decision-making, this paper focuses on the quantification of the conditional value of strain and wind monitoring information for planning the maintenance of OWT monopile support structures, with emphasis on fatigue of welded joints. Measurement of the wind speed from the SCADA system and monitoring information on stress ranges from strain gauges were obtained on a butt welded joint of the monopile support structure of a 3 MW OWT with a hub height of approximately 71m. To quantify the conditional value of the two types SHM information, a decision tree analysis is introduced.

2.1. Decision tree description

A general decision tree for Bayesian decision making contains five dimensions: information acquirement strategies $\boldsymbol{e}$, outcomes of strategies $\boldsymbol{z}$, possible actions $\boldsymbol{a}$, system states $\boldsymbol{\theta}$ and its consequences. An illustration of the decision tree process is shown in Fig. 1 with three branches: The base decision scenario is without monitoring e_0, one scenario with only wind monitoring information e_1 and one scenario with both wind and strain monitoring information e_2. With different monitoring strategies, the optimal planing of the total inspection times N_I and year t_{N_I} will be different. The outcome $\boldsymbol{z}$ describes the inspection outcome, e.g. detection of a crack (D) or no detection of a crack ($\overline{D}$), which is denoted with a chance node (circle). The action $\boldsymbol{a}$ contains the possible actions, like Do nothing (N) or Repair (R), which is represented with a rectangle. The system state $\boldsymbol{\theta}$ can be Failure (F) or Safe (S). The consequence of failure of a welded joint is assumed to be unscheduled repair, which is shown as a diamond. A decision rule is introduced, which is shown by a dashed decision node (rectangle). The dashed rectangle indicates inspections and repairs that will be repeated during the service life. In this paper, the decision rules are: if no detection of a crack, the action will be doing nothing, otherwise repair is done immediately after detection of a crack. The welded joints can only be repaired after inspection. The welded joints need to be inspected if the annual probability of failure reaches a certain threshold.

2.2. Conditional value of sample information calculation

The CSVI can be calculated by subtracting the expected total costs of the base decision scenario e_0 from the expected total costs from the enhanced decision scenario with obtained wind

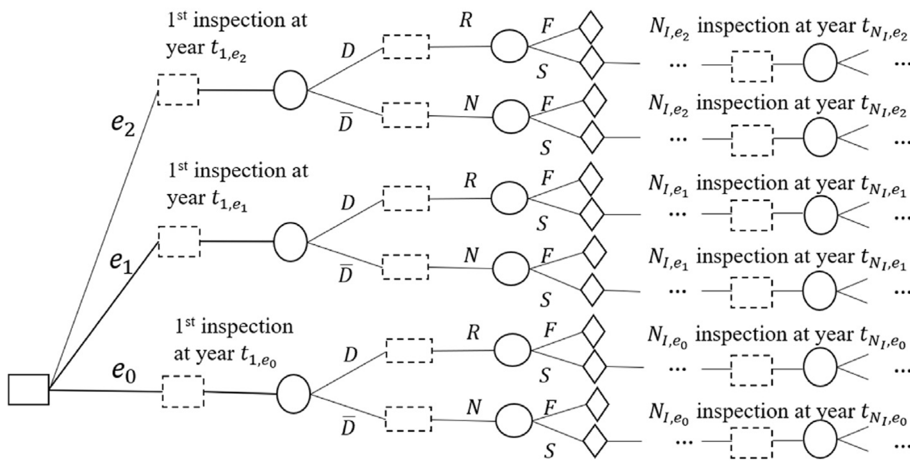

Fig. 1. Decision tree of comparing beneficial measurement strategy regards to improve future inspection and repair planning.

monitoring e_1 or both wind and strain information e_2:

$$CVSI(e_i) = E[C_T(e_0), T_{SL}] - E[C_T(e_i), T_{SL}] \quad (1)$$

For each monitoring strategy e_i, the decision tree will repeat its branch for every inspection outcome. Assuming that in total that there will be N_j branches (N_j types of combination of continous inspection outcomes) until the end of service life T_{SL}, each branch has its probability of occurrence, $P(j)$. The expected total life cycle costs $E[C_T(e_i), T_{SL}]$ of strategy e_i are the sum of all branches of expected inspection costs $E[C_I(e_i,j), T_{SL}]$, expected repair costs $E[C_R(e_i, j), T_{SL}]$, expected failure costs $E[C_F(e_i,j), T_{SL}]$ during service life and the monitoring costs C_M when monitoring is applied.

$$E[C_T(e_i),T_{SL}]=\sum_{j=1}^{N_j} P(j)\cdot(E[C_I(e_i,j),T_{SL}]+E[C_R(e_i,j),T_{SL}]+E[C_F(e_i,j),T_{SL}] \times)+C_M(e_i) \quad (2)$$

$P(j)$ is the product of probabilities of continous inspection outcomes during life cycle, e.g. the product of probability of detecting a crack P_D at each inspection year if damage is detected everytime after inspection during the service life. For each branch the expected costs of inspection, repair and failure can be calculated as follows [16,17]:

$$E[C_I(e_i,j), T_{SL}] = \sum_{n=1}^{N_{I,e_i j}} C_I \cdot \left(1 - P_F\left(t_{N_{I,e_i j}}\right)\right) \cdot \frac{1}{(1+r)^{t_{N_{I,e_i j}}}} \quad (3)$$

$$E[C_R(e_i,j), T_{SL}] = \sum_{n=1}^{N_{R,e_i j}} C_R \cdot P_R\left(t_{N_{R,e_i j}}\right) \cdot \left(1 - P_F\left(t_{N_{R,e_i j}}\right) \times\right) \cdot \frac{1}{(1+r))^{t_{N_{R,e_i j}}}} \quad (4)$$

$$E[C_F(e_i,j), T_{SL}] = \sum\nolimits_{t=1}^{T_{SL}} \Delta P_{F,e_i j}\,(t) \cdot C_F \cdot \frac{1}{(1+r))^t} \quad (5)$$

r is the discounting rate. T_{SL} is service life. $N_{I,e_i j}$ is the total number of inspections with monitoring strategy e_i in branch j. $N_{R,e_i j}$ is the total number of repairs with monitoring strategy e_i in branch j. $t_{N_{I,e_i j}}$ is the inspection year at N_I inspection time with strategy e_i in branch j. $P_F(t_{N_{I,e_i j}})$ is the accumulated probability of failure at inspection year $t_{N_{I,e_i j}}$. $t_{N_{R,e_i j}}$ is the repair year at N_R, denoting the repair time with strategy e_i in branch j. $P_R(t_{N_{R,e_i j}})$ is the probability of repair at repair year $t_{N_{R,e_i j}}$ which will be equal to $P_D(t_{N_{R,e_i j}})$ as the repair action will be taken immediately when the damage is detected. $P_F(t_{N_{R,e_i j}})$ is the accumulated probability of failure at repair year $t_{N_{R,e_i j}}$. $\Delta P_{F,e_i j}$ is the anaual probability of failure with monitoring strategy e_i in branch j. C_I is the inspection cost per time, C_R is the repair cost per time, C_F is the failure cost, which describes the unscheduled repair cost in this paper.

In the following, Section 3 will first introduce how to calculate P_F and ΔP_F based on probabilistic fatigue models integrated with monitoring data, then Section 4 will present how to predict inspection year t_{N_I}, the inspection times N_I, how to simulate P_D and update the ΔP_F from Section 3 based on inspection outcomes. Finally Section 5 will introduce the cost model of C_I, C_R, C_F, r and present the CSVI results.

3. Probabilistic fatigue model

In this paper, the failure probability of the support structure is first updated considering the SHM data in a stress-life (S–N) approach and then considering the crack inspection data in a fracture mechanics (FM) approach. The FM model is calibrated from the posterior S–N model.

There are two types of monitoring information considered in the calculation, representing two levels of SHM investment:

- Only the meteo-oceanographic data, i.e. wind speed, wave height, wave period, etc.
- Both the meteo-oceanographic data and the strain data, where the duration of concurrent measurement of the two types of data is long enough to consider most of the important load combinations, e.g. one year duration.

It is assumed that the SHM campaign is started from the beginning of the service life. At the time of assessment, three years of wind monitoring data and one year of strain data is available. The strain data measured at the same time with the wind data is used to relate wind speed distribution to the fatigue damage in the limit state function. If only the meteo-oceanogaphic data is available, the stress data can be obtained from finite element analyses.

In this section, the methodology to consider SHM data is summarized, a more detailed explanation can be found in Ref. [18].

3.1. Bayesian updating of the wind speed distribution

The wind measurement data is used to update the long-term wind speed distribution which in turn, is used in the limit state function to calculate the updated failure probability. The prior distribution of the long-term wind speed distribution is established using the design wind speed distribution and 15-year data of the 10-min mean wind speed before construction.

The long-term wind speed distribution is assumed to follow a Weibull distribution of which the scale parameter k_w is considered normally distributed with unknown mean μ and unknown standard deviation σ, see Eq. (6).

$$f_{K_w}(k_w|\mu,\sigma) = f_N(k_w|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(\frac{k_w-\mu}{\sigma}\right)^2\right) \tag{6}$$

The new information is the estimated values of k_w, obtained by fitting the measured 10-min mean wind speed data of each year into a Weibull distribution of which the shape parameter is the same as the design value.

The predictive density function of k_w given measured data becomes a Student's t-distribution as shown in Eq. (7).

$$f_{K_w}\left(k_w|\widehat{\mathbf{k}}_w\right) = f_S\left(k_w|\mu'', s''\frac{n''+1}{n''}, \nu''\right)$$
$$= \frac{\Gamma\left(\frac{\nu''+1}{2}\right)}{s''\sqrt{\nu''\pi}\Gamma\left(\frac{\nu''}{2}\right)}\left[\frac{\nu''+\left(\frac{k_w-\mu''}{s''}\right)^2}{\nu''}\right]^{-\frac{\nu''+1}{2}} \tag{7}$$

where:

- μ'', s'', n'', ν'' are the posterior parameters and μ', s', n', ν' are the prior parameters of the expectation of mean ($E[\mu]$), the expectation of the standard deviation ($E[\sigma]$), the sample size (n), and degrees of freedom (ν), respectively.
- the prior parameters are asymptotically given as:
- $E[\mu] = \mu'$
- $E[\sigma] = s'$
- $V[\mu] = \frac{s'}{\mu'\sqrt{n'}}$
- $V[\sigma] = \frac{1}{2\nu'}$
- The prior parameters of the Student' t-distribution of k_w are established using the design wind speed distribution and the 15-year wind measurement data before construction:
- $\mu' = k_w^{design} = 10.4$ (m/s)
- $n' = 15$, $\nu' = 15 - 1 = 14$
- to calculate s', it is assumed that the coefficient of variation of the mean value ($V[\mu]$) equals to that of the annual mean wind speeds of the 15-year data: $V[\mu] = 0.042$, so that $s' = V[\mu]\cdot\mu'\sqrt{n'} = 1.68$
- the posterior parameters are calculated as following, using n years of measurement data:
- $n'' = n' + n$
- $\mu'' = \frac{n'\mu' + n\bar{k}_w}{n''}$
- $s''^2 = \frac{\nu' s'^2 + n'\mu'^2 + \nu s^2 + n\bar{k}_w^2 - n''\mu''^2}{\nu''}$
- $\nu'' = \nu' + \delta(n') + \nu + \delta(n) - \delta(n'')$
- the statistical $\bar{k}_w$ and s^2 quantities are calculated for the vector of the $\widehat{\mathbf{k}}_w$ - a vector of n components corresponding to n years of wind measurement $\widehat{\mathbf{k}}_w = (\widehat{k}_{w,1}, \ \widehat{k}_{w,2}, \ \cdots, \ \widehat{k}_{w,n})$ as following:
- $\bar{k}_w = \frac{1}{n}\sum_{i=1}^{n}\widehat{k}_{w,i}$
- $s^2 = \frac{1}{n-1}$
- $\nu = n - 1$

Equation (7) is the probability density function of the random variable k_w in the limit state functions Eq. (8) and Eq. (11).

3.2. Probabilistic model for strategy $\boldsymbol{e}_0$

Before updating the long-term distribution of wind speed using measurement data, the failure probability of a welded joint can be calculated taking into account the predictive density function of k_w in Eq. (7). In this case, the posterior parameters (i.e. μ'', s'', n'', and ν'') are equal to the prior parameters.

The limit state function is based on the Palmgren-Miner rule:

$$g = \Delta - D_{total} \tag{8}$$

where Δ is the critical fatigue damage and D_{total} is total fatigue damage summed up from each bin of wind speed and from each year in the service life. The citical fatigue damage is the threshold to justify when fatigue fracture happens. A lognormal distribution with median equal 1.0 and CoV equals to 0.3 as proposed by Wirsching [29] can be used to represent Δ. Given that the stress-ranges obtained from measurement data correspond to the lower branch of the bi-linear S–N curve, the limit state function in Eq. (8) can be developed as:

$$g = \Delta - \sum_{i=1}^{T}\sum_{j=1}^{n_{U_{10}}}\frac{\left(\alpha_f X_m X_{SCF}\right)^{m_2}}{K}k_{s,j}^{m_2}\Gamma\left(\frac{m_2}{\lambda_{s,j}}+1\right)P(U_{10,j}|k_{w,i})\frac{n_{c,j}}{n_{m,j}}n_m^* \tag{9}$$

where:

T the service life in years.
$n_{U_{10}}$ number of bins of wind speed.
α_f the strain extrapolating factor from the measuring location to the location of interest.
K the random variable represents the uncertainty in the S–N curve, without having tested data established for specific design and fabrication, a typical standard deviation $\sigma_{\log K} = 0.2$ is suggested by DNV-RP-C203 [19]. The mean value is calculated from the charactristic value of the chosen S–N curve.
m_2 the negative slope of the lower branch of the S–N curve.
X_m the random variable represents the uncertainty in strain measurement, When there is no experimental data available for a specific site, Thöns [13] suggested to use a normal distribution with mean of 1 and standard deviation of 0.05.
X_{SCF} the random variable represents the uncertainty in the stress concentration factor, This uncertainty depends on the complexity of the joint and the method to calculate stress concentration factor. In this paper, a lognormal distribution with mean of 1 and standard deviation of 0.15 is used, following the background document to IEC 61400.1 ed 4 [20].
$U_{10,j}$ the 10-min mean wind speed in the j^{th} bin.
$k_{w,i}$ the random variable represents the scale parameter of the Weibull long-term wind speed distribution at the i^{th} year.
$k_{s,j}$ the scale parameter of the Weibull stress-range distribution of the j^{th} bin of wind speed.
$\lambda_{s,j}$ the shape parameter of the Weibull stress-range distribution of the j^{th} bin of wind speed.
$n_{c,j}$ number of stress cycles in the j^{th} bin of wind speed.
$n_{m,j}$ number of wind speed records in the j^{th} bin of wind speed.
n_m^* total observed wind speed records per year.

Given the lower and upper bounds of the j^{th} bin of wind speed are a_j and b_j, $P(U_{10,j}|k_{w,i})$ can be estimated as in Eq. (10), where F_W is the cumulative probability function of the Weibull distribution and λ_w is the design shape parameter.

$$P(U_{10,j}|k_{w,i}) = F_W(a_j \le U_{10} < b_j; k_{w,i}, \lambda_w) = \exp\left(-\left(\frac{a_j}{k_{w,i}}\right)^{\lambda_w}\right) - \exp\left(-\left(\frac{b_j}{k_{w,i}}\right)^{\lambda_w}\right) \tag{10}$$

The uncertainties used in Eq. (9) are detailed in Table 1:

3.3. Probabilistic model for strategy $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$

Given T_m years of wind measurement, the fatigue damage of the measurement years are known to be related to the fatigue loading. The corresponding scale parameters $k_{w,i}$ in Eq. (9) should be treated as deterministic, i.e. using directly the fitted values. The limit state function in Eq. (9) can be rewritten as Eq. (11):

$$g = \Delta - \sum_{i=1}^{T_m}\left(D_i \middle| \widehat{k}_{w,i}\right) - \sum_{j=T_m+1}^{T}\left(D_j | k_{w,j}\right) \tag{11}$$

where.

$\widehat{k}_{w,i}$ is the i^{th} component of the vector $\widehat{\mathbf{k}}_w$,
$k_{w,j}$ is the predicted value of k_w at the year j^{th},
D_i is fatigue damage of year i^{th}, $i = 1\cdots T_m$, defined in Eq. (12):

$$D_i = \sum_{j=1}^{n_{U_{10}}} \frac{(\alpha_f X_m X_{SCF})^{m_2}}{K} k_{s,j}^{m_2} \Gamma\left(\frac{m_2}{\lambda_{s,j}} + 1\right) P(U_{10,j}|\widehat{k}_{w,i}) \frac{n_{c,j}}{n_{m,j}} n_m^* \tag{12}$$

D_j is the fatigue damage of year j^{th}, $j = T_m + 1\cdots T$, defined similar to D_i but use $k_{w,j}$ instead of $\widehat{k}_{w,i}$.

3.4. Annual probability of failure

The failure probability limit state function in Eqs. (9) and (11) can be solved using a first order reliability method (FORM) as well as simulation techniques, see e.g. Ref. [21]. The updated failure probability after considering SHM is used to calibrate the FM model inSection 4. Afterward, the updated failure probability of the FM model is used with the cost model inSection 5. The annual failure probability calculated hereafter is to be used in the cost model. The annual failure probability of year t given survival up to year $(t-1)$ is calculated as:

$$\Delta P_F(t) = \frac{P_F(t) - P_F(t-1)}{1 - P_F(t-1)} \tag{13}$$

For the comparison of the VoI in this paper, failure probabilities are calculated and updated for three scenarios:

- When wind and strain monitoring data is available (e_2): the stress-range distribution is fitted for each bin of wind speed to get $\lambda_{s,j}$ and the mean of $k_{s,j}$,
- When only wind monitoring data is available (e_1): the scale parameters $k_{s,j}$ of the fitted stress-range distributions are scaled to yield the design fatigue damage (in this case, it is assumed that the joint is design to the limit).
- Without monitoring data (e_0): the design wind speed distribution is used together with the stress-range distributions in e_1.

Instead of modifying the fitted stress-range distributions in e_0 for e_1 and e_2, it is possible to use the stress-range histograms available from the design data (or perform finite element analyses using the measured wind data) to fit the distribution for each bin of wind speed.

The annual failure probabilities of the three cases are shown in Fig. 2. It can be seen that using only three years of wind data, the annual failure probability is not reduced as significantly as the case where both wind and strain data is available. It means the measured wind conditions are foreseen in the design wind speed distribution and the design stress-range distribution is conservative.

4. Updating the reliability based on inspections/repairs

In this section, the reliability of the welded joints is updated based on the information gathered from inspections. First, a fracture mechanics model is presented to quantify the deterioration and is calibrated to match the reliability estimated in Section 3. Then, an inspection model is introduced to quantify the measurement quality. The reliability is updated thereafter based on the inspection outcomes.

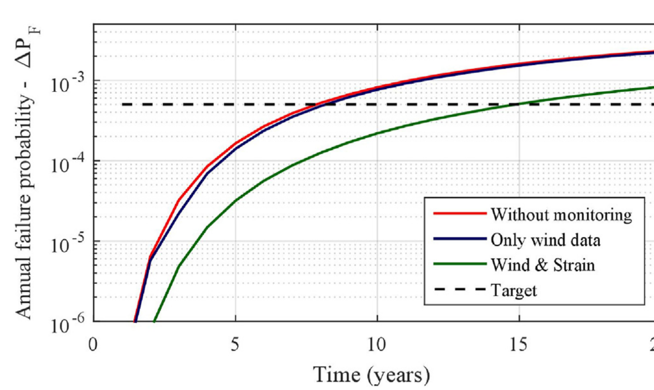

Fig. 2. Annual probability of failure.

Table 1
Details of input random variables.

RVs	Distribution	Mean or Median	CoV or Std.	Comment
Δ	Lognormal	$\tilde{m} = 1$	CoV = 0.3	following DNV-GL [19]
X_m	Normal	$\mu = 1$	CoV = 0.05	following Thöns [13]
X_{SCF}	Lognormal	$\mu = 1$	CoV = 0.15	following Sørensen [20]
K	Lognormal	$\mu_{\log K} = 16.006$	$\sigma_{\log K} = 0.2$	following DNV-GL [19]
$k_{s,j}$	Normal	fitted	CoV = 0.1	assumed; fitted $\lambda_{s,j}$ is deterministic
$k_{w,i}$	Student's t	updated	updated	$\lambda_{w,i} = \lambda_{w,design}$

Table 2
Fracture mechanics model parameters.

Variable	Distribution	Mean	CoV
a_0	Exponential	*Calibrated	–
m	Deterministic	3	–
lnC	Normal	*Calibrated	*Calibrated
S	Deterministic	19.46	–
Y	Deterministic	0.24 (Assumed)	–
n	Deterministic	$2.41 \cdot 10^7$	–

4.1. Fatigue deterioration - Fracture mechanics model

The deterioration of the structural component is estimated with the use of a SN curve/Miner's rule model during the design stage. Nevertheless, it is not possible to measure damage directly on the structure. Thus, a fracture mechanics model - which is calibrated to match the reliability obtained with the SN curve model - is preferred so as to quantify in-service deterioration. This way, the reliability can be updated once a crack has (or has not) been detected.

The linear elastic fracture mechanics (LEFM) model used in this paper is based on the Paris' law and has been derived from the formula proposed by Ref. [22]. The crack depth as function of the stress cycles can be computed according to Eq. (14).

$$a(n) = \left[\left(1 - \frac{m}{2}\right) C\pi^{m/2} S^m Y^m n + a_0^{1-m/2}\right]^{(1-m/2)^{-1}} \tag{14}$$

where, $a(n)$ stands for the crack depth and is growing as function of the number of cycles (n). C and m represent the crack growth parameters and depend on the material. The loading is incorporated through the equivalent stress range S of the measured stress-ranges from section 3 and the geometric correction factor Y which can be assumed to be a constant for simplification. The fatigue load uncertainty X_m as mentioned in Table 1 is already considered in the SN model, so it is implicitly included in the calibrated FM model. Thus, once the initial crack size a_0 is known, the crack growth over time can be computed.

A limit state is formulated in Eq. (15) to estimate the reliability of the welded joints. The failure criterion is assumed here as through-thickness crack; thus, the critical crack size a_c is defined as the plate thickness. If the number of cycles per year is assumed constant, the reliability can be computed for each year t.

$$g_{FM}(t) = a(t) - a_c \tag{15}$$

The values assigned to the fracture mechanics model are listed in the Table 2. Note that some parameters are calibrated to match the SN model's reliability.

4.1.1. Calibration of the fracture mechanics model

The initial crack size a_0 and the crack growth parameter C are calibrated to match the SN curve/Miner's reliability. A least squares optimization is conducted with the objective function Eq. (16) to minimize the error between Miner's and fracture mechanics reliability.

$$\{\mu_{a_0}, \mu_{lnC}, \sigma_{lnC}\} = \underset{\mu_{a_0}, \mu_{lnC}, \sigma_{lnC}}{argmin} \sum_{t=1}^{t_{SL}} \left(\beta_{SN}(t) - \beta_{FM}(t, \mu_{a_0}, \mu_{lnC}, \sigma_{lnC}) \right)^2 \tag{16}$$

The annual reliabilities from the calibration are illustrated in Fig. 3 and the calibrated parameters are listed in Table 3. It can be seen that while μ_{a_0} and σ_{lnC} remain similar, μ_{lnC} varies for each case.

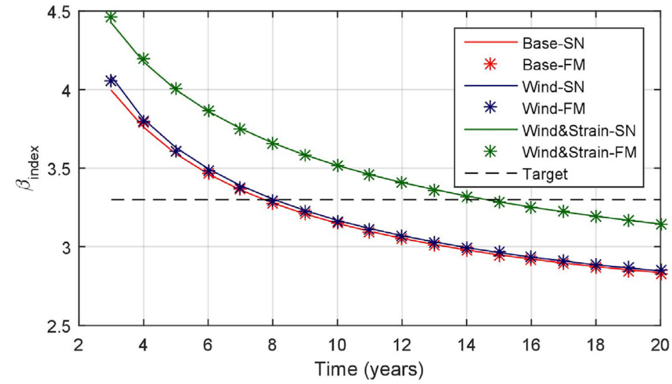

Fig. 3. Calibration of the fracture mechanics model. The line in red colour represents the base case e_0, blue colour stands for the case where the reliability is updated considering wind data e_1, and green colour for the case when both wind and strain e_2 are used for the updating. The dashed line corresponds to the target reliability. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Calibrated parameters of the fracture mechanics model.

Parameter	Base case ($\boldsymbol{e}_0$)	Wind only ($\boldsymbol{e}_1$)	Wind and strain ($\boldsymbol{e}_2$)
μ_{a_0}	$8.54 \cdot 10^{-2}$	$8.54 \cdot 10^{-2}$	$8.54 \cdot 10^{-2}$
μ_{lnC}	– 26.3	– 26.4	– 26.8
σ_{lnC}	0.9	0.9	0.9

Since the reliability increased after the update considering both strain and wind data, the resulting crack growth (μ_{lnC}) is smaller, leading to a higher reliability than the other to cases. A similar reasoning can be reached for the case when the update is only carried out considering wind data, but in this instance, the crack growth is slightly smaller than the base case.

4.2. Inspection quality - Probability of detection

During the operational life of the structure, knowledge can be gained through inspections, updating the reliability of the structural component accordingly. Yet, inspections have uncertainty associated as the measurement instrument is not perfect as well as other environmental (or human) factors that can influence the final outcome. This measurement uncertainty is commonly documented by the Probability of Detection (PoD) curves. The PoDs represent the ability of detection of a specific inspection method as function of the defect size.

Eddy current inspection is an applicable inspection method for an OWT welded joint. Since, it is not required to remove the coating before the inspection, it presents an advantage with respect to magnetic particle inspection methods. In this paper, it is assumed that eddy current inspections will be conducted and the corresponding PoD curve is documented in the DNV-GL Standard RP-210 [23], as expressed in Eq. (17). Where a is again the crack depth and the distribution parameters are defined as $X_0 = 0.45$mm and $b = 0.9$.

$$PoD(a) = 1 - \frac{1}{1 + \left(\frac{a}{X_0}\right)^b} \tag{17}$$

4.3. Updating the reliability - Dynamic Bayesian Network

The reliability of the structural component is herein computed and updated by means of a Dynamic Bayesian Network (DBN). A DBN is a type of Bayesian network where the random variables and their dependencies are represented through subsequent time steps. DBNs are also denoted as Two-Timeslice Bayesian Networks (2TBN) state-space because only the initial state and the transition space are sufficient to define the whole model. The interested reader is directed to Ref. [24,25] for a more detailed description and treatment of DBNs.

The reliability could also be computed and updated by means of Monte Carlo simulations, where a limit state is formulated for the detection event to compute the failure probability conditional on the detection outcome, as proposed by Ref. [22]. However, DBNs have increasingly gained popularity due to their computational benefits and robustness for Bayesian updating, as demonstrated by Refs. [26].

The DBN employed herein is illustrated in Fig. 4. The chance node a corresponds to the crack depth and it is dependent on the crack growth node C. In case an inspection is performed, a node Z is added and stands for the probability of detection, which is dependent on the crack size distribution. Finally, the binary node E assigns the failure probability depending on the last state of the node a. The subscripts of the nodes indicate the temporal evolution of the random variables: a_0 and C stand for the initial crack depth and crack growth parameter respectively, then, the random variables evolve from year 1 ($t = 1$) until the end of the lifetime ($t = T$).

4.3.1. Dynamic Bayesian network - Inference

In this investigation, inspections are planned based on the decision rule of conduction an inspection the year before the target reliability is reached. The target reliability defined by the Standard IEC 61400–1:2019 [27] is selected as reference, with reliability values of $\beta = 3.3$ ($\Delta P_F = 5 \cdot 10^{-4}$ with a one year reference period). Besides, it is considered that a repair will be performed once a crack is detected. After the repair, it is assumed that the welded joints will behave as a new joints following [30–32].

The reliability of the welded joints can be updated by including evidence in the DBN. More specifically, evidence gathered through inspections is included in the inspection nodes Z (Fig. 4). Once the evidence is added, the probability distribution of the subsequent nodes conditional on the inspection outcome can be inferred through a prediction inference routine. Herein, the forward operation proposed by Ref. [26] is employed for the prediction task.

4.3.2. Inspection updating - Results

The reliability of the welded joints is computed and updated according to the decision tree presented in Fig. 1 and by means of the DBN introduced in Fig. 4. The annual failure probability for all the different cases is displayed in Figs. 5–7. The inspections are represented in the figures by pointers, if the outcome is 'not-detected', the pointer is a circle and if the outcome is 'detected', the pointer is an asterisk. The annual failure probability threshold is plotted with a red line.

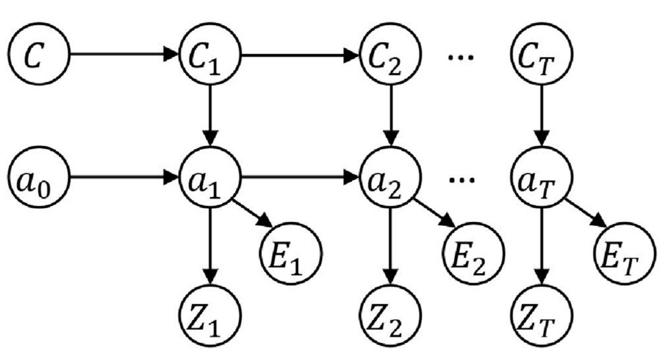

Fig. 4. Inspection updating - DBN representation.

5. Quantification the conditional value of SHM information

Based on the results from Section 4, the prediction of the number of inspections and inspection years will be different whether with or without monitoring information. The summary is shown in Table 4. t_{N_I} is the inspection year of N_I inspection times, z_{N_I} is the outcome of the N_Ith inspection time. The service life of the OWT is assumed to be 20 years. Without monitoring (e_0), the welded joints of the monopile need to be inspected three times or two times depending on the outcome of previous inspection as well as whether the planned inspection year is within the service life or not. With strategy e_1, the predicted inspections times of the welded joints will be the same namely three times or two times. But the inspections can be done slightly later with e_1 compared to e_0. However in strategy e_2, when incorporating both wind and strain monitoring data, the welded joints are only required to be inspected one time during service life.

An example of a sequential decision tree which is describing the inspection and repair plan of the base case e_0 is shown in Fig. 8. There are in total seven branches in the decision tree. The first inspection is at year 7. If a crack is detected after inspection at year 7 and repaired, the second inspection will be at year 14. If no crack is detected at year 7, the second inspection will be at year 11. Based on the outcome of the second inspection, the third inspection could be at year 18 or 16. Similar to the sequential decision tree of the base case e_0, the decision tree of the case with only wind monitoring data e_1 will have five branches, with the first inspection at year 8, second inspection at year 16 when a crack is detected and repaired at year 8 or at year 12 if no crack is detected at year 8. If no crack is detected at year 12, then the welded joints need a third inspection at year 16. With both wind and strain monitoring e_2, the welded joints only need to be inspected one time at year 14. That's because the predicted annual failure probabilities from e_2 information are much smaller than those with e_1 and e_0 information, which leads to a longer operation period before reaching the target probability for the first inspection after commissioning of the structure.

Following the formula of quantification of the VoI in Section 2 and the costs model shown in Table 5 from Ref. [28], with the results of annual probability of failure in Section 3 and the results of the probability of detection in Section 4, the value of the three monitoring strategies are quantified. When the inspection cost C_I is €1 10^4, repair cost C_R is €8 10^4, failure costs C_F (unexpected repair costs) is €1.5 10^5, cost of wind monitoring C_w is €5 10^2 which only accounts for the data processing fee due to the SCADA system already being installed in the commissioning stage, cost of strain monitoring C_s is €1 10^3 and discounting rate r is 0.02, the CVSI of wind (e_1) is €1.7 10^4 and the CVSI of wind and strain (e_2) is €4.2 10^4.

By spending 0.9% of total service life costs of strategy e_0 to obtain first three-year wind monitoring information of e_1, up to 30% of lifecycle management costs of e_0 can be saved. Even though there is a slight difference of inspection years between e_0 and e_1 (slightly later inspection years in e_1), with e_1 there will be a higher chance of only inspecting two times during the service life while with e_0 it is more likely that there will be three inspections, which leads to a positive CSVI of e_1. By spending 2.6% of total costs of e_0 to acquire the wind monitoring data of the first three-year period and one-year strain monitoring information in e_2, up to 73% of life cycle

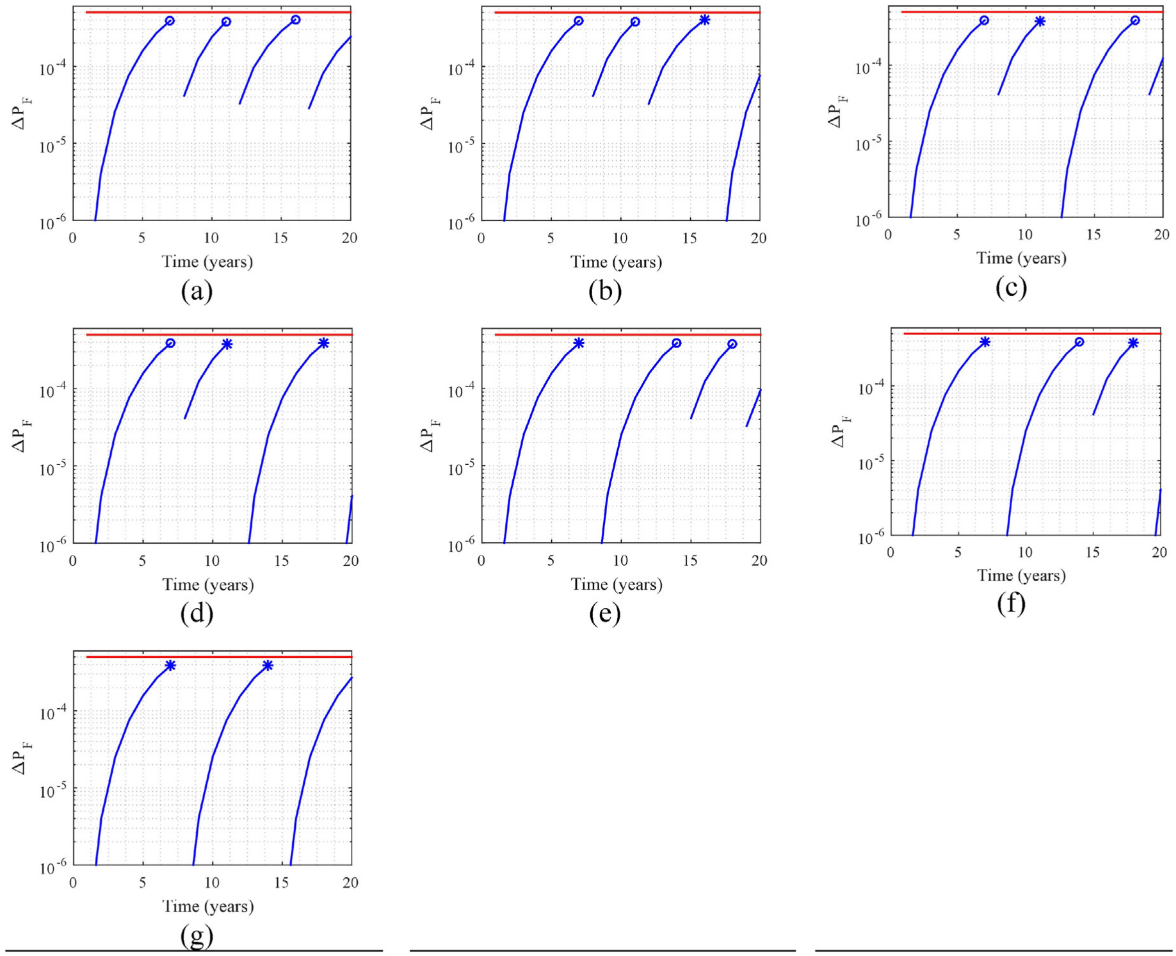

Fig. 5. Inspection updating - Base case.e_0

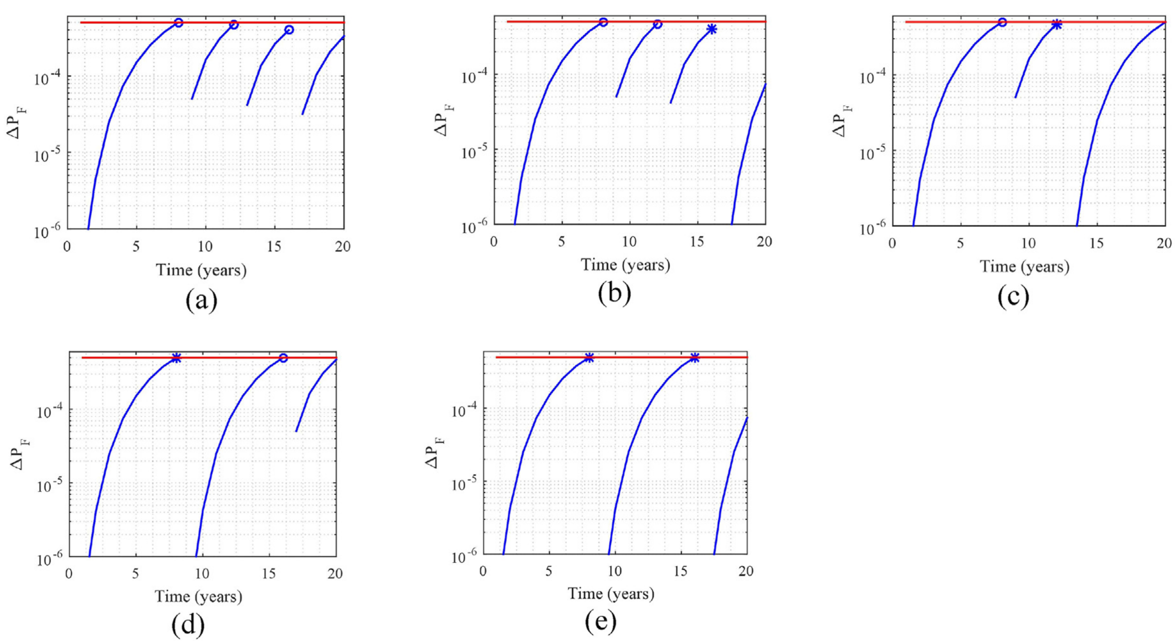

Fig. 6. Inspection updating - Only wind case.e_1

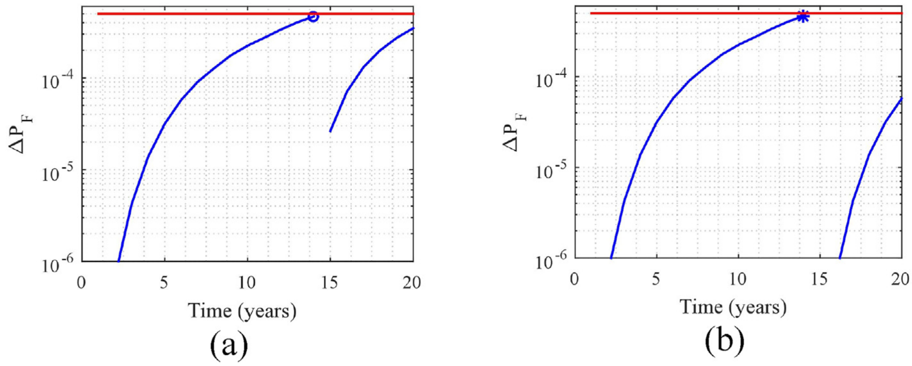

Fig. 7. Inspection updating - Wind & strain case.e_2

Table 4
Summary of the inspection plan for the three cases.

Base case ($\boldsymbol{e}_0$)					Wind only ($\boldsymbol{e}_1$)					Wind & strain ($\boldsymbol{e}_2$)	
$N_I = 1$		$N_I = 2$		$N_I = 3$	$N_I = 1$		$N_I = 2$		$N_I = 3$	$N_I = 1$	
t_{N_I}	z_{N_I}	t_{N_I}	z_{N_I}	t_{N_I}	t_{N_I}	z_{N_I}	t_{N_I}	z_{N_I}	t_{N_I}	t_{N_I}	z_{N_I}
7	D_7	14	D_7, D_{14}	23	8	D_8	16	D_8, D_{16}	26	14	D_{14}
	$\overline{D}_7$	11	$D_7, \overline{D}_{14}$	18		$\overline{D}_8$	12	$D_8, \overline{D}_{16}$	21		$\overline{D}_{14}$
			$\overline{D}_7, D_{11}$	18				$\overline{D}_8, D_{12}$	20		
			$\overline{D}_7, \overline{D}_{11}$	16				$\overline{D}_8, \overline{D}_{12}$	16		

management costs of e_0 can be saved, due to the significantly reduction of inspection times. Thus the combination of the strain and wind monitoring strategy e_2 is more beneficial than only the wind monitoring strategy e_1, and even more beneficial than without monitoring e_0 for this case.

Table 5
Summary of costs model.

C_I	C_R	C_F	C_w	C_s	r
€1 10^4	€8 10^4	€1.5 10^5	€5 10^2	€1 10^3	0.02

6. Parametric analysis

With respect to cost of failure C_F, inspection cost C_I, repair cost C_R and discounting rate r, the parametric analysis on CVSI is investigated. The results are shown in Fig. 9. With the increase of cost of failure C_F, the CVSI of e_2 and e_1 keep almost constant (a) and the CVSI of e_2 will always be higher than the CVSI of e_1, showing that the cost of failure will not influence the choice of CVSI. This is because of the applied “target threshold” decision rule, which will make the cost of failure not influence the number of inspection times and year. With increase of the cost of inspection C_I (b) and cost of repair C_R (c), the CVSI is increasing. However the difference between e_2 and e_1 is becoming larger with the increase of the cost of inspection C_I. The CVSI is decreasing with the increase of the discounting rate r as shown in (d). The CVSI of e_2 is higher than the

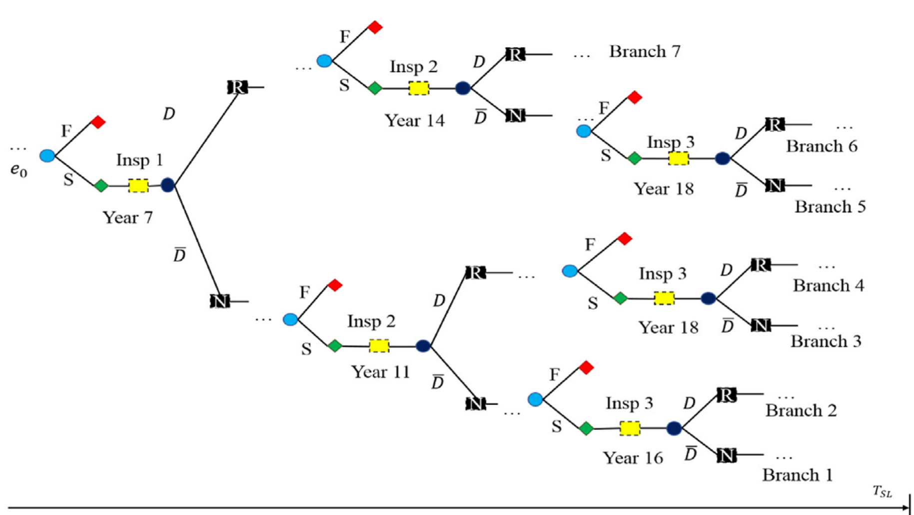

Fig. 8. Sequential decision tree of base case.e_0.

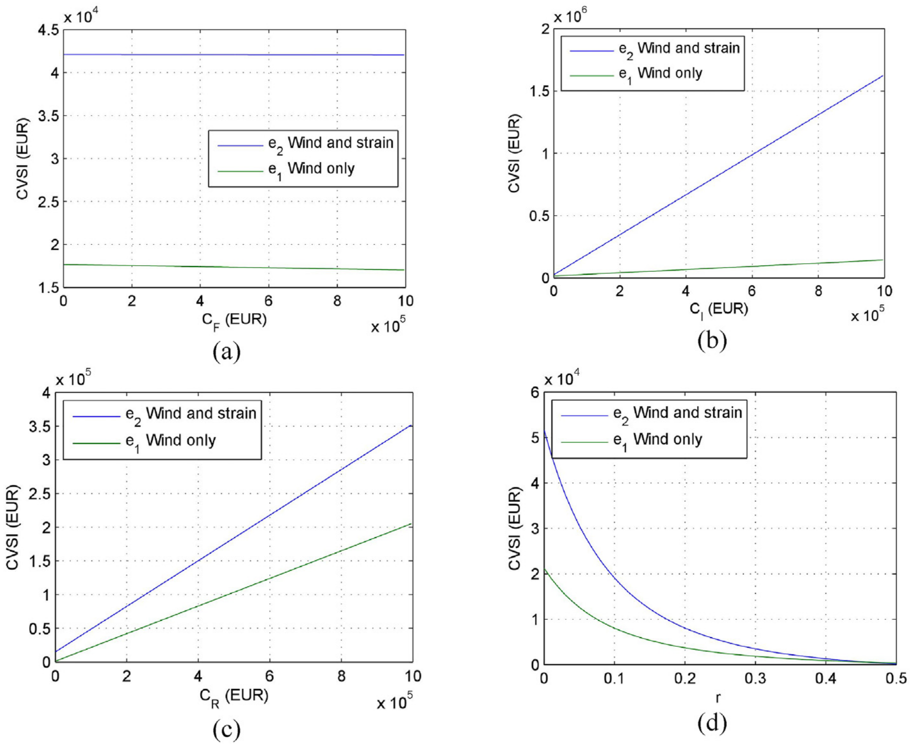

Fig. 9. CSVI independence of C_F, C_R, C_I.r

CVSI of e_1 when the discounting rate is less than 0.4. The difference between the CVSI of e_1 and e_2 is becoming smaller with increasing disconting rate. When the discounting rate is larger than 0.4, both CVSI of e_1 and e_2 become around zero, which is because the money becomes less valuable with higher discounting rate, so that it will not add value to invest on monitoring at all.

From Fig. 9 (a)–(d), it can be seen that the CVSI of e_2 is alomost always higher than the CVSI of e_1 with changes of C_F, C_R, C_I and r, which shows that the cost models will not change the fact that the combination of the strain and wind monitoring strategy e_2 is more beneficial than only the wind monitoring strategy e_1. It is however dependent on the measurement outcome. In our case the one-year strain monitoring has shown smaller fatigue loads than what can be seen from three-year wind measurements. The fatigue loads shown from the three-year wind measurements appear slightly smaller than what is expected from design. In this case the expected number of inspection and repair times from e_2 will be smaller than e_1 and the CVSI of e_2 will be higher than e_1.

7. Conclusions

Early research proposed different SHM techniques for the OWT, recent studies have improved on that by suggesting methods to quantify the value of SHM information. This work highlights that the optimal monitoring strategy for offshore wind energy support structures can be deterimined posteriori through conditional value of structural and environmental information analysis. The application on the quantification of the conditional value of three-year measured oceanographic information and one-year strain monitoring information on a butt welded joint of a monopile support structure of OWT shows that the combination of the strain and wind monitoring strategy is more beneficial than only the wind monitoring strategy, which is again better than without monitoring. However, this is based on the fact that the monitoring results have shown smaller fatigue loads than expected from design. Therefore for future research, the understanding of scenarios when the monitoring shows contrary results, e.g. strain monitoring indicates larger fatigue loads than what can be seen from the wind monitoring, will be critically important if aiming to do pre-posterior decision analysis before implementaion of SHM. This presented research work provides a decision basis for lifecycle structural integrity management by quantifying the value of structural and environmental information, with the ultimate goal to contribute to cost-efficient and sustainable energy generation through maintaining the reliability and serviceability of offshore wind energy support structures.

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CRediT authorship contribution statement

Lijia Long: Writing - original draft, Writing - review & editing, Investigation, Methodology, Software, Formal analysis. **Quang Anh Mai:** Data curation, Methodology, Software, Writing - review & editing. **Pablo Gabriel Morato:** Validation, Methodology, Software, Writing - review & editing. **John Dalsgaard Sørensen:** Supervision, Conceptualization. **Sebastian Thöns:** Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CHAPTER 7. RISK ASSESSMENT AND VALUE OF ACTION ANALYSIS FOR ICING CONDITIONS OF WIND TURBINES CLOSE TO HIGHWAYS (PAPER 5)

Sima Rastayesh, Lijia Long, John Dalsgaard Sørensen, Sebastian Thöns.

Energies

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Scientific contribution of the PhD student:

Lijia Long

- developed the decision scenario for value of action analysis based on risk model results from Sima Rastayesh.
- performed the value of action analysis.
- implemented the utility simulations.
- implemented the parametric simulation and analysis.
- wrote the section 5 and 6 of the paper and revised it according to co-authors' comments.

Scientific contribution of co-authors:

Sima Rastayesh

- performed the risk assessment for the Wind Turbines close to Highways.
- developed the risk model for the wind turbines close to highways in three scenarios.
- wrote the sections 1,2,3 and 4, and revised it according to co-authors' comments.

John Dalsgaard Sørensen.

- proposed the cooperation idea between Lijia Long and Sima Rastayesh.
- assisted in defining the decision scenario.
- assisted in formulate the utility calculations.
- carefully reviewed the manuscript and provided critical comments.

Sebastian Thöns

- assisted in defining the value of action analysis.
- assisted in finalizing the decision scenario.
- carefully reviewed the manuscript and provided critical comments.

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MDPI

Article

Risk Assessment and Value of Action Analysis for Icing Conditions of Wind Turbines Close to Highways

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Abstract: The paper presents research results from the Marie Skłodowska-Curie Innovative Training Network INFRASTAR in the field of reliability approaches for decision-making for wind turbines and bridges. This paper addresses the application of Bayesian decision analysis for installation of heating systems in wind turbine blades in cases where an ice detection system is already installed in order to allow wind turbines to be placed close to highways. Generally, application of ice detection and heating systems for wind turbines is very relevant in cases where the wind turbines are planned to be placed close to urban areas and highways, where risks need to be considered due to icing events, which may lead to consequences including human fatality, functional disruptions, and/or economic losses. The risk of people being killed in a car passing on highways near a wind turbine due to blades parts or ice pieces being thrown away in cases of over-icing is considered in this paper. The probability of being killed per kilometer and per year is considered for three cases: blade parts thrown away as a result of a partial or total failure of a blade, ice thrown away in two cases, i.e., of stopped wind turbines and of wind turbines in operation. Risks due to blade parts being thrown away cannot be avoided, since low strengths of material, maintenance or manufacturing errors, mechanical or electrical failures may result in failure of a blade or blade part. The blade (parts) thrown away from wind turbines in operation imply possible consequences/fatalities for people near the wind turbines, including in areas close to highways. Similar consequences are relevant for ice being thrown away from wind turbine blades during icing situations. In this paper, we examine the question as to whether it is valuable to put a heating system on the blades in addition to ice detection systems. This is especially interesting in countries with limited space for placing wind turbines; in addition, it is considered if higher power production can be obtained due to less downtime if a heating system is installed.

Keywords: risk assessment; value of action analysis; icing conditions; wind turbine; blade; probability; highway

1. Introduction

Wind energy is one of the leading sources of renewable energy in Denmark and other countries. Wind energy is increasingly being used in cold climate locations [1] where icing can be a significant issue that should be taken into account in a risk assessment related to the area around wind turbines. An environmental impact assessment has to be performed, e.g., when it is planned to locate wind turbines in areas where people are living and in cases where it is planned to place wind turbines near a road or highway. Generally, the safety factors used for the design of wind turbines do not cover such situations, since safety factors have been calibrated assuming that there is no or almost no risk of human fatalities in case of the failure of parts of a wind turbine. Ice accretion could have a direct impact on wind turbine operation, such as measurement errors, power losses, mechanical and electrical failures, and safety hazard problems [2]. Several investigations are ongoing in order to establish rules and guidelines related to icing. For instance, icing could affect the functionality of anemometers if they are unheated, see [3]. In Germany, wind turbines are not allowed to operate during icing situations, see [4]. Several reports are available showing that some wind turbines in Sweden during the 2002 and 2003 winters were forced to stop for seven weeks. Statistics from Sweden show that in winter months, 92% of full stops are caused because of icing [5]. In Germany, 85% of full stops of wind turbines in the mountains were caused by icing [6]. During the design stage, a functional ice detection system can be planned to be installed; subsequently, the wind turbine will be shut down if icing is detected by the ice detection systems.

Most of the de-icing and anti-icing techniques used for wind turbines are inspired by the aviation industry; all these techniques can be classified into two types: passive and active. As an example, for passive techniques, ice-phobic and hydrophobic coatings can be used; furthermore, for active techniques, electrothermal blade heating, heating with microwaves, warm air heating can be applied. However, all of them have some disadvantages. These systems are generally unreliable, and therefore energy losses occur, and the effectiveness of the system decrease [2,7,8].

Ice detection systems are needed to make de-icing and anti-icing systems work. Double anemometer and vibration sensors are often used, as they are cheap; however, they have some weak points. For example, in double anemometers, since humidity is measured relatively, it may lead to an incorrect prediction of icing, which will then affect the wind turbine operation [9]. Another weakness point for double anemometers is related to the location of where they are installed; since icing is increasing with height, a double anemometer will always predict less icing compared to the amount of icing at the most critical location, especially when the turbine is parked [10]. Another shortcoming occurs due to increased measurement errors in case of low temperatures for unheated anemometers [11]. Furthermore, vibration sensors cannot detect icing during stall operation [10]. Optical sensors or video cameras seem more reliable than the aforementioned instruments, e.g., Remote Ice Detection Equipment (RIDE) [12].

In this paper, we consider whether it is worthwhile putting heating systems on the blades when there is the possibility of icing. Situations are considered in which an ice detection system is already installed. Different failure scenarios related to blade failures and icing will be presented in Section 2. In Section 3, risk assessment is described taking to account the distance of wind turbines to highways. Risk is estimated as the probability (per km and per year) that a person in a car will be hit (and killed) by ice pieces or parts of wind turbine blades. It is assumed that a row of wind turbines is placed along the highway. The risk is determined as a function of the distance from the wind turbines to the highway. Our results could provide decision-makers with a tool for deciding whether wind turbines should be placed near a highway and whether heating systems should be installed. This risk assessment and a case study are presented in Sections 3 and 4, and can be used as decision support for designers at sites with limited space and in which wind turbines need to be placed as close as possible to highways. In Section 5, the Value of Action approach is presented as the basis for quantifying whether it is worthwhile installing a heat detection system for wind turbine blades exposed to icing, and in Section 6, a case study is presented to illustrate the decision problem and how it can be solved.

2. Failure Scenarios

The following scenarios are considered in the assessment of risks for the surroundings of a wind turbine:

(1) A part of a wind turbine blade or the whole blade may fail/collapse and be thrown away from the turbine;
(2) Icing may occur when the wind turbine is in operation, and ice pieces may be thrown away;

(3) The wind turbine may be stopped in situations with icing, but ice pieces may be thrown away due to high wind speeds.

The reasons for wind turbine blade failures may be the extremely low strength of the materials (within random variations of strength parameters), manufacturing errors, maintenance errors or extreme environmental conditions (within random variations of environmental parameters and accounting for the effect of the control system). Ice throw can be considered to be similar to a slingshot effect. Ice may be blown from the rotor blades in cases with strong wind when the wind turbine is parked or idling, or thrown away when the wind turbine is in operation. In a risk assessment, mechanical and electrical failures may lead to blade or blade fragment failures; fire and ice risks may be considered as similar events with the main difference between them in the risk assessment being related to their frequency of occurrence [13]. An icing event of a wind turbine near a highway is depicted in Figure 1.

Figure 1. Icing in a wind turbine near a highway.

A conservative rule suggested by Seifert states that the risk of ice-throw from an operational wind turbine has to be investigated for roads, paths or other objects of interest if the wind turbine is placed within the following distance from a road [3]:

$$1.5 \cdot (\text{rotor diameter} + \text{hub height}), \tag{1}$$

To determine the probability of adverse events in the affected area around the wind turbine, the following parameters should be considered [14]:

- Hub height
- Rotor diameter
- Rotor revolution under icing conditions
- Wind properties (distribution of wind speed and direction)
- Ice fragment properties

In [15], an icing model is proposed based on measurements in Germany. Some challenges were observed by this study for ice forecasting, such as the high sensitivity to parameters like liquid water content, droplets median diameter, wind, and temperature.

Ice properties/ice pieces are often classified into four scenarios based on a study by TÜV [14]:

- Rime ice, mass: 90 g (scenario A), and 240 g (scenario B);
- Clear ice, mass: 70 g (scenario C) and 180 g (scenario D).

Based on the TÜV study, which considered a typical wind turbine of 141 m hub height and 117 m rotor diameter, scenario B and D are identified as scenarios that can cause fatalities, and in cases of 90 g rime ice (Scenario A) and 70 g clear ice (Scenario C), slight injuries might occur [14].

In another study, rime ice was classified into five cases [16]: (1) 0 to 0.5 kg/m, (2) 0.5 to 0.9 kg/m, (3) 0.9 to 1.6 kg/m, (4) 1.6 to 2.8 kg/m and (5) 2.8 to 5.0 kg/m, for which observations from wind turbines in Quebec showed that the second class could be dangerous [17].

In the WECO (Wind Energy Production in Cold Climate) project [18], the frequency of ice fall events is estimated based on observations from a wind turbine by counting ice pieces around a test site in Switzerland, where 200 ice falls over three winters were measured.

3. Risk Assessment

Risk has a variety of definitions, see, e.g., the glossary of the Society for Risk Analysis (SRA) [19]. The International Risk Governance Council (IRGC) refers to risk as an uncertain and severe consequence of an event or activity [20]. Zio [21] presented a quantitative definition of risk taking into consideration accident scenarios, consequences, uncertainty, and body of knowledge. In this paper, the approach by JCSS [22] is basically applied; here, risk is defined considering an activity with n events, each with probabilities P_i and with potential consequences C_i. The risk R is defined as the sum of the products of the probabilities and the consequences [23]:

$$R = \sum_{i=1}^{n} P_i \cdot C_i \quad (2)$$

In Figure 2, the process of risk-based decision analysis in this case study is shown. First, it is necessary to consider the scenarios in an icing event to determine the influencing parameters, e.g., ice can be thrown away from the wind turbine when it is operating, or ice can be thrown away from the stopped or idling wind turbine. Furthermore, it has to be included that the wind turbine blade parts can be thrown away because of the partial or total failure of the blades. Next, the model is linked to a car passing on a highway near the wind turbine, and its properties, such as speed and number of passengers. Afterward, it is necessary to take into account possible ice detection and blade heating systems. Subsequently, risk scenarios are identified by the concept above for calculating risk, and in parallel, sensitive parameters in the model are identified. The calculated risks are compared with the accepted risks, and, using the ALARP (As Low As Reasonably Practicable) principle, risks can be considered to be acceptable or not. This process can be expanded using information from SHM (Structural Health Monitoring).

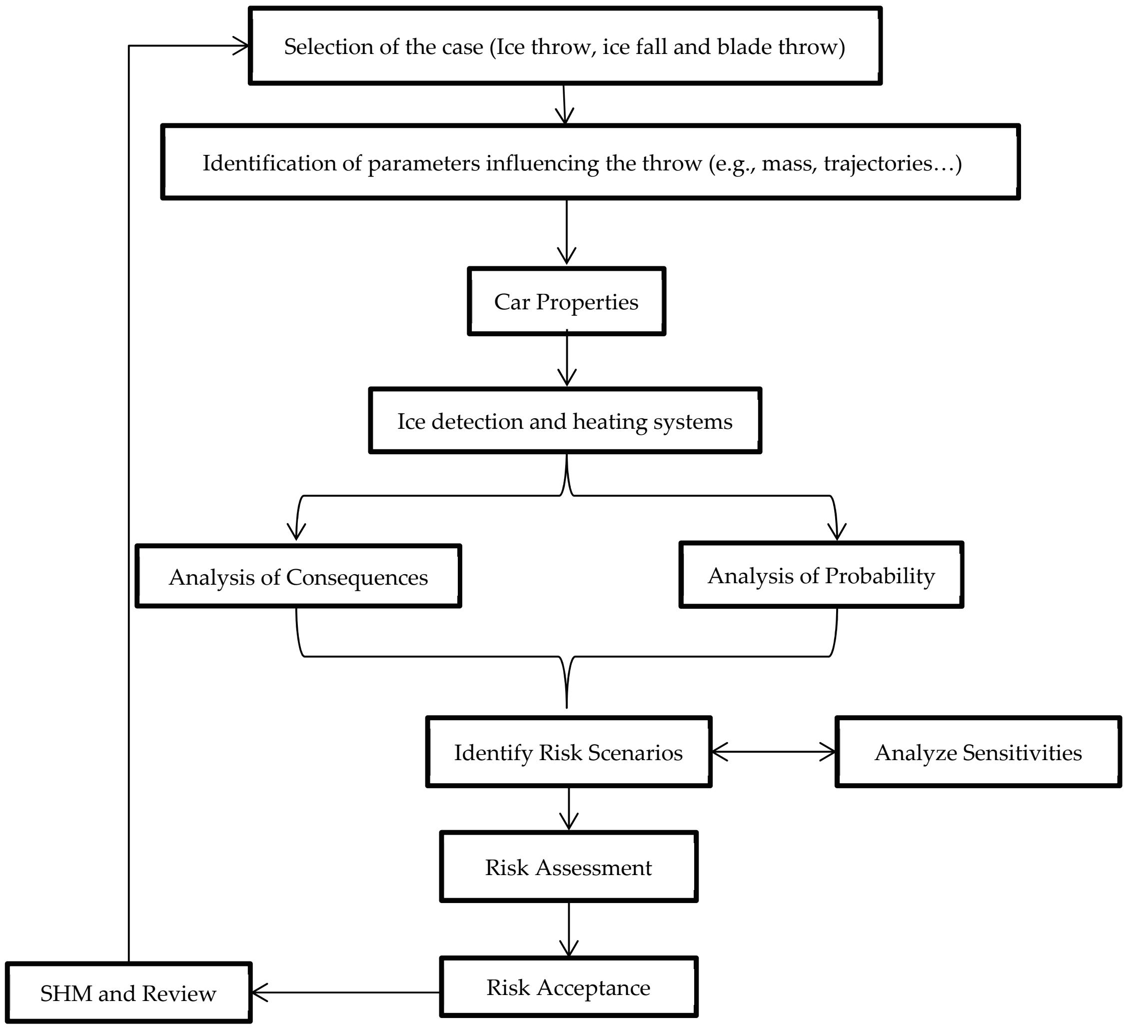


Figure 2. Risk-based decision analysis in this case study.

4. Case Study—Risk Assessment

An example of risk assessment for wind turbines close to highways in Denmark is presented in this section, accounting for the risks mentioned above from falling parts from wind turbine blades in conditions of total or partial damage, as well as ice thrown from wind turbine blades in the case of icing.

In [24], the occurrence of icing was divided into four conditions: heavy, moderate, light, and no icing; Denmark can be considered as a country with moderate icing conditions. It is presumed that a row of wind turbines is placed along a highway with a typical total height of 150 m and a spacing of 500 m along the road. Data is collected from wind turbines both in Denmark and overseas [25].

The following assumptions are made [25]:

- The average drag coefficient of ice pieces is assumed to be 0.6, the density of air is assumed at 1.3 kg/m^3 and that of ice is assumed to be 800 kg/m^3;
- Ice pieces need to be more than 2 cm in thickness in order to be thrown away without being split to smaller pieces on the way;
- The mean speed of vehicles is assumed to 88 km/h on Danish highways (based on Danish road statistics);

- 1.5 people will die in the case of hitting parts (based on Danish road statistics, on average 1 or 2 people usually sits in cars, the average is considered in this case study);
- The probability of being killed when an ice piece or blade part hits a car is assumed to be one, since only large objects are considered;
- The 10-min mean wind speeds, v_i, are assumed to discretized to 5, 10, 15, 20 and 25 m/s;
- The area of a vehicle is assumed to be 10 m², which is average for a passenger car;
- Ice pieces larger than 3 mm are used with an occurrence rate of 0.175 times per year (in Denmark). This modeling is subject to considerable uncertainty, since the ice pieces can become larger on the blades because of wind speed or during blade rotation.

In the following figures, models for each of the above three cases are derived based on the models described in [25], as well as ballistic calculations using the models in [26].

The probability (per km per year) that a car is hit by ice pieces, P_A, is estimated in icing conditions based on the following model [25]:

$$P_A = \sum_{v_i=5,10,15,20,25} [\frac{1}{V_0}\frac{1}{365 \cdot 24 \cdot 3600}\int_S P_Z(s,v_i)A(s)ds\ \frac{1}{D}]\ P(V=v_i) \quad (3)$$

where

V_0	speed of the vehicle
S	length of road section considered
$A(s)$	area of a car
D	spacing between the wind turbines placed along the highway
$P_Z(s,v_i)$	probability (per km per year) that an ice piece lands in the distance s from the wind turbine if the mean wind speed is v_i. A uniform probability distribution is assumed within the throwing distance R_i at the mean wind speed v_i. Furthermore, using a uniform directional distribution of the wind speed, $P_Z(s,v_i)$ is determined by

$$P_Z(s,v_i) = v\frac{1}{R_i} \quad (4)$$

v	number of icing events per year
$P(V=v_i)$	probability that the mean wind speed at hub height in connection with icing is equal to v_i.

The risk, here introduced as the expected number of persons, R_A, per year per kilometer that will be killed by a wind turbine, is estimated by

$$R_A = 1.5\ P_A\ P_D \quad (5)$$

where it is conservatively assumed that the probability of being killed when an ice piece or blade part hits a vehicle is $P_D = 1$.

A similar equation is presented by [25] for the last scenario.

Figure 3 shows R_A for ice throw from an operational wind turbine as a function of distance (d) to a road (in m) with the tower height of 100 m and the total height of 150 m. Approximately,

$$R_{A,TO} = 5 \cdot 10^{-9}e^{-0.050\,d} \quad (6)$$

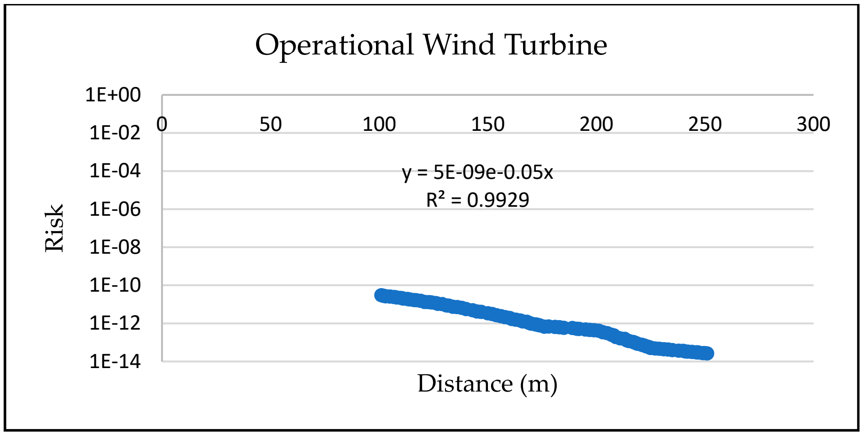


Figure 3. The risk $R_{A,TO}$ per year per kilometer due to icing events as a function of distance to the road for wind turbines in parked position, from [25].

Figure 4 illustrates R_A for an idling (parked) wind turbine as a function of distance (d) to a road (in m) with a tower height of 100 m and a total height of 150 m. Approximately

$$R_{A,TI} = 2 \cdot 10^{-9} e^{-0.068\, d} \tag{7}$$

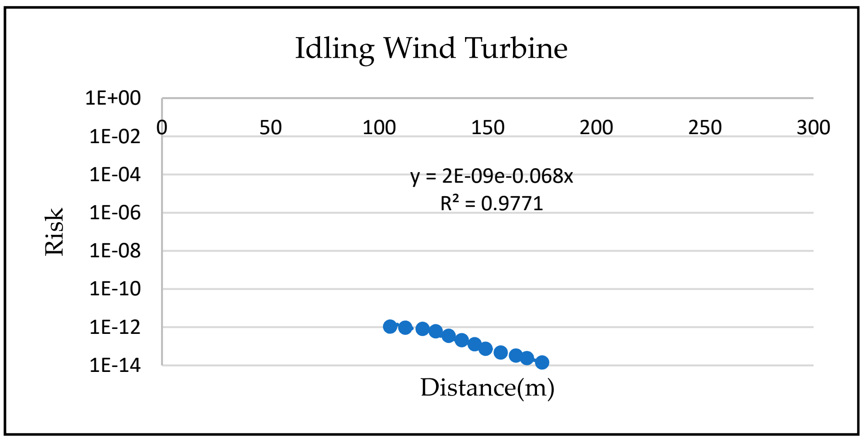


Figure 4. The risk $R_{A,TI}$ per year per kilometer due to icing events as function of distance to road for wind turbines in parked position, from [25].

Figure 5 shows R_A due to total or partial failure/collapse of a wind turbine as a function of distance (d) to a road (in m), with a tower height of 100 m and a total height of 150 m. Approximately

$$R_{A,BT} = 5 \cdot 10^{-12} e^{-0.009\, d} \tag{8}$$

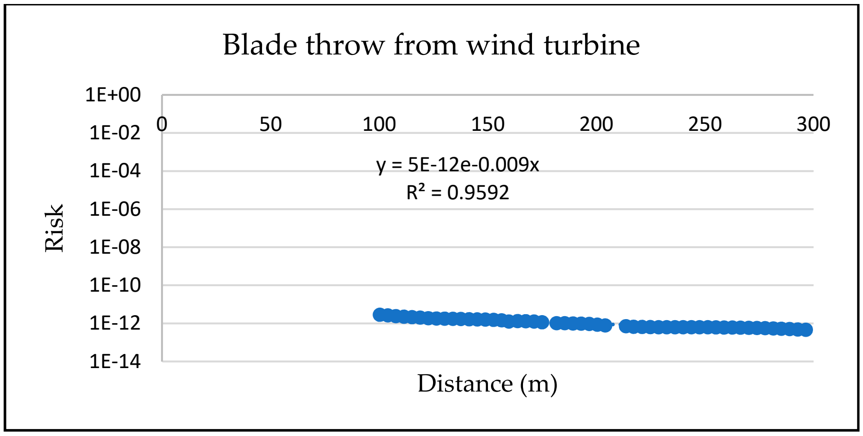


Figure 5. The risk $R_{A,BT}$ per year per kilometer as function of distance to the road for blade parts thrown away from the wind turbine, from [25].

Based on these probabilistic models, the next section presents the basis for decision making and for estimating the Value of Action (VoA). The decision problem that will be considered is whether a heating system should be implemented, assuming that an ice detection system has already been established. This is done for different distances between the road and the row of wind turbines, and can be used as a basis for determining the acceptable distance to the highway using an ice detection system, and next, whether a heating system should be installed.

5. Value of Action Analysis

The concept of Value of Action (VoA) was introduced by Thöns and Kapoor, see [27,28], and constitutes a further development of the Value of Information (VoI) analysis from Raiffa and Schlaifer in [29] and its application in engineering, see e.g., [30–33]. The VoI is defined as the expected utilities gained by obtained (conditional) or predicted (expected) information, including their costs and consequences, while the VoA is different in that the expected utility is gained only on the basis of predicted or implemented actions. The quantification of VoA can be calculated as the difference between the expected utilities of the predicted action and a system state analysis. Based on quantification of VoA, it is possible to provide a decision basis as to whether to implement an action or not. To figure out whether it is beneficial to install the heating systems on the wind turbine blades following the risk assessment results above, a VoA analysis was carried out.

As discussed above, when it is planned to locate a wind turbine location near to highways, one of the interests from owners' perspectives is in reducing risk owing to falling parts from wind turbines in the event of total or partial damage, and from ice thrown from the wind turbines in the case of icing, as shown in Figure 6. The general objective is to ensure normal and steady energy generation, which can be achieved with additional investments in SHM techniques, such as implementing an ice detection system and a blade heating system. Initial investments in SHM techniques can increase the cost of the wind turbine. However, the shutdown of the wind turbine will result in loss of energy production, thus reducing the income of the owner or reputation loss. The major constraints regarding wind turbines close to highways are that falling parts from wind turbines may lead to a traffic accident, damage to cars, and even to the injury or fatality of people. To minimize the overall cost of wind turbine management, it is essential to decide whether to implement an ice detection system, and when to turn on the blade heating system.

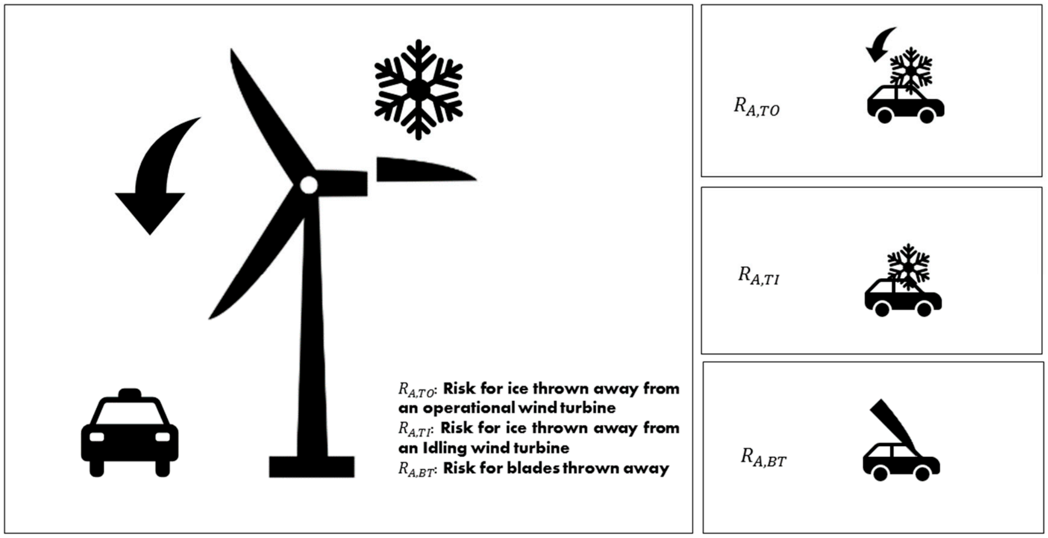


Figure 6. Illustration of risk scenarios of wind turbines close to highways.

A situation is considered in which the risks due to parts being thrown from failed/collapsed wind turbine blades are assumed to be difficult to reduce; therefore, only the reduction of risk due to icing can be reduced. It is assumed that an ice detection system has already been installed. The question is: is it worthwhile installing a heating system in the blades? When ice is detected, should the wind turbine be shut down directly, or should the ice heating system be turned on? The application of the value of action analysis with regard to the installation of heating systems in wind turbine blades in cases where an ice detection system has already been installed aims at answering the question as to whether it is of value putting a heating system on the blades.

The illustration of the full decision tree is shown in Figure 7. The decision choice is h_0, no heating system, or h_1, with the heating system. By installing the heating, there would be a heating system cost C_H. The decision choice of action will be a_0, do nothing, a_1, stop operating, and a_2, turn on the heating system; moreover, if operation stops, there will be a production loss C_L. Given the monitoring strategy e_1, with ice detection system, data of the ice mass will be collected, and when the mass of ice is over a certain threshold, a warning will be given. Two monitoring outcomes will be provided: z_1, indicating ice, and z_2, not indicating ice. For different choices of actions based on the monitoring outcomes, the wind turbine could be under different states; for example, θ_1, safe state, θ_2, at risk of blades being thrown away, θ_3, at risk of ice being thrown away when the wind turbine is non-operational, and θ_4, at risk of ice being thrown away when the wind turbine is operating. The owners' decisions with respect to actions regarding the wind turbine are based on the indication of ice detection, and the consequences, benefits, and costs. The consequences of parts falling from wind turbines may include traffic accidents, damage of cars, and even the injury or fatality of people, C_F. The most important consequences related to whether a heating system is used or not are those which affect the risk of a person in a vehicle potentially being killed due to falling parts or ice pieces from a wind turbine. If a heating system has not been installed, downtimes can last several days or even weeks due to persistent ice on the blades [34]. Therefore, the production loss C_L can range from hundreds to thousands of Euro. If a heating system is installed, the wind turbine can continue working with benefits B_L per year.

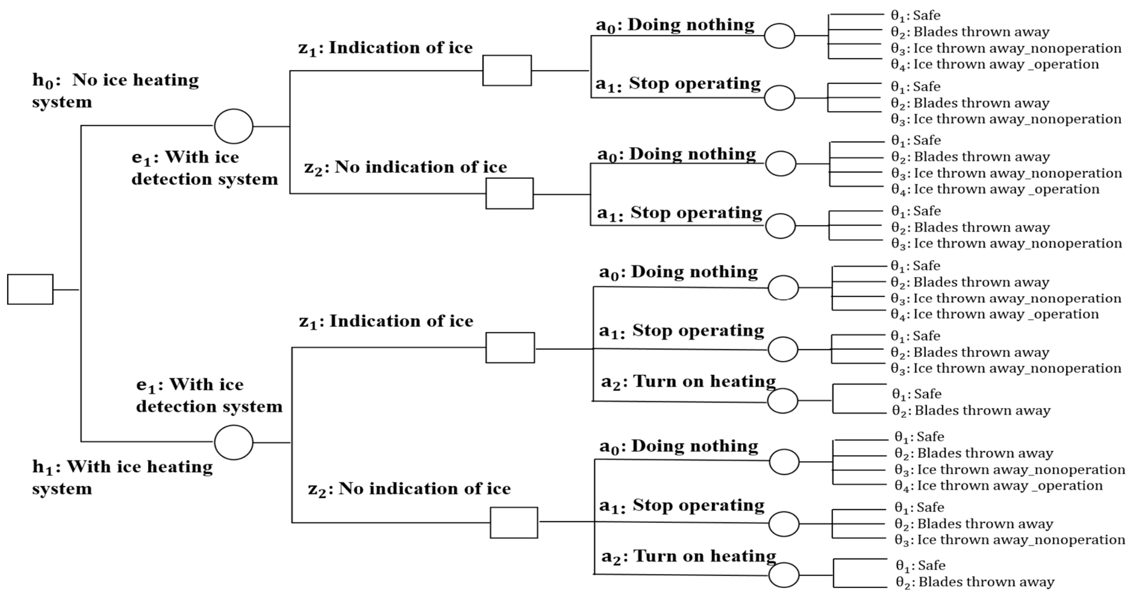


Figure 7. Illustration of the full decision tree for risk assessment of the value of action in the framework of wind turbines close to highways.

It is assumed that the ice detection system provides precise and accurate information. Therefore, if equipped with an ice heating system, when ice is detected, the choice of action could be to a_2, turn on the heating system. The wind turbine will continue working when the heating system is turned on, but there will be a cost for installation of the heating system C_H. The ice will melt after turning on the heating system, and the only risk left in this case will be the risk of blades being thrown away $R_{A,BT}$. If no ice heating system has been installed, when ice is detected, the choice of action could be a_1, stop operating; there will be a production loss during the downtime, but the risk of ice being thrown away under operation condition $R_{A,TO}$ will be reduced. However, there is still the risk of ice being thrown away under no operation condition $R_{A,TI}$, as well as the risk of blades being thrown away $R_{A,BT}$. If the ice detection system did not indicate ice, whether a heating system has been installed or not, the choice of action will be a_0, do nothing. An illustration of the choice of decision action scenario for wind turbines in icing events close to highways is shown in Figure 8.

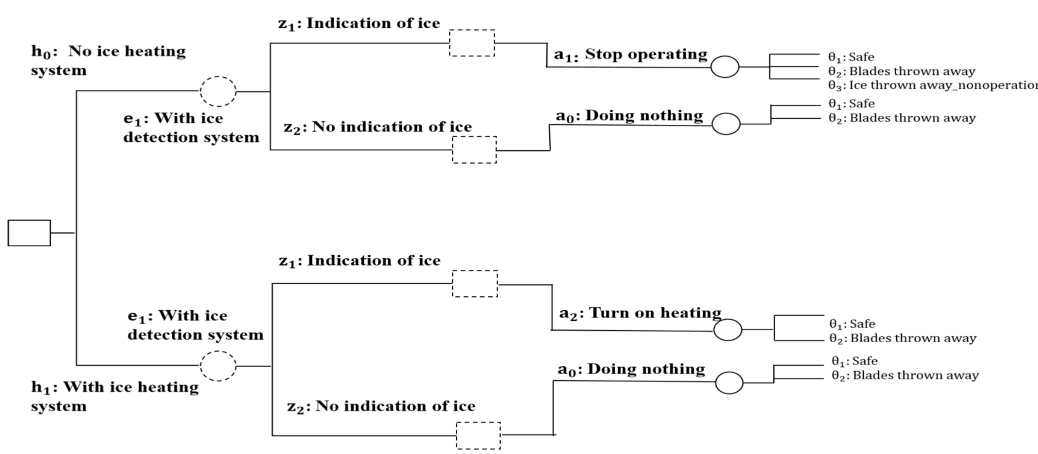


Figure 8. Illustration of the modeled decision scenario and utilized models. A dashed decision node (rectangle) stands for the use of a decision rule and a dashed chance node (circle) for the use of perfect information provided by the ice detection system.

Following the choice of decision scenario in Figure 9, when the ice detection system detects the ice, the choice of action when there is no ice heating system will be to stop operating, which leads to a utility u_{h_0}. The choice of action if the ice heating system is installed will be to turn on the heating, which results a utility u_{h_1}; the value of installing the heating system will be calculated as:

$$VoA = u_{h_1} - u_{h_0} \tag{9}$$

It is assumed that when the ice heating system is turned on, the ice will melt, and if the ice is thrown away, the risks under both operation and non-operation will be significantly reduced, leaving only the risk of blades thrown away $R_{A,BT}$ remaining, so that, considering the service life T_{SL}, the cost of the heating system C_H, the cost of possible fatality C_F and the benefits of production B_L, the spacing between wind turbines placed along a highway D, and discounting factor γ, the utility of the heating system u_{h_1} can be obtained by adding the contributions from each year T:

$$u_{h_1} = \sum_{T=1}^{T_{SL}} \left(1 - P_{A,BT} \cdot \Delta T_{BT}\right) D\, B_L \frac{1}{(1+\gamma)^T} - \sum_{T=1}^{T_{SL}} \left(R_{A,BT}\, D\, C_F + P_{A,BT}\, D\, B_L\, \Delta T_{BT}\right) \frac{1}{(1+\gamma)^T} - C_H \tag{10}$$

Here, the ratio of downtime per year in which the wind turbine will be stopped ΔT_{BT} for blade repair if blade has been thrown away is assumed.

When there is no ice heating system, and the wind turbine stops operating, given the ice detection warning, the risk of consequences of ice being thrown away under operation will be reduced, and the remaining risk will be of ice being thrown away under non-operation $R_{A,TI}$ and the risk of blades being thrown away $R_{A,BT}$. Considering the production loss C_L during this period, the number of icings per year ν, and the ratio of down time per year due to icing ΔT_{ice}, the utility of stop operation u_{h_0} will be:

$$\begin{aligned} u_{h_0} = &\sum_{T=1}^{T_{SL}} \left(1 - P_{A,TI}\, \Delta T_{ice} - P_{A,BT}\, \Delta T_{BT}\right) D\, B_L \frac{1}{(1+\gamma)^T} \\ &- \sum_{T=1}^{T_{SL}} \left(\left(R_{A,TI} + R_{A,BT}\right) D\ C_F + P_{A,BT}\, D\, B_L\, \Delta T_{BT} + \nu\, C_L\, \Delta T_{ice}\right) \frac{1}{(1+\gamma)^T} \end{aligned} \tag{11}$$

The estimate of the benefits of production B_L ($C_L = B_L$) per year is based on [35]:

$$B_L = P\ A\ f\ (S + a)\, 365 \cdot 24 \tag{12}$$

where P is the rated power of the machine MW, A is the turbine availability factor, f is the capacity factor, S is the sales price of electricity kW/h and a is the feed-in-tariff.

6. Case Study—Value of Action Analysis

The summary of the probability (per km) that a car will be hit by ice or a blade thrown away, as well as the costs and benefits analysis parameters, are shown in Tables 1 and 2, respectively. Table 2 is from [35]; the power of the wind turbine is 3.6 MW, a capacity factor of 0.45 is assumed, turbine availability factor is 0.95, feed-in-tariff is €0.12/kWh, with a rough electricity price of €0.3/kWh, so that there will be $5.66 \cdot 10^6$ Euro per year of production benefit. The total costs of the wind turbine C_I is €$2 \cdot 10^7$. The discounting factor γ is 0.05. The cost of heating C_H is assumed to be on the order of 5% of the total costs of the wind turbine, considering the equipment costs, installation costs and energy consumption costs [34], which are assumed to be 10^6 Euro. The fatality costs of 1.5 person in a vehicle being killed are assumed to be $3 \cdot 10^6$ Euro, based on [36].

Table 1. Summary of probability (per km) that a car will be hit by ice or blade thrown away.

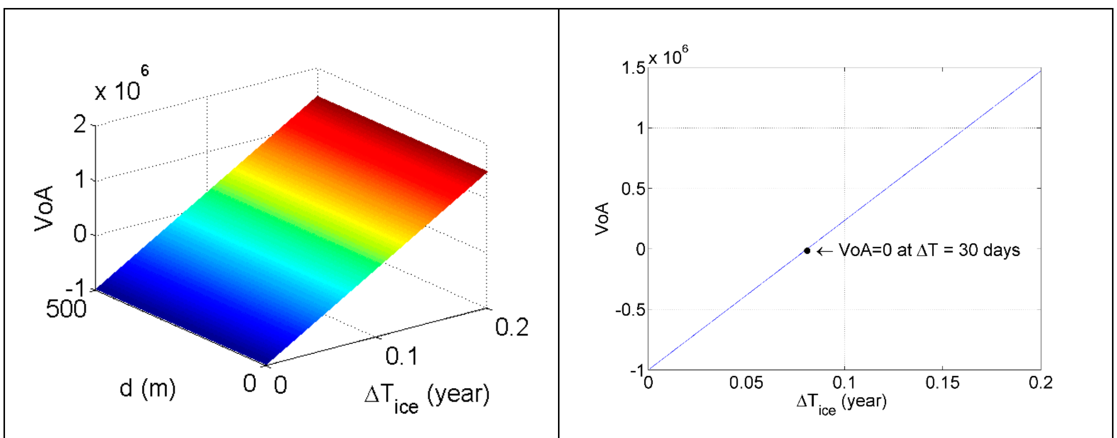
Remark	Parameter	Equation
The probability (per km) that a car is hit by ice pieces due to ice thrown from an operational wind turbine as a function of distance d to a highway	$P_{A,TO}$	$P_{A,TO} = 3.33 \cdot 10^{-9}\, e^{-0.005\, d}$
The probability (per km) that a car is hit by ice pieces due to ice thrown from an idling wind turbine as a function of distance d to a highway	$P_{A,TI}$	$P_{A,TI} = 1.33 \cdot 10^{-9}\, e^{-0.068\, d}$

The probability (per km) that a car is hit by total or partial failure/collapse of a wind turbine blade as a function of distance d to a highway	$P_{A,BT}$	$P_{A,BT} = 3.33 \cdot 10^{-12} e^{-0.009d}$

Table 2. Summary of costs and benefits analysis parameters.

Parameter and Remark	Value	Parameter and Remark	Value
C_F Cost of fatality for 1.5 person	€3 · 10^6	P Power of wind turbine	3.6 MW
C_H Cost of the heating system	€1· 10^6	A Turbine availability factor	0.95
γ Discounting factor	0.05	f Capacity availability factor	0.45
T_{SL} service life	20 years	S Electricity price: Euro per-kWh	€0.3/kWh
ν Number of icings per year	0.175	a feed-in-tariff	€0.12/kWh
D spacing between wind turbines	500 m	ΔT_{BT} down time due to blade repair if blade thrown away	1 year

Following Equations (8)–(12) and Tables 1 and 2, the computational results of VoA are shown in Figure 10. When VoA < 0, it means that it is not worthwhile installing the heating system. When VoA > 0, it is recommended that the heating system be installed. Based on Figure 9a, the VoA will increase with the increase in downtime, which means that it will be more beneficial to install the heating system if the downtime due to icing on the blades is longer. However, the impact of the distance of the wind turbine from a highway d is comparably small, which can be explained by the low variation of risk model independence of distance in Section 5. The critical downtime in the case study when VoA = 0 is at ΔT = 30 days, as shown in Figure 9b. Therefore, if the down time due to ice on the blades is less than 30 days, it is beneficial to just shut down the wind turbine instead of installing a heating system. If the downtime is longer than 30 days, it is worthwhile installing the ice heating system on the blades.



(**a**) (**b**)

Figure 9. Computational results of VoA in dependence of percentage of downtime per year due to icing ΔT and distance of wind turbine to a highway d (**a**) and VoA with critical down time point when VoA = 0 (**b**).

To investigate how the model factors, for example, the power of the wind turbine P, the electricity price S, the cost of the heating system C_H, the number of icings per year ν, and the influence the choice of action, a parametric analysis is carried out. The results are shown in Figure 10. If the down time is the same, based on Figure 10a, the higher the power of wind turbine P is, the higher the VoA will be, which means that it will be more beneficial to install a heating system on larger wind turbines. The same trend goes for the electricity sales price S in Figure 10b; it is more beneficial to install the heating system when the electricity sales price is high. This also applies to the number of icings per year, ν, in Figure 10c; it is more worthwhile installing a heating system when icing per year is greater. Meanwhile, in Figure 10d, the higher the cost of the heating system, C_H, is, the smaller the benefit of VoA will be.

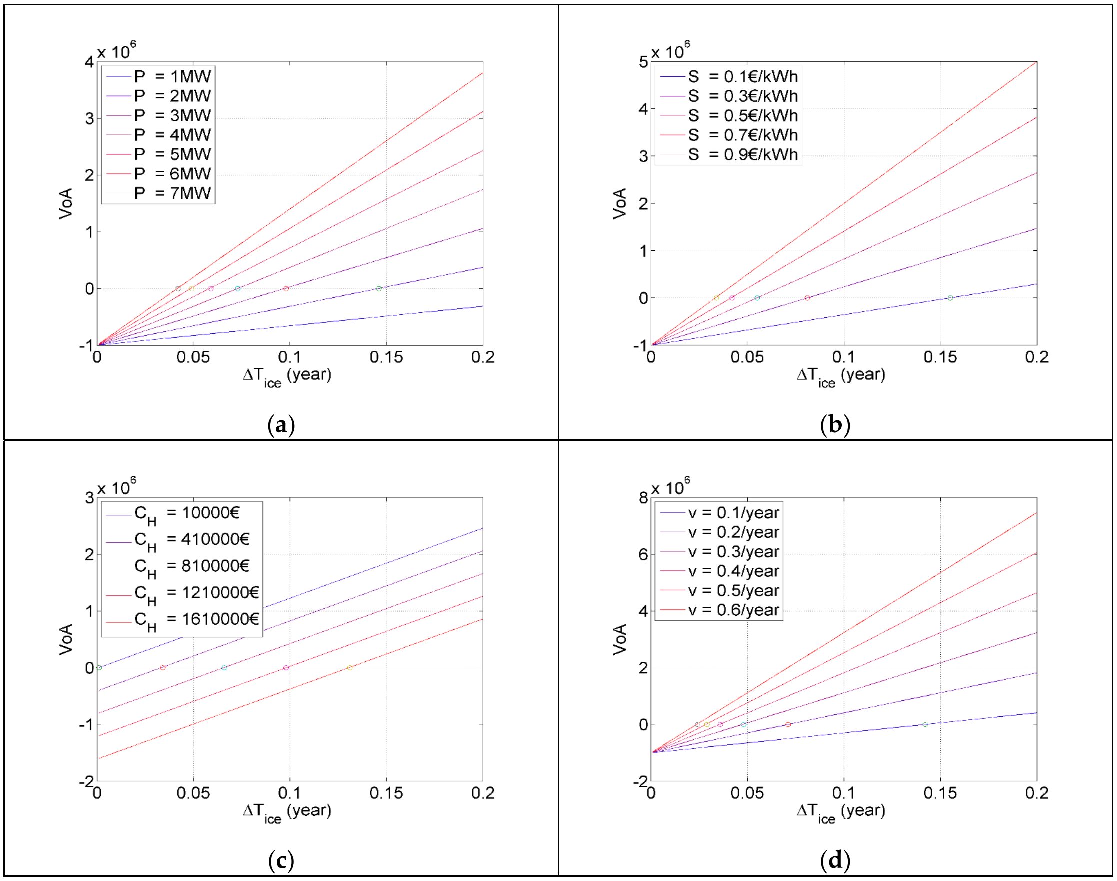


Figure 10. Parametric analysis regarding Value of Action (VoA) with respect to the power of the wind turbine (**a**), electricity price (**b**), cost of the heating system (**c**), and number of icings per year (**d**).

7. Conclusions

A probabilistic model and a risk assessment model are described for the assessing the consequences related to icing and the associated risk of ice pieces being thrown away from a wind turbine and potentially hitting a vehicle on a road near the wind turbine. In addition, the risk from blades and parts of blades being thrown away from a wind turbine in case of blade failures also needs to be accounted in the risk assessment. This paper considers the application of Bayesian decision analysis for decision-making with respect to the installation of heating systems in wind turbine blades in cases where ice detection systems have already been installed in order to allow wind turbines to be placed close to highways.

Furthermore, the application of Value of Action (VoA) is presented for the decision problem related to installation of a heating system in situations where an ice detection system is already available. Decision trees for the VoA are developed, together with the corresponding utility functions, making it possible to quantify whether it is valuable to put a heating system on the blades in addition to the ice detection systems. This is especially interesting in countries with limited space for placing wind turbines. The model makes it possible to investigate, e.g., whether higher power production can be obtained with less downtime when a heating system is installed.

An illustrative case study is considered, presenting the details of the risk modelling and the Value of Action. Risk is calculated as a function of distance from the wind turbines to the highways. The risk owing to ice throw in operation mode is slightly higher than in the parked position. The spacing between the wind turbines and the height of them did not have a major impact.

The case study with regard to quantification of the Value of Action on wind turbines close to highways with respect to icing events provides a general decision basis for deciding whether or not to install ice heating systems given the condition that ice detection systems have already been installed. The results show that the decision result is highly dependent on the duration of downtime due to ice on the blades.

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CHAPTER 8. SUMMARY, CONCLUSION AND OUTLOOK

8.1. SUMMARY

This thesis contains a methodological summary on SHM, VoI, Bayesian decision theory, detection theory, reliability analysis, structural integrity management and utility modelling for deteriorated structures in chapter 2. Conceptual and applied research for the quantification of the value of monitoring information based on a methodological basis with integration of probabilistic structural models, SHM models, cost, and benefit models as well as consequence models have been further developed in chapter 3 to 7 (Paper 1 to 5). Chapter 3 to 7 follow the methodologies of chapter 2 but with more details and different emphasizing aspects:

- The pre-posterior decision analysis is addressed in chapter 3 (Paper 1), the posterior decision analysis is illustrated in chapter 4 (Paper 2).
- The conditional value of sample information analysis is presented in Chapter 5 (Paper 3) and 6 (Paper 4). The value of action analysis is developed in chapter 7 (Paper 5).
- The discussions of influence parameters on the probability of damage and influence of structural performance parameters are addressed in chapter 3 (Paper 1), the consideration of the influence of utility modelling parameters is discussed in chapter 4 (Paper 2) and 6 (Paper 4).
- The Bayesian updating with observed events is described in chapter 5 and the Bayesian updating of observed stochastic variables is presented in chapter 6 (Paper 4).

With this thesis a framework for the determination of optimal monitoring strategies is established. This framework facilitates a consistent and comprehensive formulation of quantifying the value of SHM information encompassing:

- Development of an approach to account for damage detection information by building upon the approaches of NDT/NDE reliability.

- Provision the basis for reliability modelling of damage detection information encompassing precision of sensors, amplifiers, environmental noise, and the damage detection algorithm precision.

- Facilitation of information value by risk reduction related to structure failure, expected cost reduction for the structural integrity management and increased benefit generation by service life extension.

- The usage of information within a decision scenario and the choice of an action supported with the information.

The proposed framework has been applied in several case studies. Through quantification of the value of monitoring information for bridges and wind turbines, it has been found that the value of information-based decision can be an efficient tool to develop an SHM system design before implementation as well as optimal service life integrity management for both new and existing structures. These achievements contribute directly to the objectives of COST Action TU1402 (https://www.cost-tu1402.eu/) and INFRASTAR (https://infrastar.eu/) projects with aim to support the reliability, functionality, and sustainability of structures.

8.2. CONCLUSION

8.2.1. SPECIFIC CONCLUSIONS OF THE CONCEPTUAL RESEARCH

The extended methodological summary (Chapter 2) constitutes a comprehensive theoretical and mathematical framework to integrate research VoI theory with the domains of structural performance, utility and SHM. Furthermore, the model basis facilitates to utilize the additional SHM information for decision support. The individual conclusions for conceptual research are:

- A method is developed for identifying the structural and Damage Detection System (DDS) affecting parameters (Chapter 3/ Paper 1) which facilitates comprehensive guidance to the design of DDS, e.g., sensor number and sensor locations, to support decisions on DDS implementation according to degradation mechanisms and to determine the optimal DDS information acquirement time.

- A detailed, full probabilistic DDS performance model (Chapter 3/ Paper 1) is established based on DDS attributes and structural system deterioration characteristics. This probabilistic performance model takes basis in a specific damage detection algorithm namely stochastic subspace damage detection.

- The developed concepts for utility-based (Chapter 4/ Paper 2) and VoI-based decision algorithms can be applied to provide a decision basis for the whole service life management of the structure for minimizing the structural risk and costs.

- The approach for reliability updating from the utilization of obtained monitoring data for bridges and wind turbines (Chapter 4, 5 and 6/ Paper 2, 3, 4) facilitates to transfer SHM data into knowledge that contributes to the structural integrity management and by more accurate prediction of the system states.

- The interpretation of the parametric analysis of cost and benefit models (Chapter 5, 6 and 7/ Paper 3, 4, 5) can be used to account for different risk attitudes and opinions of decision makers towards the operation and maintenance of structures.

8.2.2. SPECIFIC CONCLUSIONS OF THE APPLIED RESEARCH

The procedure of how the value of SHM information can be utilized before implementation has been shown, to 1) help design the SHM system, e.g. sensor location and numbers, 2) support the decision on choosing the proper SHM technique, 3) contribute to monitoring planning, e.g. monitoring times and durations, 4) support the maintenance planning regarding the number, points in time and amount of maintenance during the service life and 5) to support the optimal decision for service life extension. The conclusions from each of the case studies are included:

- The case study of designing a damage detection system (DDS) for the deteriorating truss bridge girder based on value of information (VoI) (Paper 1) shows that
  a) compared to the repairing situation with no monitoring, implementing DDS before repairing is more cost and risk-reduction efficient.
  b) the optimal DDS employment year is sensitive to DDS sensor layout and structural deterioration state.
  c) the choices of sensor numbers are not following “the more the better”.
  d) the choices of sensor locations are related to the structural system degradation and failure scenarios.
  e) the optimal sensor types should be those with lowest measurement noise and Type I error.

- The case study of investigating long-term and short-term monitoring duration based on the Great Belt bridge in Denmark (Chapter 4/ Paper 2) illustrates that
  a) with an appropriate short-term monitoring strategy, higher utilities can be achieved during life cycle integrity management, and thereby is preferred to long term monitoring.
  b) the decision maker 's risk attitude is the key factor affecting the choices of the optimal monitoring option and service life extension.

- With the case study on quantification of the conditional value of SHM data for the fatigue safety evaluation of the 60-year-old viaduct Crêt de l’Anneau Viaduct in Switzerland (Chapter 5/ Paper 3), it is found that the fatigue damage and failure probability is low complying with acceptance criteria. The expected value of the saved cost and reduced risks has been quantified underlining the effectiveness of well-engineered SHM systems and information.

- In Chapter 6 (Paper 4), the usage of structural (strain) and environmental (SCADA) measurement data in the context of maintenance optimization of offshore wind turbine monopile support structures is analyzed. It is discovered that the most beneficial strategy is utilizing stain and wind monitoring combined. With only wind data usage, it is still more beneficial than without any monitoring. The main reason lies here in the fact that measurement information circumvents the high model uncertainties associated to the fatigue design of wind turbines.

- The case study on quantification of the value of action on wind turbines near highways considering icing incidents (Chapter 7/ Paper 5) indicates that the decision on whether to place a blade heating device if ice detection information is already available, is strongly depending on the period of downtime due to ice on the blades. If the downtime duration is over 30 days per year, the ice heating device is worth to be added, otherwise it is not.

8.3. OUTLOOK

The thesis has demonstrated the applicability of VoI for decision making in five case studies. It has huge potential in supporting SHM design before implementation as well as the development of efficient monitoring strategies and optimal lifecycle integrity management plans for both new and existing structures.

However, through simplifying the “real” problem with several assumptions, there are still some topics remaining worthy for further research. Among these are:

- The implementation of Artificial Intelligence and Machine Learning in the quantification of the VoI, see in [145], [146] and [147].

- Further development of a generic program (computational tool) for VoI-based decision analysis, with build-in modules of various system structure models, damage models, detection models and procedures for monitoring, inspections, and repairs as well as cost and benefit models. The input should be defining the decision scenarios with all the related parameters. The output of the program should empower the decision maker to make the optimal decision based on the presented VoI results and make it clear why this is the optimal decision.

- Further standardization of the VoI-based decision, building upon the COST Action TU1402 guidelines[17]. The standardization activities should lead to a further penetration of other scientific and standardization organizations to stimulate industrial application.

- The computational techniques in this thesis are based on applying the decision tree formulation and Monte Carlo Simulation. The current implementations of Bayesian updating are computationally demanding. For very large system with sequential Bayesian updating in every time step, the computational problem will be a challenge. Therefore, simplifications of computation need to be investigated.

- In the thesis, the cost and benefit functions have been normalized and estimated from the literature. In practice, the costs and benefits are most of time confidential, which makes them hard to obtain. Further research could work on formulating generic cost models where the users can fill in their own cost data. The generic models should be as close as possible to the industrial cost models. More research into application-specific cost and benefit functions as well as probabilistic cost and benefit modelling need to be carried out.

- The assumption of the decision makers' willingness to take risks, which is presented by the target probability threshold in the thesis, may be subject to change. The decision maker in practice may have a different criterion. Further decision scenarios should be in alignment with industrial and societal decision processes with consideration of legal restrictions, social governance, and regulations.

- Application of VoI-based decision analysis to quantify and improve the resilience and sustainability of interlinked systems containing infrastructures, social governance, regulation, and hazard subsystems with consideration of economy and environment, e.g. [143] and [144]. Further development of optimized decision strategies on design and governance of interlinked social systems.

[17] https://www.cost-tu1402.eu/action/deliverables/guidelines .

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