Toward Optimal Maintenance Planning of Existing Structures Using Monitoring Data

PhD Thesis

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EMPTY version

Sigma Clermont, February 2020

Abstract

THIS IS MY ABSTRACT

Preface

Please write all your preface text here. If you do so, don't forget to thank your supervisor, other committee members, your family, colleagues etc. etc.

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Introduction

Introduction

Maintenance of structures is considered as a set of practices performed to ensure that the structure fulfills its duties and provides an adequate level of safety and serviceability during its service life. A proper maintenance planning can prevent unexpected failures to happen on a structure. Therefore, it can be seen as a tool to ensure the return of investment for the owners of structures after an expected period of time. One should keep it in mind that the maintenance cost of civil structures (e.g. bridges, wind turbines, power plants, railways, etc.) is relatively high. Hence, the maintenance optimization of civil structures has gained more attention during the past decades since the number of aging structures is increasing while the budget for the maintenance is limited.

To understand well the importance of the maintenance planning for a given structure let's say a bridge, one can study the consequences of different failures on the structure. In the small level, failures on the bridges can cause stopping the traffic for carrying out the emergency repair actions. This can bring loss of capital and reputation for the bridge owner in one hand and wasting the time and inconvenience for the drivers. However, in the bigger scale, the failure can lead to catastrophic damages including collapse of the structure, loss of lives, and environmental and social damages. Therefore, a proper maintenance planning is very crucial for the owners of structures since it can prevent the future unexpected adverse events to occur on the structure.

Before preparing a maintenance strategy for structures, it is important to identify the failure modes of structures since each mode might need a particular maintenance actions to be able to remove or lessen the cause of failure. Statistical information form the past failures of metallic structures show that the most frequent failure mode respectively are: scour of pies/foundations, buckling, fatigue, impact, and fracture. Although, scour is an important failure mode for all bridges, fatigue and fracture taken in combinations appear to be the most critical failure mode for metallic bridges. It is obvious that a proper maintenance planning should involve different actions to mitigate the failure occurrence by any failure mode. However, failure modes that are more likely to happen will take higher attention within the maintenance framework. Therefore, one can say that maintenance against fatigue and fracture has the priority in metallic structure that work under cyclic loading.

Fatigue is one of the main degradation processes on metallic structures that are working under cyclic loading (e.g. traffic and environmental loading). Fatigue process can start with the crack initiation which can be caused by many drivers such as material imperfection, cyclic loading, local stress concentration, corrosion, etc. The initial crack will propagate under cyclic loading even if the resulting stress range on the crack region is less than the yielding stress of the material. This can deteriorate the structure and causes failure if the crack has not been detected before reaching its critical length. The crack length remains very small for a major part of the fatigue life of a structure and the crack propagation time from a detectable crack length to a critical length that causes failure is relatively short compared to the fatigue life. Therefore, it is really challenging to detect a fatigue crack before it puts the structure through a tragic failures. Another challenge in fatigue process is that accurately predicting the fatigue failure is difficult since it is associated with huge level of uncertainty. The uncertainty is related to different factors which are influencing the fatigue resistance such as fatigue loading, stress calculation, material properties, fatigue resistance data, fatigue accumulation crack growth model, weld geometry, etc. **SHM!** (**SHM!**) is a good practice that helps to reduce the uncertainty involved in fatigue resistance calculations.

One important factor that makes the existing structures different than the newly constructed ones is that they have already experienced the real life loading conditions. **SHM!** can be employed on existing structures to evaluate the state of the entire structure. **SHM!** is a process focusing on observing, measuring, recording, and processing of the actual data related to the structure in real time. It provides valuable information about the current status of a structure for the owners of the structures and decision makers. This information can be used to update the performance indicators (reliability and risk) or lifetime distributions (availability and hazard) for a given structure to perform a better maintenance planning. For instance, a reliability-based maintenance tries to keep the reliability level of the structure higher than a given threshold without considering the consequences of the failure. However, a risk-based maintenance take them into the consideration.

Considering the maintenance against fatigue, time-dependent reliability index can provide a good indicator for decision makers. The reason for choosing this indicator is that fatigue is a degradation process involving stochastic loadings and random inputs in one hand. In the other hand, a time-dependent indicator provides a better criterion for decision making process since one can estimate when in time the failure will happen. Performing the time-dependent reliability analysis is basically different than time-independent one since the objective is to find the cumulative failure probability for a given period of time. Therefore, finding this failure probability is quiet challenging for problems with non-monotonic and computationally expensive performance functions. As said before, monitoring information can be used to have an updated indicator for a better maintenance optimization.

The indicator chosen from the performance indicators or lifetime distributions can be employed as a decision variable for the optimization of the maintenance allocation. In general, minimizing the cost is the main objective of the optimal maintenance planning. Therefore the optimization model tries to search among available maintenance actions and intervention times throughout the structural service life to find the solutions with minimum costs of maintenance within the feasible domain which is defined by predetermined constraints (e.g. time between interventions, reliability threshold, maintenance types and actions, etc.). Preparing an appropriate cost model and constraints for the optimization is a very important task in this step.

According to what has been discussed shortly, it can easily be realized that improving methods and strategies in optimal maintenance planning of civil structures is a very complicated task since it covers a very big range of topics and involves many challenges coming from different sources. Therefore, to improve the current practices in structural maintenance planning it is necessary to address the available challenges within the topics explained before such as application of **SHM!**, degradation models, time-dependent risk and reliability methods, optimization models, consequence modeling, etc. In the next part, the objectives and contributions of this research towards optimal maintenance planning of structures is described.

Objective and scope of the research

The overall goal of this study is to address some of the current challenges available in the domain of optimal maintenance planning of existing structures against fatigue with the help of **SHM!** data. Considering a reliability-based maintenance optimization our objective is to address challenges related to a: fatigue reliability assessment, b: application of monitoring information, and c: allocation and optimization of maintenance strategies. Addressing these challenges can define different steps of this study. Figure 1.1 shows how different steps can be connected to each other in order to perform maintenance planning against fatigue by using monitoring data.

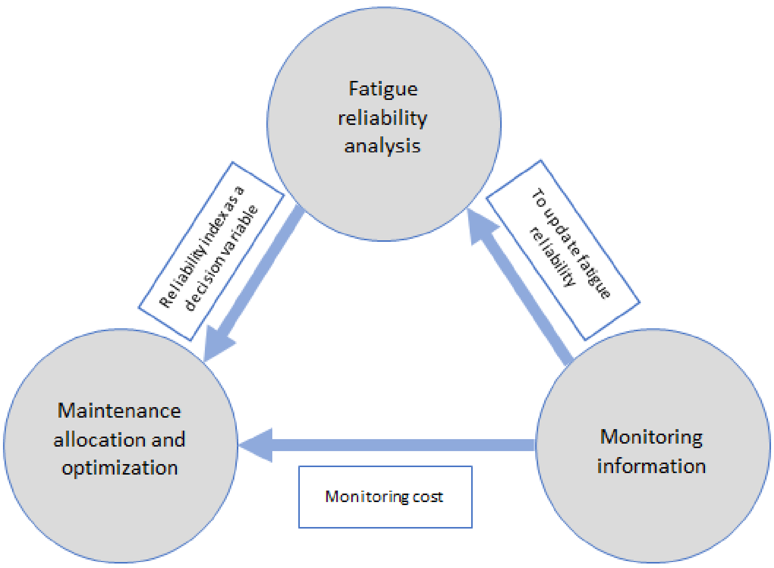

Figure 1.1: Main phases of maintenance planning against fatigue

Within the first step, fracture mechanism and S-N curves are two regular approaches that are used to evaluate fatigue damage and provide a proper limit state for fatigue reliability analysis. Employing fracture mechanism approach is depending on if inspections show a crack development in the structure, while S-N curve approach is based on experimental data which provides an estimation of number of cycles to fail. Performing the fatigue reliability analysis under a time-dependent framework seems more reasonable since it is a degradation process working under stochastic loading that is highly dependent on time. The challenge in time-dependent reliability analysis is related to the problems involving computationally expensive and non-monotonic performance functions. Hence, we have developed an efficient methodology to perform time-dependent reliability analysis that is called AK-SYS-T. This methodology uses the similarity between system reliability and time-dependent reliability in a way to apply efficient system reliability methods for time-dependent problems. In this approach, Kriging meta-modeling is used to replace the computationally expensive performance functions. The learning process in AK-SYS method helps to enrich the Kriging meta-models very efficiently without needing to an optimization process. The results show that AK-SYS-T can compete well in terms of efficiency and accuracy with the state of the art methods.

The second step is related to how to get benefit from monitoring information. **SHM!** provides us with valuable information about the current situation of civil structures. Advances in data acquisition, inspection technologies, and data management accompanied with the effective integration of **SHM!** into an intelligent system can help to improve the current practices on structural maintenance and management. Fatigue phenomenon is a function of some random and uncertain parameters such as loading, material properties, crack parameters, etc. Therefore, utilization of **SHM!** into structural fatigue life assessment can be a great help to reduce uncertainties toward fatigue life analysis. It also helps decision makers to find the best solution to prevent fatigue failures to increase the structural lifetime. The challenge here is related to the way of employing the information coming from monitoring data.

Depending on the type of monitoring data, classical statistics or Bayesian inference can be used. In case of having adequate monitoring data, classical statistics is preferred. However, if the data in not sufficient, prior information about the phenomenon in a

Bayesian inference framework will be employed to provide more informative results. With this respect and using the classical statistics, a study has been developed on long-term monitoring data available at **EPFL!** (**EPFL!**) on Chillion viaduct. Seasonal ARIMA which is a method to study time series is used to prepare a loading model for long-term monitoring data on transversal rebars in the concrete deck of the bridge. The aim is to capture seasonality effect in traffic loading and to provide a model that gives more detail about structural fatigue loading. This load model can be used within S-N approach or fracture mechanism with some adjustments.

In the last step, a study has been developed to study the crack propagation in the deck plates of the orthotropic decks under transversal tension. The crack can be initiated in the root of the fillet weld where the stiffener is welded to the deck plate. Propagation of the crack in this area towards the deck plate is very crucial because this kind of cracks are very difficult to inspect and detect while the crack length can reach the critical threshold without being noticed. Transversal tension in the deck plate can be considered as a main reason for this kind of propagation. Therefore, the goal here is to study how the transversal tension can influence the direction of the crack propagation. The transversal tension in the deck plate can be caused by traffic loads, residual stresses, and weight of the structure (for the bridges with a long cantilever arm). To conduct this study, **X-FEM!** (**X-FEM!**) implemented in Code-Aster developed by **EDF!** (**EDF!**) is used to perform crack propagation analysis, and for the crack initiation a simple **FEM!** (**FEM!**) combined with cumulative fatigue damage under cyclic loading is used. Another objective of this step is to study some maintenance strategies to prevent the crack propagation through the deck plates. Therefore we study the effect of welding some horizontal plates in the middle of stiffeners to connect stiffeners to each other to add some toughness to the structure.

As it was previously mentioned, the goal of this study is to add some contributions to optimal maintenance planning of existing structures. These contributions can help to improve the maintenance planning of structures by providing new methods and approaches to the topic which are going to be described with details in the following sections.

INFRASTAR, its objectives, and challenges to accomplish the PhD

INFRASTAR stands for "Innovation and Networking for Fatigue and Reliability Analysis of Structures - Training for Assessment of Risk". It has received funding from the European Unions Horizon 2020 research and innovation program under the Marie Skodowska-Curie actions. INFRASTAR involves twelve **ESR!** (**ESR!**) working in different research institutes, universities, and companies in five European countries (France, Germany, Switzerland, Denmark, and Poland). The host company for this PhD is PHIMECA Engineering in France in cooperation with Universit Clermont Auvergne.

The main goal of INFRASTAR is to improve the knowledge, skills, expertise, and to propose innovative solutions toward optimal maintenance and management of civil structures against fatigue (particularly for bridges and wind turbines). Three major challenges are trying to be addressed within this program: 1) advanced modeling of concrete fatigue behavior, 2) new non-destructive testing methods for early aged damage detection, and 3) probabilistic approach of structure reliability under fatigue. With this respect three work packages can be recognized where four ESRs are working under each work package. Work package one is related to "monitoring and auscultation". The second work package deals with "structure and action models", and the third one covers "reliability-based approaches for decision making".

To achieve this goal, a cross-experience and inter-disciplinary cooperation between ESRs within different research centers is necessary. For this reason different secondments in addition to training weeks are considered for each ESR to visit the other research centers within the program to be able to collaborate with other ESRs and research centers. For instance, two secondments (each one three month long) was considered for this project. The first secondment took place at **EPFL!**, department of civil engineering and the second one was carried out at IFSTTAR and Cerema. Also, three training weeks was completed during this PhD in BAM Berlin, EPFL, and University of Aalborg respectively.

Providing a framework in which each ESR has to collaborate with other ESRs and researchers in different working environments rather than staying in the host institute is an excellent opportunity for them to improve their scientific, networking, and communication skills. However, one can face different difficulties mostly concerned with secondments since they take a big portion of the PhD time which in total is about three years. To enumerate some of those difficulties one can mention the travel issues, relocating to a new city or country, integrating to new work places, and the most important one which is developing new research topics that makes a relation between the thesis subject and in the same time falls within the research interests of the hosting institute during the secondment.

To put it in a nutshell, the topics that are developed during this PhD are tried to be chosen in way that are, in one hand, related to the main topic of the thesis which is "Optimal maintenance planning of existing structures using monitoring data" to keep the consistency among the topics of the thesis. In the other hand, since some of the topics have been developed during the secondments, it has been tried to keep the hosting research centers happy and perform a study that is interesting for them also. Hence, the topic of the thesis is updated to "Towards optimal maintenance planning of existing structures using monitoring data".

Summary

According to what has been described before, four chapters have been considered for this thesis. Chapter 1 is devoted to the practices on structural maintenance planning. In this chapter it is tried to have a review on maintenance actions and indicators, structural deterioration, maintenance optimization and application of SHM for maintenance planning. The second chapter is related to time-dependent reliability analysis. The new methodology to address time-dependent problems is introduced in this chapter supported by some examples form the literature to validate the algorithm. In chapter 3, the crack propagation in orthotropic deck plates is studied. It is shown that the root of the fillet weld (connecting the stiffener to the deck plate) is a critical point and the crack can initiate from this area. X-FEM is used to perform the crack propagation under different tension levels in the deck plate to evaluate the direction of crack propagation. Finally, some applicational examples are provided in chapter 4 to connect different steps of the study. For example in one example it is tried to employ AK-SYS-T on a crack propagation case to show the efficiency and the accuracy of the method on fatigue problems. It should be noted here that the study that has been developed on "Application of time series methods on long-term structural monitoring data" has not been introduced in a chapter but the related paper is provided in the appendix since this work has not been done under the supervision of my thesis supervisors but under the supervision of professor Eugen Brhwiler at EPFL.

Background: Life-cycle management of deterioratin
structures against fatigue

Introduction

This chapter aims to provide some general information regarding to common practices within structural Life-Cycle Management (LCM) mainly for steel structures that are vulnerable against fatigue (e.g. bridges, off-shore structures, wind turbines, etc.). This is helpful to highlight the challenges during the structural LCM to be able to integrate and relate the work that is conducted in this thesis. Structural LCM is composed of different blocks in which an optimal maintenance and/or inspection planning can be derived as a result. The LCM introduced here is incorporated with the information from Structural Health Monitoring (SHM) and probabilistic modeling. This will lead to a more realistic outcomes that is very resourceful for decision makers. For this reason, the objectives and strategies of structural maintenance are introduced first. Then, models for structural performance deterioration and performance indicators are reviewed. Common methods for fatigue life assessment of steel structures accompanied with uncertainty modeling in fatigue and performance functions for fatigue reliability analysis are investigated subsequently. In the next step, some methods for monitoring, inspection, and maintenance for fatigue are summarized. In the end, life-cycle optimization of structures associated with monitoring, inspection, and maintenance is characterized.

Structural life-cycle management

Most of the civil engineering structures are built to perform their desired functions for decades. They play a crucial task to improve the economy in addition to social and environmental welfare. However, these national assets are exposed to different aging processes (e.g. fatigue and corrosion for steel structures), random loading and environmental conditions (e.g. storms, snow, etc.), and some other natural extreme events such as earthquakes and those resulting from humans such as accidents and terrorist attacks. Apart from the unexpected accidents, deterioration is one of the unpleasant processes that happens to any structure by the passage of the time, no matter how well it is designed. A sudden failure in civil structures can have major economic, environmental, and social impacts, see e.g. collapse of Genoa bridge. Therefore, the cost of a failure can be much higher than the cost required only for rebuilding or replacing the structure (Dong et al., 2013; Bocchini et al., 2014). In order to ensure the long-term functionality of structures, it then becomes crucial to plan some interventions to reduce the number of unexpected failures. These interventions can involve maintenance actions, periodic inspections, and SHM.

However, the number of scheduled interventions should be considered reasonably during the service life of a structure since it can lead to a big financial burden. Proposing an integrated framework is thus inevitable to evaluate the conflicting safety and financial requirements altogether in the context of structural LCM. Life-cycle cost optimization is one important step in LCM process since financial limitations can significantly impact further decisions. A rational trade-off between the minimization of the life-cycle cost and maximization of the expected service life is sought. The optimization part can be a computationally expensive process especially when it is performed in a probabilistic framework to account for associated uncertainties. However, recent advances in processing tools make it easier to conduct such calculations in a large-scale simulation (Okasha and Frangopol, 2010a, 2011).

A comprehensive LCM is composed of different modules that work in an integrated way which for example aim to minimize the life-cycle cost, maximize the extended service life, etc. Figure 2.1 illustrates the general framework for a LCM for deteriorating structures. Structural LCM starts with analyzing the structure under investigation to determine the deteriorating mechanisms affecting the structure. In this step, one should specify some details about the structure such as type of the structure, type of material, and details of components. Depending on the type of structure and material, different types of deterioration process can be considered. For instance, fatigue and corrosion are common processes that cause deterioration in steel structures while in concrete structures carbonation and chloride penetration are dominant. Considering each process, structural performance can be evaluated using appropriate approaches. For instance, S-N approach and fracture mechanism can be used to model the fatigue damage in steel structures. Since this study concentrates more on steel structures, S-N curves and fracture mechanism will be introduced with more details in Section 2.6. Another step in structural LCM is employing SHM data which helps to reduce the uncertainty in predicting structural performance. To make the decision making process easier some performance indicators such as reliability or risk are required in the next step. After predicting the deterioration of performance indicators over time, appropriate maintenance actions are chosen to improve the structural performance. The effect of maintenance actions associated with their costs are used in the optimization step to be able to propose appropriate outcomes such as optimum maintenance and inspection strategy, optimum expected extended service life, etc. Such framework has been presented in Frangopol (2011); Frangopol et al. (2012); Miyamoto and Motoshita (2015) that is already applied on different types of structures such as bridges (Kim and Frangopol, 2011b, 2012; Kwon and Frangopol, 2011; Okasha and Frangopol, 2010b) and sea vessels (Kim and Frangopol, 2011c,a; Frangopol, 2012; Kwon and Frangopol, 2012).

It is obvious that providing a comprehensive LCM framework facilitates the process of inspection and maintenance planning for structures within the financial restrictions. However, it can be considered as an extensive mission that requires schooling in many other fields such as structural analysis, reliability assessment, etc. Addressing challenges in the related fields , of course, can help to improve the results of LCM approaches. For such purposes, some studies focus on new methods and approaches to approximate the performance indicators such as reliability or risk indices in a time-dependent or time independent framework, while others are searching for more appropriate cost models. Quantifying uncertainties is another active field in this domain that can be of a great help to improve the practices in structural LCM. Thus, the goal of this chapter is to describe different steps in structural LCM against fatigue with more details to clarify the objectives and challenges in this framework.

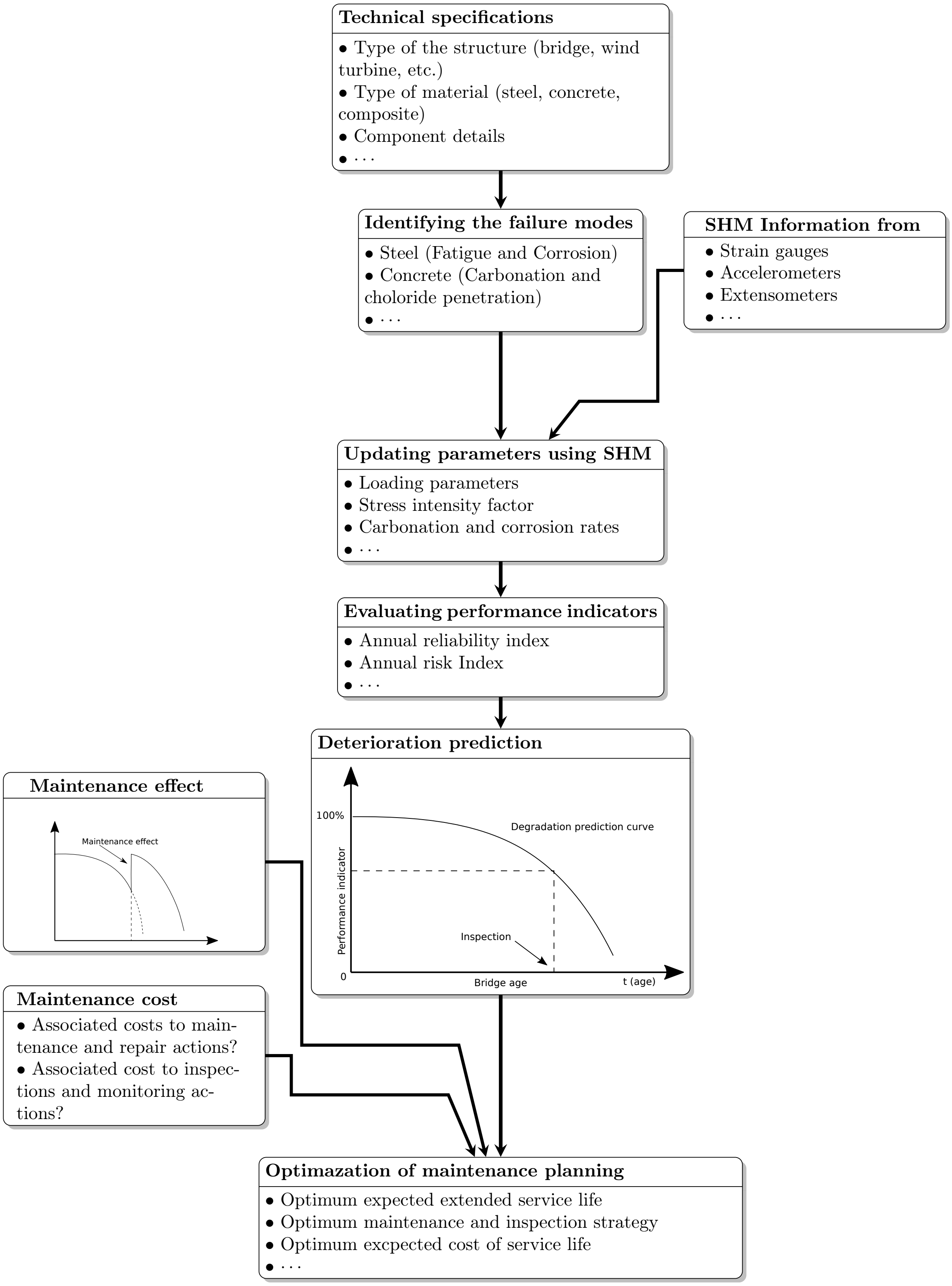

Figure 2.1: LCM framework incorporated with SHM data

Structural maintenance objectives and strategies

Simply speaking, structural maintenance means "to retain a structure in a good condition so that it can accomplish its expected tasks" (van der Toorn, 1994). This definition may imply that all the components of a structure should be in a nearly-new condition so a structure can fulfill all intended duties. However, financial and physical limitations force the managers to find more sophisticated solutions for maintaining structures in which the targets and the limitations are clearly specified and addressed. Some targets for the structural maintenance can be expressed in terms of reliability, availability, durability, serviceability, etc. Finally, the maintenance can be defined as: "All technical activities on the component level linked to each other in order to keep the structure in a condition to perform its duties properly for a specified period of time to satisfy maintenance targets (e.g. sufficient reliability, or availability, etc.)" (van der Toorn, 1994).

Maintenance targets rely on measurements that evaluate the performance of a structure which deteriorate over time due to different degradation processes. Therefore, the main goal of maintenance actions is to improve the performance of structures to meet those targets. As those measurements inherently deteriorate through time due to different aging processes, one main goal of maintenance actions is to restore the initial properties of the structure completely or at least partially in order to meet the requirements expressed in terms of maintenance targets. The cost of maintenance represents a non-neglegible portion in total the life-cycle cost of a structure since maintenance actions are meant to apply frequently during its service life and it can even be higher than the original cost of construction (Estes and Frangopol, 2001). Therefore, another objective is to search for an economically balanced maintenance allocation. In other words, this can be considered as another target that defines the financial limitations for the maintenance planning. Hence, optimizing the maintenance planning seems to be of paramount importance because it tries to find the best maintenance strategies for given level of targets and financial constraints.

Maintenance actions are generally employed to change the course of the structural deterioration. They can mainly be grouped in two categories namely preventive and corrective actions , see Figure 2.2. The goal of preventive maintenance interventions is either to stop or slow down the aging process which can help to extend the service life of a structure. Preventive maintenance actions are usually applied based on a planned schedule. However, sometimes according to the condition of the structure, preventive maintenance can be recommended. The second category of maintenance interventions are called corrective actions since they are performed to restore the performance of some components of the structure partially or totally. Corrective maintenance are usually performed when the performance indicators reaches a predefined threshold. This kind of maintenance can be planned or unplanned due to some unwanted accidents on the structure (Barone and Frangopol, 2014).

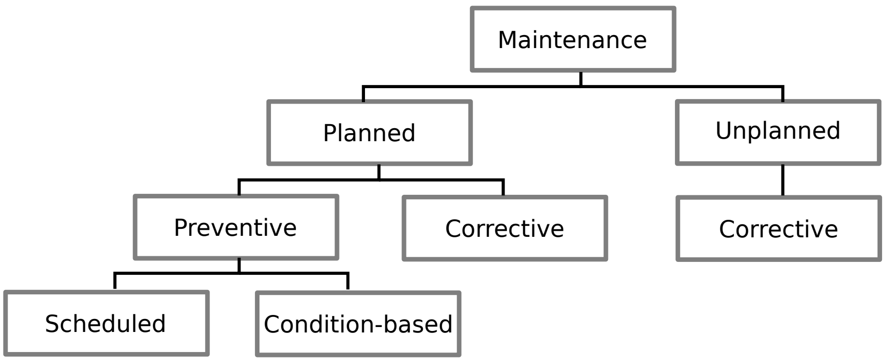

Figure 2.2: Different types of maintenance actions

The effect of preventive and corrective maintenance actions on the structural performance is illustrated in Figure 2.3 in addition to the cumulative cost of maintenance. The service life of a structure can be defined when the structural performance reaches its threshold. Preventive and corrective maintenance actions are applied to keep the structural performance above the threshold and therefore to extend the structural service life (Kong and Frangopol, 2003a,b; Neves et al., 2006). Time instants for applying the preventive maintenance actions can be preplanned considering the structural performance evolution and the cost of maintenance (Okasha and Frangopol, 2010b). The preventive maintenance actions can lead to small improvements on the performance of a structure at a lower cost compared to the corrective actions. Corrective maintenance interventions are usually performed when the performance of the structure is reaching its threshold and an essential improvement such as replacement is necessary which consequently lead to a higher cost of maintenance (Frangopol and Kim, 2019).

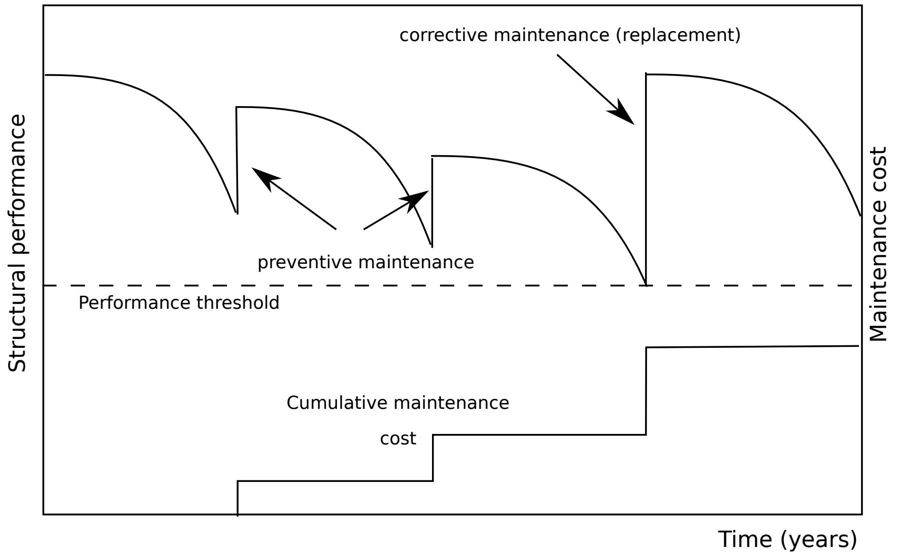

Figure 2.3: An illustration of effect of maintenance types on structural performance and cumulative maintenance cost

Structural performance deterioration models

One of the most important steps in structural life-cycle analysis is the evaluation and prediction of the structural performance deterioration (Frangopol, 2011, 2018). Aging and degradation are some other terms that are usually used instead of deterioration. Combined effect of some drivers of operating environment (more or less harsh) and mechanical stressors trigger the structure to degrade over time (Frangopol and Kim, 2019). An accurate model for structural deterioration process can be a major tool for the life-cycle management of a structure. Fatigue and corrosion are the most common degradation processes on steel structures that cause the structural performance to deteriorate gradually over time. However, there are some other extreme events like earthquakes, floods, etc. that cause an unanticipated change in the structural performance (Frangopol and Soliman, 2016).

Performance degradation of structures can have different behavior depending on the governing failure mode. Figure 2.4 illustrates some of possible deterioration patterns. For instance, the case one which is a linear degradation pattern can be used to model the corrosion process over time for many cases. Case 2 represents a process that slows down by the passage of the time which can be used to represent the carbonation and chloride penetration in concrete structures. Fatigue behavior is similar to case 3 where the deterioration is caused by the cumulative load effect over time and the failure occurs by abruptly. In some cases, the degradation process has a stepwise behavior since it happens by collisions and extreme loads (case 4). In case 5, structure experiences a sudden failure since an unexpected extreme load can exceed the structural tolerance level. As many of the components in the civil engineering structures are covered with a protection layer, they may show a two-phase degradation process, see case 6 on Figure 2.4. The first phase is related to the degradation of the protection layer and in the second phase the component degrades (van der Toorn, 1994).

Maintenance strategy highly depends on the type of the degradation model. For instance, if defects or cracks are assumed to exist before the beginning of structural service life, which is the case in a damage tolerance analysis, cracks should be detected before reaching a critical value. Therefore, regular inspections should be planned during the service life of a structure. If a crack is detected in a critical fatigue detail by inspections, preventive or corrective maintenance actions should then be performed promptly since the stable crack growth phase is not so long compared to the total service life of a structure. For a two-phased degradation process (case 6), the aging process in the first phase that is related to the protection layer can be considered as a conditional parameter for the second phase which is related to the component deterioration. If there is only one degradation phase (case 1 to 5), it is important to properly predict the behavior of the process since it is the only indicator to decide about the inspection and maintenance actions. Fatigue as one of the most important aging process for steel structures is introduced in Section 2.6 because the aim here is to contribute to the optimal maintenance planning of structures against fatigue.

The existence of uncertainties within the aging processes increases the complexity

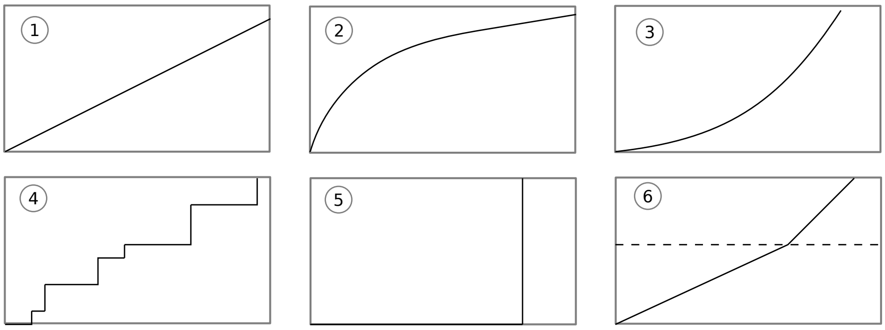

Figure 2.4: Different courses of structural performance degradation over time

of the problem for damage occurrence, propagation and detection. In general, uncertainties can be classified in two groups. The first group gathers randomness which is inherent to the parameters, and it is called aleatory uncertainty. The second group gathers uncertainties due to the lack of knowledge about a phenomenon and it is referred to epistemic uncertainties. (Rahman et al., 2018; Karanki et al., 2017; Ferchichi et al., 2017). Aleatory uncertainties are usually irreducible while epistemic uncertainties can be reduced by adding extra information to the problem (e.g with a more realistic modeling). Therefore, Structural performance indicators are better to be derived in a probabilistic framework which is suitable to account for uncertainties in the problem. One can refer to reliability, risk, availability, and hazard as indicators that take into account associated uncertainties in the problem. They are hence introduced in the next section.

Structural performance indicators for maintenance allocation

Structural performance indicators are crucial for maintenance allocation and optimization since they provide consistent criteria for decision making process (Ghosn et al., 2016). Performance indicators are time-dependent functions that can be measured and quantified. It is evident that a careful assessment of performance indicators over time can help for a better structural maintenance planning.

Condition index is one of the most common performance indicators that is attained through visual inspections (Strauss et al., 2017; Frangopol and Kim, 2019). Using this performance indicator, the condition of the structure is rated in different scales after each inspection. For instance National Bridge Inventory (NBI) and Pontis are two condition rating methods that are used in the United states (MASCIOTTA et al., 2016; Frangopol and Kim, 2019). NBI rates the condition of bridge components (such as deck, superstructures, etc) using a value ranging from 0 to 9 where 0 indicates the failing condition and 9 shows the excellent condition. In Pontis condition rating method, however, the rating is from 1 to 5 where 1 indicates "no evidence of damage in a bridge component" and 5 represents "severe damage which affect the serviceability of a bridge component". Table 2.1 describes the condition states in Pontis condition rating method (Frangopol and Kim, 2019). Other countries such as Austria and Croatia use the condition rating method that is similar to Pontis and the structural condition is described with 5 condition states (Strauss et al., 2017). Condition rating of components is prepared mostly by visual inspection within different methods and usually provides qualitative information about components of the structure (as it can be seen from Table 2.1 for Pontis condition rating). The quality of data is highly dependent on the inspector's skills, rush level of the inspector, accessibility to the inspections zone, etc.

Other relevant performance indicators can be used in the area of structural maintenance planning such as reliability, availability, hazard, and risk based indicators (Barone and Frangopol, 2014). These indicators provide quantitative information about the deterioration of structural performance that can be easier to interpret and evaluate the structural performance. Some countries like Netherlands and Denmark have started to employ those indicators more comprehensively in the field of structural maintenance planning and not only for research purposes (Strauss et al., 2017). Reliability and risk-based indicators rely on the failure probability, assessed in practice from the so-called performance function (which is described in Section 2.5.1), while availability and hazard are directly calculated according to the lifetime distribution. In the latter approach, the lifetime of a structure is considered as a random variable (Okasha and Frangopol, 2010c). A probabilistic framework for the life cycle management allows one to take into account uncertainties associated with structural resistance and loads, and therefore to compute those performance indicators. A short description for the

Condition index	***Description***
1: Good	Painting quality is good as it is intended to protect the metal surface and no active corrosion is detected
2: Fair	The painting system is distressed meaning that it shows some peeling, curling, or chalking but the metal is still covered. There is a little or no evidence of corrosion
3: Paint failure	There is no evidence of an active corrosion that may cause loss of section but the metal surface is exposed and freckled rust is common
4: Paint failure with steel corrosion	Corrosion may be present but any section loss due to active corrosion does not yet warrant structural analysis of either the element or the bridge
5: Major section loss	Section loss due to corrosion has been detected which may be sufficient to warrant structural analysis to ascertain the impact on the ultimate strength and/or serviceability of either the element or the bridge

Table 2.1: Pontis condition rating for painted steel girder element

mentioned indicators is provided hereafter.

Reliability and risk indicators

• *Reliability* measures the probability that a structure performs its duties properly for a given period of time under specified conditions. One goal of reliability analysis is to find the probability of failure of a structure from its behavior for a given failure mode that is formulated by means of a performance function $Z = G(\mathbf{X})$. $\mathbf{X}$ here denotes a vector of input random variables that encompasses for example mechanical properties, operational parameters, and load characteristics. $G(\mathbf{X}) = 0$ separates the safe domain $G(\mathbf{X}) > 0$ from the failure domain $G(\mathbf{X}) < 0$ and it is called the limit state. The probability of failure for a given failure mode is expressed by the integration of the joint probability density function $f_{\mathbf{X}}(\mathbf{x})$ of the random vector $\mathbf{X}$ over the failure domain as it is formulated in Equation 2.1 (Huang et al., 2017; Bichon et al., 2007).

$$p_f = P(G(\mathbf{X}) \leq 0) = \int ... \int_{G(\mathbf{X})<0} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x} \tag{2.1}$$

Calculating this failure probability is not an easy task and increasingly robust and efficient reliability methods have been proposed over the last decades to approximate this failure probability. This formulation is related to the time-independent reliability analysis and evaluates the failure probability for a given time instant. However, in many of engineering applications, time-dependent reliability analysis is necessary due to the temporal nature of material properties, loading, and geometrical parameters. Time-variant reliability analysis is more complicated than time-invariant analysis by introducing the time into the problem and it aims to calculate the cumulative failure probability for a given time interval. More information about methods and definitions for reliability analysis is provided in Chapter 3 where a new approach for time-dependent reliability analysis is developed. The new method is called AK-SYS-T.

• *Risk* is simply defined by multiplying the probability of failure with its associated consequences C as shown in Equation 2.2 (Barone and Frangopol, 2014). Methods and approaches for reliability assessment can also be used here to calculate the failure probability in a risk-based framework. Risk-based decision making has become an important tool for structural maintenance optimization because, in most of the cases, it is necessary to put the consequences of structural failure into consideration.

$$R = p_f \times C \tag{2.2}$$

One way to evaluate consequences of a failure is to identify the losses associated with failure and their equivalent cost. The failure cost can be divided into direct and indirect costs. The direct cost, C_{dir}, is related to the monetary loss after failure while the indirect cost C_{ind} takes into account the cost related to the impacts on the environment, society, and etc. Therefore, the Risk can be formulated by Equation 2.3, as:

$$R = p_f \times (C_{dir} + C_{ind}) \tag{2.3}$$

In real life applications, reliability and risk are generally evaluated at constant time intervals. For instance, one year time interval can be used to evaluate the annual reliability index and annual risk Barone and Frangopol (2014).

Availability and hazard indicators

Another way to provide indicators for LCM is through structural lifetime distributions (Leemis, 1995). In this way, time to failure of a component or system is considered as a continuous random variable. The random time to failure T_f is defined as the amount of time that has elapsed since the beginning of the service life until the first failure happens (Rausand and Hyland, 2003). The PDF of time to failure f_{T_f} should be determined using the statistical information of the degradation process. For a given time t and a small time interval Δt, this PDF measures the failure probability between t and $t + \Delta t$ as expressed in Equation 2.4.

$$f_{T_f} = \lim_{\Delta t \to \infty} \frac{P(t \leq T_f \leq (t + \Delta t))}{\Delta t} \tag{2.4}$$

if Δt is small it can be rewritten as:

$$f_{T_F} \Delta t \approx P(t \leq T_f \leq (t + \Delta t)) \tag{2.5}$$

With this respect multiple lifetime functions can be defined such as survivor, availability and hazard functions which have already been successfully employed for LCM of bridges (Orcesi and Frangopol, 2011b; Okasha and Frangopol, 2009b; Yang et al., 2004). Among different lifetime functions, availability and hazard are appropriate indicators that can be used for threshold-based approaches for LCM (Barone and Frangopol, 2014). Before introducing these functions, let first introduce the survival function $S(t)$. This functions measures the probability that a component or system has not failed until time t, see Equation 2.6.

$$S(t) = P(T_f \geq t) \tag{2.6}$$

The availability $A(t)$ function is based on the same definition as the survival function except that it is not monotonous with time, i.e. it can change over time by applying maintenance actions , whereas survivor function is a non-monotonous decreasing function over time.

The hazard function $h(t)$ is rather defined as the instantaneous failure rate of a component or system. It expresses that failure occurs between t and Δt given that no failure has happened before t. It finds the probability of failure at time interval $[t, t+\Delta t]$ given that the component or system is surviving at time t while this probability is averaged over the same interval and Δt tends to zero. The hazard function can also be seen as the ratio between the derivative of survivor function $*S'(t)$ and survivor function, see Equation 2.7.

$$h(t) = \lim_{\Delta t \to 0} \frac{P[t \leq T_f \leq t + \Delta t | T_f \geq t]}{\Delta t} = -\frac{S'(t)}{S(t)} \tag{2.7}$$

Providing a closed form solutions is the main advantage of the lifetime functions over performance-based indicators. However, this closed form solution can be obtained only for the systems in which the components are independent or fully correlated. Moreover, by resorting to lifetime distributions of components and therefore using availability and hazard functions, one cannot access to the sources of uncertainties. In the contrary, reliability and risk-based approaches or more generally probabilistic approaches allow one to study the effect or sensitivity of the model response, e.g. G, to each input random variable. Any level of correlation between random variables can also be considered (Barone and Frangopol, 2014).

Fatigue assessment of steel structures

Fatigue is a multi-stage process that is caused and accumulates under cyclic loadings (Ye et al., 2014). It starts with initiation of cracks at a microscopic level in the first stage. The cracks propagate under cyclic loading in the next stage and it continues until the failure of components or specimen happens in the last stage. The separation of aforementioned stages is not well defined (Ellyin, 1997). Fatigue cracks usually initiate on the surface of a specimen due to several factors (surface roughness, surface treatment, etc.) and they propagate in the same direction of the maximum shear stress. Fatigue cracking mostly happens in the regions with high stress concentration e.g. near notches, pits, scratches, or notch like valleys on the surface. The main factors that affect the fatigue life can be related to material properties, processing and manufacturing of the material, loading condition, geometry of the components, and surrounding environment. Moreover, some of these factors can be correlated meaning that a change in one would lead to a change to another (Fisher et al., 1998).

Two main life-assessment procedures exist to predict fatigue failure. The first approach named safe-life approach and it is advised when inspections are impossible, very difficult, or costly. Cracks are not allowed and must not appear during the service life. This fatigue design approach mostly relies on S-N curves which basically provide a relationship between stress levels and number of stress cycles to failure. The second approach us called damage-tolerance approach (Ye et al., 2014). It assumes that components are potentially flawed before their use and therefore, cracks are assumed to exist at important structural details. In such an approach, inspections are mandatory and the objective is to ensure that the component does not fail between inspections. This approach resorts to fracture mechanics and crack growth theories. The basics of fatigue S-N curves and fracture mechanism approaches are briefly reviewed hereafter. More comprehensive information about those approaches can be found in Ellyin (1997); Fisher et al. (1998); LUKIC (1999) for example.

S-N curve based approach

S-N or Wöhler curves usually characterize the fatigue behavior of different materials (Susmel, 2009; Susmel et al., 2011). An illustration of S-N curve is provided in Figure 2.5. S-N curves show the relation between the stress ranges S and the number of cycles N to failure for a given stress range. For stress ranges higher than ultimate stress limit S_{ut}, it does not take so long to fail and only few cycles are enough to cause fatigue failure. By contrast, if the stress range is smaller than the endurance limit S_e, if it exists, failure is assumed to never happen.

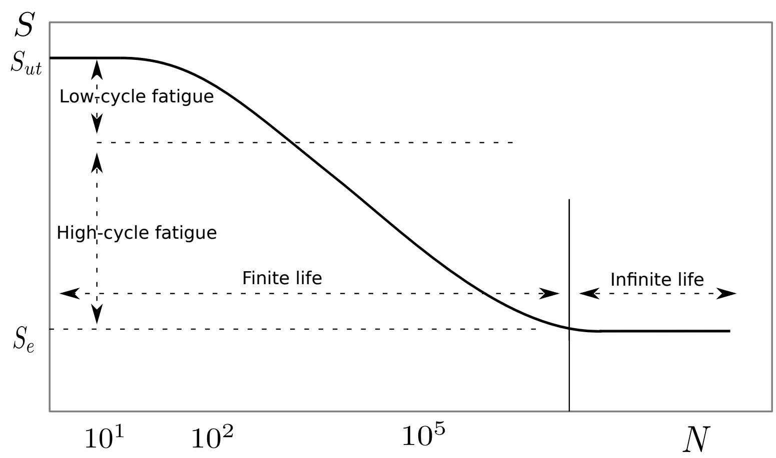

Figure 2.5: A typical S-N curve

S-N curves are obtained from fatigue test campaigns. In a fatigue test, a test specimen goes under a cyclic loading with a constant amplitude until fatigue failure happens. As the stress ranges are getting closer to the endurance limit, the number of cycles to failure increases, see Figure 2.5. The experiments are performed for given test specimen and lab conditions. Therefore, the fatigue behavior of the fatigue details, components, or structures in real conditions might be different.

A commonly used method to represent the finite life zone of the S-N curve is the Basquin model (Basquin, 1910) which can be expressed as:

$$NS^m = A \tag{2.8}$$

or

$$logN = -mlogS + logA \tag{2.9}$$

where m and A are material parameters.

One of the simplest and most common ways to calculate the cumulative damage caused by fatigue is the Miner's rule that is formulated in Equation 2.10 (Miner, 1945). Miner's rule states that the damage caused by a stress cycle belonging to a variable amplitude load history is equal to the damage caused by the same cycle in a constant amplitude load history. Therefore, the order of the cycles has no influence on fatigue damage accumulation. In the Miner's rule, n_i is the number of stress cycles for the stress range $\Delta\sigma_i$ extracted from the variable amplitude load history and N_i denotes the number of cycles to failure for $\Delta\sigma_i$ in the constant amplitude load history that can be approximated using S-N curves. it is generally assumed that failure happens when the amount of the accumulative damage D is equal to 1.

$$D = \sum_i \frac{n_i}{N_i} \tag{2.10}$$

Simplicity is one main advantage of this fatigue design procedure that makes it very well-known and explains why it remains the mostly used method in industry. However, one drawback is that this method ignores the effect of the load cycles under the endurance limit S_e (if defined) on fatigue damage, although a notable portion of fatigue damage comes from those stress cycles according to Marquis (2011); LUKIC (1999). Another shortcoming of this approach is that it is not intended to incorporate some inspection results e.g. crack dimensions. This can be an issue for aging structures for which it is desirable to extend their service life or if cracks have to be considered before the beginning of the service life. For those purposes, fatigue damage approach based on fracture mechanism is introduced in the following.

Fracture mechanism based approach

Another common approach for fatigue assessment is based on Linear Elastic Fracture Mechanism (LEFM). LEFM can be applied under linear elastic assumptions and small scale yielding at the crack tip. In such a framework, Stress Intensity Factors (SIF) denoted by $K(a, \sigma)$ represent the amplitude of the stress fields near the crack tip. According to Paris, the SIF is a driving force for crack expansion. Hence, Paris and Erdogan (1963) have proposed a model that links the crack growth speed (da/dN) to the SIF, K, see Equation 2.11.

$$\frac{da}{dN} = C(\Delta K)^m \tag{2.11}$$

where ΔK is the SIF range, and C and m are parameters related to the material. ΔK is the difference between the maximum and minimum values of stress intensity for each stress range. SIF is usually given by Equation 2.12, where $Y(a)$ is defined based on the crack and component geometry and S denotes the stress range (Broek, 1986; Ritchie and Knott, 1973). Depending on the complexity of the geometry either closed form solutions exist for ΔK or Finite Element (FE) analysis is required to assess it (Li et al., 2019; Qian and Long, 1992).

$$\Delta K = SY(a)\sqrt{\pi a} \tag{2.12}$$

As it can be seen from the Figure 2.6 crack propagation can be divided into three stages. In the first stage, for low values of ΔK near ΔK_{th} underlying mechanisms are not continuous. Before ΔK_{th}, fatigue cracks are assumed to be inactive. In the second stage, the crack propagation shows a linear behavior and it can be described by Paris-Erdogan's law. In the third stage, the crack propagation has a nonlinear behavior when K_{max} gets closer to the fracture toughness K_c. Fatigue failure happens for $K_{max} > K_c$ (Ritchie, 1999).

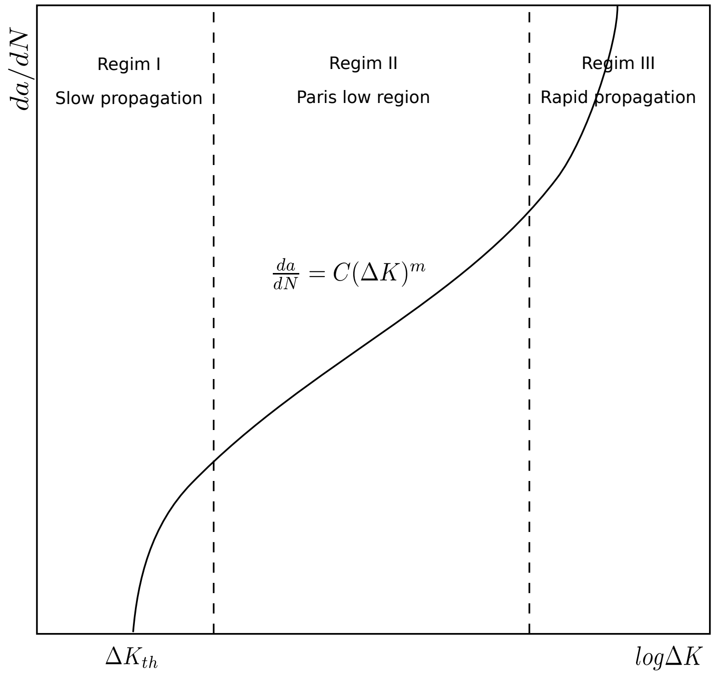

Figure 2.6: Paris law region

Fatigue crack propagation models based on fracture mechanism are appropriate tools to study structural fatigue life for existing structures since they have already experienced real life loading conditions and therefore may have developed cracks in critical locations. Characteristics of the crack, geometry, and loading conditions should be incorporated in this approach. Fracture mechanism provides a framework that allows to evaluate the time-dependent crack length which in turn can be used to decide the inspection schedule.

Before employing fatigue models, one should keep in mind that they are associated with significant amount of uncertainties. Consequently, uncertainty quantification and probabilistic modeling for fatigue life assessment is essential. In the next part, uncertainty modelling in fatigue life analysis is discussed.

Uncertainty modeling in fatigue

Fatigue life assessment is highly influenced by several sources of uncertainties which can be classified in three different types such as natural variability, data Uncertainties, and model uncertainty. These sources of uncertainty can exist in both S-N approach and fracture mechanism. For instance, Table 2.2 represents some sources of uncertainty in fracture mechanism approach. (Sankararaman et al., 2009; Ling et al., 2011). It is necessary therefore to rely on probabilistic modeling to take into account those sources of uncertainties. Performing a probabilistic fatigue life assessment requires to identify, quantify, and take them into account properly. The aim of this sections therefore is to introduce some of main sources of uncertainty in fatigue assessment.

Regarding to the uncertainties in fatigue loading, previous experimental studies have shown that fatigue life and crack propagation behavior is highly influenced by the variability and uncertainty in the loading spectrum (Moreno et al., 2003; Zapatero et al., 2005). Uncertainties in loading can be originated by characteristics of a) operational environment such as temperature, wind, road profile, etc., b) mission type or service use that can be normal or emergency use, military or commercial use, etc., and c) human factors like traffic loading, maneuvers, and customer usage. Fatigue load spectrum is usually modeled by cycle counting and random process methods. Rainflow counting is the most common method among the cycle counting methods which extracts the counting matrices from the loading spectrum that include information about the number of load cycles, the range and the mean value of each load cycle (Dowling, 1971).

Methods based on random process try to model the load spectrum as a stochastic process. Markov chain method lies in this category in which the load spectrum is

Type	Sources of uncertainty
1: Natural variability	• Loading • Equivalent initial crack size • Material properties (fatigue limit, SIF threshold)
2: Data uncertainty	• Spares data (uncertain distribution parameters for material properties) • Output measurement error • Crack detection uncertainty
3: Model uncertainty / errors	• Crack growth law • Uncertainty in calculation of SIF (FE discretization error, surrogate model uncertainty)

Table 2.2: Sources of uncertainty in fatigue crack growth

treated as a discrete time Markov chain that has a stationary probability matrix (Krenk and Gluver, 1989). Time domain and frequency domain based methods can be used to model a random process with a continuous state space. Time domain based methods are more appropriate to model load spectrum according to issues related to fatigue damage prognosis such as inspection and maintenance scheduling that are defined in the time domain (Ling et al., 2011). With this respect, time series methods such as ARMA or ARIMA are time domain based methods and they can be used to model the load spectrum (BEN, 2007). Ling et al. (2011) have investigated load models such as rainflow counting, discrete time Markov chain, and ARMA. They have assessed the predictive confidence of all models and the results show that all models work well. However, the overall confidence metric based on the presented numerical example show that ARMA has the best support from the loading data. They also have shown that additional information about the load spectrum on the structure obtained by SHM can help to update the model parameters. It should be mentioned that methods such as rainflow counting, Markov chain, and ARMA are assuming that the load spectrum is a stationary process.

In most of cases, structural loading such as traffic show a seasonality effect meaning that the traffic loading might have a different behavior in different times during the year. This causes non-stationarity in the load spectrum and previously mentioned methods are incapable of dealing with this issue. However, some methods in time series analysis such as seasonal ARIMA can deal with seasonality effect. Therefore, a study has been performed within this thesis to employ seasonal ARIMA to prepare a load model for long-term monitoring data. This study is presented in Appendix A and it proposes an approach that enables to use seasonal ARIMA for long-term monitoring data on structures. Seasonal ARIMA makes it possible to take into account the seasonal effect in traffic loading. In addition, this approach can be used also to deal with the missing data and predict the future loading somehow.

Providing suitable approaches to model the load spectrum is an important step for fatigue probabilistic modeling. However, another important issue with this respect is to calculate local stresses in the proximity of fatigue region. Local stresses are also influenced by some parameters such as overall loading, fatigue detail geometry, residual stresses, etc. Calculated stress ranges and number of stress cycles can directly be used in S-N approach to evaluate the remaining fatigue life. Within the fracture mechanism approach they are used to calculate SIF. FE analysis is a common way that is used to calculate local stresses. One of the important issues that affect the accuracy in this method is the mesh size (Sankararaman et al., 2011). Assuming that the boundary conditions are provided properly, a small mesh size will lead to almost accurate solutions. This, however, is very difficult to implement in practice since it needs a huge computation time. Surrogate models like Kriging can be used to accelerate the calculation of stresses or SIF. In this way a few FE model is evaluated for few runs to prepare the Design of Experiment (DoE) for Kriging. Kriging provide exact outputs for the DoE and for the other points provide a Kriging variance that shows the level of uncertainty on the prediction. The accuracy of the Kriging meta-model depends on the accuracy of the FE model that is used for DoE and the calculation of Kriging parameters (Sankararaman et al., 2011).

Initial crack size is another source of uncertainty related to the natural variability. Some factors such as welding procedure, type of joint, fabrication yard, etc. affect the initial crack size. The crack propagation behavior for small cracks is very unusual. Introducing an Equivalent Initial Crack Size (EICS) is one way to avoid the analysis of crack propagation in microscopic scale (Sankararaman et al., 2009; Liu and Mahadevan, 2009). Therefore, in crack propagation models like Paris law that deals with long cracks, the propagation related to microscopic cracks is replaced with an EICS. This quantity cannot be measured by experiments therefore some researchers consider its value between 0.25 to 1 mm for metals (Merati and Eastaugh, 2007; Gallagher et al., 1984). Some studies consider EICS as a random variable in which they use lognormal distribution to model the uncertainty (Wirsching, 1984).

Uncertainties in the material properties is another source of uncertainty in fatigue assessment which can be either related to natural variability or data uncertainty which exist in both S-N curves and fracture mechanism approaches. This uncertainty can be related to the type of material, manufacturing and preparation, and test conditions. In S-N curves material characteristics are represented by parameters m and A. The large scatter observed in number of cycles to failure in S-N curves is due to the uncertainty in material properties. Parameters m and A are highly correlated therefore it is useful to consider one of them as a fixed parameter and the other one as a random variable. Fatigue tests can be used to identify the parameters of the desired random variable. This is the same for material parameters, m and C, in fracture mechanism approach. similarly, there is a high correlation between these two parameters therefore one of them can be considered as a fixed parameter and the other on as a random variable (Wirsching, 1984).

As it was mentioned before, according to the Miner's hypothesis for linear damage accumulation using S-N curves, the fatigue failure occurs when the cumulative damage is equal to 1. Although, fatigue tests under varying amplitude loading shows a spread from this value which means that the Miner's sum (Δ) should be treated as random variable. This randomness can be caused because of the model error in Miner's hypothesis. It has been proposed in sum studies to treat the Miner's sum as a log-normal variable with the mean of 1 (Wirsching, 1984). According to the crack growth model, plenty of crack propagation laws can be noticed in the literature (e.g. Paris law, Foreman's equation (Mnguez, 1994), Weertman's equation (Weertman, 1984), etc.) which shows non of them can be applied commonly to all crack propagation problems. Apart from the uncertainties in the coefficients of the crack propagation model there is also a model error than needs to be considered. For instance if one uses Paris law for crack propagation, it can be formulated as in Equation 2.13 where ε_{cg} is the error for the crack growth model (Sankararaman et al., 2009).

$$\frac{da}{dN} = C(\Delta K)^m + \varepsilon_{cg} \tag{2.13}$$

Performance functions for fatigue reliability assessment

As said before fatigue life assessment is associated with large amount of uncertainties. A reliability-based fatigue life assessment is a rational way to treat uncertainties coming from natural randomness, modeling errors, and prediction imperfections (Byers et al., 1997). In this context one can define the probability of failure as the probability of violating one or more limit states. Limit state is the boundary between the failure and the safe domain defined by structural performance function denoted G in Subsection 2.5.1 which mathematically expresses a given failure criterion. For many mechanical problems, a "stress-strength" definition is used. The "stress" represents a given structural response, i.e. local Van Mises stresses, and the "strength" denotes the material capacity of the structure, i.e. the yield stress. The "stress" and "strength" can be input and output variables, e.g. the results of the propagation of input uncertainties through a mechanical model. In both S-N and fracture based approaches performance function can be expressed by the difference between the "stress" and the "strength" (Barone and Frangopol, 2014).

$$G(t) = R(t) - Q(t) \tag{2.14}$$

S-N based approach performance function can be described in different forms. A common way to provide the performance function in this approach is in terms of damage. This can be expressed by Equations 2.15 and 2.16. In the first case the cumulative damage D_L should be less than Miner's sum (in most of cases $D_L = 1$) while in the second case a the cumulative damage should be less than a target damage Δ_{target}.

$$Z = \Delta - D_L \tag{2.15}$$

$$Z = \Delta_{target} - D_L \tag{2.16}$$

Another way to express the performance function for this approach is based on the number of cycles to failure N_c. If the total number of stress cycles to failure under variable stress range is N_t then the performance function can be formulated as Equation

2.17. For further information about formulation of N_t and N_c refer to (Liu et al., 2010).

$$Z = N_t - N_c \tag{2.17}$$

As said before, it is common to assume the Miner's sum as unity and the failure happens when the cumulative damage is more than 1. The damage caused by each stress range can be estimated using S-N curves that are usually provided by performing plenty of fatigue tests under constant amplitude loading conditions for different stress ranges (Szerszen et al., 1999). To make good conclusions about the fatigue failure using this approach, it is necessary to properly estimate the stress ranges and the number of stress cycles.

Fracture based approach has been used in many studies for fatigue reliability analysis, see e.g. Park et al. (2005); Ye et al. (2014). As far as fracture mechanism of steel structures is concerned, two failure modes can be considered. The first failure mode, named brittle failure, is derived under LEFM assumptions when a crack exists in the structure. In such a framework, a static failure can be defined when the crack driving force expressed in terms of SIF (K) exceeds the fracture toughness K_c:

$$K(a, \sigma) \geq K_c \tag{2.18}$$

The fracture toughness, also named tenacity, refers to material ability to withstand unstable cracking. This equation can be equivalently rewritten by:

$$K_r = \frac{K(a, \sigma)}{K_c} \leq 1 \tag{2.19}$$

In equations 2.18 and 2.19, a stands for the current crack length and σ for the peak stress of the current fatigue cycle. The criterion K_r shows the proximity to the brittle failure.

The second failure mode, named ductile failure, happens on any structure, even on structures without cracks, subjected to an increasing loading. The criterion is expressed by Equation 2.20. Where P corresponds to the applied load, $P_L(a, \sigma_y)$ is the value of P corresponding to the plastic collapse of the material which naturally depends on the yield stress σ_y and crack length a, and L_r^{max} is the threshold value that is a function of the material flow stress and yield stress.

$$L_r = \frac{P}{P_L} \leq L_r^{max} \tag{2.20}$$

Interactions between brittle failure and pure plastic collapse (e.g. for structures without crack) for some material (i.e. with ductile behavior, for which LEFM assumptions do not apply) and/or under specific loading conditions lead to intermediate configurations known as ductile tearing. In such cases the performance function should encompass both criteria 2.19 and 2.20. One solution is to resort to the R6 curve based rule, see Figure 2.7, which has been originally proposed by Harrison et al. (1977). The performance function $G(L_r, K_r)$ may have different closed-form expressions. According to Kunz (1992) $G(L_r, K_r)$ can be represented by Equation 2.21.

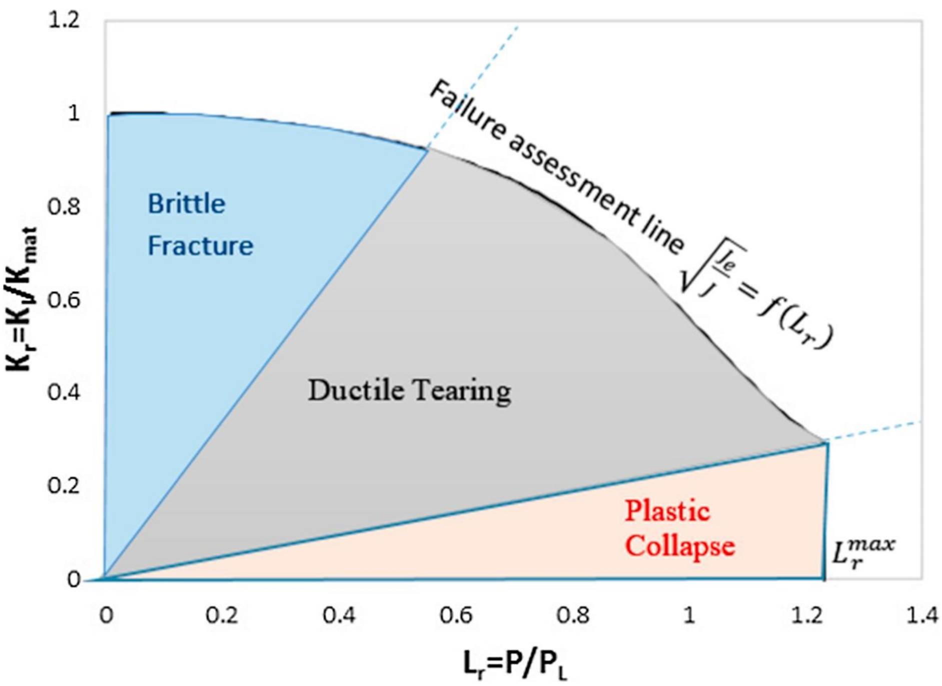

Figure 2.7: Schematic representation of different modes of failure in R6

$$G(L_r, K_r) = \begin{cases} \frac{1}{\sqrt{1+0.5L_r^2}} - K_r & L_r \leq 1 \\ 0 & L_r > 1 \end{cases} \tag{2.21}$$

Another common way to formulate a performance function within the fracture based approach is according to the crack length. In this way, the failure happens when the crack length at time t, $a(\mathbf{X}, t)$ is greater than a given critical crack length a_{cr}. Where $\mathbf{X}$ denotes the vector of input random variables. The performance function hence can be formulated by Equation 2.22.

$$G(\mathbf{X}, t) = a_{cr} - a(\mathbf{X}, t) \tag{2.22}$$

In this section, several types of performance functions for fatigue reliability assessment (according to S-N and and fracture mechanism approaches) for steel structures have been reviewed. As said before, the main goal of fatigue reliability analysis is to compute the failure probability of components that exposed to fatigue. An extensive review of methods and approaches for evaluating the failure probability is provided in Chapter 3.

Monitoring, inspection and maintenance for fatigue

An accurate prediction of structural performance is the core of structural maintenance planning and LCM. With this respect inspections and SHM can play a crucial role. SHM provides real time information about the structural responses under the real loading conditions and inspections provide information about the actual fatigue damage level for the critical locations Frangopol (2011). An accurate knowledge about the fatigue behavior in critical locations on the structure is of paramount importance for decision makers to allocate proper maintenance strategies. Maintenance actions against fatigue usually try to reduce or terminate the fatigue damage propagation. Table 2.3 summerizes some actions related to SHM, inspections, and maintenance for fatigue and the following part provides a brief introduction on some basic concepts of SHM, inspections, and maintenance for structures suffering from fatigue.

SHM

SHM is a process focusing on observing, measuring, recording, and processing of actual data related to the structure. It provides valuable information about the current state

Intervention type	Actions
1: SHM	• Acoustic emissions • Ultrasonic guided waves • Lamb waves
2: Inspection	• Visual inspection • Magnetic penetrant • Ultrasonic • Eddy current
3: Maintenance	• Surface treatment • Through thickness repair • modification of details

Table 2.3: Intervention types and related actions

of a structure under real loading conditions (e.g. loading, local stresses, crack geometry,etc.) (Cremona and Santos, 2018). During the past years, practices in SHM have significantly changed due to the developments in information technology. Advances in monitoring technology such as smart sensors, data storage, etc. make it possible to have a better snapshot of the structural behavior under different loading conditions (Cai and Mahadevan, 2016). Methods in SHM are mostly based on installing sensors on structures to continuously monitor and record their response which enables in turns to identify and localize the damage. SHM can generally be used for several reasons such as validation of design assumptions, recording the structural response under normal operating conditions, damage detection, and useful life estimation (Zhu and Frangopol, 2013a,b). SHM can be very fruitful for fatigue life assessment by providing information about crack length, stress ranges and average number of cycles on a detail, etc. Acoustic emission, ultrasonic guided waves, and Lamb waves are among several SHM techniques that are commonly used to monitor and detect fatigue damage (Ciang et al., 2008). Acoustic emission has received more attention within the past decade. In this method, special sensors are used to record the stress waves that are expelled because of the changes inside the material. The recorded information can be used to detect some damages such as crack initiation and propagation, plastic deformation, corrosion, etc. (Anastasopoulos et al., 2009). Some other fatigue related monitoring systems employ strain gauges and accelerometers for example to measure stress levels and average number of load cycles on the critical fatigue locations. Before selecting a monitoring strategy for fatigue, one should consider material and geometry of the structure, potential defects, accuracy of the monitoring data, installation cost, operation and maintenance of the monitoring system, etc. (Soliman et al., 2016).

Inspections

Inspections on the structures are usually performed visually on a regular basis. The time interval between inspection, for bridges for example, can be defined by different factors such as the volume of the traffic, age of the bridge, and the bridge condition. In the USA, 95 percent of the inspections are done at the intervals of 2 years or less. Road agencies in other countries, however, perform detailed inspections at intervals of 5 to 6 years along with less detailed check inspection at 1 to 3 year intervals (Transportation Research Board and National Academies of Sciences Engineering and Medicine, 2007). In France for instance, l'Instruction Technique pour la Surveillance et l'Entretien des Ouvrages d'Art (ITSEOA) is responsible for establishment of the procedure for inspection of most roadway infrastructures. Inspection planning for bridges according to regulations of ITSEOA is described in Table 2.4. Four types of routine inspections can be identified from this table such as routine visit, annual inspection, IQOA (Image de la Qualit des Ouvrages d'Art: Image of the Quality of Bridges) assessment, and detailed inspection (ITSEOA, 1979).

Table 2.4: Inspection types, France

Inspection Type	Interval	Performed by	Description
Routine Visit	Frequent	Road maintenance agents employed by DDE	Drive-by inspection
Annual	1 year	Road maintenance agents employed by DDE	Cursory examination during visit to bridge
IQOA	3 years	Inspection agent sometimes with certified inspector	Visual verification of conditions focusing on known defects
Detailed	9 years	Certified inspector	Robust bridges. Arms-length visual examination of all components and noting all defects
	6 years	Certified inspector	Normal bridges. Arms-length visual examination of all components and noting all defects
	3 years	Certified inspector	Ill bridges. Arms-length visual examination of all components and noting all defects
	1 year	Certified inspector	Very ill bridges. Arms-length visual examination of all components and noting all defects
Underwater	6 years	Certified inspector	Diver making arms-length touch and visual inspection

DDE = Direction Départementale de lEq uipment.

The simplest method to perform structural inspection is visual inspection that is done by human eyes and some optical devices. The quality of the inspection results are highly dependent on the visual acuity and color vision of the inspector, the rush level of the inspector, and accessibility to the inspection zone. Therefore, it is hard to ensure that inspections can detect fatal problems (Swartz and Lynch, 2009). By employing visual inspections for fatigue damage one could face notable limitations especially when fatigue cracks are small or if they occur in subsurface areas. For this reason, it is better to resort to more reliable techniques such as magnetic penetrant, ultrasonic, and eddy current methods for critical fatigue details (Fisher et al., 1998; Moan, 2005; Ciang et al., 2008). In magnetic method, magnetic particles are used to detect discontinuities in steel plates. These can be indications for existence of cracks in smooth surfaces. The accuracy of this method would decrease on welded surfaces (Demsetz, 1996). In penetrant methods, a liquid with low viscosity and high capillary is used. After cleaning the surface, this liquid with red color is applied (on the surface) and cracks become visible by spraying a developer on the surface. Like the previous method, this method is efficient on smooth surfaces (Fisher et al., 1998). High frequency sound waves are used in ultrasonic methods. A distortion in the reflected wave can be an indication of a crack. This method is good for steel plates with a thickness greater than 3 mm, but it requires high-skilled operators (Soliman et al., 2016). Eddy currents can also be used to detect cracks near surface in steel. Eddy current is produced by electromagnetic induction. Cracks then lead to some changes in the current that is detectable. Applying this method also requires well-trained inspectors (Hellier, 2012; Demsetz, 1996). Employing an inspection method to detect fatigue cracks is in general limited to a single critical location and it would be unfit to be used for scanning all the fatigue critical locations efficiently. However, monitoring systems make it possible to detect the long-term fatigue damage in multiple critical regions efficiently and reliably (Antonaci et al., 2012).

Maintenance

Maintenance against fatigue can be grouped into different categories such as surface treatments, through-thickness repair of cracks, and modification of details or structures (FHWA, 2013). Surface treatment usually involves grinding, applying Gas Tungsten Arc (GTA), and impact treatments. Grinding is used to remove a small portion of the fatigue detail that involves small cracks. Then, GTA is used to remelt (a weld toe for example) to remove the small discontinuities and to reduce the stress concentration.

Impact treatment is the last step that is used to reduce the crack initiation and propagation speed by applying a compressive residual stress on the weld toe, improving the geometry, or reshaping the weld toe (Fisher et al., 1998). Another common method to stop fatigue crack propagation through thickness is to drill a hole with a large-enough diameter at the tip of the crack. Depending on the size and location of the hole it can either be considered as long-term or short-term maintenance (Connor and Lloyd, 2017). Some repair actions aim to reproduce the same condition as before cracking. We can quote cutting out and re-fabricating some parts of components, where cracks through the thickness exist (Fisher et al., 1998). Another way to reduce fatigue crack propagation is to increase the cross sectional area by adding some cover plates. In this way the stress concentration around the crack is decreased which mitigates the crack propagation speed. An interested reader about the field would find more details about repair and maintenance methods against fatigue can be found in (Fisher et al., 1998; Connor and Lloyd, 2017; FHWA, 2013).

Life-Cycle optimization with maintenance, monitoring, and inspection

As said before an accurate evaluation of structural performance during its service life helps decision makers to decide about possible maintenance and repair actions. However, financial resources are limited and cannot cover all costs related to maintenance. Life-cycle cost is one of the most regular cost-based indicators that is used within many decision making processes to assess associated costs within the service life of a structure Frangopol et al. (1997). Including the cost of SHM (C_{mon}), the expected total life-cycle cost of a structure, C_{life}, can be formulated as:

$$C_{life} = C_{int} + C_{insp} + C_{mon} + C_{ma} + C_{fail} \tag{2.23}$$

where C_{int} is the initial cost; C_{insp} is the cost of inspection; C_{ma} is the cost of maintenance; and C_{fail} is the failure cost (Frangopol et al., 1997). Maintenance, inspection, and monitoring can be available in different types. Assuming that there are i types of inspections, j types monitoring, and k types of maintenance that are employed during the lifetime of a structure, their cost can be formulated as following equations respectively (Soliman et al., 2016).

$$C_{insp} = C_{insp}^{1} + ... + C_{insp}^{i} \tag{2.24}$$

$$C_{mon} = C_{mon}^{1} + ... + C_{mon}^{j} \tag{2.25}$$

$$C_{ma} = C_{ma}^{1} + ... + C_{ma}^{k} \tag{2.26}$$

Each type of inspection, maintenance, and monitoring can be applied for several times. Therefore, the cost for each type of inspection, monitoring, and maintenance can be calculated by following equations:

$$C_{insp}^{i} = \begin{cases} 0 & N_{insp}^{i} = 0 \\ \sum_{l=1}^{N_{insp}^{i}} \frac{C_{insp}^{i}}{(1+r)^{t_{insp}^{(i,l)}}} & N_{insp}^{i} \geq 1 \end{cases} \tag{2.27}$$

$$C_{mon}^{j} = \begin{cases} 0 & N_{mon}^{j} = 0 \\ \sum_{m=1}^{N_{mon}^{j}} \frac{C_{mon}^{j}}{(1+r)^{t_{mon}^{(j,m)}}} & N_{mon}^{j} \geq 1 \end{cases} \tag{2.28}$$

$$C_{ma}^{k} = \begin{cases} 0 & N_{ma}^{k} = 0 \\ \sum_{n=1}^{N_{ma}^{k}} \frac{C_{ma}^{k}}{(1+r)^{t_{ma}^{(k,n)}}} & N_{ma}^{k} \geq 1 \end{cases} \tag{2.29}$$

where C_{insp}^{i}, C_{mon}^{j}, and C_{ma}^{k} represent respectively the cost for single inspection of type i, monitoring of type j, and maintenance of type k. N_{insp}^{i}, N_{mon}^{j}, and N_{ma}^{k} are the number of applied inspection of type i, monitoring of type j, and maintenance of type k respectively. The annual discount rate for money is r and the time for applying lth inspection of type i, mth monitoring of type j, and nth maintenance of type k respectively are $t_{insp}^{(i,l)}$, $t_{mon}^{(j,m)}$, and $t_{ma}^{(k,n)}$. It is clear that the maintenance actions are applied to reduce the probability of failure p_f. Therefore, they can have a direct influence on the cost of failure. By taking the influence of maintenance actions into consideration one can formulate the cost of failure at year T by Equation 2.30 (Orcesi and Frangopol, 2011a).

$$C_{fail}(T) = C_{fail} \times p_f(0) + \sum_{t=1}^{T} \frac{C_{fail}(p_f(t) - p_f(t-1))}{(1+r)^t} \tag{2.30}$$

Life-cycle cost optimization is an important step within the LCM in which the optimum intervention times and types of maintenance and inspection interventions can be decided according to different objectives such as structural performance, cost, and service life (Liu and Frangopol, 2005; Frangopol and Liu, 2007). Figure 2.8 shows the relationship between the expected life-cycle cost and structural performance. It illustrates that the initial cost of a structure increase with a higher expected performance. By contrast, a high performance leads to lower costs for maintenance, and failure. An optimal maintenance and inspection strategy can be followed to maintain the structure performing its duties at a predefined performance level P^* while the expected total life-cycle cost is minimized to C^*. Decision makers usually search for the solutions that falls near this optimal value according to the owner's requirements (Frangopol et al., 1997).

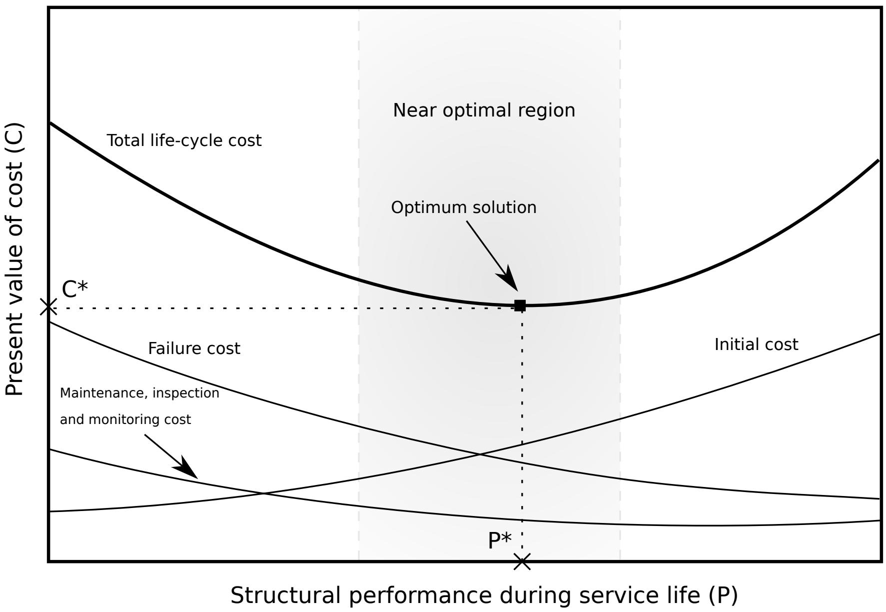

Figure 2.8: Relation between the life-cycle cost and structural performance

Decision making process for maintenance and inspection planning should be performed through an optimization process. This can be formulated as a single or multi-objective model. Including more objectives within the optimization process make it possible for more flexible decisions since multiple optimal solutions are provided for the problem according to the trade-off between the importance of each objective (Kim and Frangopol, 2017, 2018a). Different objectives that are considered for the multi-objective optimization can be related to the cost, reliability index, damage detection, and service life.

A multi-objective optimization problem can be generally formulated as following (Augusto et al., 2012):

$$Minimize: \quad \mathbf{f}(\mathbf{X}) \tag{2.31}$$

subject to

$$g_i(\mathbf{X}) \leq 0, \quad i = 1, ..., m \tag{2.32}$$

$$h_j(\mathbf{X}) = 0, \quad h = 1, ..., l \tag{2.33}$$

$$\mathbf{X}_{inf} \leq \mathbf{X} \leq \mathbf{X}_{inf} \tag{2.34}$$

where

$$\mathbf{f}(\mathbf{X}) = [f_1, f_2, ..., f_k]^T \quad : \mathbf{X} \rightarrow \mathbb{R}^k \tag{2.35}$$

represents the vector containing the objective functions that are going to be minimized. Decision variables (or design variables) are collected in vector $\mathbf{X}$ and they are defined within the design space $\mathbb{R}^n$. Decision variables can be bounded between the lower bound $\mathbf{X}_{inf}$ and upper bound $\mathbf{X}_{inf}$. The three equations 2.32-2.34 define the feasible region for the optimal solutions where $g_i(\mathbf{X})$ represents the ith inequality constraint function and $h_j(\mathbf{X})$ is the jth equality constraint function. Inequality functions here are of type "less than or equal" functions that can represent functions of type "greater or equal" if they are multiplied by -1. likely, for the "minimization" of the functions that can be transformed to "maximization" in the same way as constraints.

Often, minimizing the cost is one of the main objectives within life-cycle optimization. With this respect some studies try to minimize life-cycle cost Lukic and Cremona (2001), and others search for the minimum maintenance cost (Orcesi et al., 2010). Other cost-related objectives can be linked to minimizing the failure, inspection, and monitoring costs (Soliman et al., 2013; Orcesi and Frangopol, 2011a). Improving the structural performance by maximizing reliability index (Kim and Frangopol, 2018b) or minimizing probability of failure (Kim and Frangopol, 2018a) is another objective for life-cycle optimization. Another objective that is defined in some studies is related to fatigue damage detection. Regarding to this Soliman et al. (2013) aims at maximizing the probability of fatigue damage detection whereas Kim and Frangopol (2011c) try to minimize the damage detection delay. Maximizing the extended service life can also be an objective within the multi-objective optimization process that has been considered in (Kim and Frangopol, 2018a; Soliman et al., 2016). Among possible decision variables that can be used in the multi-objective optimization, inspection times and types, maintenance times and types, monitoring starting times and durations are among the most used (Soliman et al., 2016; Kim and Frangopol, 2018a; Orcesi and Frangopol, 2011a).

An exemplary formulation for a bi-objective maintenance optimization can be formulated as following (Okasha and Frangopol, 2009a).

- Find

$$Maintenance\ application\ times:\ \mathbf{t}_{ma} = \{t_1, t_2, ..., t_n\} \tag{2.36}$$

$$Maintenance\ types:\ ma_{t_1}, ma_{t_2}, ..., ma_{t_j} \tag{2.37}$$

- Objectives

$$Minimize\ the\ C_{life} \tag{2.38}$$

$$Maximize\ annual\ reliability\ index\ \beta\ or\ minimize\ P_f \tag{2.39}$$

- Such that

$$t_n - t_{n-1} \geq T_{min}\ years \tag{2.40}$$

$$\beta \geq \beta_{min} \tag{2.41}$$

The goals of the optimization process are a) to minimize the life-cycle cost C_{life} and b) to maximize the annual reliability index β. Decision variables for this problem are maintenance times, $\mathbf{t}_{ma} = \{t_1, t_2, ..., t_n\}$, and maintenance types $ma_{t_1}, ma_{t_2}, ..., ma_{t_j}$. The optimization algorithm should search for the optimal solutions under given conditions such as the minimum time between two consecutive repairs should be greater than a given minimum value T_{min}, and also it should search within annual reliability indices that are greater than a given minimum value β_{min}.

Conclusion and contributions of this study to LCM

As it was discussed in this chapter, Structural LCM is framework combined from different steps and each step performs given duties to play a part in accomplishment of the overall LCM objectives. Optimizing the structural maintenance planning can be considered as one of the goals of the structural LCM. It is an exhaustive task in which different challenges and obstacles need to be properly addressed. To enumerate some of the challenges in steel structures one can refer to performance prediction under uncertainty, employing SHM data to reduce uncertainties, crack propagation behavior for given components, reliability- and cost-informed decision making, and effect of maintenance actions among others.

In this thesis, studies have been performed to enhance the capabilities of the structural LCM by proposing methods and approaches related to previously mentioned challenges. With this respect, a new time-dependent reliability method is proposed in Chapter 3 that is called AK-SYS-T. This method provide an efficient and accurate tool to evaluate time-dependent reliability of a component compared to other available methods. It is worthy to mention that time-dependent reliability analysis is necessary in this context since the performance deterioration (such as fatigue) is a time-dependent process and it is associated with time-dependent parameters, e.g. fatigue loading.

As said before, another contribution of this study to structural LCM is to employ time-series methods such as seasonal ARIMA to provide a load model for long-term fatigue loading that can capture more details of the loading scenario regarding the seasonal effects in traffic loading which is an important advantage of this method compared to other methods (e.g. rainflow counting). This approach can be used for long-term monitoring data that are recorded with high frequency. It should be noted that employing time series methods for such data is not a straightforward task. More details for this method is provided in Appendix A.

Another related topic that is performed in this context is studying the crack propagation in the root of a fillet weld that is a common fatigue detail in bridges with orthotropic deck plates. One important issue that is investigated here is the influence of the transversal tension in the deck plate on the direction of the crack propagation. It is shown that increasing the transversal tension in the deck plate changes the crack propagation towards the deck plate. Such cracks are considered dangerous since they are hard to inspect and detect. To perform this study, advanced tools such as FEM and X-FEM (Extended Finite Element Method) are utilized. This study is detailed in Chapter 4.

AK-SYS-T: a new approach for time-depenent reliability analysis

Introduction

It was well elucidated in previous chapter that a proper assessment of structural performance will lead to a better optimal planning of interventions to extend the service life of existing structures. Performance indicators provide a measure to evaluate the deterioration of structural performance through time. With this respect time-dependent reliability can be employed to provide a well-suited indicator for structural LCM against fatigue. It enables to take into account the associated uncertainties in the phenomenon and provides an estimation of cumulative failure probability for a given time interval. Having the time as an input parameter amplifies the difficulty of dealing with reliability problems. One challenge in this domain is dealing with non-monotonic performance functions especially when the performance function is costly-to-evaluate. Therefore, the goal of this chapter is to propose a new time-dependent reliability method which tries to tackle this issue.

The new methodology is called AK-SYS-T. The idea behind this method is to relate the time-dependent reliability problems with system reliability problems to be able to take advantage of efficient system reliability methods. This can be dome by discretizing the desired time interval into a finite number of time nodes. AK-SYS is a recently developed efficient system reliability method. In this method, performance functions for components are replaced with Kriging meta-models and an active learning process is used for the enrichment of the Design of Experiments (DOE). AK-SYS owes its efficiency to its learning process owing to the fact that it only searches among the most vulnerable components to update the DOEs. This learning process is used towards time-dependent reliability problems and the result is AK-SYS-T. This method is introduced in this chapter.

Accordingly, the rest of this chapter is organized as follows.

Time-independent reliability analysis

The main goal of structural reliability analysis is to find the probability of failure under given conditions and for a given period of time. In reliability analysis, failure does not refer to the structural failure (such as structural collapse) only. In most cases, failure is defined as a situation when the structural performance exceeds a given threshold. The concept of limit state is therefore employed to define the failure. Generally, two types of limit states can be realized for structures: 1) ultimate limit states and 2) serviceability limit states. Failure modes within the former limit states are related to the loss of load carrying capacity such as weld rupture, fatigue rupture, formation of plastic hinge, etc. The latter limit states include failure modes related to gradual deterioration, user's comfort, etc. Undesired deflections, corrosion, and excessive deformations are some examples of the failure modes related to serviceability limit states.

Structural reliability problem are generally formulated by a so called performance function. As mentioned before, a "stress-strength" approach is used to define the structural performance function. Considering only one load effect Q and one resistance R, the basic form of the performance function can be formulated as $G = R - Q$. For many problems it is not feasible to reduce the structural performance function to a simple formulation of R versus Q. By considering all the basic variables $\mathbf{X}$ involved in the problem, R and Q can be expressed as $R = G_R(\mathbf{X})$ and $Q = G_Q(\mathbf{X})$ respectively. In this way, the resulting performance function can be written in a general form as $G(\mathbf{X})$ where $G()$ is a function that expresses the structural performance as a relationship between basic variables. The equation $G(\mathbf{X})$ defines the limit state which is the boundary between the safe domain $G(\mathbf{X}) > 0$ and the failure domain $G(\mathbf{X}) < 0$. Different concepts in structural reliability analysis are illustrated in Figure 3.1.

Given the general form of the performance function $G(\mathbf{X})$, the failure probability can be calculated by integrating the the joint probability density function $f_{\mathbf{X}}(\mathbf{x})$ of n-dimensional vector $\mathbf{X}$ of the basic variables over the failure domain $G(\mathbf{X}) < 0$ (see Equation 3.1).

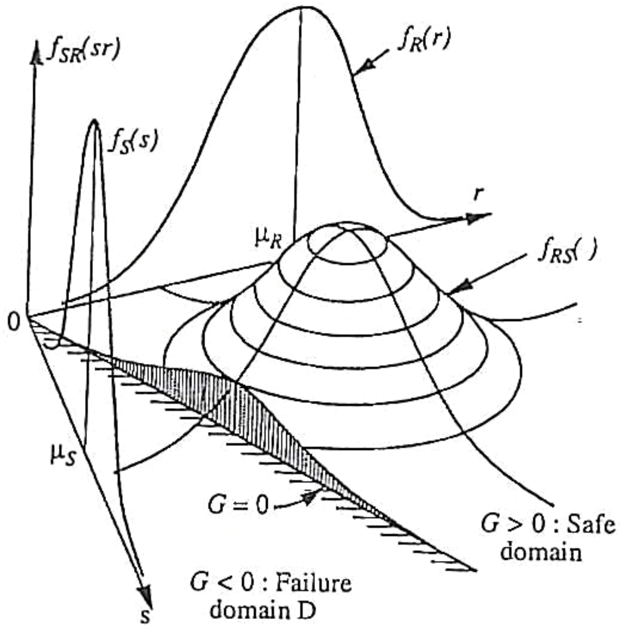

Figure 3.1: An illustration of different concepts in reliability analysis: failure domain $G < 0$, safe domain $G > 0$, limit state $G = 0$, joint density function $f_{rs}()$, and marginal density functions $f_r()$ and $f_s()$

$$P_f = P(G(\mathbf{X}) < 0) = \int ... \int_{G(\mathbf{X})<0} f_{\mathbf{X}}(\mathbf{x})d\mathbf{x} \tag{3.1}$$

Given that the basic variables are independent, the joint probability density function can be simplified as:

$$f_{\mathbf{X}}(\mathbf{x}) = \prod_{i=1}^{n} f_{x_i}(x_i) \tag{3.2}$$

where $f_{x_i}(x_i)$ denotes the marginal density function for the basic variable X_i.

General context of reliability analysis

As said before, structural reliability is defined over a given period of time and it tries to evaluate the probability that a structure accomplishes its intended duties under specified conditions by taking into account the uncertainties associated with material properties, geometry, and loading. Performing structural reliability analysis requires a performance function G that take into account the effect of all uncertainties as input.

The basic form of the performance function is based on "stress-strength" definition as mentioned in 2.6.4. The performance function hence can be formulated as $G = R - Q$ in which R and Q represent respectively the resistance capacity (strength) and the load effect (stress). Accordingly, a limit state $G = 0$ can be defined to separate the failure domain $G < 0$ from the safe domain $G > 0$.

In real world cases, structural performance function can be a time dependent process (such as the performance functions for fatigue in Section 2.6.4) that is associated with a set of random variables $\mathbf{X}$ (e.g. material properties, geometry, etc.) and a set of stochastic processes $\mathbf{Y(t)}$ (such as service and environmental loading, wind velocity, etc.). Therefore, the general form of the performance function can be represented as $G(\mathbf{X}, \mathbf{Y}(t), t)$. Dealing with time is an important issue in reliability analysis since it introduces extra complexity to the problem. For this reason, reliability problems can be categorized in two groups: 1- time-independent and 2- time-dependent problems.

Methods in the first group try to find the failure probability at a give time instant t_i as it is formulated in Equation 3.3.

$$P_{f,i}(t_i) = \text{Prob}(G(\mathbf{X}, \mathbf{Y}(t_i), t_i) \leq 0) \tag{3.3}$$

Methods in the second group, however, try to deal with the complete aging process and loading history for a given time interval $[t_0, t_l]$. Therefore, the aim of time-dependent reliability methods is to find the cumulative failure probability which is defined as: "the probability of having at least one failure during a given time interval $[t_0, t_l]$", see Equation 3.4. Figure 3.2 illustrates the differences between these two failure probabilities.

$$P_{f,c}(t_0, t_l) = \text{Prob}(\exists \tau \in [t_0, t_l], G(\mathbf{X}, \tau) \leq 0) \tag{3.4}$$

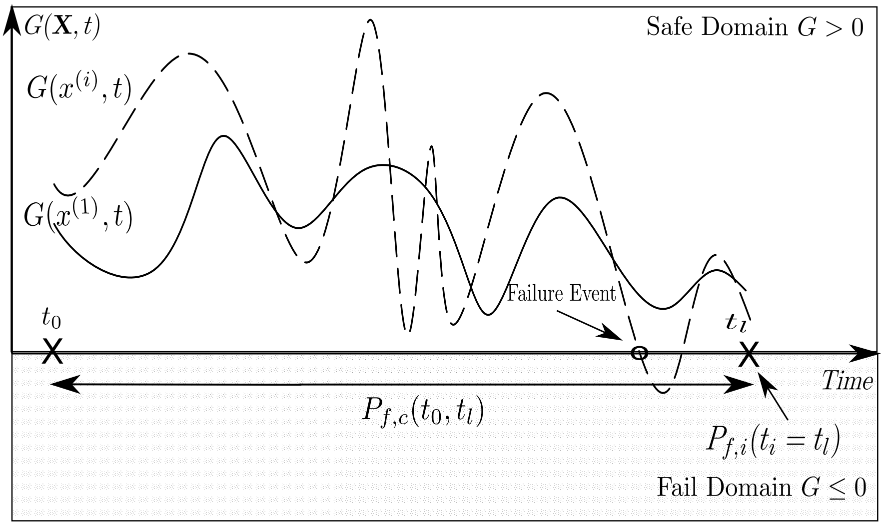

Figure 3.2: An illustration of instantaneous and cumulative probability of failure

Time-independent reliability analysis and methods

Time-dependent reliability analysis and methods

Time adds extra complexity to the problem. Compared to the time-independent problems, the limit state in time-dependent reliability is changing by time and one should also consider the complete aging process and load history of a structure. The general form of the performance function for a time-dependent reliability problem can be expressed as $G(\mathbf{X}, \mathbf{Y}(t), t)$ where $\mathbf{Y}(t)$ is the vector of input random processes. Random processes can be decomposed into random variables using some appropriate random process representations such as Karhunen-Loeve (KL) expansion (Loeve, 1977) or spectral representation method (Li and Kiureghian, 1993). Therefore, the performance function can be represented by $G(\mathbf{X}, t)$ for the rest of this study. The parameter of interest in time-dependent reliability analysis is to find the cumulative probability of failure $P_{f,c}(t_0, t_l)$ (see Equation 3.4). Calculating this failure probability is, in principle, possible using sampling methods such as crude MCS, importance sampling, etc. However, the computational cost of using MCS for time-dependent reliability problems is enormous which makes this method useless in the time-dependent context. The challenge in time-dependent reliability methods is to achieve a reasonable trade-off between efficiency and accuracy especially for the problems with non-monotonic performance functions that are costly-to-evaluate and have high dimensionality. Available methods for time-dependent reliability analysis can be categorized into two groups: out-crossing-based methods and extreme-value-based methods. Methods in the second category can provide a better accuracy, however, computational cost in the first category is lower. These methods will be briefly reviewed in Section **??**.

In most of time-dependent reliability methods, discretizing the time interval of interest into a finite number of time nodes is the main strategy to tackle the complexity that is added to the problem by time parameter. In addition to time, input stochastic processes must be discretized. This is a bit more complicated since it needs to approximate a stochastic process with a combination of some random variables and explicit functions of time. In this way the process uncertainty can be separated from its time dependency. After the discretization, one can introduce an instantaneous performance function for each time node, hence, the problem will be converted to a time-independent one. Failure at each node implies the failure of whole structure. This is equivalent to finding the probability of failure in a serially connected system in which each component represent the time nodes after discretization. This brings the idea to employ efficient system reliability methods to address time-dependent reliability problems. Therefore, the goal of this chapter is to present a newly developed time-dependent reliability method that is called AK-SYS-T. This method is based on AK-SYS that developed for system reliability analysis using Kriging meta-modeling and an active learning process. AK-SYS is reviewed is Section 3.5.2.

The rest of this chapter is organized as follows: Section **??** provides a background information about time-dependent reliability assessment and current methods in this field. Fill this part after the chapter is finished.

Background and review of time dependent reliability methods

Addressing time-dependent reliability problems is always a challenge. Different challenges that need to be addressed in this domain are related to problems with low failure probabilities, high dimensionality, complex and computationally expensive performance function, or a combination of them where finding a balance between efficiency and accuracy is always pursued. Several methods have already been developed for time-dependent reliability analysis and they can mainly categorized into two main groups namely Out-Crossing-Based (OCB) methods and Extreme-Value-Based (EVB) methods. The aim of the methods in the first group is to find the crossing rate of the performance function from the safe domain to the failure domain while methods in the second group are searching for the extreme value of the performance function (the extreme value here refers to the minimum value of the performance function).

OCB methods

The cumulative probability of failure, within the methods in OCB, is linked to the first-time-to-failure or the first passage t_f. The first-time-to-failure is a random variable and it corresponds to the first time instant that the performance function crosses the limit state. The formulation of $P_{f,c}(t_0, tl)$ can be hence written as:

$$P_{f,c}(t_0, t_l) = \mathrm{Prob}(t_f < t_l) \tag{3.5}$$

This equation implies that the cumulative probability of failure within $[t_0, t_l]$ is equal to the probability of having at least one out-crossing event from the safe to the fail domain. If $N_{[t_0,t_l]}$ counts the number of out-crossing events within the desired time interval, the previous formulation for cumulative probability of failure can be converted to the Equation

$$P_{f,c}(t_0, t_l) = P(G(\mathbf{X}, 0) \leq 0 \cup N_{[t_0,t_l]} \geq 1) \tag{3.6}$$

It has been shown that the cumulative failure probability can be bounded such as:

$$\max_{t \in [t_0,t_l]} P_{f,i}(t) \leq P_{f,c}(t_0, t_l) \leq P_{f,i}(0) + E[N_{[t_0,t_l]}] \tag{3.7}$$

where $E[N_{[t_0,t_l]}$ is the mean value of out-crossing numbers. The problem therefore lies in estimating the mean value of out-crossings during the desired period of time $[t_0, t_l]$. This requires the estimation of the out-crossing rate $\nu(t)$. The mean value of out-crossings can be formulated by Eq.3.8.

$$E[N_{[t_0,t_l]}] = \int_{t_0}^{t_l} \nu(t)dt \tag{3.8}$$

Calculating this rate is a complicated task for the methods in this category. If the performance function can be expressed as a stationary and differentiable univariate process that is added to a constant threshold, then the Rice's formula can be used to find the out-crossing rate Rice (1944). Employing Rice's formula, analytical formulations of out-crossing rate has been obtained for a stationary Gaussian process in Lutes and Sarkani (2004) and also for a general Gaussian process (stationary and non-stationary) in Lutes and Sarkani (2009); Sudret (2008).

It can be easily shown that the $N_{[t_0,t_l]}$ follows a binomial distribution using some basic probability theories. Binomial distribution tends to be a Poisson distribution for long-term reliability assessment. Under this assumption, one can neglect the dependence between the out-crossing events. Therefore, the rate for first-time-to-failure is equal to the out-crossing rate Ponte (1985). The out-crossing rate can be also approximated by sampling techniques like importance sampling Singh et al. (2011). Ignoring the dependency between the out-crossing events for problems with high reliability levels (low probability of failure) can cause a big amount of error in calculations Zhang and Du (2011); Lutes and Sarkani (2009); Sudret (2008). Researchers have tried to mitigate this deficiency by using joint out-crossing rates Hu and Du (2013) and first order sampling approach Hu and Du (2015).

One of the most popular methods in this category is PHI2 method Andrieu-Renaud et al. (2004) that is extensively used for its numerical efficiency. This method is based on system reliability analysis. A parallel system hence is considered for time instant t and $t + \Delta t$. The out-crossing happens if the system is in safe domain at time t and in the fail domain at time $t + \Delta t$. Accordingly, the out-crossing rate can be formulated as:

$$\nu(t) = lim_{\Delta t \to \ 0^+} \frac{Prob((G(t) > 0) \cap G(t + \Delta t \leq 0))}{\Delta t} \tag{3.9}$$

PHI2 tries to approximate this out-crossing rate using FORM which is a time-independent reliability method. For this reason, two FORM are used. One to estimate the probability of failure associated with $G(t) > 0$ and the other one for $G(t+\Delta t \leq 0)$. In this method there is no need to discretize the time interval the input stochastic processes can be replaced with two random variables $Y(t)$ and $Y(t + \Delta t)$ for time instants t and $t + \Delta t$. PHI2 method provides an upper bound for failure probability that causes underestimating the reliability level. The choice of the time increment Δt is crucial and affects the accuracy of this method. An approximation should be made on the choice of time increment, see (Sudret, 2008). For this reason, PHI2+ has been proposed in Sudret (2008). This method is an improvement of the initial PHI2 method that tries to stabilize the effect of the time increment Δt. However, it should be noted that PHI2+ may lead to significant errors in case of highly nonlinear limit states. More recently, a method named mean value first passage method has been proposed in Zhang and Du (2011); Du (2012) for kinematic reliability applications. Up-crossing rates are derived analytically (under simplifying assumptions) and time-dependent reliability can be calculated by integrating those analytical equations. The integration process has been done using a numerical procedure proposed in this study. In general out-crossing-based methods use FORM to approximate failure probability. Therefore their accuracy for highly nonlinear performance functions is questionable.

EVB methods

Methods in this category search for the extreme values of the performance function (global minimum here). The cumulative probability of failure then can be defined as the probability that the global minimum of the performance function becomes negative which is formulated in Equation 3.10.

$$P_{f,c}(t_0, t_l) = P(\min_{t \in [t_0, t_l]} G(\mathbf{X}, t) \leq 0) \tag{3.10}$$

Finding the global minimum (G_{min}) of the performance function requires the discretization of time and random processes and it is defined as following equation.

$$G_{min}(\mathbf{X}) = \min_{t\in[t_0,t_l]} G(\mathbf{X}, t) \leq 0) \tag{3.11}$$

G_{min} is a random variable and the cumulative probability of failure can be accurately calculated if the probability distribution of the extreme response is well parametrized. Defining this distribution for highly nonlinear performance functions is a challenging task since ,in one hand, it is difficult in engineering applications to obtain the extreme responses of a system. In the other hand, structural analysis is performed over a long period of time and this can cause dimensionality problem when the problem involves stochastic processes. MCS approach can be used to evaluate the probability of failure. However, this can lead to a huge computational cost especially when costly-to-evaluate performance functions are involved. Therefore, methods in this category try to use meta-model based simulations to reduce the computational cost. Existing methods in this category are generally based on Kriging meta-modeling. In some studies, however, Polynomial Chaos Expansion (PCE) is also used. Methods in this category are shortly reviewed in this section.

Proposed methodology: AK-SYS-T

From time-dependent reliability to system reliability

AK-SYS method

Validation and case studies

Conclusion and perspectives (on the full curve and descritization)

Second Real Chapter

And the second real chapter.

Conclusions

Write your conclusions here.

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My First Appendix

In this file (appendices/main.tex) you can add appendix chapters, just as you did in the thesis.tex file for the 'normal' chapters. You can also choose to include everything in this single file, whatever you prefer.