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Sede: Facoltà di Ingegneria - Università di Pavia - via Ferrata 1 – 27100 Pavia – Italy

Dottorato di Ricerca in Ingegneria Civile V Nuova serie (XIX Ciclo)

Integration of Structural Health Monitoring into the Design, Assessment, and Management of Civil Infrastructure

Ph.D. Thesis

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Preface

Acknowledgments

The author wishes to express his sincere gratitude for both the opportunity and guidance received in the completion of this Thesis. In specific, to Professor Fabio Casciati as coordinator for envisioning, creating, and supporting a non-traditional arrangement that allowed me to complete all university program requirements balanced with other professional commitments and ambitions. Without his support, this thesis would not have been possible and travel opportunities to conferences and professional schools would have been missed. To Professor Dan Frangopol, the research advisor of my Ph.D. thesis, who provided the topic, challenge, and countless hours of feedback through revisions and concept assistance. Thanks to Professor Frangopol, I have had the opportunity to meet many of the leaders in the field and the authors of the books, codes, articles, and papers I've studied. From this, I've also been placed into a relevant field of study and one within which opportunities are presenting themselves. To Colonel (Retired), Professor and Head Al Estes who introduced me to the topic, to Professor Frangopol, and whose previous work provided a roadmap to get started. It is worth noting that all three of these individuals took me into their homes and families in order to grow me both professionally and personally. Their kindness, professional expertise, and generosity will always be remembered. Lastly, the support of my family is gratefully acknowledged and specifically to my wife Sara for her support, inspiration, assistance, and guidance.

About the Author:

The author is a graduate of the United States Military Academy (BS - Civil Engineering) and of Stanford University (MS – Structural Engineering) and holds a professional engineering license in the state of Missouri, USA. After 13 years of military service in the US Army Corps of Engineers, he has used this Thesis as a vehicle to transition out of military service and into industry in the field of structural health monitoring and the life-cycle performance prediction of structures. The author's last assignment in service was as an assistant professor at the US Military Academy at West Point for the topics of Statics, Mechanics of Materials, and Probability and Statistics at the undergraduate level. These experiences have influenced how this thesis is organized and written. With a passion for education and hands-on experience with soldiers, projects, and construction activities, it is hoped that this thesis is clear, concise, plainly written, practical, honest, and understandable to readers new to the subject area. The thesis topic is a new beginning for the author and he is pleased to soon have the opportunity to work in the subject area with Italian engineering consulting company D'Appolonia S.p.A. headquartered in Genova, Italy.

About the Thesis:

This thesis is not the application of a particular method to a demonstration activity. It is also not the development of a focused topic or approach to a pointed problem of interest. Instead, this thesis has been an ongoing investigation into the open and active question of how to integrate structural health monitoring technologies into civil infrastructure management programs and in specific, reliability-based life-cycle management approaches for highway bridges. Much of the research has been motivated by and has evolved through participating in technical committees, mini-symposia, and workshops dedicated to civil infrastructure, monitoring, reliability concepts, life-cycle concepts, and risk. To date, this investigation has resulted in the publication (in various stages) of two book chapters, one journal article, 3 keynote lectures, 3 invited book contributions, 2 invited conference papers, and 10 traditional conference papers. The strength of this thesis is its breadth in how to approach the problem and its linkages across multiple disciplines. However and correspondingly, its weakness is a lack of depth on the study of any particular application and as part of a larger research question and an open field of activity, it does not reach a definitive conclusion that finalizes the needed research in the topic area. However, several procedural and technical contributions developed herein represent important steps in that process.

In assessing the quality of any effort of this magnitude, it may be difficult to determine what work is original and what work is taken from other sources and applied. For this reason, the author's primary contributions to the body of knowledge are highlighted as follows:

Procedural

- Developing strategies for the top-down design of SHM systems at the program level and at the structural level. (Chap 4)
- Developing a framework for the incorporation of structural health monitoring (SHM) in life-cycle management (LCM) approaches. (Chap 2-4)
- Developing the equations for the comparison of Life-Cycle costs for monitoring vs. non monitoring alternatives. (Chap 4)

Technical

- Developing a method to account for time-effects with respect to monitoring-based live loads through the application of extreme value statistics. (Chap 5)

- Developing a method to account for parameter uncertainties with respect to the characterization of monitoring-based distributions for use in a reliability analysis. (Chap 5)
- Revisiting the basic principles of reliability and structural reliability concepts to link the use of monitoring data, classical reliability concepts, structural reliability theory, and the use of lifetime functions. (Chap 6)

Description of the Ph.D. Course*

Settore :	Ingegneria
Field :	Engineering
Sede amministrativa non consortile:	Università degli Studi di Pavia
Administrative location:	University of Pavia
Durata del Dottorato:	3 anni
Duration:	3 years
Periodo formativo estero:	Come previsto dal regolamento del Dottorato di Ricerca
Period in external organization:	As required by the School by-law
Numero minimo di corsi:	6
Minimum number of courses:	6

* This two page description is provided first in Italian and then is repeated in English.

Italiano

Il dottorato di ricerca in Ingegneria Civile dell'Università degli Studi di Pavia è stato istituito nell'anno accademico 1994/95 (X ciclo). Il corso consente al dottorando di scegliere tra quattro curricula: Idraulico, Sanitario, Sismico e Strutturale. Egli svolge la propria attività di ricerca presso il Dipartimento di Ingegneria Idraulica e Ambientale per i primi due curricula, quello di Meccanica Strutturale per i rimanenti. Durante i primi due anni sono previsti almeno sei corsi. Il Collegio dei Docenti, composto da professori dei due Dipartimenti (e da esterni cooptati in mancanza di competenze interne), organizza i corsi con lo scopo di fornire allo studente di dottorato opportunità di approfondimento su alcune delle discipline di base. Corsi e seminari vengono tenuti da docenti di Università nazionali ed estere. Il Collegio dei Docenti, cui spetta la pianificazione della didattica, si è orientato ad attivare ad anni alterni corsi comuni sui seguenti temi:

- Meccanica dei solidi e dei fluidi.
- Metodi numerici per la meccanica dei solidi e dei fluidi.
- Rischio strutturale e ambientale.
- Metodi sperimentali per la meccanica dei solidi e dei fluidi.
- Intelligenza artificiale.

più corsi specifici di indirizzo. Al termine dei corsi del primo anno il Collegio dei Docenti assegna al dottorando un tema di ricerca da sviluppare sotto forma di tesina entro la fine del secondo anno; il tema, non necessariamente legato all'argomento della tesi finale, è di norma coerente con il curriculum, scelto dal dottorando. All'inizio del secondo anno il dottorando discute con il Coordinatore l'argomento della tesi di dottorato, la cui assegnazione definitiva viene deliberata dal Collegio dei Docenti. Alla fine di ogni anno i dottorandi devono presentare una relazione particolareggiata sull'attività svolta. Sulla base di tale relazione il Collegio dei Docenti, "previa valutazione della assiduità e dell'operosità dimostrata dall'iscritto", ne propone al Rettore l'esclusione dal corso o il passaggio all'anno successivo. Il dottorando può svolgere attività di ricerca sia di tipo teorico che sperimentale, grazie ai laboratori di cui entrambi i Dipartimenti dispongono, nonché al Laboratorio Numerico di Ingegneria delle Infrastrutture. Il "Laboratorio didattico sperimentale" del Dipartimento di Meccanica Strutturale offre:

- una tavola vibrante che consente di effettuare prove dinamiche su prototipi strutturali;

- opportuni sensori e un sistema di acquisizione dati per la misura della risposta strutturale;

- strumentazione per la progettazione di sistemi di controllo attivo e loro verifica sperimentale;

- strumentazione per la caratterizzazione dei materiali, attraverso prove statiche e dinamiche.

Il laboratorio del Dipartimento di Ingegneria Idraulica e Ambientale dispone di:

- un circuito in pressione per effettuare simulazioni di moto vario;

- un tunnel idrodinamico per lo studio di problemi di cavitazione;

- canalette per lo studio delle correnti a pelo libero.

English

The Graduate School of Civil Engineering at the University of Pavia was established in the Academic Year of 1994/95 (X cycle). The School allows the student to select one of the four offered curricula: Hydraulics, Environment, Seismic engineering and Structural Mechanics. Each student develops his research activity either at the Department of Hydraulics and Environmental Engineering or at the Department of Structural Mechanics. During the first two years, a minimum of six courses must be selected and their examinations successfully passed. The Faculty, made by Professors of the two Departments or by internationally recognized scientists, organizes courses and provides the student with opportunities to enlarge his/her basic knowledge. Courses and seminars are held by University Professors from all over the country and abroad. The Faculty starts up in alternate years common courses, on the following subjects:

- solid and fluid mechanics,
- numerical methods for solid and fluid mechanics,
- structural and environmental risk,
- experimental methods for solid and fluid mechanics,
- artificial intelligence.

More specific courses are devoted to students of the single curricula. At the end of each course, for the first year the Faculty assigns the student a research argument to develop, in the form of report, by the end of the second year; the topic, not necessarily part of the final doctorate thesis, should be consistent with the curriculum selected by the student. At the beginning of the second year the student discusses with his Coordinator the subject of the thesis and, eventually, the Faculty assigns it to the student. At the end of every year, the student has to present a complete report on his research activity, on the basis of which the Faculty proposes to the Rector his admission to the next academic year or to the final examination. The student is supposed to develop either theoretical or experimental research activities, and therefore has access to the Department Experimental Laboratories, even to the Numerical Laboratory of Infrastructure Engineering. The Experimental Teaching Laboratory of the Department of Structural Mechanics offers:

- a shaking table which permits one to conduct dynamic tests on structural prototypes;
- sensors and acquisition data system for the structural response measurements;
- instrumentation for the design of active control system and their experimental checks;
- an universal testing machine for material characterization through static and dynamic tests.

The Department of Hydraulics and Environmental Engineering offers:

- a pressure circuit simulating various movements;
- a hydrodynamic tunnel studying cavitation problems;
- micro-channels studying free currents.

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MARCELLINI Alberto Dirigente di Ricerca, CNR - Milano.

[§] Deceduto il 30 gennaio 2007
Deceased 30 January 2007

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Chapter 1

INTRODUCTION

1.1 Underlying Grant and Research Topic

This thesis is motivated by and constructed in support of the below listed US National Science Foundation Grant, with my research advisor, Professor Dan M. Frangopol, Lehigh University, as the Principle Investigator.

NSF Grant Title: Integrated Maintenance-Monitoring- Management Framework for Optimal Decision Making in Bridge Life-Cycle Performance (Principal Investigator: Professor Dan M. Frangopol, University of Colorado at Boulder 2005-2006, and Lehigh University 2006-2009).

Abstract: In this proposed research, an **analytical and computational framework** for integrated maintenance-monitoring- management systems (IMS) of highway bridges will be developed. This framework will combine in a novel manner emerging health monitoring techniques, time-dependent structural reliability theory, life-cycle costing, Bayesian updating approaches, highway transportation network analysis, and optimization. **Methodologies for**

predicting lifetime safety and performance of highway bridges with and without monitored data will be developed. Particular emphases will be placed on **proper treatment of various uncertainties** associated with loading, environmental stressors, structural resistances, deterioration processes, and monitoring and maintenance activities. **Cost-effectiveness of different health monitoring technologies** in improving both the prediction of bridge performance and the quality of subsequent management decisions will be systematically addressed. The proposed IMS will be formulated as a nonlinear, discrete, combinatorial optimization problem for which multiple and conflicting objectives will be considered. These objectives will address bridge safety and performance as well as long-term economic consequences. Evolutionary computation will be performed to produce a group of Pareto-optimal tradeoff solutions for the decision-making process.

1.2 Organization of the thesis

This thesis is only one contribution of several to the proposed research topic. Main areas of contribution and focus for the author have been highlighted in the grant abstract and include

- Analytical and computational frameworks
- Methodologies for predicting lifetime safety and performance
- Proper treatment of uncertainties
- Cost effectiveness of SHM

The contributions of this thesis are divided into 7 chapters. Two chapters are organizational (Introduction and Conclusion), two are informational/procedural (Chapter 2 and Chapter 3), two are technical (Chapter 4 and Chapter 5) in nature, and Chapter 6 is mixed (procedural/technical). Each chapter is briefly summarized below:

Chapter 1: *Introduction*

Chapter 1 simply serves as an organization of the thesis and provides a short abstract of each chapter.

Chapter 2: *Motivation, Aim, and Scope*

Chapter 2 provides the reader an introduction to the subject material. The aging infrastructure problem is described and the motivation and necessity for the improved assessment, performance prediction, and management of civil infrastructure is presented. Several prominent books, journals, professional associations, research centers, and conferences are provided as references for researchers new to the field. Basic concepts surrounding the life-cycle assessment, performance prediction, and management of civil infrastructure are provided with references to important works. The same is provided for the field of structural health monitoring. Several mathematical models and decision making approaches that enable life-cycle management and structural health monitoring are detailed. These include reliability concepts, risk-based decision making, Bayesian updating, system analysis, and time dependent reliability. After the presentation of these basic concepts, the aim and scope of the thesis is presented.

Chapter 3: *Effect of Monitoring on the Reliability of Structures*

Chapter 3 investigates the question of how more accurate information and reduced uncertainty change the design, assessment, and performance prediction of civil infrastructure. To fully explore this question, the evolution and state of the art of design methods, inspection programs, assessment models, and management programs are presented. How structural health monitoring can serve as a catalyst to improve the state of the art in each discipline is provided. An application that demonstrates risk-based decision making based off total expected cost is developed. In this application, one approach for the standardization of the calculation of the consequence of failure cost and the potential benefit of SHM using established code based guidelines is presented.

Chapter 4: *Integration of Health Monitoring in Asset Management in a Life-Cycle Perspective*

Chapter 4 is the main procedural contribution of the thesis and develops a top-down approach to the integration of SHM in asset management. Beginning at the strategic level, considerations for the development of national monitoring programs are presented. Differences in funding, ownership, codes, and public policy are highlighted between different countries. For adoption by any nation, a paradigm of mutually supporting adoptions-in-concert aimed to facilitate coordinated and synchronized actions amongst different interested parties involved in solving the aging infrastructure problem is provided. At the national level, network level, and individual structural level, the procedural steps required to allocate monitoring resources to the most critical structures, for the most critical materials and failure modes, at the most critical locations, at the optimal point in times are discussed. Frameworks for the inclusion of SHM in LCM are provided to include the development of the equations necessary to incorporate SHM in life-cycle calculations. An application is provided that sequentially builds a time-dependent reliability analysis of increasing complexity with a critique of the assumptions and modelling limitations for at each step.

Chapter 5: *The Development of Monitoring-Based Live Load Effects for Use in a Reliability analysis*

Chapter 5 is the main technical contribution of the thesis and explores in detail the characterization of monitoring-based live loads for use in a reliability analysis using the statistics of extreme values. The theory of extreme values is presented and simulations are developed to demonstrate that extreme value distributions can be observed via peak picking (instead of predicted from an underlying baseline distribution) and that the convolution of multiple random processes converges to an extreme value distribution. The accuracy and stability of monitoring-based distribution parameters are directly correlated to the amount of data used for their characterization and how that data is processed. Two separated approaches are developed and presented to treat this parameter uncertainty to provide a framework for its inclusion in a reliability analysis. The process is demonstrated on a case study of the Lehigh River Bridge located in Pennsylvania, USA using approximately 90 days of monitoring data.

Chapter 6: *Lifetime Structural Health Monitoring Based on Survivor Functions, Hazard Functions and Cost*

Chapter 6 investigates several different approaches to the solution of the time-dependent reliability problem. Classical reliability concepts, lifetime functions, and their extension to structural reliability concepts are discussed. Assumptions, advantages, and limitations of the different models are provided. The application of Chapter 4 is continued using one time-dependent reliability approach with the inclusion of risk calculations. This chapter is important because it revisits the basic principles for the construct of the performance profiles which drive the safety assessment, scheduling, and conduct of maintenance and repair activities.

Chapter 7: *Conclusions*

Chapter 7 briefly outlines conclusions and proposed areas for future research based off this study.

Chapter 2

MOTIVATION, BASIC CONCEPTS, AIM AND SCOPE

Abstract

Active management of aging civil infrastructure is a 21st century problem that has to be solved as the condition and safety of existing structures deteriorate. Transcending national borders, this problem will challenge our thinking, methodology, and ability to incorporate new technologies into existing approaches and real-world applications. Although great progress in the fields of civil infrastructure management, construction, and structural health monitoring has been made, integration of the milestones in each field remains an area in need of research. This chapter provides many of the underlying principles for these fields as well as the existing state of the art. References to important works are provided as well as the identification of important journals, societies, conferences, and books. Highlighted basic concepts explained in this chapter include life-cycle concepts, structural reliability, time dependent reliability analysis, bridge management programs, inspection scheduling and planning, maintenance activities, risk-based decision making, Bayesian updating, and

structural health monitoring. Lastly, the aim and scope of this thesis is provided.

2.1 Motivation

2.1.1 General

Structural health monitoring (SHM) is likely the enabling technology that will lead to the next significant evolution of the design, assessment, and management of civil infrastructure. Similar to the impact brought about by computers and structural analysis programs, access to site-specific data across a variety of measurements provides the capability to implement several concepts, methods, and ideas that have existed for some time, but have not yet matured in practical applications. These include, among others, the smart system concept, multifunctional materials, performance and durability based design, life-cycle design, reliability-based structural assessment, and damage detection capabilities. Although effort is typically given to a very specific part of the problem, such as perhaps the design of a particular sensor, a very interesting perspective is brought about by considering how such capabilities will ripple through public policy, code specifications, inspection programs, and educational courses as well as the processes of design and assessment.

Developing and leveraging the use of monitoring technologies for civil applications requires insight, planning, and will remain an open area of research for the foreseeable future. The rapid pace of advances in SHM technologies provides a sharp contrast when compared to the time required to affect changes in civil engineering, a field governed by laws, codes, time-tested experience, and where projects themselves may span decades. Although SHM offers great potential, it should be anticipated that such technologies will not be adopted unless they are subsidized, required by code, or proven cost-effective due to competing resource demands from the backlog of required maintenance and rehabilitation activities on existing structures. As such, metrics and methods that calculate and communicate the costs and benefits associated with monitoring must be identified and employed so that alternatives may be adequately compared.

Change is a natural and inherent part of civil engineering. The past several decades have witnessed design methodologies shift from deterministic-based approaches, such as allowable stress design, to the semi-probabilistic approaches found in current codes such as American Association of State Highway and Transportation Officials (AASHTO, 2007), the Canadian Highway Bridge Design Code (CHBDC, 2000), and the European Highway Agency Eurocodes (EUROCODES, 2002). In the near future, performance-based design will likely be adopted as progress in materials, design software, construction methods, and structural health monitoring empower the structural engineer to better address the uncertainties inherent to the design and operation of civil structures. Although the methods have continued to evolve over time, their intent has remained constant. Each approach (deterministic, semi-probabilistic, and probabilistic) seeks an optimal balance between economical design and safe performance.

2.1.2 Reasons and Catalysts for Change

Change is typically brought about by opportunity, necessity, or tragedy. Over the course of study for this thesis and at this point in time (August, 2008), all three aspects have captured worldwide attention to some extent.

2.1.2.1 Catalyst for Change: Opportunity

Opportunity has presented itself through technological advancements and improvements to existing methodologies. With respect to monitoring technologies, reductions in size, wireless capabilities, improved energy performance, and reductions in cost are making SHM practical for civil structure applications. Although monitoring devices have existed for some time, they have typically required a controlled environment, hard wired cables, and immense effort to obtain data making their application in a field environment difficult. Recent improvements in these devices are now making it feasible to obtain site-specific response data cost effectively and offer great potential with respect to the design, assessment, maintenance, and rehabilitation of civil infrastructure (Frangopol and Messervey, 2007a).

With respect to existing methodologies, lessons learned maintaining existing structures and the emergence of life-cycle concepts have also presented the opportunity to improve the state of the art. Most often, structural design, or purchasing in general, focuses on obtaining the least cost solution that fulfills specified requirements. Over the past several decades, efficiencies have been gained through reductions in structural weight as material properties, construction methods, and design software technologies have improved (Estes and Frangopol, 2005a). Although it is implied that concrete will require repair, roofs will need to be replaced, and paints be reapplied, the intended service life of a structure is often left unspecified. In such cases, project bids consider only the initial costs of design and construction and upon completion the structure is turned over to the owner with the absence of a maintenance plan. Maintenance and repair activities are then likely to become an ad-hoc reaction whenever a defect manifests itself at which time a maintenance program is developed (Bijen, 2003). Unfortunately, in terms of expense, research in the field of life-cycle management has shown that the costs of inspecting, maintaining, and repairing a structure over its useful lifespan often dwarf those associated with the initial design. This is compounded by the frequent desire to extend the service life of a structure beyond that originally intended. The result is a non-optimal allocation of resources over the life of the structure.

2.1.2.2 Catalyst for Change: Necessity

Sustainable economic growth, productivity, and the well being of a nation are intimately linked to the reliability and durability of civil structures such as buildings, bridges, dams, and transportation networks (Frangopol and Liu, 2006). To this end, comparisons across countries in varying stages of development can be used to show that Gross Domestic Product (GDP), life expectancy, and infrastructure development are highly correlated. As a result, society relies on its engineers and government to design, maintain, and regulate structures that are safe and perform as intended over their service lives. In terms of magnitude, new civil engineering construction is the largest industry in the world representing approximately 10% of annual GDP. Of this 10% of GDP spending, an estimated 5-10% is the result of the failure (not necessarily collapse) of existing structures (Bijen, 2003). For most countries, existing structures and civil infrastructure are their most valuable assets and their upkeep represents one of their most significant investments. Unfortunately, these assets are deteriorating at an alarming rate due to overuse, overloading, aging or damage (Chong et al., 2003).

Highway bridges are likely the subset of civil infrastructure in the most critical condition and provide an excellent example of the problem. In the United States, many of the bridges constructed as part of the Eisenhower Interstate expansion in the 1950s, 1960s, and 1970s are approaching the end of their planned service lives. These structures serve as critical nodes that link highways, interstates, and provide river crossings. By their very nature, bridges are vulnerable to and are constantly subjected to aggressive environments which include chemical attack from de-icing salts, environmental stressors such as wind, temperature, and water, as well as continuously increasing traffic volumes and heavier truck loads (Frangopol and Liu, 2007). The point of increasing traffic volumes and heavier vehicles is non-trivial and is highlighted in Figure 1 which shows typical New York City traffic when most its major bridges were constructed (early 1900s) compared to today.

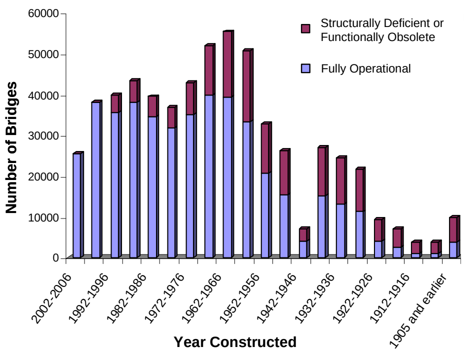
Figure 2.1. NYC traffic of the early 20th Century across the Brooklyn Bridge (Esther Bubley at Brooklyn Museum online) and traffic of the early 21st Century across the George Washington Bridge (Seth Holladay at flickr online).

The same scenario of increasing traffic loads and frequencies is present worldwide. In Denmark, traffic in terms of kilometres driven nationally doubled in a single decade during the period 1992-2002 (Enevoldsen, 2008). Considering Europe as a whole, the European Union currently projects a doubling in freight volumes that travel by road in the period 2000-2030 (Enevoldsen, 2008). In order to accommodate such increases in traffic either new highway networks must be constructed or allowable truck weights must be increased. In already congested urban areas, the construction of additional highways may be impossible. From an assessment and management perspective of existing bridges, two questions are immediately apparent. First, did the original (deterministic) design envision and provide adequate levels of safety for modern traffic loading and frequency? Second, have traffic increases resulted in faster rates of deterioration across bridge joints, members, and systems?

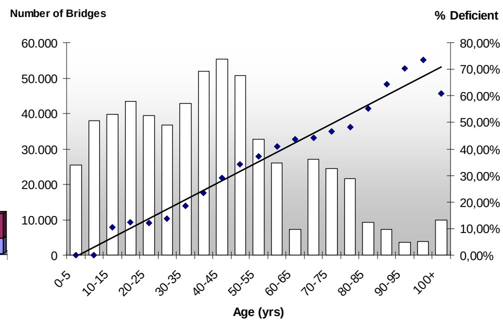
The deterioration of highway bridges in North America, Europe, and Japan is well documented and publicized. In general, highway networks reached maturity in the mid 20th century and attention shifted from construction techniques to inspection and management programs. In the United States, several bridge failures in the 1960s, including the tragic collapse of the Silver Bridge due to instantaneous eyebar fracture, focused national attention on the deterioration of existing bridges with emphasis on bridge safety (Small and Cooper, 1998a; Small and Cooper, 1998b). As a result, the Federal Highway Act of 1968 established the requirement for regular bridge inspections. This act was soon followed by the AASHTO "grey book" Manual for Maintenance Inspection of Bridges (1970) and the Federal Highway Administration (FHWA) has revised national bridge inspection standards (NBIS) almost yearly as methods and the base of knowledge in the field have improved. Although it may be comfortable to think of such bridge failures as a problem of the past, the recent failures of highway bridges at the Laval Overpass in Canada (2005) and the I-35W Bridge in Minneapolis, USA (2007) serve as reminders that this is also a problem of today.

Now containing approximately 40 years of inspection results, the National Bridge Inventory (NBI) is a richly populated database classifying the state of U.S. bridges based primarily on biannual visual inspections (FHWA, 2007). In 1998, the American Society of Civil Engineers (ASCE) began publishing a Report Card on the Nation's Infrastructure which was again updated in 2001, 2003, and 2005. This report currently consists of 15 categories of which one is bridges. It is likely that this ASCE report card has brought the most attention to the current status of bridges in the USA (ASCE, 2005).

In the United States, 25.8% of the 596,808 existing bridges were structurally deficient or functionally obsolete as of the end of 2006 (FHWA, 2007). Structurally deficient bridges are closed or restricted to light vehicle traffic due to deteriorated structural components. Functionally obsolete bridges are those which no longer meet code requirements and warrant replacement or retrofit. It is worth noting that the percentage of deficient bridges is higher in urban areas (31.6%) than in rural areas (25.6%). This is likely correlated to the higher volume of traffic as well as the tendency to postpone maintenance and repairs on urban bridges due to the traffic disruptions and the additional congestion created during their repair. Using statistics from the U.S. National Bridge Inventory (NBI), Figure 2 provides a graphical representation of the problem.



(a)



(b)

Figure 2.2. Two representations of the classification of highway bridges using US NBI statistics (data taken from FHWA, 2007).

Figure 2a depicts the number, classification, and year constructed for the U.S. bridge population. Figure 2b provides this same information but clearly identifies the expected trend that a larger percentage of older structures are deficient. From these figures it is noted that the majority of U.S. bridges are clustered between the ages of 30 and 50 years old and that this group of structures is approaching an age where a larger percentage is projected to become deficient. For this reason, we are approaching what some describe as the age of "mass maintenance" with similar trends being reported in Europe and in Asia (Peil, 2003, Fujino and Abe, 2004). It is not clear if current repair and rehabilitation efforts are keeping pace with the rate of new deficiencies.

Placing a dollar amount on the highway bridge problem is difficult. In the United States, an estimated annual investment of $9.4 billion for the next 20 years is required (ASCE, 2005). However, this data point was as of 2005 and the U.S. has since seen a tripling of commodity prices and bond-funded projects have been impacted by a credit crisis. Such figures also do not take into account the negative impact on commerce and productivity due to the traffic delays and congestion typically associated with bridge replacement or repair. It is estimated that hundreds of billion ton-miles of goods and materials along with several trillion passage-miles are transported on highway networks in the United States every year (BTS, 2003) and that this connectivity has made significant contribution to the Nation's economy and quality of life (Tolliver, 1994). For all previously listed reasons, there is a great need for methods and technologies to help assess these structures, prioritize repairs, and enable the efficient allocation of funds.

2.1.2.3 Catalyst for Change: Tragedy

Over the past several decades, the challenges associated with the maintenance, safety, and condition of civil infrastructure worldwide have passed from an issue handled and discussed amongst a relatively small group of engineering professionals, to one that has essentially become common public knowledge. In the U.S., the ASCE infrastructure report card is published, available online, and frequently cited by researchers and news agencies. In addition, the Federal Highway Administration publishes and makes available online its strategic plan, provides data on bridge replacement and rehabilitation projects, and maintains the National Bridge Inventory database which contains over 40 years of bridge inspection results (FHWA, 2008). Bringing this information to an even wider audience and to draw attention to the issue, the internet news portal MSNBC now maintains an interactive map system allowing users to enter the route they travel which will then display the statistics of each bridge along that route highlighting those deficient (Dedman, 2007a, b, c). For the author, it has been interesting to research an issue over the span of a few years and to watch it repeatedly make national and international news with increasing frequency.

Figure 2.3. From top left to bottom right, the U.S. Northeast Blackout of 2003 (Defence Meteorological Satellite Program), a failed levee in New Orleans during Hurricane Katrina in 2005 (Associated Press), the 2006 collapse of an interstate overpass in Laval, Canada (CCTV News), and the 2007 Collapse of the I35W Bridge in Minneapolis, Minnesota (Minnesota State Department of Transportation).

As is often the case with engineering, disasters, mistakes, and tragedies often act as the catalyst for change. Figure 3 shows four recent infrastructure failures that have acted as agents for change and that that contain pertinent and recurrent themes. In 2003, overgrown tree branches led to a blackout of the Northeast power grid that left over 50 million people without power shutting down transportation networks, airports, and nuclear facilities (Wikipedia, 2008a). This event exposed the fragility and lack of robustness in the power grid. The issue of robustness was (and still is) already topic under investigation in response to the structural collapses associated with the terrorist attacks of 9/11. In 2005, Hurricane Katrina devastated the New Orleans area resulting in massive financial losses and the significant loss of human lives (Wikipedia, 2008b). The focal point of this tragedy became the failure of over 50 protective levees surrounding New Orleans. Although investigations by the U.S. Army Corps of Engineers have determined that a design error contributed to the failure, an equally or more important contributing factor was that the levee system was designed for hurricanes up to Category 3 intensity whereas Katrina was a Category 5 storm. Although strengthening and increasing the height of the levee system had been proposed, it was never adopted due to the high costs of such a project. This raises the questions: How safe is safe enough? What level of risk is appropriate? and who is the decision authority? In 2006, an interstate highway overpass collapsed during routine usage in Laval, Canada killing 6 people (CTVNews, 2006). The cause of the collapse was the debonding of the internal steel reinforcement due to corrosion at the deck-column interface for the reinforced concrete structure. Important facts related to this collapse are that the bridge had recently passed its periodic visual inspection, that hours before the event transportation officials were alerted to and cleaned up spalling material that had dropped onto the motorway below the overpass, and that immediately prior to the event, motorists reported a noticeable drop as they began crossing the bridge. This tragedy highlighted the ongoing question of the effectiveness of visual-based inspections and whether or not they provide an adequate level of safety. Because there was some type of advanced warning as motorists reported irregularities, this event also raised the question of what are the appropriate response mechanisms, communication channels, and decision authorities as an incident develops. Lastly, in 2007 the I35W Minneapolis Bridge in Minnesota, USA collapsed while in service killing 13 and injuring 100 people (Cho & Van Hampton, 2008). The failure was likely due to a design error of the thickness of a gusset connection. Important factors related to this collapse are that the structure had already been listed as deficient for 17 years during successive visual inspections, in 2005 it was rated in the bottom 5% of its peer group (high-traffic bridges) with its superstructure rated as "poor", and that major repairs were delayed on several occasions due to budgetary constraints (Dedman, 2007, Associated Press, 2008). Additionally, heavy construction equipment was operating on the structure conducting minor repairs when the structure collapsed. This failure in specific epitomizes the aging infrastructure problem – that known existing deficiencies across over 200,000 bridges can result in sudden failure with high consequence. Additionally, the event and ensuing investigation have placed scrutiny on all aspects of bridge safety to include design practices, considerations for non-redundant structures, inspection and management programs, and the proper conduct of maintenance and repair activities. Lastly, this tragedy serves as a reminder of the magnitude and severity of the indirect costs associated with such failures which include the loss of public confidence and trust, site cleanup expenses, emergency inspections of like structures, user delays, longer travel distances, decreases in productivity, and legal ramifications. Collectively, these four failures (and others) have focused worldwide attention on questions engineers face daily regarding safety, risk, and the optimal allocation of resources.

Against this backdrop, monitoring technologies have the potential to improve the design, assessment, and management of civil infrastructure in several ways: (a) performance-based design can be conducted by recording site specific conditions such as wind, load demands, or temperature, (b) inspections can be scheduled on an "as needed" basis driven by structure specific data when indicated by monitoring data, (c) the accuracy of structural assessments can be improved by analyzing recorded structural response data, (d) as a result of more accurate information provided as input to analytical models, maintenance, repair, and replacement activities can be optimally scheduled which results in cost savings, and (e) performance thresholds can be established to provide warning when prescribed limits are violated. However, these benefits also come with an associated life-cycle cost as monitoring systems must be purchased, installed, maintained, and their information processed and assessed. As a result, a truly optimal and efficient design needs to consider and evaluate the costs and benefits of different strategies and approaches.

2.2 Basic Concepts

The greatest challenge in researching and contributing to this field of study is its breadth and the time required to identify and correctly apply the concepts across the associated disciplines. Additionally, the balance between theoretical work (models), design manuals and code provisions (legality), technical feasibility (sensor limitations), practicality for infrastructure managers, and cost must always be considered. This thesis is only a starting point. For the interested researcher, the below sources are highlighted. The list is by no means inclusive, is certain to leave many important sources unmentioned, and should be regarded primarily as a personal listing experienced by the author.

Books

Fibre Optic Methods for Structural Health Monitoring (Glisic and Inaudi, 2007)
Durability of Engineering Structures: Design, Repair and Maintenance. (Bijen, 2003)
Probabilistic Risk Assessment of Engineering Systems (Stewart and Melchers, 1997)
Structural Reliability Analysis and Prediction, 2ed (Melchers, 1999)
Probability Concepts in Engineering Planning and Design Vol. I & II (Ang and Tang, 1984, Ang and Tang, 2007)
Reliability: Probabilistic Models and Statistical Methods (Leemis, 1995)

Journals

Structural Control and Health Monitoring (ed. Lucia Faravelli)

Structure and Infrastructure Engineering (ed. Dan M. Frangopol)
Structural Health Monitoring (ed. Fu-Kuo Chang)

Professional Associations

IABMAS (International Association for Bridge Maintenance and Safety),
IABSE (International Association for Bridge and Structural Engineering)
IALCCE (International Association for Life-Cycle Civil Engineering)
ISHMII (International Society for Structural Health Monitoring of Intelligent Infrastructure)
SAMCO (European network of Structural Assessment Monitoring and Control)

Research Centers

ATLSS (Advanced Technology for Large Structural Systems) at Lehigh University
CIBrE (Center for Innovative Bridge Engineering) at the University of Delaware
CIMSS (Center for Intelligent Material Systems) at Virginia Tech
EMPA (Swiss Institute of Materials Science) at Dubendorf, Switzerland
ISIS (Intelligent Sensing for Innovative Structures) at the University of Manitoba, Canada
LIST (Laboratory for Intelligent Structure Technology) at the University of Michigan
SFB398 (Co-operative Research Center for Lifetime Oriented Design Concepts) at the Ruhr-University Bochum, Germany
SISTeC (Smart Infra-Structure Technology Center) at Kaist, Korea
SFB477 (Collaborative Research Center on Life-Cycle Assessment of Structures via Innovative Monitoring)

at the Technical University of Braunschweig, Braunschweig, Germany
SSTL (Smart Structures Technology Laboratory)
at the University of Illinois at Urbana-Champaign

Major Conferences

IABMAS: Biannual
IALCCE: Biannual
ICOSSAR: Every 4 years
IWSHM: Yearly, alternating between US and Europe
SHMII: Biannual
SMART: Biannual

2.2.1 Life-Cycle Performance Prediction

The intended service lives of buildings, bridges, and dams span decades or even centuries. During this period of time and aside from routine and anticipated loads, these structures are possibly subjected to abnormal loadings of different types that include natural hazards (e.g., earthquake, flood, hurricane) as well as manmade disasters (e.g., fire, vehicle collision, terrorist attack) (Frangopol and Liu, 2006). Meanwhile, structural safety and condition gradually deteriorate due to normal wear and tear as well as exposure to aggressive environmental stressors (heating and cooling cycles, chloride ingress from de-icing salts, and freeze-thaw effects). In general, steel corrodes, concrete spalls, wood rots, and all materials crack as they age and progress through their service life. In each case, the capacity of the structure to safely carry loads is reduced and the functionality of the structure may be impaired. Due to the uncertainties surrounding in-service loads and deterioration processes, the performance of the structure may not follow initial predictions as depicted in Figure 2.4 (Without Maintenance). This can result in either unacceptable levels of performance or the failure of the structure to reach its intended service life.

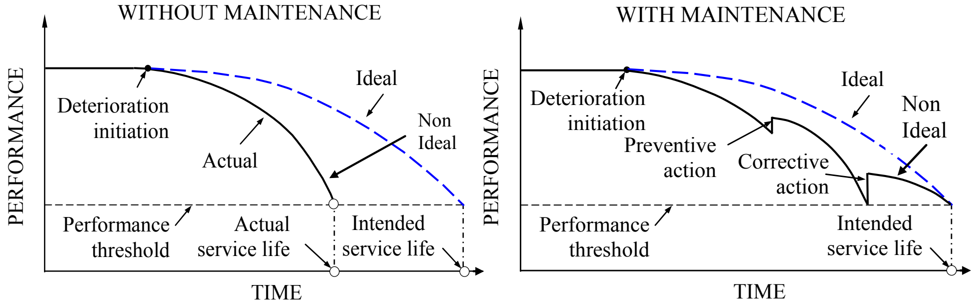


Figure 2.4. Lifetime structural performance without maintenance and with maintenance (adapted from Frangopol, 1998, Frangopol and Liu, 2006).

In response to these concerns, maintenance and risk mitigation are required to ensure satisfactory performance over the life of a structure as shown in Figure 2.4 (With Maintenance). Maintenance actions can be preventive in nature (e.g. the application of sealer on a bridge deck) or corrective (e.g. the replacement of a structural member or system). Because maintenance needs are often greater than available funds, decisions and scenarios for maintaining infrastructural systems, such as the ground transportation network, must be based on a life-cycle cost (LCC) analysis (Frangopol, 1998, Frangopol et al., 2001, Kong and Frangopol, 2004). The goal of any such analysis is to cost-effectively allocate resources such that condition, safety, and performance are optimized for individual structures as well as the network within budgetary constraints. Computationally, this requires (a) reliable modeling of loadings, including extreme loads, and continuous deterioration processes and their effects on structural capacity, (b) accurate prediction of structural safety and performance evolution, (c) good estimation of costs of interventions such as maintenance, repair, and replacement over the specified time horizon, and (d) generations of solutions that balance life-cycle costs and lifetime structural performance in an optimum way (Frangopol and Liu, 2006).

The general form of the expected life-cycle cost can be calculated as (Frangopol et al. 1998)

$$C_{ET} = C_T + C_{PM} + C_{INS} + C_{REP} + C_F \tag{2.1}$$

where CET = expected total cost, CT = initial design/construction cost, CPM = expected cost of routine maintenance, CINS = expect cost of performing inspections, CREP = expected cost of repairs and CF = expected cost of failure. Within this framework, all future costs are converted to their net present value using

$$NPV = \frac{FV}{(1+r)^n} \tag{2.2}$$

where NPV is the net present value, FV is the future value, r is the discount rate, and n is the year in which payment occurs. Traditional structural design typically focuses only on the initial cost of a structure. If instead life-cycle concepts are utilized in the design process (also referred to as durability-based design or design with the inclusion of warranty periods), an optimal design solution can be determined as shown in Figure 2.5.

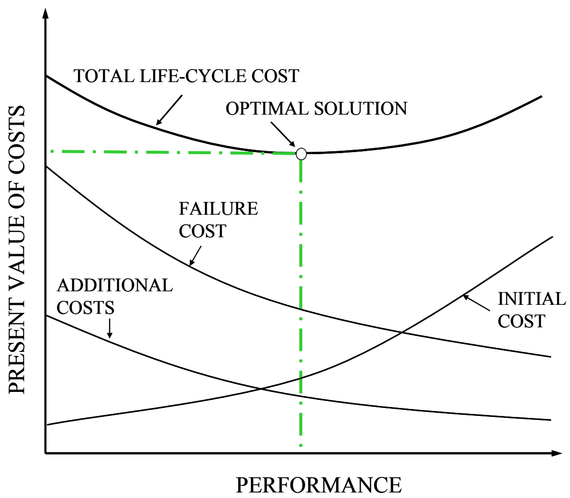


Figure 2.5. The Optimum design solution based on life-cycle cost minimization (adopted from Frangopol and Liu, 2005)

Figure 2.5 depicts the relationship between the initial cost, the failure cost, and additional costs (including maintenance, repair, and operational costs, among others). At the extreme right of this figure, a high initial cost (overdesign) results in a lower failure cost (lower probability of failure) and lower required additional costs. In contrast, the left side of this figure shows that the lowest initial cost (minimum safe design) is paired with higher failure and higher additional costs. The optimal solution locates the lowest total life-cycle cost.

2.2.2 Bridge Management Systems

Most countries have developed and employ bridge management systems (BMS) to optimally maintain acceptable levels of performance across deteriorating bridges. It is important to note that separate, but related, programs exist between different levels of government (national, state, local) and that in some cases certain highway networks are privatized and for profit. The historical development and evolution of BMS across different countries and levels of responsibility share a very similar background. Generally, bridge inspections began in the 1960s and 1970s. This collection of information created databases leading to the task of managing deficient structures. In the 1980s and 1990s, the adoption of semi-probabilistic design methods (e.g. LRFD) and the increase of the permissible weight allowances of highway trucks amplified the amount of deficient or obsolete structures. A larger than feasible amount of required repair and rehabilitation efforts led to focused research into bridge management systems themselves.

Currently, most countries have formalized bridge inspection programs. A report from international technology exchange program of the Federal Highway Administration (FHWA, 2005), documents differences in bridge preservation and maintenance programs across North America, Europe, and South Africa. This document (and others) serve as an excellent resource and are available online at www.international.fhwa.dot.gov. In this particular study, attention is given to how different countries pay for highway upkeep, what management systems and databases are employed, how condition ratings and defects are reported, what types of maintenance actions are conducted, which performance indicators and deterioration models are used, what types of inspections are required and at what frequency, which inspector training programs are utilized, and how permit loads are obtained for abnormal truck weights. Almost exclusively, bridge management programs are based on visual inspections. In special cases, non-destructive evaluation (NDE) tests are performed and although relatively few, there is a growing number of monitoring applications. However, such tests or uses of SHM are generally on an ad-hoc basis to target a specific fault and are not integrated into the overall maintenance and management hierarchy.

Despite differences between countries, levels of authority, or ownership classifications, most BMS or organized into modules that perform the functions depicted in Figure 2.6 which are described in the following sections.

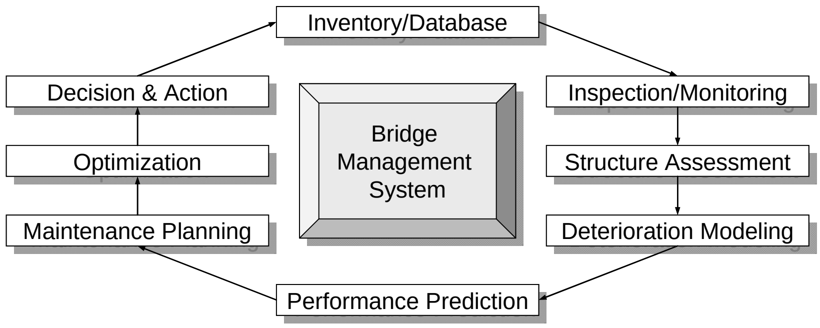


Figure 2.6. Main modules / functions of a bridge management system.

2.2.2.1 Inspection Methods and Database Management

The Inventory/Database module is used to store historical data by member and structure. The collection of information (via inspection) varies considerably across countries to include what type of information is gathered, at what frequency, by what authority, and with what level of certification. Table 2.1 highlights some of the differences. The source for Table 2.1 is the previously mentioned FHWA international technology exchange program report (FHWA, 2005). Detailed information for the U.S. National Bridge Inspection Standards (NBIS) is available at the FHWA website online at http://www.fhwa.dot.gov/bridge/nbis.htm. Notably, these references provide information on the country specific manuals, regulations, and procedures for bridge inspections. Also of interest, these references define what constitutes a bridge, what types of bridges require inspection based on the type of traffic they carry and who owns the bridges, and how inspections are to be carried out based on the type of structure, amount of traffic, bridge importance, failure mode, and other factors.

Table 2.1. Selected bridge inspection procedure data (Source: FHWA-PL-04-007)

Country	Inspection	Interval	Inspector
Denmark	Daily		Road Patrol
	Semiannual		Road Patrol
	Principal	6 years	Road Directorate trained inspector
France	Routine	Frequent	Road Maintenance Crew
	Annual		Local agencies
	IQOA Condition Evaluation	3 years	Local agency certified inspectors
	Detailed	3 to 9 years (6 on average)	National certified inspector
Norway	General	1 year	General knowledge of bridges
	Major	5 years	Civil engineering degree and general knowledge of bridges
United Kingdom	General	2 years	Training and quality control by engineering consultants
	Principal	6 years	Training and quality control by engineering consultants
United States	Routine	2 years	Team leader and certified inspection personnel
	Underwater	5 years	Team leader and certified inspection personnel
	Fracture critical member	2 years	Team leader and certified inspection personnel
	Damage, in depth, special	as required	Team leader and certified inspection personnel

Although there are differences between the inspection types, intervals, and personnel carrying out the inspections in Table 2.1, all programs generally follow the general intent of the U.K. defined inspection types detailed as follows (BD63/94, BA63,94):

Superficial Inspection: Cursory check for obvious deficiencies such as clogged drainage, impact damage, flood damage, or anything out of the ordinary.

General Inspection: Checklist driven visual inspection from ground or deck level to record condition results. Binoculars may be required.
Principal Inspection: Checklist driven, close examination (touching distance) of all inspectable parts of the structure. Limited field testing (e.g. half cell potential, cover and carbonation) may be required.
Special Inspection: Examination of a particular area or defect causing concern. It is usually carried out to investigate a specific problem identified during other inspections or to assess the effectiveness of a repair.

2.2.2.2 Structural Assessment, Deterioration Modelling and Performance Prediction

Structural assessment is the defining difference between various bridge management systems to include the development of new approaches. The distinguishing characteristic that separates methods is the performance metric utilized to assess structures and to predict future performance. It is highlighted that Figure 2.4 shows only performance on the ordinate axis. Several examples of performance metrics adopted by different countries are provided here to note differences. Sweden uses a lack of capital value (LCV) as a fraction of bridge replacement cost and an exponential deterioration model. South Africa computes a bridge condition index (BCI) and employs a linear deterioration model. Finland uses two performance indicators: KTI, a repair index based on defect severity and average daily traffic and UTI, a rehabilitation index based on functional deficiencies that can indicate a need for improvement rather than repair.

The most common performance metric in practice for structural assessment is the condition state or condition index. A condition state is a somewhat subjective evaluation from trained inspector as to the status of a bridge or that of its components based off a visual inspection using a set of established guidelines. As an example of how condition states are assigned, Table 2.2 details the criteria for an open steel girder using Pontis guidelines adopted by the Colorado Department of Transportation (CDOT, 1998). Pontis is currently the most widely adapted bridge management system in the United States.

Table 2.2. Colorado DOT PONTIS condition ratings for steel painted girders (according to Neves et al., 2006a)

Condition Rating	Description
1	No evidence of active corrosion. Paint system is functioning as intended to protect the metal surface.
2	Little or no active corrosion. Surface or freckled rust has formed or is forming. Paint system may be chalking, peeling, curling or showing other early evidence of paint system distress but there is no exposure of metal.
3	Surface or freckled rust is prevalent. The paint system is no longer effective. There may be exposed metal but there is no active corrosion which is causing loss of section.
4	The paint system has failed. Surface pitting may be present but any section loss due to active corrosion does no yet warrant structural analysis of either the element or the bridge.
5	Corrosion has caused section loss and is sufficient to warrant structural analysis to ascertain the impact on the ultimate strength and/or serviceablility of either the element or the bridge.

Once condition is assessed, a transition probability relates the current state with a maintenance action to a future state using a Markovian process. The Markov property indicates that the probability of deteriorating to another state depends only on the last condition and action but not on the history of the process. The time of transition from one state to another may follow specified probability distributions. For these reasons, condition-based Markov model is flexible to be adapted to visual inspection data. However, this approach is not able to capture the propagation of uncertainties during the entire service life and accuracy is lost due to a limited number of discrete condition states (Frangopol and Liu, 2007). For condition-state models, the performance profiles are decreasing step functions over time. Both of the predominant bridge management systems in the United States, Pontis (Thompson et al, 1998) and BRIDGIT (Hawk and Small, 1998) use such an approach. Although there is concern regarding the loss of accuracy due to the use of a Markov model, the primary concerns of condition state models are that visual appearance may not correlate to structural safety and that visual inspections are prone to human subjectivity and/or error.

Safety-based or reliability-based assessment of civil infrastructure began in the 1970s and was initially applied to the assessment of offshore structures e.g. Benjamin and Cornell (1970), Ang and Tang (1975), Thoft-Christensen and Baker (1982), etc. (Rafiq, 2005). The first major research on the reliability based management of bridges was supported by the European Union (Thoft-Christensen, 1993, Thoft-Christensen and Hansen, 1993) and since this time it has been an active area of research. Amongst the extensive list of contributors in this field some widely cited references include Cesare et al. (1993), Das (1994), Micic et al. (1995), Corotis (1996), Das (1996), Thoft.Christensen et al. (1996), Frangopol et al. (1997b), Estes (1997), Val et al. (1997 and 1998), Das (1998b), Thoft-Christensen (1998), Enright and Frangopol (1999), Frangopol and das (1999), Fragopol et al. (2000), Val et al. (2000), Sterrit et al. (2001), Chryssanthopoulos and Sterrit (2002), Kong and Frangopol (2003), Neves and Frangopol (2004), Estes and Frangopol (2005a and 2005b), Rafiq (2005), and Neves et al. (2006a, 2006b, 2006c). The development and migration toward models that instead use safety (reliability-based methods) as the primary performance metric are further detailed in Chapter 3.

2.2.2.3 Maintenance planning and optimization

Most bridge management systems employ the life-cycle concepts outlined in Section 2.2.1 to develop maintenance and rehabilitation alternatives. However, due to budgetary constraints or the need to analyze a period shorter than the life of a structure, non-optimal strategies may be adopted. In order to develop management alternatives, deterioration rates, types of maintenance, and the effect of maintenance on performance must be modelled. Deterioration initiation times and deterioration rates are in particular very difficult to model and predict. Estes (1997) provides a method and examples for steel members based upon section loss. Rafiq (2005) provides an approach using widely accepted deterioration models updated via SHM using Bayesian updating techniques.

Conceptually, Figure 2.7 shows one way of relating performance, deterioration, maintenance, and time. Here, it is assumed that deterioration or damage does not begin immediately. Preventive maintenance may result in an increase in performance and a decrease in the rate of deterioration. Figure 2.7 models both of these effects. Essential maintenance can restore performance to its initial level or any lesser amount depending upon what type of maintenance is conducted (repair vs. replacement) and what is being modelled (member or system). Not modeled in Figure 2.7 are multiple instances of preventive maintenance or essential maintenance and the time associated with each.

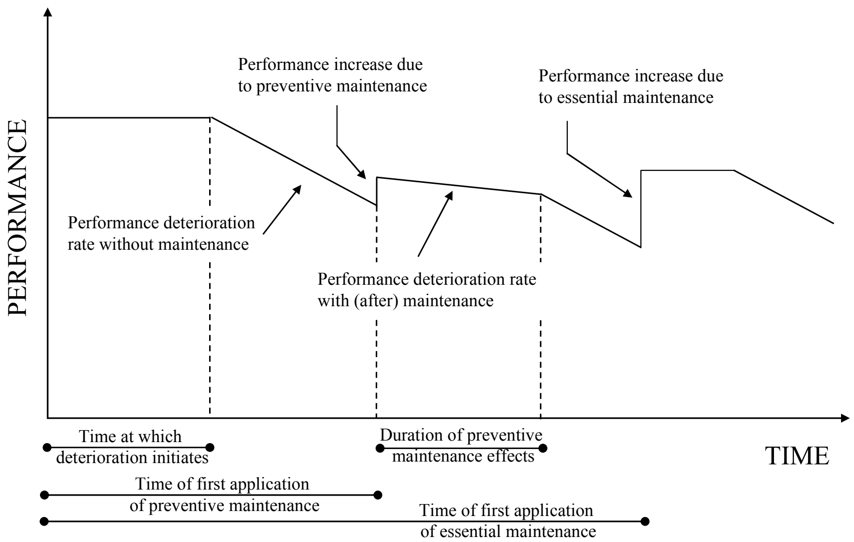


Figure 2.7. Effects of preventive and essential maintenance (adapted from Frangopol, 1997).

Once the effects of deterioration and maintenance on performance are modeled, simulation methods can be utilized to determine the management strategy with the lowest life-cycle cost (Estes and Frangopol, 1999). In reality, multiple and conflicting objectives may need to be considered simultaneously in order to obtain a well balanced solution (e.g. condition, safety, cost, risk tolerance, network performance, etc.) (Neves and Frangopol, 2006c). As such, the maintenance planning can be formulated as a multiobjective optimization problem in order to optimize life-cycle structural performance, based on simulated performance profiles and life-cycle costs of different origins. This leads to a group of alternative solutions that exhibit the optimized tradeoffs among conflicting objectives as shown in Figure 2.8 (Frangopol and Liu, 2007).

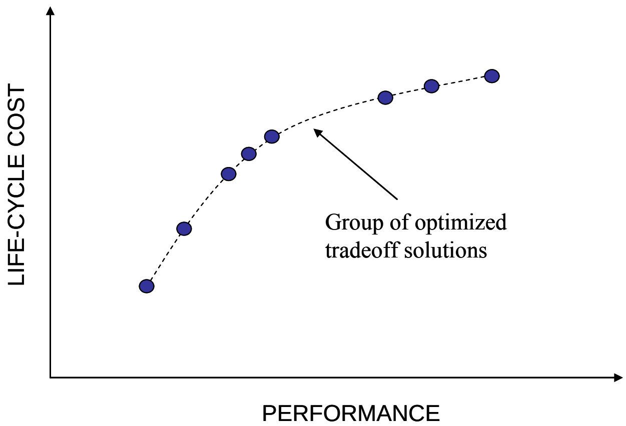


Figure 2.8. Tradeoff solutions between conflicting objectives (Frangopol and Liu, 2006).

2.2.3 Reliability and Structural Reliability Concepts

2.2.3.1 Uncertainty

Uncertainty is an inherent and unavoidable in structural design and assessment. Structural models and their idealizations, deterioration mechanisms, material resistances, geometries, equipment/sensor error, and especially loads are highly uncertain. For these reasons, a life-cycle performance profile can be considered as shown in Figure 2.9 where a degree of uncertainty is associated with each time and each action represented by the letters A through G. At each point, probability density distributions are utilized to characterize the uncertainty associated with the ability to accurately characterize performance. Most important to the scheduling of future maintenance activities is the initial performance assessment (A), the rate of deterioration (C), and the time of initiation for deterioration (B) (Kong and

Frangopol, 2005). Because these parameters are random, the optimal number and timing of preventive and corrective actions is also uncertain (E and G). Likewise, the level of performance after any preventive or corrective action is also uncertain (D and F). In addition, it is noted that as the model predicts further into the future, the uncertainty associated with prediction of all parameters increases. Lastly, it is noted that Figure 2.9 is a general or conceptual performance profile. It is not stated how the level of performance is obtained (calculated, observed, or based on belief) and it is not stated if the profile represents a member, system, or structure.

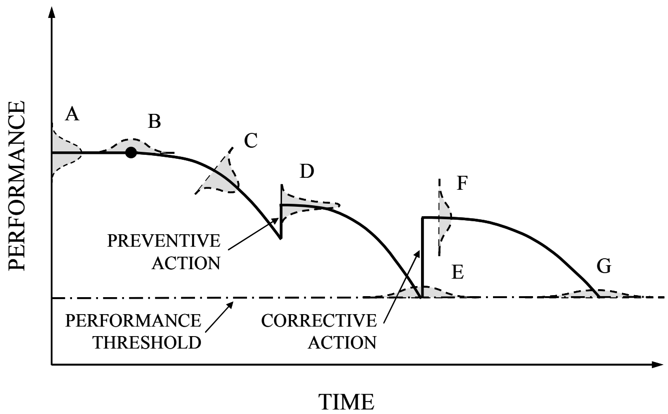


Figure 2.9. A life-cycle performance profile under uncertainty

Uncertainty can be considered in two broad categories, aleatory and epistemic as described by Ang and Tang (2007). Aleatory uncertainty describes the inherent randomness of phenomenon being observed and cannot be reduced. Natural variations in temperature are an example of this type of uncertainty. Epistemic uncertainty describes the error associated with imperfect models of reality due to insufficient or inaccurate knowledge (Ang and Tang, 2007). Error associated with predicting stresses in a structural member through use of an analytical model is an example of this type of uncertainty, as material properties, geometry, and loads are never deterministic. Melchers (1999) further breaks the sources of uncertainty in the following categories: phenomenological, decision, modelling, prediction, physical, statistical, and uncertainties due to human factors. It is noted that the uncertainties related to human factors (e.g. errors in design or construction) are often unaccounted for in analytical models but are often the primary drivers of infrastructure failure.

It is necessary to quantify and evaluate the significance of uncertainty in order to provide an adequate level of safety. Historically, this has been accomplished through the use of a factor of safety. Usually based upon past experience and expert opinion, a factor of safety is intended to account for all sources of uncertainty. Although simple to use, it is limited in its ability to provide consistent levels of safety across a variety of structures and may result in significant over/under design. To address these limitations, the theory of structural reliability was developed to provide a rational approach to account for the uncertainties encountered in engineering applications. Excellent references include Ang and Tang (1975, 1984, and 2007) and Melchers (1999).

2.2.3.2 Reliability and Structural Reliability

Reliability is a mathematical formulation of the probability of failure. In its most basic sense, reliability can be defined as

$$\mathit{Reliability} = 1 - p_f \tag{2.3}$$

where p_f represents the probability of failure and can be defined descriptively as (Leemis, 1999):

The reliability of an item is the probability that it will adequately perform its specified purpose for a specified period of time under specified environmental conditions.

This general (or classical) definition of reliability is typically associated with the lifetime of organisms, products, machines, parts, components, or systems. In this definition, careful attention must be given to the specified purpose, the specified period of time, and the consistency (e.g. constant) of the environmental conditions. The units associated with the resulting probability of failure are numbers of failures per the time interval considered under the environmental conditions experienced. The lifetime characteristics of an item are usually obtained through the statistical observation of the performance of a large number of items under the conditions of interest. A further (and more detailed) discussion of lifetime characteristics, lifetime functions, how they relate to structural reliability and monitoring is provided in Chapter 6.

Structural reliability is a subset or close relative of classical reliability. They are closely related but there are also several sharp distinctions. The need for structural reliability (distinct from classical reliability) arises from two factors. First, the long lifetimes of civil infrastructure, the randomness and infrequency of extreme loads of interest, and the dynamic nature (constantly changing) of environmental conditions make it impossible to statistically observe all structure types of interest in all conditions of interest (to define lifetime lifetime characteristics). Second, structural applications are most often concerned with measures of performance that may be impossible to observe. These measures of performance, or requirements, are termed limit states and resulting reliability calculations are concerned with the violation of these limit states. Typical limit states for civil infrastructure are given in Table 2.2 (adapted from Melchers, 1999).

Table 2.3. Typical limit states for civil infrastructure (adapted from Melchers, 1999)

Limit state	Description	Examples
Ultimate (safety)	Collapse, partial collapse, impending collapse	Tipping, sliding, plastic mechanism, fracture, corrosion, fatigue, etc.
Damage	Damage	Excessive cracking, presence of cloride in concrete, loss of prestress, permanent deformation, etc.
Serviceability	Disruption of normal use	Excessive deflections, vibration, local damage, poor condition

As such, a structural reliability analysis begins with a limit state equation (performance function) or series of equations that govern the performance of a structure. In general and with respect to safety, a structure is considered safe if its capacity R (strength, resistance, fatigue life, etc.) exceeds the load demand L (load, moment, stress ranges, fatigue cycles, etc) such that

$$R > L \qquad \text{or} \qquad R - L > 0 \qquad \text{or} \qquad \frac{R}{L} > 1 \tag{2.4}$$

An evaluation of these expressions provides a measure of the likelihood that the demand will exceed a structure capacity to resist that demand. The capacity of a structure, the expected loads, the uncertainties associated with each, and the effects of the loads are represented by random variables. Random variables can take on different values and the likelihood of any particular value is described by the probability density function. The most important metrics used in describing a random variable are its mean, median, mode values and its standard deviation which provide a measure of dispersion.

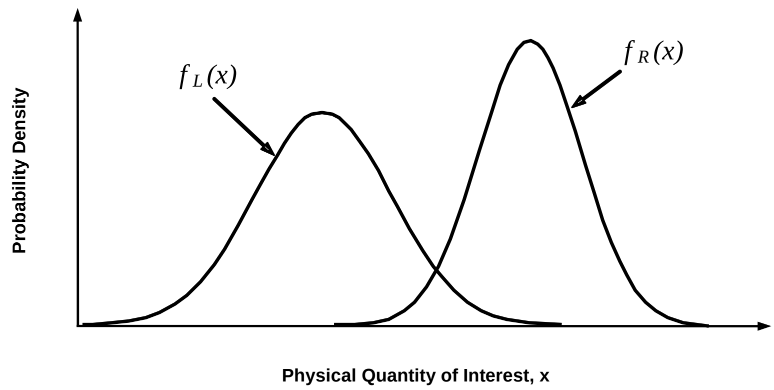


Figure 2.10 Graphical representation of the structural reliability concept.

Structural reliability is utilized to conduct a probabilistic assessment of the performance function $g = R - L$, where R and L are the resistance and load effect, respectively. Provided that the capacity, R, and load effect, L, are random and can be quantified, the probability of safe performance, p_s, can be expressed as

$$p_s = P(R - L > 0) = \iint_{R>L} f_{R,L}(r,l)drdl \tag{2.5}$$

where $f_R(r)$ and $f_L(l)$ are the probability density functions (PDFs) of R and L are shown (for one possible example) in Figure 2.10, and $f_{R,L}(r,l)$ is their joint PDF. If R and L are independent, $f_{R,L}(r,l) = f_R(r)f_L(l)$ such that Eq.2.5 becomes

$$p_s = P(R - L > 0) = \iint_{R>L} f_R(r)\, f_L(l)drdl \tag{2.6}$$

Most often, the capacity R and demand L are themselves function of many other random variables. In such cases, a limit state function $g(\boldsymbol{X})=0$, describes the performance of the system in terms of the vector of basic random variables, $\boldsymbol{X}$, and defines the failure surface, which separates a survival region from a failure region. Formulation of the probability of safe performance p_s then becomes

$$p_s = \int_{g(\boldsymbol{X})>0} f_{\boldsymbol{X}}(\boldsymbol{x})dx \tag{2.7}$$

which represents the volume integral of $f_{\boldsymbol{X}}(\boldsymbol{x})$ over the safe region $g(\boldsymbol{X}) > 0$.

2.2.3.3 Solving for the Reliability Index

The solution of the integrals found in Eq. 2.5 and Eq. 2.7 can quickly become too complex to solve. To address this problem, "Level II" methods FORM (First Order Reliability Methods) and SORM (Second Order Reliability Methods) provide an iterative approach to estimating the failure probability by locating the shortest distance to a multi-dimensional plane tangent to the failure surface of the limit state equation in the standard normal space. In contrast, Monte Carlo Simulations can also be utilized to provide estimates of the probability of failure. A Monte Carlo approach simulates a large number of "experiments" by randomly choosing instances of the involved random variables. The failure probability can then be estimated by comparing the number of trials that produced a failure condition to the total number of trials conducted. Until recently, optimization schemes and variance reduction techniques were extremely important in the conduct of Monte Carlo simulations due to the amount of simulations required and corresponding processing times. Although these concerns have been mitigated through improvements in technology (processing speeds), they will likely still be required for the solution of complex structures/systems. Further details on reliability and Monte Carlo simulation can be found in Madsen et al. (1986) or Melchers (1999).

Equations 2.5-2.7 calculate the reliability of a single component or failure mode. In reality, structures are composed of multiple members and may experience multiple failure modes. By investigating the interrelationships between members and failure modes (system analysis), several advantages can be obtained. These advantages include that the reliability of systems are often higher than individual components, recognizing that some repairs are more important than others is possible, and that it may be possible to recognized that although an individual component is safe, the structure as a whole may be unsafe (Estes and Frangopol, 2005a). Structural members can be considered in series, parallel, or a combination of each as shown in Figure 2.11.

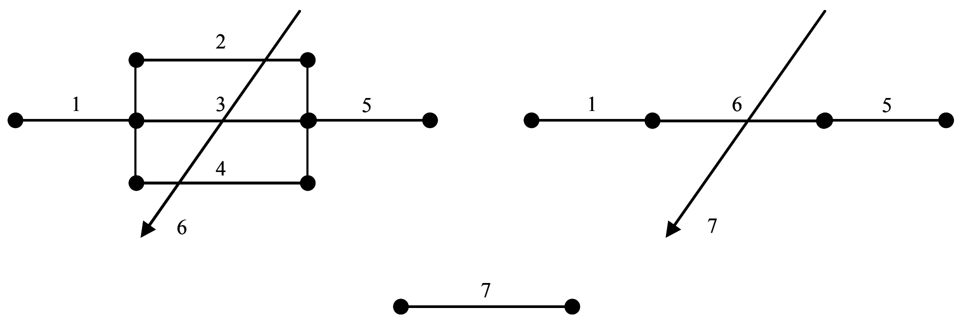


Figure 2.11. Members arranged in series, parallel, and the reduction of a series-parallel system (Adapted from Estes and Frangopol, 2005a).

For members arranged in series, the failure of a single a single element will lead to the collapse of the entire structure. For a structure of z elements, the probability of failure of the system $p_{f,\,series}$ can be written as the probability of a union of events

$$p_{f,series} = P\left(\bigcup_{a=1}^{z}\left\{g_a(X) \le 0\right\}\right) \tag{2.8}$$

where $g_a(\boldsymbol{X})$ is the performance function of member a. For members arranged in parallel, the failure of all elements is required for the collapse of the entire structure. For such a system, the probability of failure of the system can be written as the probability of an intersection of events

$$p_{f,parallel} = P\left(\bigcap_{a=1}^{z}\left\{g_a(X) \le 0\right\}\right) \tag{2.9}$$

A general system is one consisting of combinations of series and parallel systems. Considering a series system consisting of y parallel systems where each parallel system a has z_a components. The probability of failure $p_{f,\,series\text{-}parallel}$ is given by

$$p_{f,series-parallel} = P\left(\bigcup_{a=1}^{y}\bigcap_{b=1}^{z_a}\left\{g_a(X) \le 0\right\}\right) \tag{2.10}$$

The solution to Equation 2.10 can become very complex. Generally, FORM and SORM can be utilized after where the reliability of a complex system is solved by sequentially breaking the system into simpler equivalent subsystems as shown in Figure 2.11 (Estes and Frangopol, 2005a). Additionally, all system reliability calculations need to account for the correlation between members and failure modes (Cornell, 1967).

For the practicing engineer, the theoretical aspects of structural reliability may be embedded in software applications utilized to solve a particular problem. Commercially available software for time-invariant reliability analysis include STRUREL, CALREL, PROBAN, and RELSYS. References for each of these programs are provided.

Typically, the probability of safe performance is a number very close to and less than 1.0. For civil engineering applications where the probability of failure is very small, it is usually reported in terms of the reliability index β to make analysis results more simple to express. In the special case where R and L are independent and normally distributed, the reliability index can be equated to the probability of failure using the standard normal variate as $p_f = \Phi(-\beta)$ as

$$\beta = \frac{\mu_R - \mu_L}{\sqrt{\sigma_R^2 + \sigma_L^2}} \tag{2.11}$$

where μ_R and μ_L are the mean values of the resistance and load effect respectively, and σ_R and σ_L are the standard deviations. Mathematically, this index provides a measure of the number of standard deviations that the margin of safety (R-L) falls on the safe side. Similar calculations can also be conducted for log-normally distributed random variables. For this reason, Eq. 2.11 is perhaps the most common starting point for estimating the reliability index as many random variables follow or can be approximated as normal or log-normally distributed. Common values for β range from 2 to 8 in civil engineering applications. Values between 2 and 4 are typically specified for structural assessment and code calibration efforts. Table 2.4 lists the reliability index and its relationship to the probability of failure for the range of 0 to 5.

Table 2.4 Relationship between the Reliability Index and the Probability of Failure

Reliability Index (β)	Probability of Failure (p_f)
0	0.5000
1	0.1587
2	0.02275
3	0.00135
4	0.0000316
5	0.000000286

2.1.2.4 Time Dependent Reliability

The previous section detailed the calculation of structural reliability at a point in time. Such calculations assume that the resistance R and load L remain constant over the period of interest. These calculations are appropriate for the assessment of a structure against a specified loading condition (e.g. the 75 year design load).

Although assessment is a critical step in the management of civil infrastructure, predicting future performance is what allows the efficient scheduling of inspections, maintenance, repairs, and replacements. Such predictions are the basis of life-cycle management methods, durability-based design approaches, and whole-life cost approaches (nearly equivalent terminology). In general, the capacity (resistance) of a structure decreases over time as the structure deteriorates and the load demand increases as shown in Figure 2.12.

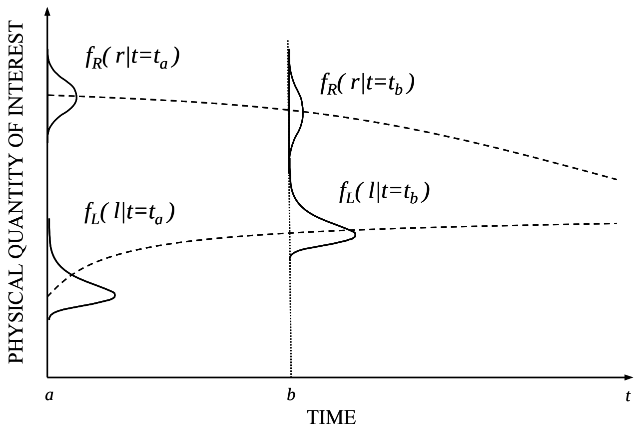


Figure 2.12. Trace of the structural resistance R and load effect L in a time dependent reliability analysis (adapted from Melchers, 1999).

The increase in the load effect is a function of several considerations. First, the mean load being placed on highway structures has increased at a fairly consistent and predictable rate over the last several decades (Gindy and Nassify, 2006). Second, all live loads are a function of time or the amount of loading events experienced (e.g. average daily truck volume). Statistically, as a distribution is repeatedly sampled, the probability of encountering a large value at the upper tail of the distribution increases. This load effect is can be modeled by the statistics of extreme values and is treated in detail in Chapter 5. The decrease in structural resistance R is due to deterioration effects over time. The deterioration of various materials is a widely researched topic. Enright et al. (1996) compiled a survey of deterioration models for concrete structures. Deterioration of concrete structures is typically divided into two categories, chemical and physical deterioration mechanisms. Chemical deterioration includes chloride attack, carbonation, acid attack, and alkali-aggregate reaction while physical deterioration involves freeze-thaw, leaching, erosion, and cracking (Rafiq, 2005). For transportation networks, chloride penetration of the concrete and subsequent corrosion of the reinforcing steel is the primary cause of capacity degradation. For steel structures, corrosion models predict where and when corrosion will result in section loss of the steel shape. Albrecht and Naeemi (1984) first developed a model for steel girders that was later improved by Thoft-Christensen et al. (1996) to include values for random variables. The vulnerability of steel structures to corrosion is largely determined by regional/environmental conditions, proximity of a specific member to exposure, and the presence of aggressive agents. A treatment of such conditions for a composite steel girder concrete deck bridge structure can be found in Estes (1997). For wood, its durability can be difficult to predict and depends largely on environmental conditions, specific wood type, and preservation efforts. Generally, the performance of wood structures decreases over time due to natural weathering, decay, biological attack (fungus or insects), or chemical attack and service life can range from a short period up to 500 years (Bijen, 2003). A further development of performance-based time-dependent reliability profiles is the topic of Chapter 6.

2.2.4 Risk, Risk-Based Decision Making, and Updating

Risk is a complex topic as any determination of an acceptable level of safety is somewhat subjective. Although the reliability index provides a measure to compare different designs and to calibrate against existing safe designs, it does not yet account for the consideration of societal norms, preferences, and risk tolerances (Estes and Frangopol, 2005b). For example, societal expectations are likely to be much less accepting of fatalities resulting from the collapse of a bridge than those associated with increasing the speed limit on a public motorway. Even when faced with statistical evidence to the contrary, such as the hazard associated with living close to a nuclear facility and that of driving after a glass of wine, people's decisions are often driven by other factors. Corotis (2003a, b) develops this idea to suggest that people's perception of risk depends upon whether the risk is objective or subjective, aleatoric or epistemic, familiar or unfamiliar, and voluntary or involuntary. Because decisions and preferences are based upon these perceptions of risk, such metrics should be reflected in future codes and a rational method is needed to objectively assess and quantify the benefit of resources allocated. To this end, Rackwitz (2004) introduces the concept of a Life Quality Index to monetize the amount of money society is able and willing to pay towards risk reduction by providing a measurement of the longevity, quality, and value of human life as it is balanced against competing resources.

Within the field of engineering, risk typically has two meanings. In structural engineering, risk often refers to the probability of failure from all possible causes. When used herein (this thesis), this meaning is simply termed the probability of failure p_f or hazard when conditioned on past safe performance. The second interpretation of risk refers to the magnitude of failure in monetary terms and is typically associated with insurance or a notional cost associated with the failed state of a structure. This meaning for risk is the intended meaning herein and is used to quantify the utility of monitoring solutions and to construct complete life-cycle costs.

The most basic and common expression for evaluating the risk R (also termed the expected cost of failure C_F) is the product of the likelihood of an event and the associated consequences given the event occurs as

$$Risk = R = C_F = p_f C \tag{2.12}$$

where p_f represents the probability of failure and C the consequence of failure in monetary terms. The notation of risk R is typically utilized in risk-based approaches and the cost of failure C_F is typically utilized in LCM methods. The terms are equivalent. It is noted that the probability of failure can come from multiple sources: belief, statistical observation, updated data, or analytical methods (e.g. reliability calculations). It is also noted that the consequence of failure can vary dramatically depending upon what costs are considered. Lastly, it is important to observe that this calculation provides a point-in-time snapshot of risk specific to the conditions associated with the calculation of p_f. These three points are further discussed in Chapter 3, Chapter 4, and Chapter 6.

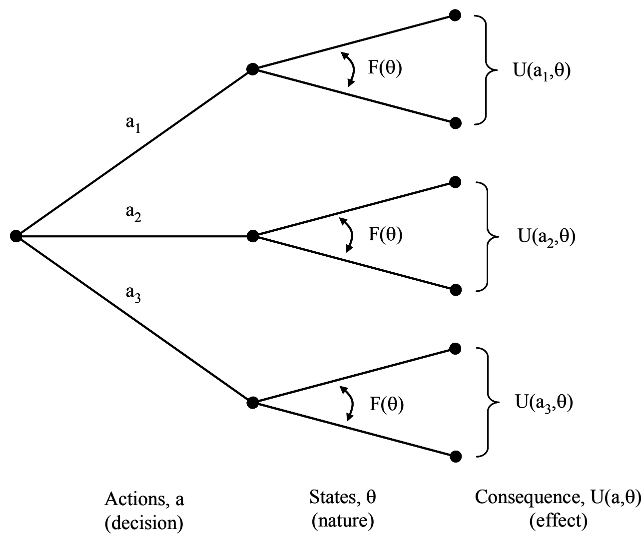


Figure 2.13: Decision/Event tree for prior and posterior analysis (adopted from Benjamin and Cornell, 1970)

Risk-based decision making (also commonly referred to as Bayesian statistical decision making) approaches provide a probabilistic estimate of the total expected cost associated with different alternatives at a point in time (Stewart and Melchers, 1997). A decision tree as shown in Figure 2.13 can be utilized to organize the calculations. The branches can represent actions or hazards. The summation of the probabilities of the branches extending from any node must be equal to one. Decisions are typically made by comparing the total expected cost (or utility U) of each of the branches to determine the least cost solution. The states $F(\theta)$ represent the probabilities associated with each action a (e.g. the probability of failure and the probability of safe performance after a maintenance action is taken). It is often feasible, but not necessarily economical, to obtain more information about the states before choosing an action from various alternatives (Rafiq, 2005). Based upon what information is available/considered, the decision analysis is divided into three main categories:

- Prior Analysis: Uses given/available information
- Posterior Analysis: Uses given new information
- Pre-Posterior Analysis: Uses new unknown (estimated) information

The pre-posterior analysis is often conducted to estimate whether or not the collection of additional information is economical.

Depending upon the quality of information (available, new, or estimated), either may be appropriate for use in the analysis. Most often, it is desirable to combine existing and new information in a rational manner. Such an approach is provided by Bayes Theorem which in its most basic form is given in Equation 2.13. This form and other forms (e.g. for different distribution, discrete data, and continuous data) can be found in Ang and Tang (2007)

$$P(E_i \mid A) = \frac{P(A \cap E_i)}{P(A)} = \frac{P(A \mid E_i)P(E_i)}{\sum_{i=1}^{n} P(A \mid E_i)P(E_i)} \tag{2.13}$$

where

$P(A)$ = the probability of occurrence of event A
$P(E_i)$ = the probability of occurrence of event Ei
$P(A|E_i)$ = the probability of occurrence of A given Ei has taken place
$P(E_i|A)$ = the probability of occurrence of Ei given A has taken place
and the events E_i are mutually exclusive and collectively exhaustive.

The left side of Figure 2.14 outlines the procedural steps utilized in risk-based decision making (RBD) and the right side outlines the general steps utilized in the life-cycle management methodology (LCM) (e.g. Figure 2.7, 2.8, etc.). It is important to note that RBD and LCM are two similar but separate methods. In researching the literature or in applying or developing either approach, one must take care to correctly and consistently treat the assumptions and limitations of each approach. Because the approaches are similar, terminology associated with each is often used interchangeably. Moreover, LCM can occur within RBD and RBD can occur within LCM. Although the approaches are complimentary, RBD typically focuses on risk mitigation whereas LCM typically focuses on maintenance and repair actions.

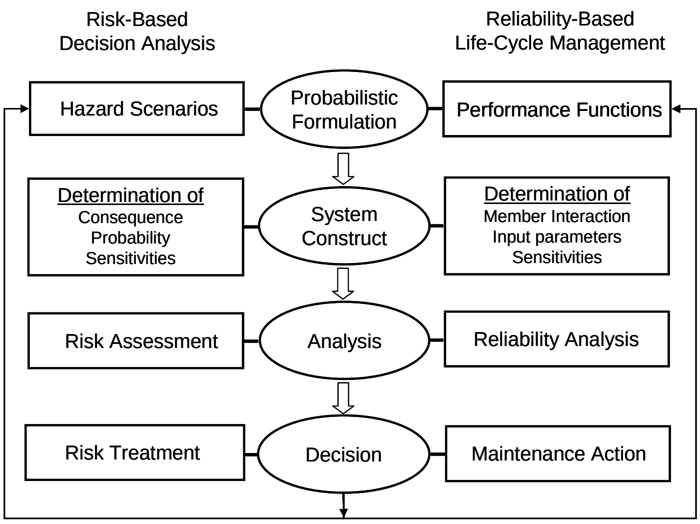


Figure 2.14 Risk Based and Life Cycle Management decision making frameworks (adopted from Frangopol and Messervey, 2007b).

Both RBD and LCM use a probabilistic formulation of a problem to deal with uncertainty. Once modeled, a system is assessed and consequences or benefits of different possible decisions can be evaluated. Once a particular decision is chosen, the model can then be updated and the system reevaluated in terms of consequence, safety, performance, cost, or condition at a future time interval. Both approaches are complimentary in nature as each uses a subset of the other within its framework. For structure management systems, risk-based decision making typically utilizes a reliability analysis to obtain the probability of failure for each outcome within the risk assessment. For reliability life-cycle cost analysis, risk concepts are typically utilized to identify and consider the appropriate life-cycle costs associated with the cost of failure and exposure to different hazards (Ang & De Leon, 2005).

It should also be noted that both approaches provide a natural and flexible decision making methodology in the presence of uncertainty. Using either provides the capability to assess multiple courses of action, new information can be introduced into the models, and managers have the ability to include their preferences or experience. As such, one approach need not replace or supersede the other. Instead, the approaches can be utilized in parallel or the strengths of each can be leveraged in a combined approach.

2.2.5 Structural Health Monitoring

To objectively evaluate the condition of existing structures and to design better structural systems, researchers are exploring novel sensing technologies and analytical methods to identify the onset of damage (Liu and Tomizuka, 2003). Called structural health monitoring (SHM), this new paradigm offers an automated method for tracking the health of a structure by combining damage detection algorithms with structural monitoring systems (Lynch and Loh, 2005). Inspired by the human central nervous system which has the capability to sense and detect injury, the SHM community has adopted the following four damage assessment levels for the development of damage detection algorithms (LANL, 2003). The are:

- Detection: Is damage present?
- Localization: Where is the damage located?
- Diagnosis: How severe is the damage?
- Prognosis: What is the remaining safe lifetime?

To date, SHM has been mostly performed at a global level, with a limited number of sensors distributed over a relatively large area of a structure. Such sensing systems, with gross spatial resolution, can only detect major damage conditions. The experiences of the last two or three decades have shown that global vibration characteristics of a structure are not sensitive to all but the most severe damage, which is inherently a local phenomenon (Glaser et al., 2007). However, recent progress in micro electro-mechanical systems (MEMS) and the introduction of comprehensive miniature sensing platforms that co-locate sensing or actuation, signal processing, computational power, and wireless communication are enabling the creation of dense sensor networks. These platforms are called “Motes” or “smart” sensors (Lynch and Loh, 2006).

SHM damage detection approaches can be categorized into the following three groupings which are shortened and paraphrased below from Glaser et al. (2007).

<u>Physics-based damage detection</u>: Such methods attempt to identify deterioration by solving an inverse problem through the construction of analytical models (e.g. finite element) or Green’s functions. The goal of such approaches is to infer the physical characteristics of a structural system, which cannot be measured directly, through the correlation of mathematical models and experimental input/response data. A critical issue for these approaches is the uncertainty associated with measured data, a lack of sensitivity to local or small levels of damage, and the inability to characterize sensor bias errors. Several notable studies in this area include Farrar et al. (1994), Bucher et al. (2003), Beck and Katafygiotis (1998), and Sohn and Law (1997).

Data-driven damage detection: Signal-based unsupervised learning techniques can be utilized to avoid direct dependence on analytical models. Such techniques include novelty/outlier analysis (Ruotolo and Surace, 1997), statistical process control charts (Sohn, et al., 2000), auto-associative neural networks (Chan, et al., 1999), and simple hypothesis testing (Lapin, 1990). These methods are generally limited to level one and two damage assessment (detection and localization). Often, numerical simulations of an analytical model are used to augment scarce or lacking data associated with an undamaged structure. Signal-based supervised learning techniques include neural networks (Masri, et al. 2000), response surface analysis (Inada, et al. 1999, Casciati, 2004), Fisher's discriminent (Garcia and Stubbs 1997), nonlinear auto-regressive moving-average (NARMA) models (Loh and Huang 1999), genetic algorithms (Ruotolo and Surace 1997), and support vector machines (Worden and Lane 2001).

Statistical models: All SHM can be viewed as problems in statistical pattern recognition in which changes in data against a baseline indicate damage. These approaches also benefit from complex and power consuming calculations associated with structural analysis or the transmission of large amounts of data. The largest challenge facing such methods is that it is often desirable to assess an in-service structure where no baseline data is available and building the database can take a considerable amount of time due to the need to compare like environmental conditions. Notably, advances in memory capacity and lower power consumption is allowing the storage of the collected baseline data and comparison calculations to occur at the individual sensor location. Promising work in this area includes Sohn et al. (2001), Nair and Kiremidjian (2007), and Kiremidjian et al. (2008).

Currently, there is a gap between SHM and bridge inspection and management methods (Glaser et. al, 2007) "Whereas SHM has focused primarily on damage detection, bridge managers want answers to serviceability and reliability issues: (a) has the load capacity or resistance of the structure changed? (b) what is the probability of failure of individual structural members and the whole structure? (c) what preventative maintenance needs to be performed? and (d) what are the chances of catastrophic failure?" Ultimately, the goal of SHM should be to facilitate rational decision-making regarding the safety and reliability of a structure, and proper actions to take when safety concerns are raised. Is it also noteworthy that although SHM equipment mostly used on new long-span bridges, the majority of structures in need of repair and monitoring are aged smaller bridges.

2.3 Aim and Scope

2.3.1 Aim

A first step in conducting a reliability-based analysis for the life-cycle management of bridge structures is to model the problem. Failure modes, random variables, and deterioration models as well as cost and maintenance options must be selected and are subject to engineering judgment and debate. A challenge preventing wider use and acceptance of reliability-based life-cycle management methods is that even after a bridge is modeled, slight variations in the input parameters can produce radically different results, thus decreasing the confidence and perceived value of the process (Estes 1997). In literature, researchers developing life cycle management models often cite the need to improve their knowledge of the actual deterioration and failure mechanisms and load effects in the structure of interest.

The use of Structural Health Monitoring (SHM) in civil infrastructure is increasing as sensors become smaller, more affordable, less power consuming, and wireless. Although bridge managers and engineers may have access to a wealth of structural response data, more research is required on how to effectively manage, process, and utilize it. In a review of lessons learned from structural health monitoring conducted on three in service bridges, it is highlighted that in some cases the goals of the academic community are different from the needs of bridge managers whose concerns are most likely upon bridge safety or unusual bridge behavior (Brownjohn et al. 2003).

Additionally, this review states that although detecting, locating, and quantifying damage may still be in the future of health monitoring, significant insight can be gained now into the actual structural behavior and loading conditions on a monitored structure. Most commonly, this information is utilized to validate or improve finite element models.

It is evident that both communities (Life-Cycle Management (LCM) and SHM)) stand to benefit from combining the strengths offered by each approach. Reliability-based life-cycle management offers bridge managers a practical predictive view of cost, safety, and condition, but in many regards lacks knowledge of actual structural performance. Structural Health Monitoring techniques effectively capture structural behavior and demands on a structure, but are not as effective in translating this information into actionable data for bridge managers. The goal of this thesis is to realize progress towards incorporating data obtained via structural health monitoring into the calculation of bridge reliability and life-cycle management.

2.3.2 Scope

This work does not aim to identify a specific damage detection method or technology that works for all structures. Instead, the idea is to develop a general framework and process adaptable to any structure of interest that takes advantage of the best possible information obtainable. This information could include theoretical and empirical models for deterioration, visual inspection data, and data obtained through structural health monitoring. SHM provides the ability to capture actual load demand and actual structural responses. Additionally, technologies exist that can effectively monitor existing damages. This information can and should be utilized to update and calculate the reliability of structure. The client of this work is the bridge manager, who likely has limited funds to maintain multiple structures. Ultimately, this work will provide him or her with an additional tool to assess and optimize maintenance options for a single bridge or a network of bridges. It is openly acknowledged that this work is a starting point.

Chapter 3

EFFECT OF MONITORING ON THE RELIABILITY OF STRUCTURES

Abstract

This chapter was inspired by the invitation to contribute to a new book entitled “Monitoring technologies for bridge management: state of the art” edited by Professor Baidar Bakht and Professor Aftab Mufti. The book is scheduled for publication in 2009. The intent of the new book is summarized in a paragraph from its preface as follows:

The use of SHM requires the interaction of several different disciplines, being for example civil engineering, electrical engineering and physics. There are a large number experts in each of the various disciplines. Similarly, specialist technical literature abounds in each area of expertise. When experts in different fields come together for an SHM project, the communication becomes difficult because each expert does not understand even the basics of the other’s field of expertise. This book has been written for the purpose of providing mainly bridge engineers most of the information about SHM of

bridges in one document. In chapters dealing with subjects not familiar to civil engineers, the language has been kept relatively simple so as not encumber the civil engineer reader with unfamiliar technical terms.

The specific chapter contribution titled "Effect of monitoring on the reliability of structures" (Frangopol and Messervey, 2009) is not reproduced here, however, the main ideas, as well as others, are presented.

3.1 Introduction

The question of how monitoring affects the reliability of structures is intricate, timely, and well-posed. On its surface, one could argue that monitoring has no effect at all. For example, given two identical bridges, does the placement of a structural health monitoring (SHM) system on one of the bridges make that bridge any less likely to fail under anticipated loads? No. In itself, the mounting and use of a sensor do nothing to improve the performance or safety of an actual structure (in contrast with the addition of a stiffener or replacing a deteriorated member). However, if one considers that structural design codes are calibrated against risk, the reduction of uncertainty through increased information obtained by SHM is of benefit if this data is captured and reflected in the codes through calibration updates over time. In terms of bridge management, it is clear that the managers of a SHM enabled structure should be better postured to make decisions concerning the maintenance and future disposition of the bridge, provided the management system can incorporate probabilistic data and a mathematical linkage can be made between service loads (based on routine usage) and extreme loads (based on return periods). Given that the design and ensuing management of civil infrastructure will likely always take place in a resource constrained environment, the expected benefit of SHM must be balanced against its cost implying the use of a life-cycle cost analysis or durability-based design. Although conceptually and financially correct, these methods have yet to become common practice in industry.

As the question "What is the effect of monitoring on the reliability of structures?" is examined, one discovers that the question truly under investigation is how does monitoring affect the way structures are designed, assessed, and managed? Since these disciplines have and will continue to evolve over time, and because they are not yet standardized, any such discussion must be carefully framed and the correct context provided. For example, the use of SHM data and associated mathematical techniques differ if one is referring to code calibration, structural system identification for a finite element analysis, or the updating of random variables in a structural reliability analysis. Although the final objective is clear (optimally efficient structural designs with the ability to assess in-service conditions to predict future behavior), how to reach this endstate is not as clear and is currently in the process of being developed. In general terms, one would expect to realize the relationships shown in Figure 3.1 in the design and employment of monitoring solutions. As the use of monitoring is increased, the level of uncertainty is reduced. In turn, this increases the reliability of the structure and decreases the life-cycle cost. However, the realization of such relationships is contingent upon the use of methods and models appropriate for such calculations. The goal of this chapter is to review such methods and investigate how monitoring can serve as a catalyst to develop the next set of design codes, assessment procedures, and management systems.

Monitoring ↑ Uncertainty ↓ Reliability ↑ Cost ↓

Figure 3.1 Relationships in the use of SHM systems (the symbols ↑ and ↓ represent increase and decrease, respectively).

3.2 Monitoring as a Catalyst to Improve Design

3.2.1 Linking Monitoring and Design

The extension of monitoring technologies into design codes and methods requires foresight and time for the field to mature. Upon initial consideration, it may appear that there is no linkage as monitoring is best suited to probabilistic methods (structural reliability) which are to date not generally used in design practice. In fact, codes that incorporate the reliability index in assessment guidelines, such as the Canadian Highway Bridge Design Code, specifically state that the guidelines will not be utilized for design purposes (CHBDC, 2006). It is perhaps for these reasons that monitoring is associated almost exclusively with assessment applications and most frequently to troubleshoot a particular defect. However, one must recall that assessment is a natural and inherent part of the design process and that studies of existing structures have resulted in the codes currently in use. In terms of probabilistic methods, although the reliability index β is not currently used for design, this index is used to calibrate and recommend the appropriate load and resistance factors for design or evaluation specifications (Ghosn et al. 2003). As such, any technology that improves assessment can also be utilized to benefit design if the information collected is utilized in future code revisions. This is not a new process, but again a natural extension of what has already been occurring to ensure that the codes are living documents that serve the best interest of society.

3.2.2 State of the Art

The past several decades have witnessed significant change in the design of civil infrastructure as our understanding of and ability to manage the uncertainties involved with material resistances and load demands has improved. Improvements have been the result of material research, testing, the establishment and study of performance databases, and better computational methods and platforms. Reflecting these advances, design methodologies have shifted from deterministic-based approaches, such as allowable stress design, to the semi-probabilistic approaches found in current codes such as Load Resistance Factored Design (AASHTO, 2007), the Canadian Highway Bridge Design Code (CHBDC, 2006), and the European Highway Agency Eurocodes (EUROCODES, 2002). In the near future, performance-based design will likely be adopted worldwide as progress in material science, design software, construction methods, and structural health monitoring have empowered the engineer to better address the uncertainties inherent to the design and operation of civil structures. In general, this evolution of design practice is shown in Figure 3.2.

Allowable Stress *(Deterministic)*	Factored (LRFD) *(Semi-probabilistic)*	Performance-Based *(Probabilistic)*
$ECS \leq \frac{STRENGTH}{FS}$	$\phi_n R_n \geq \sum \gamma_i L_i$	$R - L > 0$

time / improved knowledge / improved treatment of uncertainty

Figure 3.2. Evolution of Design Methods

In allowable stress design, safety has been assumed to exist if elastically computed stresses (ECS) did not exceed allowable working stresses (i.e., a preset fraction of the concrete strength, yield strength). Uncertainty is accounted for through the use of a factor of safety (FS) obtained through expert opinion. In factor-based methods such as the LRFD, load and resistance factors have been developed through expert opinion and calibration efforts. In performance-based approaches, the engineer is responsible for the specification of all random variables contributing to loads and resistances. The primary motivation to adopt a probabilistic-based approach is to change the design experience from "specification-based" and "process-oriented" to "performance-based" and "product-oriented" to allow the engineer more flexibility to leverage new materials and technologies (Aktan et al., 2007). Despite differences in their treatment of uncertainty, each method (deterministic, semi-probabilistic, and probabilistic) seeks an optimal balance between economical design and safe performance.

Figure 3.2 serves as an important reminder that any discussion of the role of monitoring must be placed into the context of which design method is being considered. Also interesting is that these methods are not completely standardized across country, type of project, or educational platforms. For example, most back-of-the-envelope calculations, introductory engineering courses, small local projects, and many military engineering manuals utilize allowable stress design. Generally, where design is regulated at the national level as is the case for public buildings, roads, and bridges, a semi-probabilistic, factored design approach is utilized. Factored design (i.e., Load and Resistance Factor Design (LRFD)) is usually taught in upper-level educational courses and is the predominant method currently used in practice and prescribed by current codes. Fully probabilistic, performance-based design is typically left for graduate level courses and leading researchers in the field believe that this approach is the next step in the evolution of design methodology (AASHTO, 2005)

3.2.3 Using SHM to Improve Design Factors and Methods

Within this context, the answer to the question on how monitoring can be utilized to improve design is twofold. First, monitoring can provide data that can be utilized to confirm or improve existing load factors, resistance factors, and load combinations for extreme events used in existing code provisions (semi-probabilistic). For example, in studying the effect of live loads to calibrate the LRFD for the design of highway bridges, the statistical database of truck weights was primarily obtained from a 1975 survey of 9,250 trucks collected at a weigh station over a two week period in Ontario, Canada (Nowak, 1993). Although appropriate at the time, it is possible that heavier trucks may have avoided the weigh station creating the need for more sample data and more importantly, the trucking industry has undoubtedly changed over the past 30 years. Recently, weigh in motion (WIM) studies have been utilized to create much larger databases for truck weights. One such study (Gindy and Nassif, 2006) examines an 11-year period across 33 WIM sites located in the state of New Jersey and consists of millions of records. Truck volumes, types, and weights, as well as seasonal effects and the implication of short collection periods are addressed. Such studies, based upon monitoring information, can provide the data necessary to re-examine the assumptions utilized in existing codes. Truck weights are of course only one example. Also interesting is how these trucks affect bridge reliability. To answer this question many studies have been done on traffic simulation to investigate the impact of vehicle spacing, vehicle speed, and the frequency of side-by-side design truck occurrences (O'Connor and O'Brien, 2005; Cohen et al., 2003; Zokaie, et al. 1991). With respect to the conduct of a system reliability analysis, past studies have estimated system reliability factors that account for redundancy present in typical bridge configurations (Ghosn and Moses, 1998). Current ongoing studies are investigating how such factors (e.g. load distribution factors between girders) can be more accurately modelled using SHM (Peil, 2003). Again, these are just several examples. Indeed, the question becomes what assumptions are the most important across existing codes/models and which would serve as candidates for validation through monitoring efforts.

In addition to refining load and resistance factors, existing codes all use load combinations to provide an adequate measure of safety for the occurrence of simultaneous extreme, or design load, events. In a report titled the Design of Highway Bridges for Extreme Events (Ghosn et. al 2003), the authors recommend adjustments to the LRFD load combinations after determining that the existing factors and combinations exhibit large discrepancies between the reliability levels for the different extreme events under consideration. This study, based on existing safe structures, did not make use of monitoring data but provides great insight into the amount of uncertainty remaining in existing codes and of the process required to evaluate and modify target safety levels. Adding information obtained from monitoring is logical progressive step for a future update.

The second way monitoring can be utilized to improve design is by providing the engineer with the statistical information necessary to employ reliability-based / performance-based / fully probabilistic design (equivalent terms). As such, monitoring would serve as the catalyst to enable a change in methodology itself. In this approach the designer has much greater flexibility, but also bears the responsibility of quantifying and appropriately treating all of the uncertainties that determine member resistances, load effects, and load combinations. Although reliability based design has been proposed in several countries and some provisions allow more flexibility for its use, this method to date has not been widely adopted. Expanding upon Figure 2.5 (optimal design based on life-cycle costs), it is reasonable to expect that the use of a SHM-enabled, reliability-based approach would lead to a more optimal design solution as shown in Figure 3.3. Although monitoring does not change the relationship between the costs (i.e. that higher initial costs result in lower failure and additional costs) monitoring does change each cost itself. Specifically, the initial cost is increased (upfront SHM system cost), the failure cost is decreased (less risk), and the additional costs are decreased (improved optimal management decisions) across the entire profile. This reduction in total life-cycle cost is also expected to be paired with a higher level of performance.

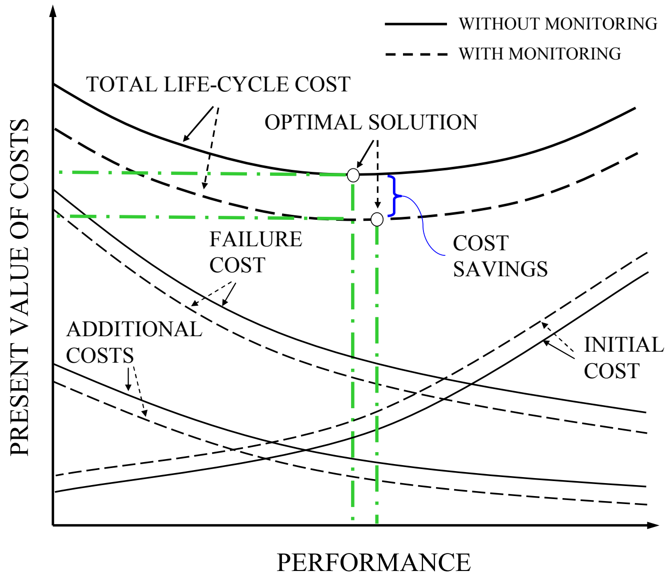


Figure 3.3. Optimum design solution based on life-cycle cost minimization with and without monitoring (adapted from Frangopol and Liu, 2007)

Collecting the information necessary to re-examine existing codes or to provide consistent guidelines for the application of performance-based design is an interesting challenge. Data is required from multiple structure types across various locations over long periods of time. With respect to highway bridges, superbridges are currently the most common monitoring candidates due to their complexity and high cost. However, short-span bridges typically have lower target reliability indexes due to higher live-load to dead-load ratios (Ghosn, 2000). Additionally, a higher ratio of short-span bridges are classified deficient. To apply consistent levels of safety across the fleet, bridges of all span-lengths must be considered. As a result, engineering experts will need to come to a consensus for data collection methods and the appropriate models for their use. Due to cost and the amount of information required, such a collection effort will likely require coordination from national and international agencies. An example of the successful implementation of such a program can be found in the field of structural health monitoring for damage detection. Within this field, a benchmark study of a progressively damaged frame structure has been established and data was posted online to provide researchers with a common reference to develop damage detection algorithms (ASCE, 2000). Although replicating such a program for bridges is of substantial effort, the potential benefit is also significant. Once enough data is collected, it is reasonable to assume that by measuring, instead of modelling, demands upon and the performance of in-service structures, the result would be more efficient and safe designs.

3.3 Monitoring as a Catalyst to Improve Assessment, Performance Prediction, and Management

3.3.1 State of the Art

Similar to the analysis of how monitoring can be leveraged to improve design, the impact of SHM on infrastructure assessment, performance prediction, and management largely depends upon the model and methodology considered. As with design, this field continues to develop, exists in different forms across different codes and countries, and is one where the implementation of ideas from research into practice can take many years. As such, it is appropriate to consider how monitoring could be phased into existing methods while serving as a catalyst for the development of new methods centered around the collection of real-time structural response data.

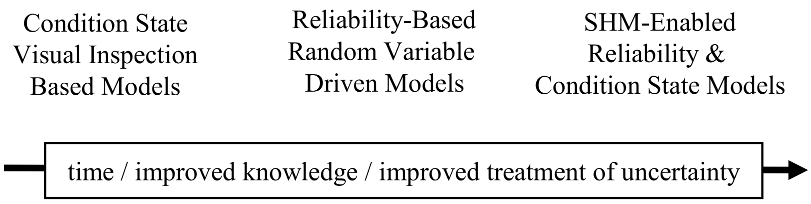


Figure 3.4. Likely Evolution of Assessment, Prediction, and Management Models (adapted from Frangopol and Messervey, 2008b)

Figure 3.4 shows the likely evolution of assessment, prediction, and management models. In contrast with Figure 3.2 (design methods), management programs are still in the earlier stages of development located at the left side of Figure 3.4. It is believed that SHM technologies will facilitate the development and adoption of more advanced methods where management decisions are based on structure specific performance and condition data simultaneously. As detailed in Chapter 2, existing bridge management programs are almost exclusively based on visual inspections. In special cases, non-destructive evaluation (NDE) tests are performed and although relatively few, there is a growing number of monitoring applications. However, such tests are generally on an ad-hoc basis to target a specific fault and are not integrated into the overall maintenance and management hierarchy. As such, how to integrate new technologies into existing systems is a logical next step which can begin with two of the primary functions of management programs, assessing or certifying bridge capacity, and planning for maintenance and rehabilitation actions.

3.3.2 Using Monitoring to Improve Bridge Capacity Ratings

Several countries use bridge capacity ratings as an assessment and management tool. Canada is one such country. Section 14 of the Canadian

Highway Bridge Design Code (CHBDC, 2006) provides inspectors with the guidelines and methods to determine if an existing bridge will carry a particular set of loads. The end result is a posting of allowable truck weights and/or certification that a particular bridge still meets acceptable safety requirements for traffic along a specified route. The approach can be likened to the LRFD in that it is semi-probabilistic in nature. Reliability-based calibrated load and resistance factors are provided for use under different loading configurations of design trucks. The reliability index β is used, but in an inverted sense. Instead of determining the probability of load demand exceeding capacity as is the case in structural reliability, the index is used as a calibrated factor to ensure an adequate level of safety. Values for the reliability index are determined by the behavior of the bridge, type of inspection being conducted, and type of traffic loading being considered. Values for normal traffic and for permit-regulated heavy loads not requiring supervised escort are provided in Table 3.1 (there are several such tables in the CHBDC for varying types of traffic considerations).

Table 3.1 Target reliability index, β for normal and non-escorted permit traffic (according to the CHBDC)

System behavior category	Element bahavior category	Inspection level		
		INSP1	INSP2	INSP3
S1	E1	4.00	3.75	3.75
	E2	3.75	3.50	3.25
	E3	3.50	3.25	3.00
S2	E1	3.75	3.50	3.50
	E2	3.50	3.25	3.00
	E3	3.25	3.00	2.75
S3	E1	3.50	3.25	3.25
	E2	3.25	3.00	2.75
	E3	3.00	2.75	2.50

System behavior is used to account for the presence of multiple load paths using the following designations: S1 – element failure leads to total collapse, S2 – element failure probably does not lead to total collapse, and S3 – element failure leads to local failure only. Element behavior is utilized to account for the failure mode/mechanism of a member using the following designations: E1 – element is subject to a sudden loss of capacity with little warning (buckling, rebar pullout, brittle behavior), E2 – element is subject to sudden failure but retains post failure capacity (concrete with adequate rebar, steel with post-buckling capacity) and E3 – element is subjected to gradual failure with apparent warning signs (steel in bending or tension). Inspection levels are utilized to account for the ability to obtain information during an inspection on the member of interest as: INSP1 – A component is not inspectable (inside of a box girder), INSP2 – inspector is able to obtain a qualitative assessment, and INSP3 – the inspector is able to obtain and document a quantitative assessment.

Within this type of approach, monitoring would most directly affect the inspection level. Where applied, it is reasonable to conclude that the use of SHM would lead to the selection of INSP3. If changes to the method were considered, an INSP4 column might be appropriate. It is also possible that monitoring would allow a more accurate system behavior assessment. However, it is likely there is less error associated with the classification of system behavior than there is with the collection of quantitative inspection data implying a lower benefit/cost ratio for SHM applied strictly to the investigation of system behavior.

Once selected, the reliability index is used in one of two methods to determine the live load capacity factor, *F*. In the first method (primary), β determines the selection of appropriate dead and live load factors, α_D and α_L, respectively. As an example, Table 3.2 shows the selection process for the live load factor for normal traffic. Although there is only one row for Table 3.2, other tables for the selection of this factor (e.g. for permit traffic) also delineate span length and the type of analysis as selection criteria.

Table 3.2. Live load factors a_L, for normal traffic and all types of analysis (according to the CHBDC, 2006)

Span	Target Reliability Index, β						
	2.50	2.75	3.00	3.25	3.50	3.75	4.00
All Spans	1.03	1.04	1.05	1.06	1.07	1.08	1.09

Once selected from the appropriate tables, α_D and α_L are utilized to calculate the live load capacity factor F as (CHBDC, 2006)

$$F = \frac{UR_r - \sum \alpha_D D - \sum \alpha_A A}{\alpha_L L(1+l)} \tag{3.1}$$

In general, the first term of the nominator specifies the resistance, the second term dead load, the third term load effects (wind, creep, shrinkage, temperature, and settlement) when considered, and the denominator is the factored live load with l representing the unfactored dynamic component of the live load expressed as a fraction of the nominal static life load effect. Once computed, F enables the determination of a posting factor from a graph that then specifies allowable bridge capacity. Within this approach, aside from the determination of the live and dead load factors, SHM data could also be utilized to provide more accurate material resistance properties and to better account for load effects such as wind and temperature.

The second, or alternate, method of determining the live load capacity factor F is called the mean load method. This method is more appropriate for the direct inclusion of monitoring as it incorporates statistical data. Using the alternate method, F is determined as (CHBDC, 2006)

$$F = \frac{\overline{R} \times \exp\left[-\beta (V_R^2 + V_S^2)\right]^{0.5} - \sum \overline{D}}{\overline{L}} \tag{3.2}$$

In general, the first term of the nominator is the product of the mean resistance and a reduction factor determined by the desired level of safety (β) and the coefficients of variation of the resistance (V_R) and total load effects (V_S). The second term accounts for the mean dead load effect and the denominator accounts for the mean live load effect. Although the mean resistance, mean dead load, and mean live load are calculated as specified in the standard method, the bias coefficients and coefficients of variation for each of these factors may be taken from technical publications or field measurements. As such, there is room for monitoring to play a larger role in the determination of F.

3.3.3 Using Monitoring to Improve Reliability-Based Assessment

Much work has been done in the development of reliability-based life-cycle bridge management models (Akgul and Frangopol, 2005; Frangopol and Liu, 2005; Neves et al., 2005, Enright and Frangopol, 1999). In the most basic sense, these models determine a structure's initial state, model its deterioration, and seek a Pareto solution to optimize its lifetime cost, performance, safety, and condition across a range of maintenance options and inspection intervals. To do this, such models seek to simulate or calculate all parameters affecting structural performance and are well suited to account for structural redundancy through system analysis. However, a challenge preventing the wider use and acceptance of Life-Cycle Management (LCM) methods is that even after a bridge is modeled, slight variations in the input parameters can produce radically different results, thus decreasing the confidence and perceived value of the process (Estes, 1997). In literature, researchers developing LCM models often state the need to improve the base of knowledge governing deterioration, failure mechanisms, and load effects in the structure of interest. To this end, Catbas et al. (2008) state that the consideration of the uncertainty associated with critical loading and structural parameters is one of the most critical issues in assessing the condition of existing civil infrastructures.

Although the general form of the reliability calculation given by Equation 2.4 (P(R - L > 0) is very simple, its application to a performance function for an actual structure quickly becomes more complicated. To illustrate some of the considerations, Equation 3.3 provides the general form of the performance function for a reinforced concrete slab analyzed with respect to moment capacity.

$$g(1) = M_{Capacity} - M_{Demand} = M_u - M_{dl} - M_{ll} \tag{3.3}$$

where M_u is the ultimate moment capacity, M_{dl} is the moment demand due to dead load, and M_{ll} is the moment demand due to live load. Using a case study of a bridge in Colorado, Estes (1997) evaluated each of these terms as functions of random variables. To illustrate some of the complexities/considerations, these equations are shown here in their general format. For the ultimate moment capacity

$$M_u = \frac{A_t f_y d_{eff}}{12} - \frac{a_t^2 f_y^2}{244.8 f_c^{'}} \tag{3.4}$$

where A_t is the area of the tensile reinforcement, f_y the yield strength of the tensile reinforcement, d_{eff} the depth of the reinforcement, at the effective depth of the equivalent concrete compression block, f'_c the concrete compression yield strength. For the dead load moment demand

$$M_{dl} = \frac{ws^2 C_f}{8(1000)} \tag{3.5}$$

where w is the combined weight concrete and asphalt, s the unsupported slab length, and C_f a continuity factor based upon how many girders the slab crosses. The live load moment demand is calculated as

$$M_{ll} = \frac{L_{trk}(s+2)}{32} C_f I_f \tag{3.6}$$

where L_{trk} is the load from a single wheel of the HS-20 truck and I_f is an impact factor. Each of the variables in Equations 3.4-3.6 are random variables. They can be modeled using accepted uncertainty factors and bias coefficients, they can be measured or monitored, or they can be taken as accepted factors from existing codes and guidelines. It is noted that Equations 3.4-3.6 are developed for a specific case study and should not be applied to another example.

The complexity of evaluating Equation 3.3 increases in two ways (from beyond the characterization of the random variables). First, a time dependent reliability analysis must characterize the deterioration (or change) of the random variables over time. Deterioration and its effect on capacity is in particular highly uncertain. Secondly, a system analysis must model how this performance function relates to other failure modes and other structural members or systems. To facilitate a solution to this complex problem, SHM provides the capability to reduce the uncertainty associated with the initial characterization of the random variables, to reflect changes in the random variables over time by updating, and the ability to better quantify system effects. A sensitivity analysis as part of a reliability analysis shows which random variables and which performance functions are most important to the analysis of a structure. This would indicate where allocate monitoring resources. Again using a general view of the reliability problem, Figure 3.4 updates Figure 2.10 (general structural reliability concept) to incorporate the expected result of including monitoring data.

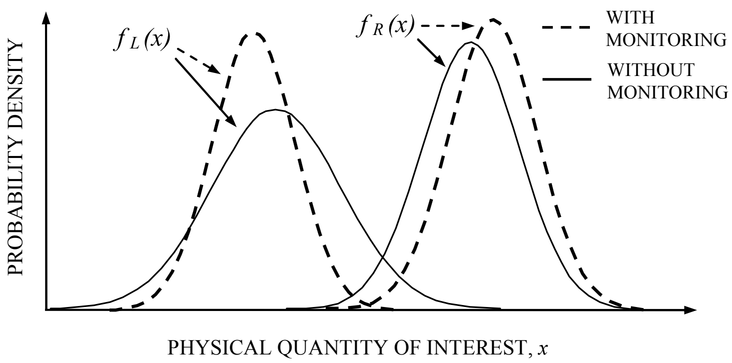


Figure 3.5. Structural reliability concept with and without monitoring (adopted from Frangopol and Messervey, 2008c)

The modeled mean load effect is decreased, the mean resistance is increased and the standard deviation of each is decreased. Monitoring has the greatest impact upon the characterization of the load effect (dynamic vs. static random variables). It is also noted that a more accurate characterization of L and R also affects the probability of failure (i.e. P(R–L < 0)). Although this is the anticipated result, it is possible that monitoring could also provide a confirmation of modeling assumptions or indicate that the actual quantities are worse than anticipated.

3.3.4 Using Monitoring to Improve Inspection Scheduling

Inspections (unless there is a problem) are performed at pre-determined intervals according to the type of inspection being performed. As shown in Figure 3.6a, this can result in inspections that are not needed or not optimal (such as when a structure is new). In addition, any inflexible inspection schedule runs the risk of having performance fall below an established threshold during the inspection interval. A more optimal method to schedule inspections is to schedule them based on performance as shown in Figure 3.6b. Using such an approach, inspection intervals may vary and occur as often or as infrequently as needed.

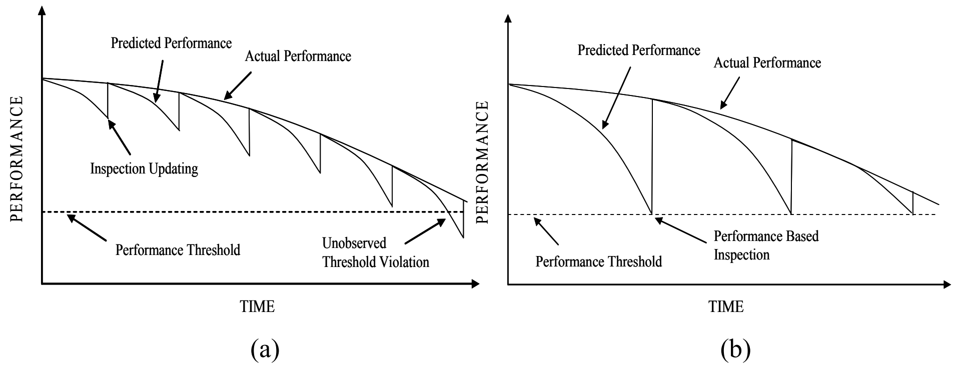


Figure 3.6 Inspection scheduling/conduct (a) based off time and (b) based off performance prediction (adapted from Frangopol, 1998, Rafiq, 2005).

Monitoring makes a performance-based inspection program more attractive by reducing the uncertainty associated with performance between inspection intervals. Continuous monitoring would also reduce the risk of an unobserved drop below a performance threshold. SHM could also facilitate a hybrid-type inspection scheduling approach where cursory (less expensive) inspections occur periodically at prescribed intervals and more detailed and expensive inspections become performance driven.

3.3.5 Using Monitoring to Improve Performance Prediction and Management Models (Bridge Management Programs)

3.3.5.1 Condition State Models

Condition state models (as detailed in Sec. 2.2.2.2) assess structural performance based on visual appearance. The main advantage of condition state models is their ease and simplicity of use. Current versions of Pontis facilitate user input of inspection data, make recommendations on preservation actions for individual bridges as well as networks, have provisions to account for failure costs, and provide low cost maintenance alternatives for periods up to 30 years (Roberts & Shepard, 2002). The main disadvantages of such models is that the actual infrastructure safety level is not explicitly or adequately accounted for and that discrete stochastic transitions between condition states fail to account for previous structural behavior and prohibit more accurate continuous modeling approaches (Frangopol and Liu, 2007). Additionally, there are several limitations associated with visual inspections. Successful visual inspection depends on considering all possible damage scenarios at all critical locations, not an easily accomplished task even for an experienced inspector (Aktan et al, 2001). Human error is also a consideration. One recent study reported that in some cases more than 50% of bridges are being classified incorrectly via visual inspections (Catbas et al., 2007). Although certainly not the norm, a separate recent article highlighted the falsification of bridge inspections by contractors to keep up with timelines for reporting purposes (Dedman, 2008b). Lastly, as the bridge population continues to worsen in terms of magnitude and severity, it is questionable whether or not existing appraisal methods will be adequate (Susoy et al, 2007).

Due to the limitations of condition state models, maintenance management decisions made on the basis of infrastructure condition states alone are not necessarily optimal with respect to safety or cost. For example, it is possible that a reinforced concrete structure with satisfactory visual condition states could actually be structurally unsafe. This would occur when invisible flaws such as corrosion of the embedded reinforcement or unseen cracking exists. In such a case, maintenance funding would not be allocated. However, it is also possible that a structure may be structurally sound despite a poor visual condition status. In this situation, only minor repairs may be necessary and costly retrofit could be avoided if better information becomes available (Frangopol and Liu, 2007). To address some of these limitations, several authors have investigated incorporating safety into condition state models by assigning an associated amount of section loss as a random variable to each condition state and by discretizing inspected members to better pinpoint where deterioration is present for structural analysis (Estes and Frangopol, 2003; and Hearn and Frangopol, 1996).

The use of monitoring to improve condition state models is somewhat limited as the model is based upon the simplicity of correlating visual indicators and experience to bridge performance. However, the practical implementation of SHM will likely first occur as an addition or evolutionary step to programs such as Pontis as experience with and validation of SHM occurs. Within condition state models, monitoring could be used to address the concern of safety by establishing performance thresholds, or safeguards, that would be triggered for action of a bridge manager in the event of overloading or abnormal behavior. A simple example would be a stress, strain, or deflection threshold. Once in place, observable trends in the monitoring data could serve to validate, improve, or create new deterioration processes to replace the stochastic transition model currently in use or to better define its transition probabilities.

3.3.5.2 Reliability Models Based on Simulation

The development of structural reliability theory and improved computing power has led to the development of reliability-based bridge management models that explicitly account for structural safety (Cruz et al. 2006; Watanabe et al. 2004; Casas et al. 2002; Das et al. 1999; Frangopol 1999; Frangopol et al. 1998). Such models use the reliability index as the performance metric and treat deterioration in a probabilistic allowing for a continuous treatment of the structure over time with respect to safety. Figure 3.7 depicts the three and eight random variable profiles proposed by Frangopol (1998) and Frangopol et. al (2001) to model the reliability index profile without and with preventive maintenance.

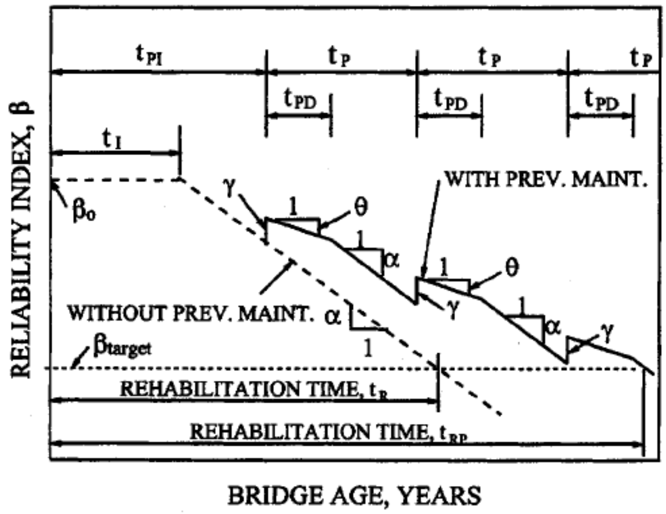


Figure 3.7. Reliability profile models with and without preventive maintenance (adopted from Frangopol, 1998).

Based on the study of a database of existing bridge and bridge studies, each of the factors that affect bridge performance over its service life with respect to safety are described as random variables. These random variables include the initial reliability index β_0, the time associated with the onset of deterioration t_I, the rate of deterioration without maintenance α, the rate of deterioration after preventive maintenance θ, the increase in reliability due to preventive maintenance γ, the time to the first preventive maintenance action t_{pI}, the time to successive preventive maintenance actions t_p, the duration of preventive maintenance effects t_{PD}, the time to rehabilitation without maintenance t_R, and the time to rehabilitation with preventive maintenance t_{RP}. Once an initial reliability index is calculated, or selected from a database of like structures, Monte Carlo Simulation is conducted to investigate and optimize different maintenance and repair strategies over time. This model has been applied to individual and groups of bridges in the United States and in the United Kingdom (Frangopol et al. 2001; Frangopol, 2003; Frangopol and Neves, 2003; Neves and Frangopol 2004; and Petcherdchoo et al. 2004).

Careful attention is required when researching the literature or when applying the three and eight random variable models to ensure their proper understanding and use. The model can be used to describe the performance of an entire structure (global approach), to the performance of a system (e.g. deck), or to that of an individual member (e.g. girder). The initial estimates for the random variables of this model were obtained empirically with regard to global parameters and many following studies have refined the approach for specific applications, systems, or members. As such, any use of or reconstruction of the model must pay particular attention to the random variable descriptors selected and the type of analysis being conducted.

The use of monitoring to improve reliability models based on simulation is attractive. Typically, the evaluation of random variable descriptors associated with any nondeterministic performance model is time consuming and expensive. In addition, the random variables are inherently structure-specific but require the empirical observation of similar structures experiencing different environmental conditions for their estimation resulting in a loss of accuracy/higher degree of uncertainty. These dynamics are important because such models predict far into the future and the results are extremely sensitive to the random variable input parameters. For these reasons, monitoring offers great potential to facilitate the characterization of these variables, enhance model accuracy, and enable the use and acceptance of this model in practice by obtaining and updating random variable input parameters over time. In general, to minimize cost and maximize benefit monitoring effort should focus on the most significant variables affecting the performance of the chosen model. With respect to the eight variable model shown in Figure 3.7, this work has already been completed in part by Kong and Frangopol (2005b). In this work a sensitivity analysis of the eight random variables determined that the initial characterization of bridge reliability β_0 and the rates of deterioration, α and θ, were most significant. As such, any organized data collection effort employing SHM to better understand these parameters would benefit this approach.

As it can be argued that condition state models do not account for safety, it can be also be argued that reliability-based models do not account for condition. For example, a very safe structure may have a deck full of potholes hazardous and damaging to vehicular traffic. In such a case, repairs must be conducted despite a high level of structural safety. To resolve this problem, Neves and Frangopol (2004) applied the same random variable profile approach to the condition profile over time as shown in Figure 3.8.

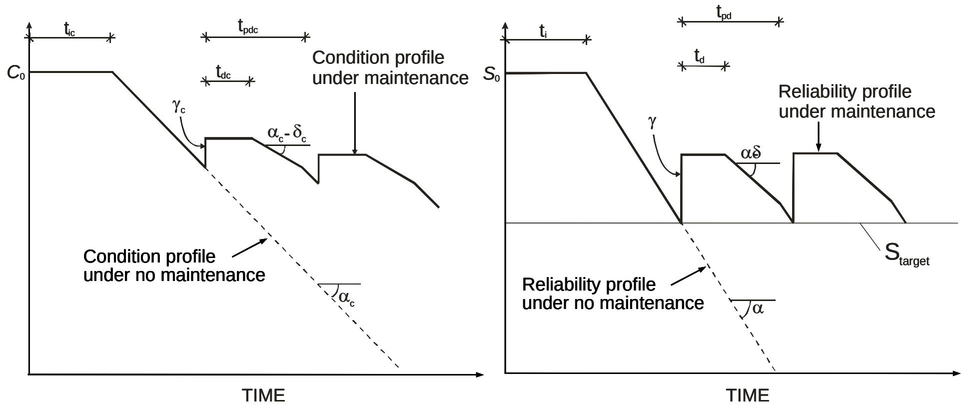


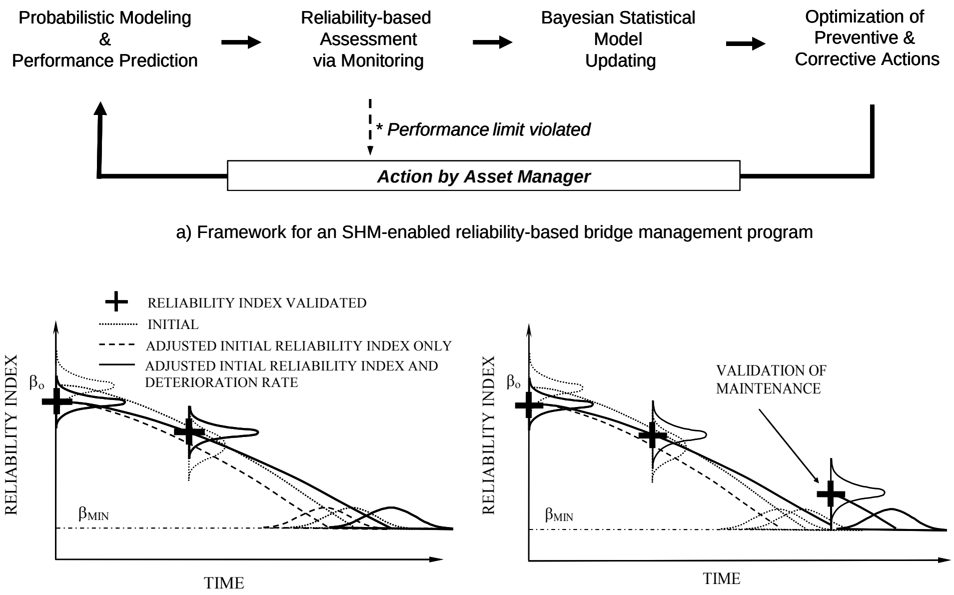
Figure 3.8 Random variable model of the condition and reliability profiles considered simultaneously using a target safety level (adapted from Neves and Frangopol, 2004)

Using such an approach, safety, condition, and cost can be considered simultaneously as a multi-objective optimization problem to determine Pareto optimal maintenance and repair strategies. Such work is investigated in (Neves and Frangopol, 2004; Neves et al., 2006a; Liu and Frangopol 2006a; Furuta et al. 2006; Neves et al. 2006b; Bucher and Frangopol, 2006). As is the case with the reliability-based model, monitoring information would significantly improve the combined approach as there more random variables under consideration as well as the correlations between these variables to determine.

3.3.5.3 Reliability Models without using Simulation

Reliability models without using simulation attempt to construct an analytical and predictive model of structural performance using structural reliability concepts. Ideally, a bridge management program using such an approach would allow for individual or bridge network assessment, maintenance, inspection, and repair planning based on real-time structure-specific data. However, the approach is obligated to characterize all loads and their effects, structural resistance and its deterioration over time, the interaction of different failure modes, and the consideration of system effects. By its very nature, this method is heavily dependent upon monitoring data and is the goal of many researchers worldwide (Frangopol and Messervey, 2007c; Catbas et al, 2007; Moon and Aktan, 2006; Budelman and Hariri, 2006; Messervey and Frangopol, 2007a; Klinzmann et al., 2006).

Figure 3.9 shows a general schematic for the reliability based model without simulation. Figure 3.9a presents a general framework for the inclusion of monitoring data into a reliability-based model. Figure 3.9b shows how SHM data can be utilized to update the reliability profile at any time and Figure 3.9c indicates the validation of performance after a maintenance action. The process begins with a reliability-based treatment of the structure that helps determine a task-oriented monitoring solution and initial performance prediction. Once in place, an assessment loop begins in which monitoring data is used to update the structural model. Once the predictive model is updated, maintenance actions can be optimized for decision by the asset manager. If the monitoring solution employed is permanent (continuous), performance flags can serve as a warning system to alert the asset manager immediately of any violation of a critical threshold or unexpected distress. The result of any such integrated LCM/SHM approach is an adaptive, self-learning management system with the capacity to improve the underlying theoretical-based models through structure specific response data over time. A more accurate model provides the potential for cost savings through optimal maintenance and inspection scheduling, and a decrease in risk through the reduction of uncertainty (Frangopol and Messervey, 2007b).



a) Framework for an SHM-enabled reliability-based bridge management program

b) Validation of the reliability profile over time

c) Validation of maintenance

Figure 3.9. Framework and reliability profiles of an SHM life-cycle reliability-based bridge management program.

It is important to note the difference between the three bridge management approaches. Condition state models assess a structure using a visual inspection and deterioration occurs at discrete intervals using a stochastic process based on historical records. Reliability models based on simulation assess a structure through a reliability analysis, or by using the reliability of like structures, and then an equivalent model is developed (not unlike the process of determining an equivalent member for a finite element analysis) that approximates the effects of deterioration over time and optimizes maintenance and repair efforts. Reliability models without simulation assess a structure and its deterioration by defining all random variables and their behavior over time through the evaluation of performance functions. Although such a model is desirable, it has been slow to gain acceptance because of the amount of data required, its sensitivity to small changes in the input parameters, and the complexity of the analysis (Estes, 1997). Although SHM is best suited for the last approach (i.e. reliability models without simulation) and will likely be the catalyst that enables further use and acceptance of this method into practice, how monitoring can be used in each approach is important as all three models (i.e., condition state models, reliability models based on simulation, reliability models without simulation) will exist and be implemented for the foreseeable future. Table 3.4 provides a summary of the assessment mechanism, advantages, and disadvantages for the bridge management program approaches. Included in Table 3.4 are hybrid models that incorporate both safety and condition. The summary for reliability-based models includes both with and without simulation approaches.

Table 3.4. Types and evolution of Bridge Management Programs with assessment mechanisms, advantages, and disadvantages

Model Type/ Performance Metric	**Condition State Models**	**Reliability-Based Models**	**Hybrid Models Safety + Condition**
Assessment mechanism	Visual Inspection NDE	SHM Analytical models Statistical data collection	SHM Analytical models Visual inspections
Main advantages	Simplicity Ease of implementation	Consideration of safety Model flexibilty	Structure-specific treatment of safety and condition
Main disadvantages	Absence of safety quantification Prone to human error Discrete transition states	Absence of condition quantification Sensitivity and need for accurate input parameters	Higher initial costs Increased complexity

3.4 Application

A simple example is provided to begin to illustrate some of the concepts presented in Chapters 2 and 3. By using accepted procedures in existing codes and information from a recent bridge failure, the intent of the example is demonstrate how a risk-based decision making approach can be utilized to quantify monitoring benefit.

Use of Equation 2.12 ($R = p_f C$) is desired which calls for a reasonable estimate of the consequence of failure *C*. The consequence of failure can vary widely depending on what costs are included and its evaluation is somewhat subjective. In addition to site clean up and the design/construction of a replacement structure, these costs can include those associated with the loss of life, lawsuits, new legislation, loss of productivity, and user costs. This term, in particular, would benefit from standardization guidelines for its calculation. In the absence of providing specific guidelines, a reasonable starting point could be the designation of three levels of consequence depending upon the structure size, importance, and function: low, medium, and high. Estimates for the three levels could be obtained by researching historical failures. An example of a high consequence level is developed here using reports and information surrounding the recent collapse of the I35W bridge collapse in Minneapolis, USA. A similar analysis of the Laval overpass collapse (2005) would provide a reasonable estimate or a medium consequence level (not conducted in this example).

Using news reports and studies in the months following the collapse of the I35W Bridge, Table 3.3 lists the estimated consequence of failure for the tragedy (Podoba, 2007, Jardin, 2007).

Table 3.3. Estimated costs associated with the collapse of the I35W bridge in Minneapolis, Minnesota, USA, 2007 [11, 12]

Site Recovery Costs	\$400 million
Estimated user costs: 140,000 vehicles/day, 10 mile detour, IRS allocated .48 cent/mile, and 365 day construction time of new bridge	\$245 Million
Winning bid for new structure	\$234 million
State liability cap of \$1 million on 13 deaths	\$13 million
Estimated \$10,000 hospital bill on 100 injured	\$ 1 million
Lawsuits, legislation, loss of productivity, and investigation	*(not estimated)*
Total Estimated Consequence of Failure	US\$893 million

Particular attention is provided to the calculation of user costs which are often vary dramatically. Here, these costs are estimated as

$$\textit{User Costs} = \textit{ADT} \times \textit{Detour length} \times \textit{Government rate} \times \textit{Construction time} \tag{3.7}$$

where ADT is the average daily traffic. Applying the government approved rate for mileage and a simple internet map search for the detour length remove subjectivity from the user costs although lost time/productivity is not included. Additionally, applying a liability cap for casualties removes the difficult job of placing value on human life. For the purpose of this example, a high level consequence of failure is taken as US \$893 million.

To obtain probabilities of failure from existing accepted methods, row S1 (element leads to total collapse), E3 (element shows warning of failure), is selected from Table 3.1 (reproduced from the CHBDC). This selection is motivated by investigating what is the utility associated with the quality of available information represented by the type of inspection conducted. The target reliability indexes corresponding to S1/E3 are 3.5, 3.25, and 3.0 respectively. Using \$893 million as the consequence of failure (Table 3.3), the application of Equation 2.12 yields the following results for the failure cost:

$\beta = 3.5$	$p_f = 0.000233$	$C_f =$ \$208,069
$\beta = 3.25$	$p_f = 0.000577$	$C_f =$ \$515,261
$\beta = 3.0$	$p_f = 0.001350$	$C_f =$ \$1,205,550

Comparing the differences in the failure cost provides one estimate for the benefit associated with changes in the target reliability index through more accurate structural information (monitoring).

An event tree as shown in Figure 3.10 can be utilized to begin to incorporate life-cycle costs and to formulate a risk-based decision based off the least total expected cost. Here, the decision is to select either a visual inspection program or a monitoring program. The cost of the visual inspection program is estimated as a life-cycle cost at a 4% discount rate with the cost of each inspection is estimated as $10,000 for a large-scale bridge structure (Dedman, 2008a). The time period considered is 30 years with the first inspection taking place at time t = 0 (assuming this analysis is for an existing structure) and the last inspection occurring on year 30 for a total of 16 inspections. A first estimate for the cost of the monitoring program is $500,000. This estimate can be adjusted pending the analysis outcome and can serve as a design constraint to develop monitoring alternatives as long as a monitoring benefit is present in the result. The failure probabilities are taken from the prior calculations using β= 3.0 (p_f = 0.001350) for the visual inspection program and β = 3.5 (p_f = 0.000233) for the monitoring program.

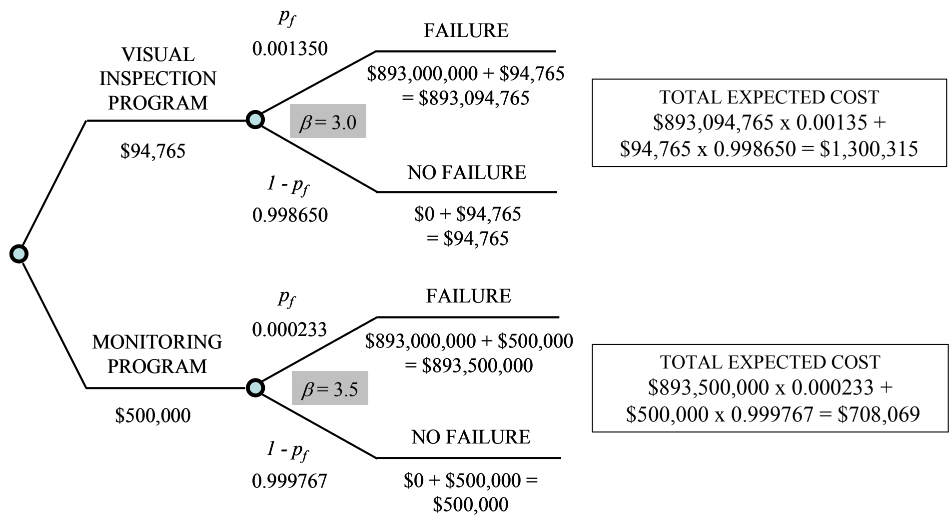


Figure 3. Risk-based decision tree evaluating the expected costs of a visual inspection program and a monitoring program.

Further defining and standardizing appropriate values for the reliability index in this type of analysis needs further investigation. Based on historical trends in civil engineering, it is reasonable to assume that such values (a) can first estimated by a panel of experts, (b) can then be improved / calibrated as more and more monitoring systems come online, and then (c) performance-based methods can be developed for structure-specific use. The end result of the calculations for this analysis is a difference of US \$592,246 (i.e., \$1,300,315 - \$708,069). It is worth noting that standardization and guidelines are important in such calculations as the results are sensitive to the length of time considered for life-cycle costs, the discount rate, the probability of failure, and the consequence of failure.

Extending this example to incorporate the effect of time and to optimize management decisions requires modeling changes in probabilities (deterioration) and a more complete treatment of comparing life-cycle costs between monitoring and non monitoring approaches. These topics are addressed in Chapter 4. Additionally, a risk-based decision approach is best suited for a point-in-time analysis. A careful treatment of loads effects (Chapter 5) and risk costs in time (Chapter 6) are required. For such an approach, a time-dependent reliability analysis is more appropriate.

3.5 Conclusion

How the employment of monitoring technologies affects the reliability of structures directly poses the larger question of how better information and reduced uncertainty change the design and assessment of civil infrastructure. Investigation into this issue quickly reveals that the problem must be carefully framed as both design methods and assessment techniques exist in different forms from location to location, across different types of projects, and across varying political systems. As such, the potential impact on monitoring depends in part upon the context of its use. However, and more importantly, monitoring provides the capability and catalyst to revisit and improve existing design codes, assessment methods, maintenance, and management techniques. Because of the importance and value of civil infrastructure to the society it supports, designing better and managing more efficiently is necessary and timely, especially as focus turns to managing existing aging structures. With respect to design, monitoring will likely enable and promote the use of performance based design methods. With respect to bridge management programs, monitoring will likely enable further development and the adoption of reliability-based life-cycle bridge management. In short, monitoring has the potential to significantly aid engineers and managers in making optimal resource allocations by providing site-specific real-time information.

As this field is developed, researchers and engineers will face a number of challenges often not considered in current practice. Probabilistic modeling, rates of deterioration, predicting costs, sensor placement, information management, and linking this information to accepted design and assessment standards are some of the issues to name a few. To justify the initial and follow-up costs of employing SHM, the development and use of metrics that quantify and communicate their utility are crucial to the acceptance adoption of monitoring systems in practice. To achieve this end, engineers and managers must become more comfortable in the assessment and design of civil structures within a performance-based, life-cycle, risk inclusive context.

Chapter 4

INTEGRATION OF HEALTH MONITORING IN ASSET MANAGEMENT IN A LIFE-CYCLE PERSPECTIVE

Abstract

From the strategic to the structure level, this chapter discusses the integration of SHM and LCM in a life-cycle context. The investigation of this topic quickly reveals that it involves many disciplines and many interested parties. Furthermore, it requires a change in how SHM is typically employed (e.g. as bottom-up approach) and the coordination and cooperation of the interested parties. For example, the inclusion of SHM into LCM requires supporting public policy as much as it requires new innovative sensor technology and the methods that can leverage structure specific data.

This chapter was driven in part by the invitation to contribute to a new book entitled "The Encyclopedia of Structural Health Monitoring" scheduled for publication in January 2009 and edited by Professors Christian Boller, Fou-Kuo Chang, and Yozo Fujino. The intent of this 2000 page, 3 volume encyclopedia is summarized from its preface as follows:

The Encyclopedia of Structural Health Monitoring is intended to provide all the background information required to understand and apply structural health monitoring, and to set out the basis of configuring structural health monitoring systems. This multi-volume work will provide an invaluable guide and reference for all engineers, engineering managers and scientists active in the field of structural design, operational management and maintenance. Application areas range through aerospace; road, rail and sea transport; heavy machinery; and all types of civil infrastructure, including specialist subjects such as land fills or disaster (i.e. earthquake) management.

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The specific invited chapter contribution was to be titled "Maintenance Principles for Civil Structures Using Structural Health Monitoring (SHM)" (Frangopol and Messervey, 2008a) with the intent of investigating how to plan for, utilize, and optimize SHM data in a life-cycle context. This thesis chapter was also largely motivated by the participation in multiple working groups, symposia, and special sessions dedicated to the topic and whose results have led to the presentation of three keynote papers/lectures. The main ideas from the compilation these efforts, as well as other ideas, are presented herein.

4.1 Introduction

The use of Structural Health Monitoring (SHM) in civil infrastructure is increasing as sensors become smaller, more affordable, less power consuming, and wireless. Although bridge managers and engineers may have access to a wealth of structural response data, more research is required on how to effectively manage, process, and utilize it.

To best leverage the potential of SHM technologies, several considerations and actions must be taken that are in contrast to how monitoring is currently most often employed. Instead of a bottom-up reaction to specific deficiency, a top-down approach to the development of monitoring systems within a life-cycle context is necessary. Such an approach requires the adoption of methods and metrics suited for probabilistic data and capable of quantifying the benefit of increased levels of safety over time. For an existing structure, this implies a reliability-based life-cycle management approach with the inclusion of risk. For a new structure, this implies performance-based and durability-based design. It must also be considered that the design, management, and use of civil infrastructure involves a unique composition of interested parties that may compete for resources or have conflicting interests although they share the same goal of safe and efficient structures. To ensure the best use of limited resources, common metrics, methodologies, and means of communication must be agreed upon. Despite the pressing need for new innovations, the integration of structural health monitoring will likely be incremental. As such, how these technologies can benefit existing methods while serving as a catalyst for future change is of interest.

4.2 Consideration of Funding, Ownership, Responsibility, and Public Policy

This section serves as a placeholder or reminder that SHM systems must grow within an environment of established codes and guidelines. As important as developing the technology itself, parallel efforts must occur in public policy and code revision efforts to establish the conditions to leverage the legal use of the technology once developed. Because codes may be eligible for revision at 5, 10, or 15 year intervals, it is important these efforts begin as soon as possible.

Bridge ownership can vary across levels of government and political structures. In the U.S. these divisions are generally federal, state, county, and local. In contrast, in several European countries, highway bridges are owned and maintained by a private for profit organization funded through tolls. Other bridges fall under their respective municipalities. Such divisions in ownership create the potential for differences in standards, conduct, and clarity with respect to bridge inspections and maintenance. Following the I35W Minneapolis Bridge collapse, the internet news portal MSNBC initiated a series of special reports on the state of the nation's bridges (Dedman, 2008a). One of these reports highlights how the issue can become complex. In this report, several officials at the state level described how bridges at the local level were not their concern because the structures were owned by the local municipalities. However, federal regulations clearly specify that although the task of bridge inspections can be delegated, the responsibility for their completion cannot be delegated. Another concern for local authorities is that funding and inspector training for each small district is hard to obtain and possibly inefficient.

The report (Dedman, 2008a) goes on to highlight that enforcement of existing guidelines is also a difficult task. In the United States, although federal officials are aware of many practices that violate federal regulations, no penalty has been levied on any particular state in over 15 years. The concern is that any withholding of federal funds would only worsen the problem. Restrictions on funding also complicate the matter. Although experts attest that well allocated maintenance funding would significantly reduce life-cycle costs, states and consequently local governments in the United States were until recently precluded from using federal funds for bridge maintenance purposes. Instead, highway gas tax funds were restricted for new bridge construction and the replacement or rehabilitation of existing bridges (Roberts and Shepard, 2002). As a result, a large number of local governments and several state governments are only within the last several years beginning to implement bridge maintenance programs. Although it is not the role of a monitoring program to address these issues, it is important to understand the political and funding structure the program must fit within. Additionally, agreements on how to classify monitoring (as part of maintenance or rehabilitation) may directly impact what types of funds are available.

4.3 Strategic Level Adoptions in Concert

Solving a multi-faceted and multi-disciplinary problem requires the establishment of common methods, metrics, and benchmarks. These actions are necessary to facilitate communication and to enable different people to work on small parts of a larger problem. One of the challenges in the selection of common methods, metrics, and benchmarks specifically for SHM is that each structure and each scenario is unique. Optimal solutions will vary for different monitored parameters (mechanical, physical, or chemical), duration of monitoring (short term, mid term, or long term), type of monitoring (local vs. global measurements), type of structure (new construction or existing construction), and type of construction material (steel, concrete, timber, etc.) (Glisic et al., 2007). Testament to this concept, a US-China Joint Working Group has recently formed a collaborative research program in integrated structural health monitoring which identifies the need for and selection of "test-beds." Test beds are selected structures for monitoring experiments with agreed upon performance metrics that capture what the engineering community cares about. The summary of this agreement (Glaser et al., 2007) states:

Test-beds should be selected to exhibit as many of these scenarios (different environments) as possible. For example, test-beds as a minimum should consist of one long-span bridge over salt water, one short-span bridge in a city surrounded with electromagnetic and other forms of interference, and one mid-span bridge in a remote location with no in-situ electrical supply. The test-beds should be located in locations with harsh environments, including ones with high winds, extreme temperature changes, high heat and humidity, and acid or alkaline exposure. Bridges of different materials and ages should also be part of the test-bed.

A second challenge in the selection of common methods, metrics, and benchmarks for SHM applications is the diversity and number of interested parties related to the safe performance of the civil infrastructure. From public officials, to infrastructure users, and owners, although the goal of optimally designed and managed structures that ensure public safety over their useful lifespan is most likely not disputed, determining how to achieve this goal is more difficult. Differences in methods, assessment metrics, competing interests and competing demands quickly complicate the discussion. Figure 4.1 depicts these interested parties.

Builders	Managers	Users
Researchers Code Authorities Designers Contractors	Political Officials Infrastructure Managers Inspectors	Trucking Industry Public Transportation Private Users

Figure 4.1. Interested parties with potentially conflicting interests with respect to bridge management (adapted from Frangopol and Messervey, 2008d).

For example, in an environment of limited resources it is likely that researchers would request funding to develop more efficient management techniques whereas infrastructure managers would prefer using this funding to repair existing defects. The trucking industry desires heavier allowable truck weights to improve productivity whereas bridge managers desire lower limits to reduce wear and tear on their structures. Public officials are responsible for public safety but must also accept some level of risk as its elimination is not feasible or affordable.

Because monitoring technologies enter this environment of limited resources amongst interested parties with potentially conflicting objectives, coordinated and synchronized actions (adoptions-in-concert) are necessary to facilitate synergistic and efficient solutions. Technologies must be adopted by and work within the programs utilized for asset management. In turn, asset management must be supported by and exist within the broader context of performance-based engineering. Instrumental and inherent to the entire hierarchy is that resources are optimized, safety is assured, and condition is adequate. Figure 4.2 shows such a hierarchy which has been adapted from the call for the mini-symposium on Integrating Health Monitoring and Life-Cycle Management of Bridges and Highways at IABMAS-08. Added to the figure are key players at each level, several end products or responsibilities, and four common links required to achieve synergy between the interested parties. The added linkages are common code provisions and performance metrics.

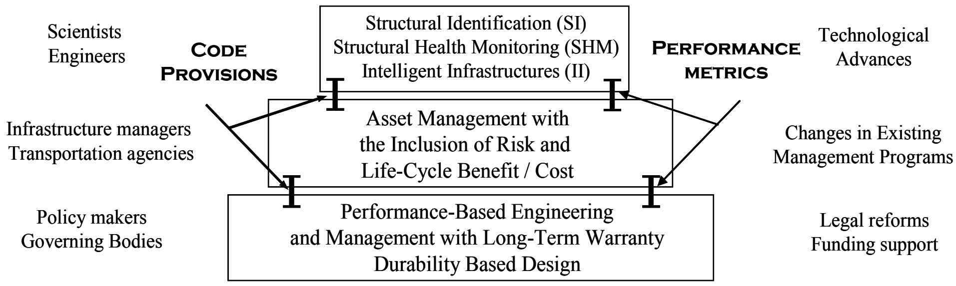


Figure 4.2. Paradigm for the integration of health monitoring into the life-cycle management of bridges and highways (adapted from the October 30th, 2007, call for the mini-symposium on Integrating Health Monitoring and Life-Cycle Management of Bridges and Highways at IABMAS-08 (Mini-Symposium Organizers: Aktan, A.E., Meng, X., Klatter, L., and Furuta, H.).

Although easily stated, the realization of such a paradigm is not as easily achieved. Differences in design methods, assessment techniques, management programs, legal systems, and political processes are important when answering the question on how to best integrate health monitoring. Because the creation and implementation of this paradigm will have to span these differences, an introspective analysis within the engineering community is appropriate to agree on several key rules and standards. Particular attention is needed to standardize and include risk in the calculation of life-cycle costs and as a metric to compare alternatives that do and do not employ SHM. Also necessary is a common period of time (warranty period) over which to calculate maintenance costs for newly constructed structures. In doing so, solutions with and without monitoring can be fairly compared. Minimum performance thresholds need to be agreed upon to indicate when corrective actions are required. Lastly, the "test bed" concept should be implemented at the highest possible level (national or international) for the formation of focused data collection efforts. Although much information is required to update codes and to better understand in-service structures, it is likely that specific failure modes across certain types of bridges are of greatest concern at this point in time. Focusing research funding and effort on such identified problem areas and by making the data available to different researchers for benchmarking, will result in more coordinated, efficient, and timely solutions. One very encouraging program recently created for this purpose is the Long Term Bridge Performance (LTBP) program (FHWA, 08) The LTBP program is a US $25 million 20 year research effort funded by the FHWA to collect, document, and make available high-quality quantitative performance data on a representative sample of bridges. The objective of the program is to increase knowledge on bridge performance and degradation, develop better design methods and performance predictive models, and support advanced decision-making tools for bridge management.

4.4 Structure Level Frameworks for the Inclusion of SHM

Figure 4.3 introduces a framework to utilize structural health monitoring to improve life-cycle management models by better defining random variable input parameters. The idea is analogous to the common practice of using modal analysis to validate or improve a finite element model. Figure 4.3a depicts a typical profile of the reliability index for structure that deteriorates over time. Figure 4.3b shows a framework to improve the modeling of the reliability index profile using SHM. The framework begins with selecting and modeling critical failure modes using performance functions. A sensitivity analysis of random variables in these equations determines which random variables are most critical to monitor via SHM. This allows for the development of a task-oriented monitoring solution. In this initial framework, the monitoring solution could be permanent or could also be specific test with mobile equipment brought to the site. Once collected, SHM data is utilized to validate or improve the random variable input parameters. The LCM model is adjusted and the reliability index is recalculated. Figure 4.3c depicts a case in which SHM validation results in a downward adjustment of the initial reliability index and a shorter predicted lifespan. Because the initial calculation of the reliability index incorporates actual structural data, the standard deviation of the PDF associated with the initial reliability index is decreased indicating a more accurate assessment of the actual structural behavior. This process would not require a permanent monitoring solution but certainly does not preclude one. In some cases, a SHM update or validation could be as simple as positioning a known load on the structure of interest and recording strain values.

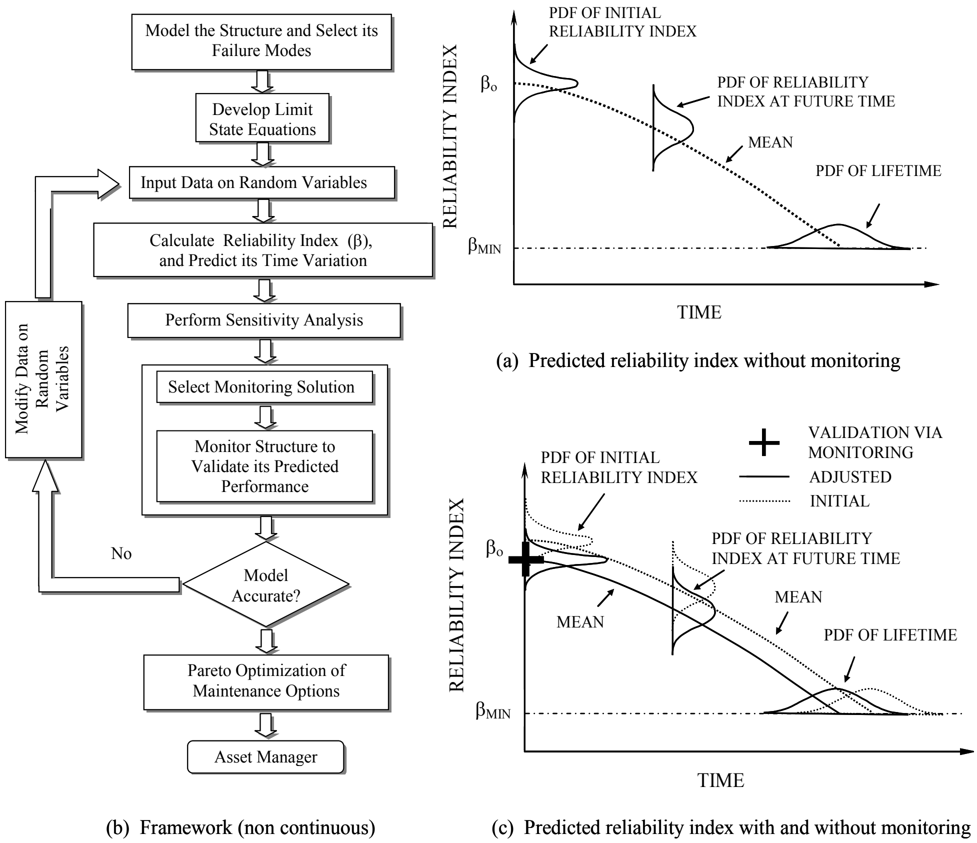


Figure 4.3. Framework to use SHM to validate a LCM model of the reliability index (adapted from Messervey et al., 2006)

A natural extension of the previous example is to consider multiple validation points over time by incorporating a SHM inspection plan or by a permanent monitoring system as shown in Figure 4.4.

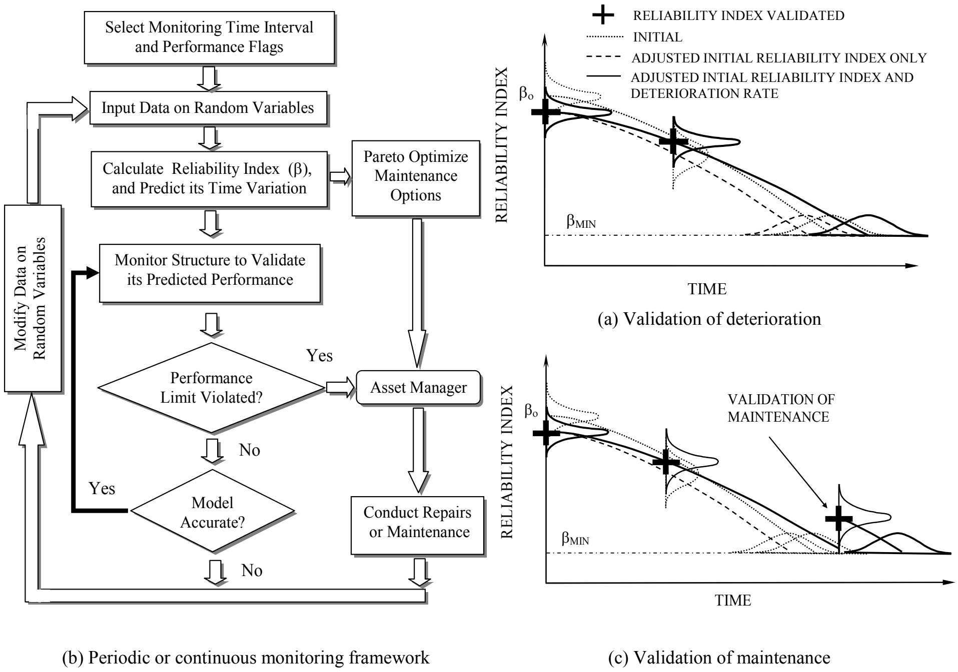


Figure 4.4. Framework to incorporate periodic or continuous monitoring (adapted from Messervey et al., 2006)

The framework requires input and interface with the asset manager and has the potential to provide him or her with a powerful management tool. SHM allows for the establishment of performance flags. These could easily be critical levels of strain, rotation of a joint, corrosion initiation, crack width, or critical loads that require inspection or maintenance. Once indicated, these flags provide actionable information on a specific area of interest for the asset manager. Concurrently, structural data can be utilized to validate whether or not the structure is performing as predicted. The structure and updating process require no action until the LCM model and SHM data diverge. At this point, random variable input data is modified, the LCM model is updated, and the asset manager is provided with an updated optimization of reliability, cost, lifespan, and maintenance options. Figure 4.4a depicts a case in which the deterioration rate of a structure is updated resulting in a longer predicted lifespan. SHM also provides the ability to validate maintenance actions. Figure 4.4c depicts an increase in the reliability index due to maintenance and a longer predicted lifespan. Each time structural performance data is introduced into the model via SHM, uncertainty is changed and confidence in the model and its predictions are increased. As such, the framework becomes a "living" process and could readily incorporate data from non-destructive evaluation testing, visual inspections, or the inclusion of additional sensors or random variables.

4.5 Top-Down Approach to the Design of SHM Systems

This section presents key concepts in the formulation of monitoring strategies. Here, a top-down approach is developed which is in sharp contrast to how SHM is often utilized. Currently, monitoring is generally used as a bottom-up, diagnostic tool in response to an existing problem or defect or to conduct system identification for a finite element model. Equipment is brought to the sight, measurements are recorded, the equipment is removed, and the data is studied. In time, as technologies, metrics and methods are developed that are convincingly cost-effective, the use of permanent (or systematic) monitoring systems will become more common. To ensure these assets are employed effectively, they need to be applied at the most critical structure, at the appropriate location, and at the right time.

The formulation of a monitoring strategy should consider (i) historical failures and current assessment of the type of structure of interest; (ii) how the structure fits within a larger network; (iii) the type of measurement desired (global vs. local) and what sensing mechanisms are most appropriate; (iv) what types of uncertainty are present and how they will be modeled; (v) how assets will be prioritized at the structure level with respect to member importance, system effects, and time; and (vi) the optimization of sensor placement and usage with respect to time and spatial effects. Across these considerations, cost effectiveness is imperative. Because maintenance demands will likely outpace available resources for the foreseeable future, infrastructure managers will likely not invest in monitoring unless it either becomes code driven or there is a return on their investment. Otherwise, money spent on monitoring will simply reduce the funds available for maintenance and repair.

4.5.1 Consideration of Past Failures and the Current Condition of Existing Structures

Historically, albeit unfortunately, structural failures and collapses have acted as the catalysts that have shaped design codes, construction methods, and management practices. Several notable studies have been conducted in this area and serve as an excellent resource. Matousek and Schneider (1976) studied 800 reported failures and errors in the field of structural engineering across several classes of structures. Stewart and Melchers (1997) summarized parts of a number of studies involving structural failures. Blind (1983) analyzed initiating events and causes for dam failures. Bertrand and Escoffier (1987) studied the failures of offshore structures; Anderson and Misund (1983) studied the initiating events for the failures of pipelines; and Scott and Gallaher (1979) studied the failure of components and systems in nuclear power plants. A recent and applicable study to one of the most pressing needs today is a 2004 analysis of the reasons for reconstruction across 1691 bridges in Japan (Joint Task Committee, 2004). The results of this study are shown in Figure 4.5. Figure 4.5a details the primary reason for reconstruction. Serviceability concerns and the upgrade of highway routes account for the majority (49%). Damage and strength concerns account for 34% with most problems arising in the superstructure which is most subjected to environmental exposure and traffic load effects. Figure 4.5b details the primary cause of specific to the superstructure damage cases of figure 4.5a. Problems with the deck (48%) are about even with problems of the supporting girders (48% for steel and concrete girders combined). However, it is noted that problems specific to reinforced concrete account for 87% of the failures. From these results, it appears that monitoring strategies for concrete may be of particular interest for bridge managers as slab failure and concrete spalling/cracking accounted for most of the superstructure failures.

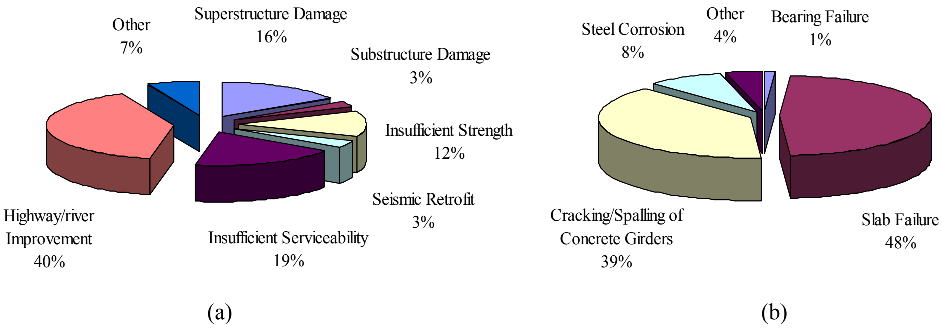


Figure 4.5. Study of 1691 recent bridge reconstruction projects in Japan: (a) reasons for reconstruction for all bridges and (b) for the bridges reconstructed due to superstructure damage, the primary cause of that damage (adapted from Joint Task Committee (2004)).

To continue investigating the topic of bridge failures, the author conducted a study of reported bridge failures in the calendar year 2006. Although gained from press releases, uncorroborated, and likely to contain errors, the information is interesting nonetheless and was reported in Frangopol and Messervey (2007c). Table 4.1 summarizes the results of this study from which several trends can be observed in the data. First, bridge problems are not country specific. Second, bridge failure ages seem to be polarized. Masonry structures (typically abutments failing due to pier scour) are all greater than 100 years of age and reinforced concrete structures (typically due to cracking and corrosion induced reinforcement debonding) cluster around 40 years. Third, bridge collapses can be lumped into four general categories, flood related failures, collapses during construction, collapses due to design and/or construction errors, and collapses due to maintenance neglect. In only two cases, both construction related collapses, were no problems identified and reported before failure. Instead, the cause of collapse was most often documented well in advance and was under observation or awaiting funding. Also of interest, all flood related casualties reported were the result of overloading coupled with high water. These events most often occurred when people and vehicles gathered on the bridge to observe the water passing underneath as the support structure eroded.

Table 4.1. Several reported bridge collapses in 2006.

Date	Location	Event Description	Online News Source	Structure Age (yrs)	Casualties
17-May-06	Minxian, China	In service high water collapse	China Economic Net accessed 19 December, 2006	34	0
30-May-06	Meherpur, India	Collapse During Construction	United News of Bangladesh accessed 14 January, 2007	New	4
7-Jun-06	Shandong, China	Stone arch collapse during construction Unstable groundwork in wet conditions	China SD News accessed 14 January, 2007	New	5
17-Jul-06	Gallaudet University, Washington DC	Sudden collapse of a large reinforced concrete pedestrian overpass, age, cracking, maintenance neglect	RidorLIVE accessed 19 December, 2006	30	0
20-Jul-06	Kala Amb, India	In service high water collapse, maintenance neglect, upstream mining resulted in gushing water	Tribune News Service accessed 20 December, 2006	46	4
23-Jul-06	Quanzhou, China	High water collapse of an ancient pedestrian bridge	People's Daliy Online accessed 20 December, 2006	800	0
8-Aug-06	Mardan, Pakistan	In service collapse, bridge overcrowed by vehicles and pedestrians observing high water	BBC News accessed 14 January, 2007	Not Reported	44
5-Aug-06	Karachi, Pakistan	Sudden collapse of a railway bridge due to abutment scour, problem identified in 2003, high water	Dawn Internet News accessed 19 December, 2006	100	0
29-Aug-06	Xiamen, China	Collapse during construction	AboutXinjiang Online accessed 19 December, 2006	New	0
6-Sep-06	Yekaterinburg, Russia	3RC beams collapse during construction of automobile bridge possible design error	Wikipedia accessed 20 December, 2006	New	0
30-Sep-06	Laval, Canada	Sudden in-service collapse of a 3-lane highway overpass	CBC News accessed 19 December, 2006	36	6
5-Nov-06	Shimoga, India	In service high water collapse age, severe cracking, increased traffic loading	The Hindu accessed 19 December, 2006	38	0
2-Dec-06	New Delhi, India	Footbridge overpass being deconstructed collapses as train passes underneath, vibration	Express News Service accessed 19 December, 2006	150+	34
13-Dec-06	Guinobatan, Phillipines	In service high water collapse Overloaded by relief trucks after typhoon	Science Daily accessed 20 December, 2006	Not Reported	0

Although past failures certainly provide insight, the current condition and classification of existing structures must also be considered when developing a monitoring strategy. In the US, the National Bridge Inventory (NBI) provides statistics on bridges by bridge type, classification, location, age, and current condition. Statistics are also available that detail replacement, rehabilitation, and new construction projects as part of the Highway Bridge Replacement and Rehabilitation Program (HBRRP). Combining this data better enables the design of monitoring approaches for assessing existing structures as well as those newly constructed. Using information from the NBI as of 2006, Figure 4.6 details (a) the makeup of the NBI by bridge type, (b) the makeup of deficient brides by type, (c) the makeup of newly constructed bridges (2003 and 2004), and (d) the makeup of bridge replacement and rehabilitation projects (2003 and 2004).

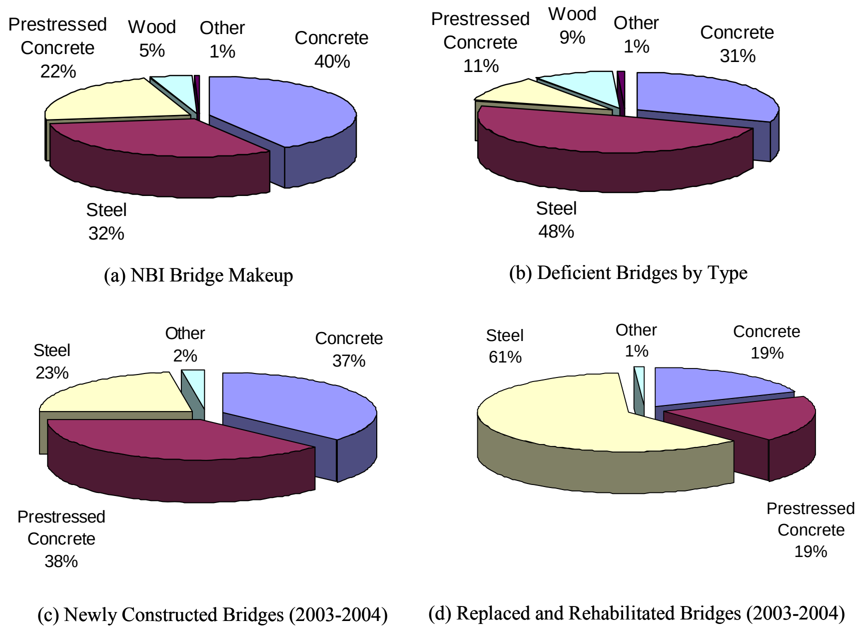


Figure 4.6. National Bridge Inventory (NBI) statistics of interest for developing national level monitoring priorities. (a) NBI bridge makeup, (b) deficient bridges by type, (c) newly constructed bridges (2003–2004), and (d) replaced and rehabilitated bridges (2003–2004).

From these statistics one can conclude that (a) most of the existing bridges in the United States are concrete, (b) steel bridges represent the largest proportion of deficient bridges, (c) most new construction is concrete, and (d) most rehabilitation projects are steel. Because steel bridges are generally older, it is not surprising that these bridges are disproportionately deficient. Additionally, since steel bridges make up the bulk of rehabilitation projects, it is reasonable to assume that many of these older bridges are located in urban areas where new construction is difficult without significantly disrupting traffic flow. From these statistics, if viewing monitoring from the perspective of forming national priorities, effort should focus on concrete SHM for new construction and upon steel SHM for structures being assessed.

4.5.2 Consideration of Structures within a Network

Bridge Characteristics in Colorado Highway Network

Bridge Name	Number of Spans	Bridge Length (m)	Year Built	Average Daily Truck Traffic
Presstressed concrete				
E-16-MU	1	34.1	1994	810
E-16-LA	2	77.9	1983	450
E-16-DM	2	44.5	1990	390
E-16-QI	2	74.1	1995	1,335
E-16-LY	3	74.3	1985	1,610
E-16-NM	2	64.6	1991	2,955
E-16-MW	2	72.7	1987	230
Steel I-Beam bridges				
E-16-FK	4	69.2	1951	1,370
E-16-FL	4	54.0	1951	765
E-16-QI	5	82.3	1953	890
Steel plate girder bridges				
E-17-LE	4	68.6	1972	992
E-17-HS	4	64.5	1963	5
E-17-HR	4	64.0	1962	306
E-17-HE	4	67.7	1962	1,290

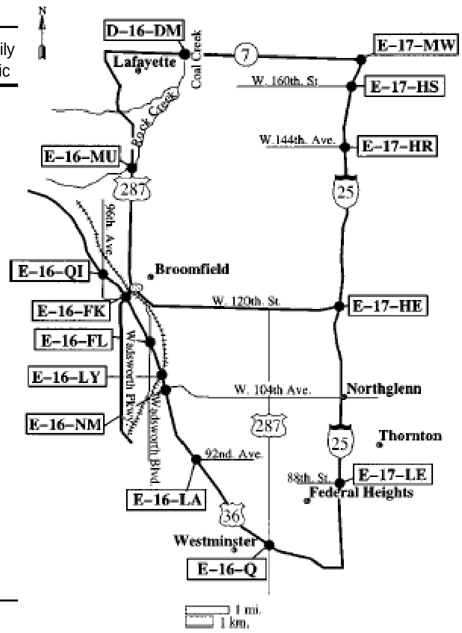


Figure 4.7. An existing bridge network near Denver, Colorado (table adapted from and figure reproduced from Akgul and Frangopol, 2003).

Rarely is the management of a structure considered in isolation. Whenever possible, inspections, assessments, and maintenance actions should be taken in context of where the allocated resources will provide the most benefit. For a transportation network where bridges serve as critical nodes, analysis requires consideration of network connectivity, user satisfaction, and network reliability (Liu and Frangopol, 2006a). Monitoring can be allocated to the most important bridge within a network with respect to any of these three metrics or to a bridge with known defects. Figure 4.7 shows an existing bridge network near Denver, Colorado to highlight some of the necessary considerations. Within this 14 bridge network, bridges are of different types, ages, span lengths, and traffic characteristics. Each of these differences, to include other factors such as political importance or historical/cultural value, can influence monitoring priority.

An appropriate starting point to establish bridge importance is to relate individual bridge reliability to the reliability of the bridge network. The reliability importance factor (RIF) for any bridge is defined as the sensitivity of the bridge network reliability β_{net} to the change in the individual bridge system reliability $\beta_{sys,i}$ as (Liu and Frangopol, 2005; Liu and Frangopol, 2006a):

$$RIF_i = \frac{\partial \beta_{net}}{\partial \beta_{sys,i}} \tag{4.1}$$

Using this metric, the bridge for which changes in performance have the largest impact on the reliability of the bridge network can be identified for monitoring priority. Assuming monitoring reduces the probability of failure of any associated bridge component or system and likewise increases the network reliability index, a multi-objective approach can be utilized to optimize bridge network maintenance as presented in Liu and Frangopol (2006b). Such an approach also enables the investigation of the application of a single common maintenance application, traffic weight increase, or mobile monitoring instrument to the performance of the network.

4.5.3 Developing Monitoring and Analysis Strategies: Right tool for the right task

Monitoring strategies are broadly categorized in two groups, global and local. Both provide different types of information and in general support different analysis types. Figure 4.8 depicts global and local monitoring strategies, the type of information collected, and the associated measurement types.

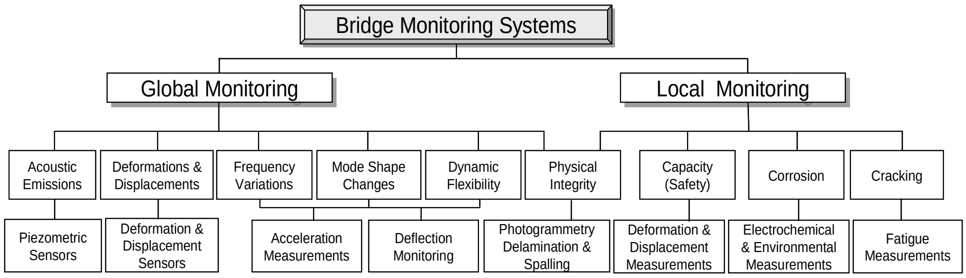


Figure 4.8. Common monitoring strategies for civil infrastructure (adapted from Rafiq, 2005)

Selecting an appropriate strategy might be dictated by the structure, type of analysis, or both. For example, one may be limited to a global monitoring approach when accessibility to specific parts of the structure is impossible. Conversely, one may desire global monitoring methods when working with an analysis that creates an equivalent structure. A common example would be the characterization of the stiffness, or modal characteristics in a finite element model. For this, accelerometers would be an appropriate instrument. This would not necessarily be the case when analyzing a specific structural failure mechanism such as flexure, shear, fatigue, or corrosion. In this case, information would be desired about member geometries, material properties, loads being imparted on the structure, and environmental effects. Figure 4.9 shows several common SHM instruments for these types of measurements. It should be noted any such listing is typically outdated before published due to rapid advancements in the field. Two state of the art studies dedicated to sensor types for SHM applications include Rafiq (2005), and Lynch (2007).

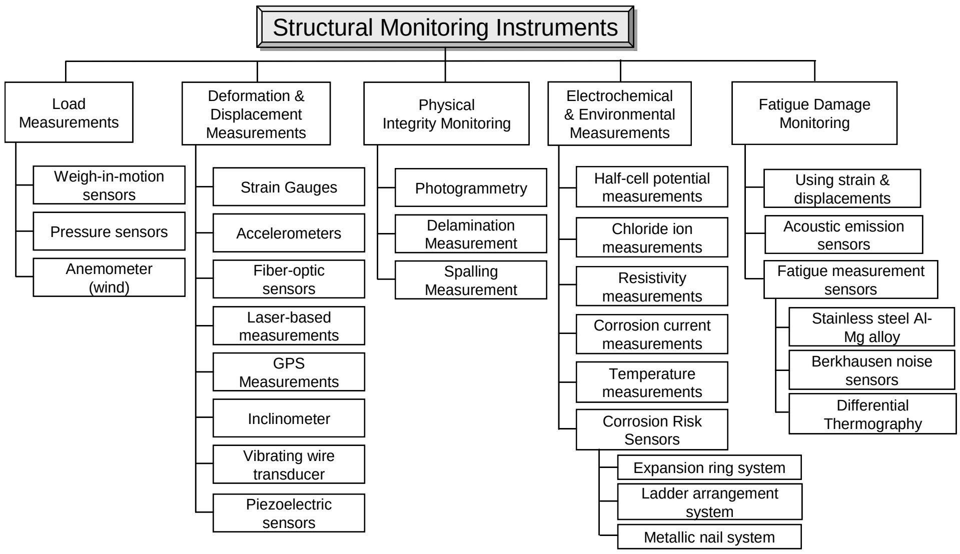


Figure 4.9. Common monitoring instruments for civil infrastructure (adapted from Rafiq, 2005)

With respect to novel monitoring strategies, three trends are quickly highlighted. The first trend is the fabrication of sensor-embedded materials with application specific acquisition systems and data analysis software. One research project in this area that the author is working on is the EU project POLYTECT, "Polyfunctional Technical Textiles against Natural Hazards." This project is developing sensor-embedded textiles at the industrial level for geotechnical and masonry applications. Project details can be found at www.polytect.net. The second trend targets simplifying the analysis of structural assessment and performance prediction by developing algorithms based only upon a statistical analysis of the response data itself (Nair and Kiremidjian, 2007). Such methods conduct statistical pattern recognition in search of a damage sensitive feature. One such method is based on the

Mahalanobis distance between the undamaged state and various damage states of a structure of interest where the data are modelled as a Gaussian mixture. This approach is outlined in Kiremidjian et al. (2008) and is showing to be very promising. Such methods are desirable because of their computational efficiency making them particularly suitable low power demand wireless monitoring solutions. The last highlighted trend is the monitoring of multiple structures or spans with one monitoring asset. For the foreseeable future, it will not be possible to allocate monitoring systems across all bridge structures. Even for a single structure, the optimal location for sensor placement is uncertain. This is especially true for bridges with multiple identical spans. Although a theoretical analysis can provide likely optimal locations, it is typically a structural irregularity due to member fabrication differences, construction error, or differential settlement that will cause one span to be critical. A promising approach and area of research is how to employ one monitoring asset to gain a general idea of structural performance that allows the development of a more focused monitoring effort (Fujino, 2008). In Japan, this is occurring with a railcar instrumented with accelerometers that collects data periodically across railway bridges. Changes in the vibration signature of the bridges crossed can serve as a damage indicator. For a multi-span highway bridge structure, the same concept is being investigated to seek irregularities between similar spans as well as changes over time with the use of an SHM instrumented car. The advantage is that one car can quickly obtain information over a large number of structures. The disadvantage is of course the generality of the data.

4.5.4 Consideration of Structure Level Asset Prioritization with respect to Member Importance, System Effects, and Time

At the structure level, monitoring must be allocated to the most important members, for the critical performance functions, to characterize the most significant random variables, at the appropriate point in time. For structural components (such as bridge decks) and individual members (such as girders), how these elements perform within the context of the larger structure will determine their importance with respect to monitoring. For elements arranged in series where the failure of any one member or element leads to the failure of the larger system as shown in Figure 4.10a, the *weakest* member, or member with the highest probability of failure (e.g., p_f = .001), member #1 is most important. Conversely, if members are arranged in parallel, such that the failure of one member does not lead to the failure of the larger system, than the *strongest* member with the lowest probability (e.g., p_f = .0002), member #3 is most important. Of course, the degree of correlation between the failure modes of elements in Fig. 2, affects the system failure probability. Therefore, failure mode correlation has to be accounted in establishing monitoring priorities.

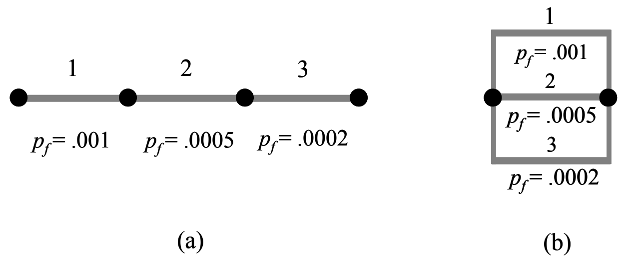


Figure 4.10. System Analysis of Elements in (a) Series and (b) in Parallel

Varying rates of deterioration may also affect monitoring priorities or when monitoring is needed. Figure 4.11a depicts the reliability profiles of two members arranged in series. Member #1 deteriorates more rapidly than member #2. As such, monitoring priority would first be given to member #2 until the reliability indexes intersect at point X after which priority would shift to member #1. In contrast, if these same two members are arranged in parallel as shown in Figure 4.11(b), monitoring priority would first be given to member #1 and then to member #2 after the intersection of the reliability profiles. In both cases, the concept of monitoring the weakest element in series and the strongest element in parallel remain the same but the critical element changes over time due to varying deterioration rates. Although fairly intuitive for different bridge components or components made of different materials, this could also find application amongst like elements. An example could be exterior steel girders being subjected to a higher corrosion rate than interior girders due to a greater exposure to de-icing salts.

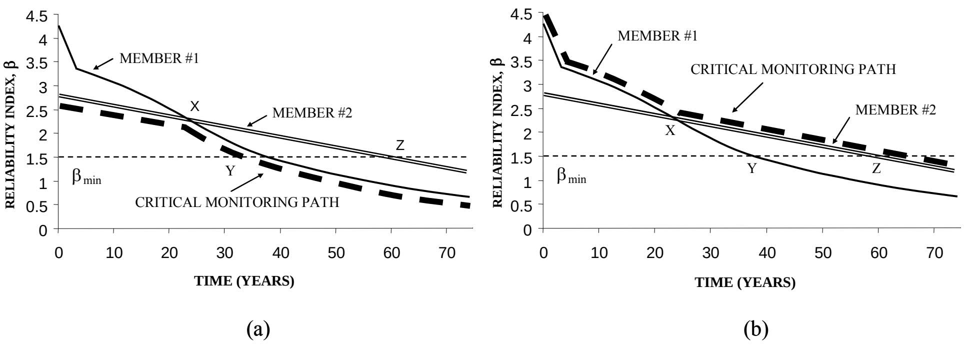


Figure 4.11. Time variant system monitoring of elements in (a) series and (b) parallel

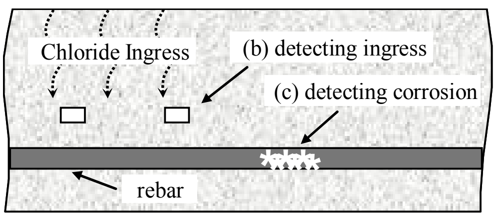
Such an analysis could also be utilized to answer the question of when to monitor. Again using Figure 4.11, if a minimum reliability threshold is established, one could conclude that monitoring would be appropriate on member #1 at the time corresponding to Point Y in series and on member #2 at Point Z in Parallel (given perfect information). In the absence of perfect information, Monte Carlo simulation of the model parameters can be utilized to estimate the earliest possible crossing of the minimum reliability threshold. This would be appropriate for a monitoring system with high operational costs that can be turned on or off, or for a non-permanent monitoring solution that must be scheduled.

4.5.5 Consideration of Uncertainty

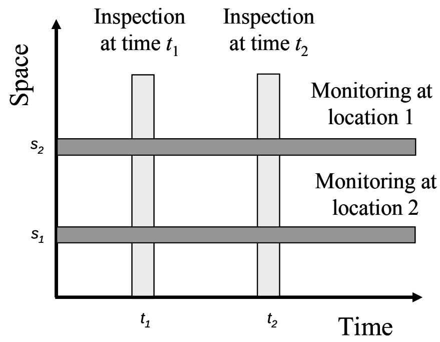
The goal of monitoring is to reduce the uncertainty associated with critical loading and structural parameters. To maximize the benefit of SHM, the type of uncertainty present and how it affects what is being monitored should be determined. The contributors to uncertainty in civil structural systems are discussed by Frangopol (2007). As previously defined, uncertainty can be partitioned in two broad categories, aleatory and epistemic where aleatory uncertainty describes the inherent randomness of the underlying phenomenon exhibited in the observed data whereas epistemic uncertainty deals with imperfect models of reality due to insufficient or inaccurate knowledge (Ang and Tang, 2007). Both types of uncertainty are of interest as related to infrastructure assessment but require different treatment. In terms of prediction, one must focus upon epistemic uncertainty as the future randomness associated with aleatory uncertainty cannot be reduced. Hence, during operation, it would be reasonable to envision that monitoring effort would focus on key random variable input parameters (epistemic) such as the those random variables used to predict the rate of corrosion. However, with respect to system identification, aleatory uncertainty can be very significant. Indeed, reducing epistemic uncertainty (modelling error) may not be possible without capturing pertinent aleatory uncertainty. For example, thermal stresses (aleatory) can greatly influence a system identification model (epistemic). Unless actual temperatures are catalogued and considered in the analysis, system identification models may be inaccurate. An example of using SHM captured thermal stresses to improve system identification modelling is provided in (Catbas et al, 2007). In this work, a comparison of system reliability analyses with and without thermally induced stresses shows that the inclusion of temperature significantly decreases the component and system reliability indexes.

4.5.6 Measurements: Time and Spatial Effects and the Optimization of Sensor Placement

Closely related to and conducted in parallel with the shaping of a monitoring strategy, the type of measurement desired and how to optimally obtain that measurement it is an important topic of discussion. Figure 4.12 demonstrates concepts related to measurement types, time, and space. Figure 4.12a shows a cross section of reinforced concrete subjected to chloride attack. The measurement decision is whether to detect the chloride ingress (indicator) or to detect the corrosion itself (result). The economics of the decision are that the detection of chloride ingress away from the rebar allows the stripping of the upper layer of concrete and its replacement (less expensive repair) as opposed to replacing the entire reinforced concrete beam or deck (more expensive repair). Figure 4.12b shows an important distinction between inspections and monitoring. Generally, inspections or NDE testing provides information about an entire structure at a point in time whereas monitoring provides information continuously at a specific location over time. To balance this difference, inspections must occur at appropriate intervals of time and sensors must be placed at appropriate intervals in space.



(a)



(b) (adapted from Rafiq (2005))

Figure 4.12. Measurement considerations: (a) in a RC deck or beam detecting ingress vs. detecting corrosion itself and (b) spatial and temporal differences between inspections and monitoring.

Once the type of data desired is determined, the question of how to obtain the data in the most cost-effective manner becomes important, which is currently an ongoing, open field of research. The type of sensor selected and the density of the associated network are dependent upon sensor cost, sensor performance, and the uncertainty associated with the measurement of interest. As these are competing criteria, multi-objective optimization is an appropriate method for the design of a sensor network as demonstrated in (Marsh and Frangopol, 2008). In general, the idea is to record enough information to extrapolate to other parts of the structure in a manner that is statistically significant. For example, on a truss structure with 100 members, knowledge that one is in perfect condition provides a certain level of confidence.

Knowledge that ten are in perfect condition provides a greater level of confidence. The task is to balance the value of increased information vs. its associated cost. Another promising method specific to vibration measurements is demonstrated in (El-Borgi and Choura, 2005). In this work, a program named FEMTools is utilized to create simplified measurement schemes that can be simulated to compare the ability of different sensor configurations to capture the response of a finite element model. Through this process, the program also identifies “maps” or zones sensitive to the measurement of interest on the structure allowing the number of sensors required for accurate measurement to be reduced. Combining the idea of simulation and sensor reduction with life-cycle multi-objective optimization techniques is an area for future study.

4.6 Estimating the Utility of Monitoring Solutions in a Life-Cycle Context

Researchers and practitioners globally are exploring how to best encourage and facilitate the use of SHM and LCM methods. From discussions, working groups, and presentations, ideas generally fall into the following categories:

Required by Code: Working discussion groups in Europe are considering a code requirement that construction projects must be submitted with a 100 year maintenance plan. If such a measure were to be adopted, this would be the firmest manner to encourage the use of SHM by requiring a life-cycle approach for design and management.

Incentivized: The use of SHM/LCM can be incentivized through tax credits/tax breaks or through lower insurance rates if insurance on civil structures becomes mandated. Such an approach has often come up in working sessions and usually from Asian members of the group. Group members that have presented the incentivized approach also highlight the advertising value available if owners understand and value that they have a technologically superior and safer building or bridge.

Profitable: Perhaps the strongest motivation for SHM/LCM methods is if they can be shown to increase profit with either constant or improved performance. If profitable, the concept is easily adaptable worldwide but the for profit argument is typically first on the agenda for group members in the USA.

The optimal solution of how to best encourage and faciliate SHM/LCM is likely a combination of the above, e.g. an available/acceptable design alternative recognized in the code, with some incentives for those who choose to use it, with the likelihood that over time the system will be profitable through more optimal management actions. Against this backdrop, it becomes necessary to develop the mathematical framework for the inclusion of SHM costs in a life-cycle analysis.

The minimum expected life-cycle cost with respect to lifetime performance is the most widely used criterion for design optimization of a new structural system. The general form of the expected life-cycle cost can be calculated as (Frangopol et al. 1997):

$$C_{ET} = C_T + C_{PM} + C_{INS} + C_{REP} + C_F \tag{4.2}$$

where C_{ET} = expected total cost, C_T = initial design/construction cost, C_{PM} = expected cost of routine maintenance, C_{INS} = expect cost of performing inspections, C_{REP} = expected cost of repairs and C_F = expected cost of failure. Inclusion of monitoring into this general form results in:

$$C_{ET}{}^0 = C_T{}^0 + C_{PM}{}^0 + C_{INS}{}^0 + C_{REP}{}^0 + C_F{}^0 + C_{MON} \tag{4.3}$$

where C_{MON} = expected cost of monitoring which is best treated with respect to a life-cycle cost as:

$$C_{MON} = M_T + M_{OP} + M_{INS} + M_{REP} \tag{4.4}$$

where M_T = expected initial design/construction cost of the monitoring system, M_{OP} = expected operational cost of the monitoring system, M_{INS} = expected inspection cost of the monitoring system, and M_{REP} = expected repair cost of the monitoring system. The operational cost of the monitoring system would include the cost of power (battery or electricity), as well as the costs associated with data processing and data management. The benefit of the monitoring system, B_{MON}, is then captured through a comparison of the expected life-cycle total cost with and without monitoring by subtracting Equation 4.3 from Equation 4.2:

$$B_{MON} = C_{ET} - C_{ET}{}^{0} \tag{4.5}$$

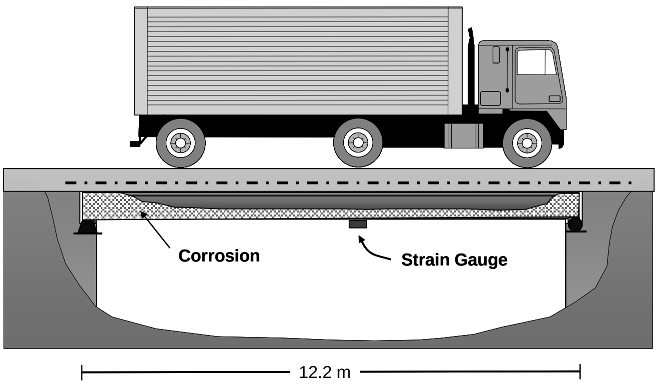
Unless code-driven and using cost as the criterion, monitoring would only be justified if $B_{MON} > 0$ meaning that monitoring is cost effective. Although a specific monitoring approach may not be designed to directly impact each term identified in Equation 4.2, monitoring has the capacity to reduce these costs by optimally scheduling maintenance and inspection activities, conducting the correct repairs at the correct time, and reducing the likelihood of failure. It is noted that the approach is best suited for a probabilistic analysis (SHM data and other parameters are uncertain) that includes risk (inclusion of the cost of failure) and which explicitly considers structural safety (use of reliability methods).

4.7 Application

An application is presented to illustrate the calculation and comparison of reliability-based life-cycle calculations with and without SHM. This example built in this application was developed over a series of papers, Messervey et al. (2006), Messervey and Frangopol (2007a), Messervey and Frangopol (2007b), and Frangopol and Messervey (2007c) that demonstrated monitoring, the reduction of uncertainty, and updating in a life-cycle context for use in a time-dependent structural reliability analysis. The evolution of the example over several papers is presented to highlight modeling choices, assumptions, model limitations, lessons learned by the author, and how it shaped further research questions for investigation.

Scenario and Load Condition of Interest:

Messervey et al. (2006) begins the investigation of the reliability of a short span, simply supported, W610 x 101 steel beam bridge subjected to corrosive effects over time with respect to the HS-20 truck load as shown in Figure 4.13. This study is motivated by any typical short to medium-span, simply supported, steel beam/girder highway bridge. The bridge would likely not be state of the art, would be part of a larger network, and the bridge manager might be adverse to a monitoring/management solution that was expensive or required much oversight. Perhaps the HS-20 design load for this bridge and the initial traffic volume estimate was overly conservative and if this conservativeness can be identified, the information could be used to make the best possible resource allocations amongst the bridge network and for maintenance and inspection scheduling of the bridge of interest. Within this scenario, the idea is what could be done with the least amount of information and with an appropriate level of confidence?



4.13. Typical short-span, simply supported, highway bridge subjected to the HS-20 truck load and corrosion over time.

A beam spacing of 2.1 m and concrete deck slab of 0.3 m are assumed generating a 15.32 kN/m distributed dead load across the span. The beam is also assumed to be continuously braced (lateral torsional bucking is not considered). The live load selected is the AASHTO HS-20 truck (AASHTO 1992) positioned slightly off center of the beam to maximize the live load moment demand which occurs at the beam's center as shown in Figure 4.14.

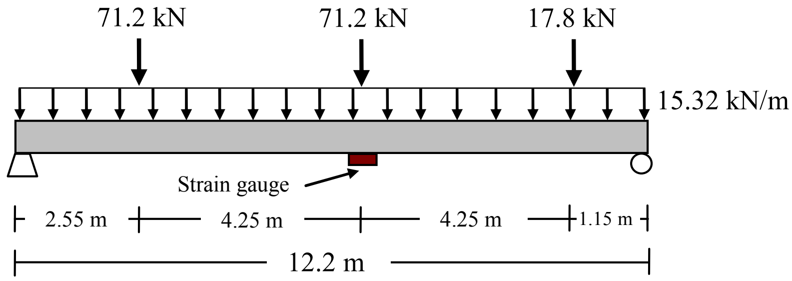


Figure 4.14. Loading condition for analysis

The maximum moment, M_{max}, for this loading condition is

$$M_{\max} = 305kN - m \tag{4.6}$$

Two performance functions are utilized to investigate the reliability of the girder with respect to flexure:

$$g(1) = f_y S - M_{DL} - M_{LL} \tag{4.7}$$

$$g(2) = f_y - E\varepsilon_{Monitored} \tag{4.8}$$

Equation 4.7 is a theoretical model of the problem which considers moment capacity versus the moment demand. Moment capacity is calculated as the yield stress (f_y) multiplied by the section modulus (S) and the moment demand considered is simply the dead load (M_{DL}) and live load moments (M_{LL}). Each term is modelled as a random variable. Equation 4.8 is instead a monitoring-based equation that investigates the reliability by examining the yield stress versus the actual stress placed on the structure. Actual stress is obtained via Hooke's Law which multiplies the modulus of elasticity (E) and the monitored strain value ($\varepsilon_{Monitored}$).

<u>*Deterioration Model*</u>:

The elastic section modulus is decreased over time utilizing Albrecht and Naemmi's (1984) study predicting the depth of corrosion over time as $C(t) = At^B$ where A and B are normally distributed, correlated random variables. In this example, an urban environment is assumed in obtaining values of A and B. Urban environments are more corrosive in nature due to the presence of sulphur and nitrogen oxides. Table 4.2 shows the characteristics of the random variables A and B.

Table 4.2. Descriptors for A and B for predicting corrosion propegation in an Urban environment for interior and exterior girders (Adopted from Albrecht and Naeemi, 1984)

Parameter	A	B
Mean value, μ	80.2	0.593
Coefficient of Variation, σ/μ	0.42	0.4
Correlation coefficient, $\rho_{A,B}$	0.68	-

Next, a corrosion pattern at midspan (for analyzing moment) must be assumed. The model assumed follows approaches utilized by Hendawi (1994) and Estes (1997) where corrosion extends one quarter of the way up the web at center span due to water pooling on the bottom flange of the beam as shown in Figure 4.15. Using this model, cross sectional area, location of the neutral axis *cg*, and elastic section modulus *S* are calculated as a function of d_{corr}.

$$Area = cr + gs + t_w p + b_f t_f \tag{4.9}$$

$$cg = \frac{\frac{r}{2}(c)(r) + (r + \frac{s}{2})(s)(g) + (r + s + \frac{p}{2})(t_w)(p) + (d - \frac{t_f}{2})(t_f)(b_f)}{(c)(r) + (s)(g) + (t_w)(p) + (t_f)(b_f)} \tag{4.10}$$

$$\begin{aligned} S = (&\frac{1}{12}(c)(r)^3 + (c)(r)(cg - \frac{r}{2})^2 + \frac{1}{12}(g)(s)^3 + (g)(s)(cg - r - \frac{s}{2})^2 + \\ &\frac{1}{12}(t_w)(cg - r - s)^3 + (t_w)(cg - r - s)(\frac{cg - r - s}{2})^2 + \frac{1}{12}(t_w)(d - cg - t_f)^3 + \\ &(t_w)(d - cg - t_f)(\frac{d - cg - t_f}{2})^2 + \frac{1}{12}(b_f)(t_f)^3 + (b_f)(t_f)(d - cg - \frac{t_f}{2})^2)/cg \end{aligned} \tag{4.11}$$

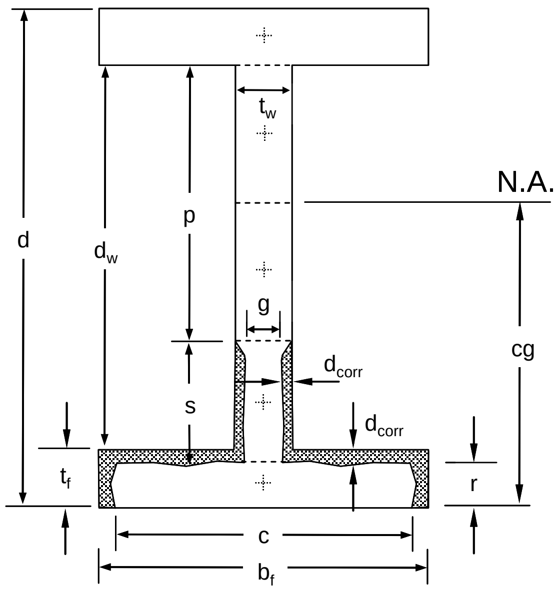


Figure 4.15 Corrosion pattern at midspan (adopted from Estes, 1997)

For a plastic analysis, the equations for the location of the neutral axis cg and the plastic modulus Z are

$$cg = d - t_f - \frac{(Area/2 - t_f b_f)}{t_w} \tag{4.12}$$

$$Z = (cg - \frac{r}{2})(r)(c) + (cg - r - \frac{s}{2})(s)(g) + \frac{(cg - r - s)}{2} t_w (cg - r - s) + (\frac{d - t_f - cg}{2}) t_w (d - t_f - cg) + (d - cg - \frac{t_f}{2})(t_f)(b_f) \tag{4.13}$$

The mean and standard deviation of the elastic section modulus S at any time t can be calculated using the Point Estimate Method. This method accounts for correlation between random variables by using weighted probability distributions. A and B are the only random variables in the analyis. There are four possible probability combinations P_{AB}: P++, P+-, P-+, and P-- where + indicates mean plus standard deviation and – indicates mean minus standard deviation. The weight assigned to each possibility is (USACE, 1992)

$$(P_{A+})(P_{B+}) = (P_{A-})(P_{B-}) = (0.5)(0.5) + (0.25)\rho_{AB} \tag{4.14}$$

$$(P_{A-})(P_{B+}) = (P_{A+})(P_{B-}) = (0.5)(0.5) - (0.25)\rho_{AB} \tag{4.15}$$

Table 4.3 shows the results of the Point Estimate Method for the mean and standard deviation of the elastic section modulus of a W610x101 beam subjected to the corrosion pattern in Figure 4.15 at time t = 30 years by applying equations 4.10, 4.11, 4.14, and 4.15. Calculation of the residuals in Table 4.3 is conducted after the probabilistic mean is calculated.

Table 4.3 Point Estimate Method Results for the calculation of the mean and standard deviation of the section modulus at time t=30

Iteration	A	B	d_{corr} (micrometers)	S cm^3	probabilistic combinations P_{AB}	residuals using probabilistic mean
(A+)(B+)	113.9	0.83	1916.61	2102.40	0.42	192.54
(A+)(B-)	113.9	0.356	382.28	2412.76	0.08	-117.82
(A-)(B+)	46.5	0.83	782.46	2332.53	0.08	-37.58
(A-)(B-)	46.5	0.356	156.07	2457.89	0.42	-162.94
$S(30)_{mean}$ = 2294.8 cm^3						
$S(30)_{stdev}$ = 334.3 cm^3						

Figure 4.16 shows the mean value of the section modulus across time as well as the mean minus the standard deviation. It is noted that the uncertainty associated with the mean value increases over time. This progressively increasing uncertainty in fact has more of an impact on the calculated value of the reliability index than the anticipated decrease in the section modulus itself.

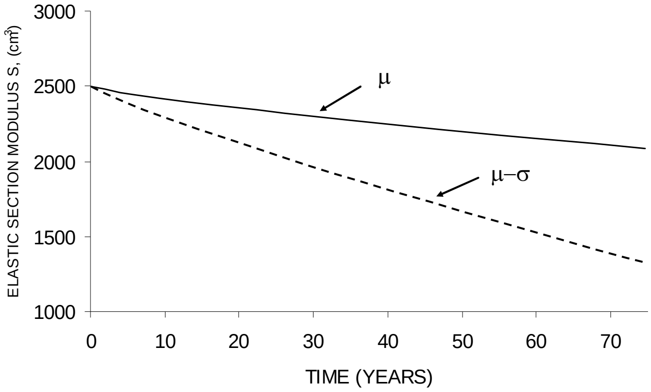


Figure 4.16. Deterioration of the elastic section modulus over time

Role of Monitoring, Parameter Descriptors, and Results:

Any hypothetical example must make assumptions about the role of monitoring and the simulated monitoring data created for the example. Because the literature often cites the effect of uncertainty on analysis results, this example was designed to investigate the effect on the calculated reliability index through the reduction of uncertainty. This is accomplished by taking the deterministic total moment demand of 590 kN-m divided by the predicted mean values of the section modulus over time. The results are hypothetical monitored stress values that confirm the structure is deteriorating and being loaded at expected values but with a higher degree of certainty. A coefficient of variation of 0.015 is assigned to the simulated monitoring data to account for sensor uncertainty. Commonly accepted values for the coefficients of variation of the other random variables are taken from Nowak and Yamani (1995). Table 4.4 reports the random variable descriptors for the analysis.

Table 4.4. Analysis random variables, descriptors, and sources

Random Variable	Distribution type. Mean, and Std. Deviation	Coefficient of Variation	Source
Yield Stress, f_y (MPa)	N[386, 42.5]	0.11	Nowak and Yamani (1995)
Elastic Section Modulus, S (cm^3)	variable with time	-	calculated
Dead Load Moment, M_{DL} (kN-m)	N[285, 14.2]	0.05	Nowak and Yamani (1995)
Live Load Moment, M_{LL} (kN-m)	N[305, 78.7]	0.258	Nowak and Yamani (1995)
Elasitic Modulus, E (MPA)	N[200, 12]	0.06	Nowak and Yamani (1995)
Monitored Strain Rdg, ε (cm/cm)	anticipated mean value	0.015	assumed

The reliability program RELSYS (Estes, 1997) was utilized to calculate the reliability index across time. This program constructs the reliability profile at discrete points in time (e.g. annually) by defining the appropriate resistance and load parameters for each step of the analysis.

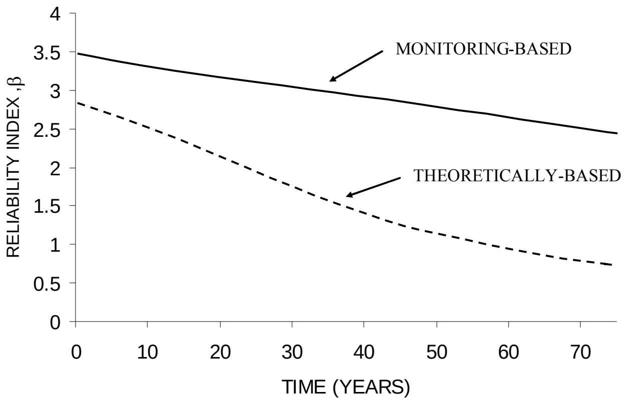


Figure 4.17. Reliability analysis results.

Figure 4.17 shows the results of this analysis, e.g. a time-dependent reliability profile over a 75 year period. Two distinct reliability profiles (with and without monitoring) are present and provide one estimate of how the reduction of uncertainty can impact the estimation of structural safety over time.

<u>*Example Critique*</u>: This example begins an interesting discussion: what is the benefit of the reduction of model uncertainty via monitoring? However, it is limited in two important ways. The first is the treatment of the live load and as

such the scope of the analysis itself. This analysis calculates the reliability over time against an invariant but random loading condition, the HS-20 truck. Live load effects are not accounted for which model the effect of multiple loading iterations (e.g. traffic). As such, the model is not reflective of actual traffic nor appropriately tied to code required return periods for live loads to conduct an appropriate safety assessment.

Inclusion of Bayesian Updating:

One section of Messervey and Frangopol (2006a) expands upon this example by investigating the use of Bayesian updating to combine monitoring and non monitoring reliability profiles. Because there are two estimations of the reliability index at any point in time, the question becomes which reliability profile should be utilized to make management decisions and to allocate resources? Perhaps, an immediate reaction would be to utilize the monitoring-based performance function as it captures the actual structural data. However, it could be the case, especially early in the life of the structure or soon after monitoring has begun, that the monitoring-based information is not mature or not representative of the 25, 50, or 100 year load demands for which the structure was designed. "Non mature" monitoring data would likely result in the higher estimation of the reliability index. However, would the treatment of the monitoring-based data change if its use resulted in the calculation of a lower reliability index than predicted by the theoretical model? Since the reliability indices of both performance functions are in themselves random variables, Bayesian updating may provide an effective method to combine the theoretical and monitoring-based data.

Let the normal distributed random variable X describe the true reliability index with a mean and variance of $N(\theta, \sigma^2)$ and suppose that monitoring eventually provides enough information to describe these parameters. Likewise, let the prior distribution of θ be $N(\mu, \tau^2)$ and suppose the theoretical model serves as the best estimate for the prior distribution. Assuming a normal distribution, the expected (mean) value and variance of the true reliability index given the observed event of a monitoring value x for the reliability index are (Casella and Berger, 2002):

$$E(\theta|x) = \frac{\tau^2}{\tau^2+\sigma^2}x + \frac{\sigma^2}{\sigma^2+\tau^2}\mu \quad (4.16)$$

$$Var(\theta|x) = \frac{\sigma^2\tau^2}{\sigma^2+\tau^2} \quad (4.17)$$

where μ represents the theoretical mean, τ^2 the theoretical variance, x the monitoring-based mean, and σ^2 the monitoring-based variance. The theoretical parameters (μ, τ^2) are being updated by an observation of monitoring-based information (θ, σ^2) where the importance, or weight, of each set of information is determined by the respective variances.

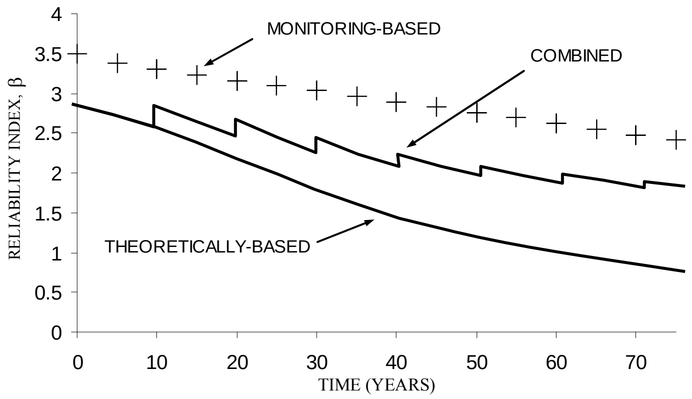


Figure 4.17. Combined reliability index profile via Bayesian updating

For this example, the theoretical variance is assumed to be τ^2 = 0.5 (less uncertain) and the monitoring-based variance is assumed to be σ^2 = 1 (more uncertain). Applying this approach to the data shown in Figure 4.17 at ten year update intervals yields a combined reliability index as shown in Figure 4.18.

<u>*Example Critique*</u>

Although this approach shows promise in combining theoretical and monitoring-based data, some limitations must be considered. First, the

Bayesian updating process utilized above assumes that the “true” population curve is fixed and that each sample observation leads to a closer approximation of this curve and the parameters utilized in its modeling. However, in the case of a deteriorating structure subjected to potentially increasing loads, the “true” parameters of the structure change over time so this assumption is not correct for this application. Secondly, and as a result of the assumption of fixed “true” parameters, the application of Equation 4.17 is in question. Through this equation, the variance of the updated information reduces with each successive update. Hence, each additional sample observation has less and less impact on the updated data because the theoretical/updated data becomes less uncertain. This can be observed in Figure 4.17 by smaller jumps at each update interval. After several updates the combined curve becomes fairly insensitive to updating.

Perhaps more important is the assumptions required for the variability of the monitoring and non-monitoring reliability indexes. Here, $\tau^2 = 0.5$ and $\sigma^2 = 1$ were assumed to demonstrate the concept but had no realistic foundation. Empirically through expert opinion, one can assign uncertainty to the estimation of the reliability index as done in this example. Analytically, this is a much different concept. By definition, a reliability analysis accounts for the uncertainty of all random variables in the analysis and the result is a single, invariant estimation of the reliability index. In order to achieve variability of the reliability index, the parameters within the reliability analysis must be random variables themselves. This case requires multiple iterations of the reliability analysis and does result in a distribution of the reliability index. This topic is addressed further in Chapter 6 and is the subject of Ang (2007) in which the concept is applied to the failure of the levee system in New Orleans after Hurricane Katrina.

Lastly, and also critically important, is the frequency of updating. In this example, 10 years was arbitrarily selected. However, had 1 year been selected, the combined curve would have very rapidly approached the monitoring based curve. Instead, if 25 years had been selected, the combined curve would have varied very little from the theoretically-based curve. Important in this discussion is the decision of how much time is required for monitoring data to become "mature" for highway bridges. How to account for this specific aspect of time in reliability-based analysis is an open question.

Inclusion of Live-Load Effects

Messervey and Frangopol (2007b) included live load effects and investigated the inclusion of an updating scheme based upon monitoring data and the statistics of extreme values. Several live load models are available to account for live load effects. These models account for multiple occurrences of a load demand distribution by the number of instances n, or over time. The live load described by Nowak (1993) was the basis for the calibration of the live load factors of the AASHTO LRFD Bridge Design Code (1994). Based on a study of 9250 trucks in Ontario, Canada, the main result of this study was a series of graphs that related span length, the average truck, the HS-20 design truck, and time. For the current application being developed, the Nowak graph for the mean moment at a span length of 12.2 meters and for a 75-year live load return period, indicates a factor of 1.75 with respect to the HS-20 truck. As such, the appropriate invariant live load for use in a reliability analysis that considers live load effects would be (305 kN-m)(1.75) = 533.75 kN-m. The resulting reliability index would represent the structural safety with respect to the 75-year design load for the resistance (capacity) utilized at that time in the analysis.

In some cases, it is desirable to construct the reliability profile over time as the structure progresses through its service life using a time dependent reliability analysis. Such an analysis requires the use of the statistics of extreme values from which are treated in further detail in Chapter 6. However, a brief introduction is provided here to continue the application.

The maximum expected value Y_n is a random variable and therefore has its own distribution. Equations are available that provide the asymptotic transformation of the baseline distribution to that of the maximum expected value. Graphically, the transformation of a baseline normal distribution to a Type I (Gumbel) extreme value distribution is shown in Figure 4.18.

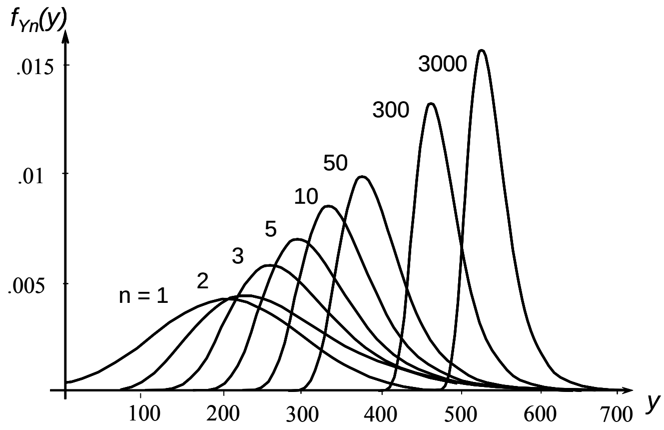


Figure 4.18. Transformation of a normal distribution to a Type I (Gumbel) extreme value distribution for increasing values of *n*.

The construction of a time dependent live load requires the characterization of the average (baseline) truck distribution and the average daily truck traffic (ADTT). Then, the appropriate live load can be calculated at different points in time for use in the reliability calculation. From Figure 4.18 and assuming an ADTT of 300 trucks where n = 1 describes the average truck distribution, the distribution associated with n = 300 would be appropriate for a reliability assessment for the period of one day and n = 3000 would be appropriate to assess the reliability for a period of 10 days.

An average daily traffic of 500 trucks is assumed. The HS-20 truck can be related to the average expected truck (Nowak, 1993). For this 12.2 meter span the coefficient for maximum moment is 0.75 and the coefficient for its standard deviation is 0.93. Using these coefficients, the distribution of the maximum moment changes from N(305, 78.7) *kN-m* for the HS-20 truck to N(228.75, 73.2) *kN-m* for the average expected truck. It is the average expected truck that is utilized for the calculation of live load effects based upon the actual number of trucks crossing the bridge and this distribution becomes the baseline distribution for n = 1. The mean and standard deviation of the Type I Gumbel EVD is defined from this baseline (normal) distribution by (Ang and Tang, 1984)

$$\mu_{Yn} = \sigma_X \mu_n + \mu_X + \frac{\gamma \sigma_X}{\alpha_n} \quad (4.18)$$

$$\sigma_{Yn} = \left(\frac{\pi}{\sqrt{6}} \right) \left(\frac{\sigma_X}{\alpha_n} \right) \quad (4.19)$$

where γ = .577216 (Euler's number), σ_X and μ_X are the descriptors of the baseline normal distribution (average truck), and μ_n and α_n are the characteristic value and shape factor of the EVD defined as

$$\alpha_n = \sqrt{2\ln(n)} \quad (4.20)$$

$$\mu_n = \alpha_n - \frac{\ln[\ln(n)] + \ln(4\pi)}{2\alpha_n} \quad (4.21)$$

Using these equations, the appropriate live load moment demand distribution at t = 1 year is

n = (500 trucks/day)(365.25days/year)(1 year) = 182,625 trucks (4.22)

$$\alpha_n = \sqrt{2\ln(182625)} = 4.92 \quad (4.23)$$

$$\mu_n = 4.92 - \frac{\ln[\ln(182625)] + \ln(4\pi)}{2(4.92)} = 4.41 \quad (4.24)$$

from which the Type I Gumbel mean and standard deviation are

$$\mu_{Yn} = 73.2(4.41) + (228.75) + \frac{(.577216)(73.2)}{4.92} = 560.15kNm \quad (4.25)$$

$$\sigma_{Yn} = \left(\frac{\pi}{\sqrt{6}} \right) \left(\frac{73.2}{4.92} \right) = 19.07kNm \quad (4.26)$$

Figure 4.19 shows the mean value of the maximum expected live load moment over time. The load experiences a sharp initial increase that tapers off over time. Not visually apparent on the graph but present in the data and consistent with Figure 4.18, the standard deviation deceases over time.

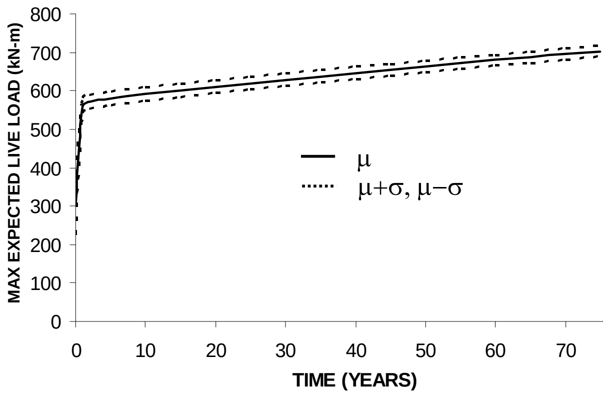


Figure 4.19. Moment demand live load effects for an ADTT of 500 trucks

The consideration of live load effects significantly affects the analysis. For this application, it was necessary to “redesign” the beam to a larger cross section. A W690x125 is selected and the same deterioration process is used for the elastic section modulus as outlined above which results in the profile of the section modulus over time shown in Figure 4.20.

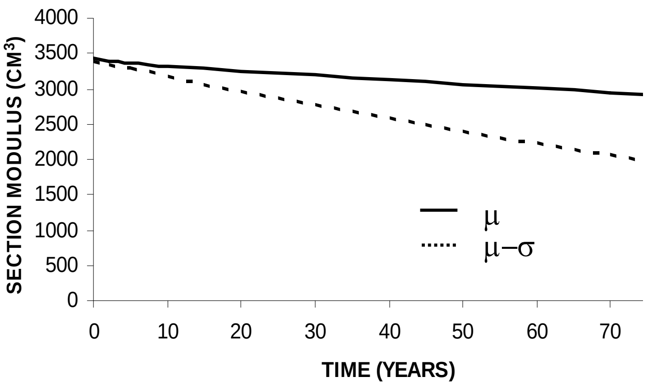


Figure 4.20. W690x125 elastic section modulus deterioration

Repeating the reliability analysis with the updated live load profile and the updated section modulus profile results in the reliability index profile shown in Figure 4.21. The immediate drop in the reliability index is indicative of a model that includes live-load effects.

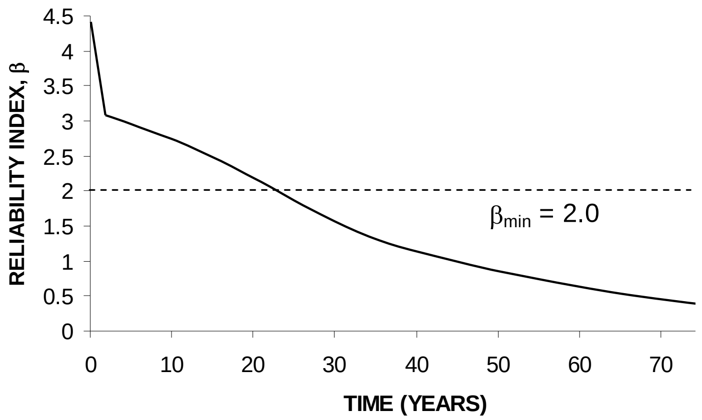


Figure 4.21. Reliability analysis results

Messervey and Frangopol (2007c) introduced and investigated the idea of updating the average truck distribution (baseline) and the average daily truck traffic with monitoring data by leveraging the asymptotic behavior of the transformation between the baseline and the extreme value distributions. Table 4.5 shows the scenario of interest.

Table 4.5. Scenario for monitoring based updating of the inital traffic distribution and ADTT

Scenario	Mean Moment Demand μ_X (kN-m)	Std Dev of Moment Demand σ_X (kN-m)	Number of Trucks	Utility
HS20 Design Truck	305	78.7		Used to calculate the initial reliability index, basis for the theoretical average truck.
Nowak (1993)	228.75	73.2	500	Initial moment distribution based on the average expected truck. Used to calculate live load effects.
Simulated Data	167.5	77.2	300	Based on the Gindy and Nassif (2006) study. Replicates SHM data. Used to update the intial estimated moment distribution and volume of traffic.

The scenario contains two distinct distributions. One is the theoretical data likely to be used for design (Nowak charts). The second distribution is based on a recent study of 10 years of weigh-in-motion (WIM) data conducted by Gindy and Nassif (2006). This study collected data across 33 sites in New Jersey, USA, and consists of millions of truck records. The average truck from this study is less than the HS-20 to average truck ratio provided by the Nowak charts. Placing the average truck on the 12.2m span at the location of maximum moment results in the maximum moment demand of N(167.5, 77.2) *kN-m*. This distribution is used for the monitoring data. In addition, a different average daily traffic is selected, n = 300 trucks. As such, the initial performance prediction is based on different data than the structure actually experiences over time. The research question investigated is: can this difference be observed and updated using monitoring data and the statistics of extreme values?

Monitoring data is created by simulating 300 random instances of the baseline distribution N(167.5, 77.2) *kN-M*. From these 300 data points (1 day), the maximum value is selected. This process is repeated for 90 days at which time 90 maximum values are available to characterize the monitoring based daily extreme value distribution. 90 days is selected as a reasonable amount of time for the data to "mature" (e.g. for the distribution parameters to stabilize).

The transformation of the theoretical data (e.g. N[228.75, 73.2] for n = 500 trucks) should match the observed monitoring based distribution if and only if the structure experiences the same loading condition as predicted. Any deviation indicates a disparity and updating is required. For this example, the simulation was designed specifically to obtain differences in the predicted and observed data. Messervey and Frangopol (2007c) details the equations and relationships utilized to average/update the transformed extreme value distributions (both theoretical and observed) and then the equations utilized to map the transformed (updated) distribution back to the baseline distribution (n = 1) to change both the average truck mean moment demand and the average daily traffic. This process produces a new baseline distribution for use in future performance prediction. The results of the updating process are shown in Table 4.6.

Table 4.6. Updating theoretical traffic parameters using monitoring information

Parameters	Mean Moment Demand μ_X (kN-m)	Number of Trucks	Std Dev of Moment Demand σ_X (kN-m)
Nowak (1993)	228.75	500	73.2
Simulated Data	167.5	300	77.2
Updated Parameters			
6 mo.	200.0	410	73.4
12 mo.	182.0	296	73.5
18 mo.	176.9	311	73.7
24 mo.	176.0	303	73.7

The results show that the baseline distribution is updated to reasonably match what is actually occurring on the structure after a period of two years. Including this updated information in a reliability analysis results in the live load moment demand profile and the reliability index profile shown in Figure 4.22 and 4.23. The updated profiles would lead to different optimal management actions and lower life-cycle costs.

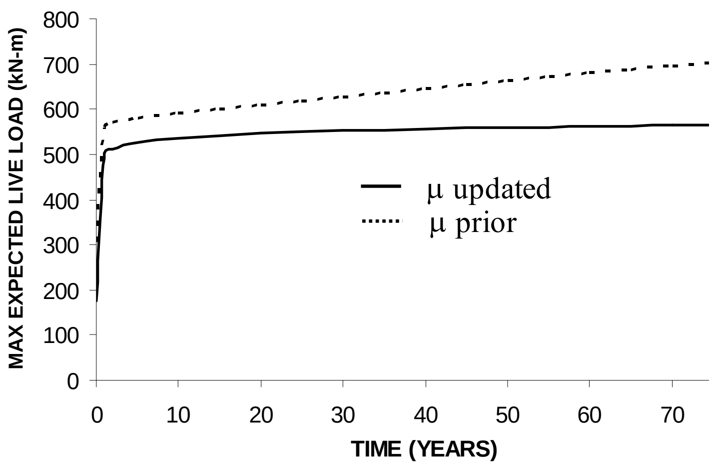


Figure 4.22. Updated maximum expected live load

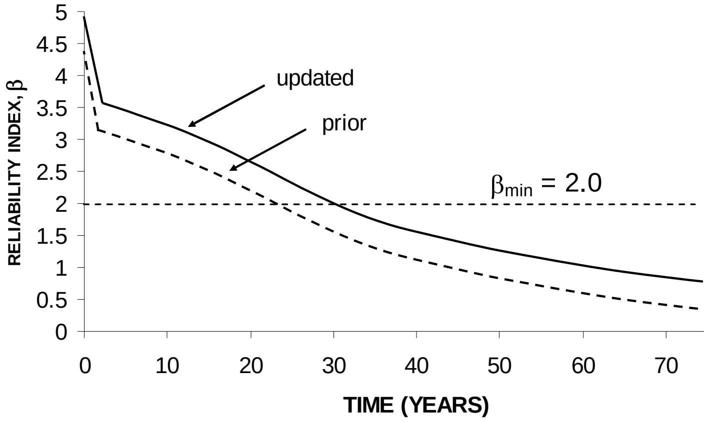


Figure 4.23. Updated reliability profile

<u>*Example Critique*</u>

The example illustrates several important points and novel ideas: 1) The inclusion of live-load effects results in significantly higher load demands, 2) Monitoring can be utilized to update initial assumed loading conditions, and 3) Extreme value statistics provide an interesting tool to manage and make use of monitoring data through the selection of maximum values in a specified observation timeframe. However, the example has several key limitations and is mostly academic in nature. For this example to find practical application, a bridge would have to be subjected to only the truck load each day for the specified and non-changing average daily traffic. In reality, this is of course not the case. Traffic varies daily although fluctuations could be reduced by considering weekly or monthly timeframes for analysis. More importantly, live load demand is a function of other random variables and processes to include multiple truck crossings, varying spacing intervals, wind loads, temperature effects, etc. For this reason, the intent of this example (updating the average daily truck distribution characteristics) is much too specific. Instead a much broader view of the live load demand is appropriate.

Despite these limitations, this example raised several critical research questions: What exactly is being observed when monitoring structural responses? How long must monitoring data be observed in order to characterize a distribution? How can monitoring data be related to code specified return periods? Are extreme value distributions appropriate? What is the variability of monitoring based distribution parameters? How should monitoring uncertainty be treated in an analysis? The investigation of these questions led to the most important contribution of this thesis, the characterization and use of monitoring-based live loads for use in a reliability analysis which is the topic of Chapter 5.

4.8 Conclusions

Chapter 4 has examined the inclusion of monitoring in asset management in a life-cycle perspective. In doing so, a sharp contrast has been provided in how monitoring is currently typically employed (e.g. an ad hoc reaction to a specific problem or defect). Considerations for the inclusion of SHM have been provided from the strategic and program level, to the network level, to the formation of monitoring strategies at the structural level, and down to the inclusion of SHM data within a particular performance function for the evaluation of safety with respect to a particular failure mode. All considerations have been constructed to occur in a life-cycle context. In shaping modeling choices and conducting analyses, it is important to be clear what type of model and assumptions are present. Is the model empirical/equivalent in nature (e.g. based upon the best possible belief or reasonable statistical data) or is the model performance-based/analytical in nature (e.g. based upon structure specific structural engineering calculations)? In some cases, the overall model is a combination empirical and analytical data/methodology. Keeping track of the limitations and assumptions of each is necessary.

A progressive simple example for a time dependent reliability analysis was introduced. This example highlighted the conduct of a reliability analysis, how the reduction of uncertainty can change the reliability analysis, the incorporation of life load effects, and the introduction of model updating through the use of monitoring based live load distributions. The example will be revisited in Chapter 6 to include the calculation of the difference of life cycle costs between monitoring and non-monitoring approaches.

Chapter 5

THE CHARACTERIZATION OF MONITORING-BASED LIVE LOADS FOR USE IN A RELIABILITYANALYSIS

Abstract

This chapter was motivated by an investigation on how to relate time and monitoring information. Given that most monitoring programs are non permanent and collect only short periods of data, what can be done with this information and how can it be related to code requirements? Moreover, extreme events (hurricanes, floods, or overloaded trucks) are rare, actual structural response data for such events is lacking, and such events will most likely not be part of any available dataset. Statistical errors, their quantification and treatment are also of concern. For example, if one uses one week of monitoring data to describe a mean and a standard deviation, those descriptors will not match the mean and standard deviation if a second week of data is collected and considered. Obviously more data will reduce uncertainty but more data also leads to higher costs implying optimization is required.

This chapter develops an answer to many of these questions through the application of extreme value statistics to monitoring data. After a theoretical background is presented, simulations are conducted to (a) confirm that a known distribution can be observed via "peak picking," and (b) to confirm the extreme value statistics. Next, (c) a method to optimize the observation timeframe (daily, weekly, monthly) in which to characterize monitoring based parameters is developed, and (d) an approach to quantify the uncertainty of the monitoring based parameters within the optimal timeframe is presented. The approach is demonstrated on a case study using 90 days of in-service data collected from a bridge located in Pennsylvania, USA.

Preliminary results of this work have been presented at the First International Symposium on Life-Cycle Civil Engineering (Messervey and Frangopol, 2008) and a journal article entitled "Application of the statistics of extremes to the reliability assessment and performance prediction of monitored highway bridges" is in the final submission stage.

5.1 Introduction

The collection of in-service monitoring data over a period of time with the intent of defining the distribution of a random process poses several unique challenges. Unlike recording a singular structural response to a specific load (e.g., a park test where a vehicle of known weight is positioned on the structure and the response recorded) or the detection of the presence or absence of a particular indicator (e.g., corrosive agents such as chloride), defining a distribution is sensitive to the amount of data collected raising two important questions. First, how does the observed information relate to safety or code requirements? To answer this question, another dimension, time, must be addressed. For example, if a structure is monitored for a short period and only light load demands are recorded, one cannot conclude that the structure is safe. One could conclude that the structure *was safe* for the loads encountered during the period monitored, but does not adequately convey the safety of the structure over its intended service life. When considering the entire life of a structure, it becomes clear that extreme events such as combinations of overloaded trucks, hurricanes, earthquakes, and other foreseen events must be considered. For this reason, probabilistic models must be formulated such that they can be used to address both the serviceability and ultimate limit states during the entire life of a structure (Faber, 2000). The second question that arises when using in-service data is how to ensure an accurate characterization of the monitoring based distribution and how to account for the uncertainty of the defined parameters. With fluctuations in daily traffic, changes in temperature, periodic wind forces, and other load demands, live loads are highly random. As such, any method to characterize the live load distribution must balance determining the appropriate timeframe in which to observe load effects upon the structure with how many independent timeframes are required to define the distribution parameters. Because the end result will be point estimates based on one data set, a rational method to account for the potential variability of the parameters must be utilized.

This chapter examines how extreme value statistics can be leveraged to simplify and enhance the assessment and performance prediction of monitored highway bridges by proposing an approach to obtain a monitoring-based live load for use in a reliability analysis. By describing the distribution of the largest observed value in a specified timeframe, the statistics of extremes is well suited for structural safety assessment. Furthermore, since the approach targets only maximum values it is efficient in terms of data reduction. An important characteristic of extreme value distributions (EVDs) is their asymptotic behavior. Once defined for a specific sample size or for a given timeframe, a simple transformation defines the distribution for a larger sample size or a longer desired timeframe. Leveraging this property, information observed in reasonably collectable period of time (days, weeks, or months) can be related to the much longer code specified return periods for use in a reliability analysis. As such, both serviceability and ultimate limit states can be addressed. Lastly, a method to identify, minimize, and to properly account for the epistemic uncertainty inherent to any monitoring record within a reliability analysis is presented. The approach can be utilized to plan data collection efforts or to maximize the utility of a fixed or limited amount of data.

5.2 Theoretical Background and Application to the Design and Assessment of Highway Bridges

The design and assessment of civil infrastructure is often concerned with the largest or smallest (extreme values) of a number of random variables. For example, buildings must withstand maximum wind loads, dams maximum flood levels, and bridges maximum traffic loads for a given time period (Ang and Tang, 1984). With respect to monitoring, this concept can be used as the selection criteria for what data to keep. In permanent monitoring approaches, the magnitude of a continuous data stream across hundreds of sensors becomes a management problem in itself. Selecting, logging, and maintaining peak values is one way to efficiently manage data (Frangopol and Messervey, 2007b).

An extreme value is the largest (or smallest) value from a set of n samples from a known distribution of a random variable X. As the distribution X is repeatedly observed, the behavior of the maximum values Y_n can be treated as a random variable itself

$$Y_n = \max\,(X_1, X_2, X_3, \ldots, X_n) \qquad (5.1)$$

If the underlying distribution of X has an exponentially decaying upper tail, then the cumulative distribution function (CDF) and the probability density function (PDF) of the distribution of the extremes Y take the forms (Ang and Tang, 1984), respectively:

$$F_{Y_n}(y) = [F_X(y)]^n \qquad (5.2)$$

$$f_{Y_n}(y) = n[F_X(y)]^{n-1} f_X(y) \qquad (5.3)$$

which is to say that the final distribution of the extreme values is a function only of the initial distribution and the sample of size n. This asymptotic behavior shows that if an extreme phenomenon can be defined in a specific timeframe of interest (or number of sampling occurrences), its distribution can be transformed to any other timeframe of interest. Depending on how the tail of the underlying distribution decays in the direction of the extreme, Equations 5.2 and 5.3 can lead to one of three well known asymptotic forms: the Type I double exponential (Gumbel), the Type II single exponential (Fisher-Tippett), or the Type III bounded exponential (Weibull). The equations that govern the transformation of several common distributions into these asymptotic forms can be found in (Ang and Tang, 1984; Thoft-Christensen and Baker, 1982).

To clearly illustrate in a very practical manner the concept of extreme values, a simple simulation is conducted. Let X have an initial Gamma distribution ~Gamma(160.6, 8.8, 18.25) where 160.6 is the mean value and 8.8 and 18.25 are the alpha and beta parameters respectively. These parameters are chosen because they characterize the best fit Gamma distribution for the average truck data found in the Gindy and Nassif (2006) weigh-in-motion study. Microsoft Excel is utilized to simulate this distribution 10 times to observe what happens to the average expected maximum value, μ_{Yn} , within each sample of size n. Table 5.1 shows the result of the 10th simulation for each sample of size n = 1 to size n = 4, and the behavior of Y_n treated as a random variable across the 10 simulations.

Table 5.1 Simple demonstration of the EVD concept

Sample Size n	10th Random Realization (kN)				Sample Maximum Yn (kN)	Avg of Sample Maximum Values μ_{Yn} (kN)	Std Dev of Sample Maximum Values σ_{Yn} (kN)
1	147.5				147.5	169.5	64.3
2	300.7	167.7			300.7	198.5	59.2
3	121.1	154.9	161.7		161.7	195.1	17.0
4	101.1	161.3	242.9	99.6	242.9	207.2	51.0

Figure 5.1 extends this simulation and plots the distribution of Y_n for samples of size n = 1, 5, 100, and 500 successively. It is noted that the underlying Gamma

distribution is transformed into a Type I Gumbel EVD which has an increasingly higher mean and invariant standard deviation as the sample size *n* is increased.

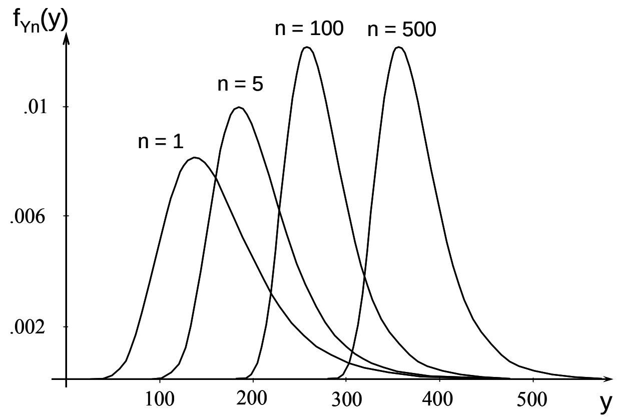


Figure 5.1. Simulation and transformation of a Gamma distribution to a Type I Gumbel extreme value distribution (EVD).

The use of extreme value statistics is already well established in both the design and assessment of highway bridge structures. With respect to design, the statistical treatment of combinations of extreme events has been utilized to calibrate load factors, resistance factors, and load combinations across different bridge types and spans with the goal of providing uniform levels of structural safety (Ghosn and Moses, 2003). Particular attention has been given to the development of appropriate models for design trucks. Researchers conducting a reliability analysis can consider the time effect of any recurring live load using the transformation governed by Equations 5.2 and 5.3. Such an analysis defines the distribution of the most likely maximum value provided the number of times the original distribution has been observed. Figure 5.2 illustrates this concept and the asymptotic behavior of extreme value distributions. Figure 5.2a depicts the transformation of an underlying normal distribution into a Type I Gumbel as the number of times the underlying distribution is sampled, *n*, increases. Applied to a bridge reliability analysis, if the average daily truck traffic was 300 trucks, the distribution for n = 300 would be appropriate for a daily analysis while the distribution for n = 3000 would be appropriate to assess the safety for a 10 day timeframe. Typically, this transformation is carried out to 75 years, consistent with the return period required for live loads. Examples of such analyses can be found in (Estes and Frangopol, 2005). Figure 5.2b illustrates a scenario of particular interest. In the special case where the underlying distribution or the observed phenomenon is itself a Gumbel distribution, the transformation to a larger number of samples (or longer timeframe) involves no change in the shape of the distribution and is instead a simple shift.

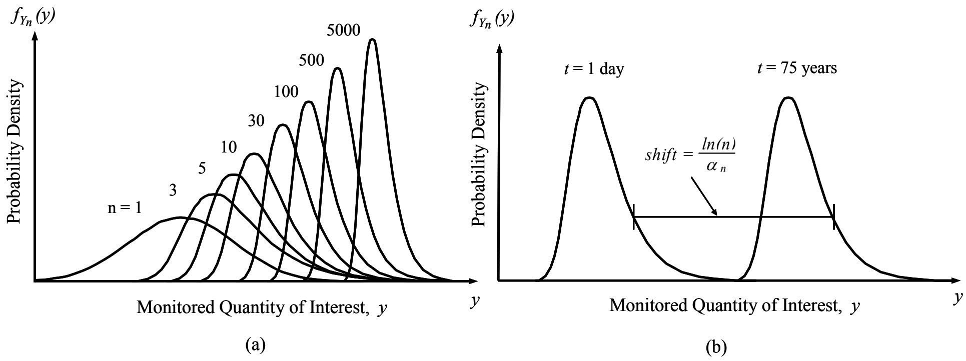


Figure 5.2. Transformation of: (a) an underlying normal distribution to an extreme value distribution, and (b) a Gumbel distribution transformed from one timeframe to another.

The extension of coupling extreme value statistics with monitoring as applied to the assessment of highway bridges is different than the transformation previously discussed. By peak picking monitoring data within a specified timeframe (for example selecting the maximum daily strain response from a monitoring record), one observes and defines the extreme value distribution directly instead of beginning with the underlying distribution. Goodness of fit can be tested for each of the three types of EVDs to determine which extreme distribution is most appropriate. However, the Type I Gumbel offers two significant advantages. First, the parameters necessary to define the distribution can be obtained directly from the mean and standard deviation of the recorded extreme values without requiring numerical methods or tables. Second, the transformation to a 75 year live load is very simple (Figure 5.2b). For these reasons, this work develops a method to specifically leverage these simplifying characteristics of the Type I EVD.

There are significant and compelling advantages to the use of SHM technologies to improve specifically the modeling of live loads on highway bridge structures which are summarized as follows: (a) improvement of existing models, (b) simplicity and efficiency, (c) bridge specific consideration, (d) performance updates over time, and (e) warning against extreme loads. First, there is the possibility to improve the accuracy of existing models and code provisions on the basis of more complete and up-to-date data. For example, it is reasonable to assume that the 1975 study of 9,250 trucks used for LRFD calibration of the first AASHTO LRFD Bridge Design Specifications (Nowak, 1993) is no longer representative of current truck traffic. Recently, weigh in motion (WIM) studies have been utilized to create much larger databases for truck weights. One such study performed by Gindy and Nassif (2006) examines an 11-year period across 33 WIM sites located in the state of New Jersey and consists of millions of records. Truck volumes, types, and weights, as well as seasonal effects and the implication of short collection periods are addressed. Such studies, based upon monitoring information, can provide the data necessary to re-examine the assumptions utilized in existing codes. Developing a design truck is only part of the problem. Vehicle speeds, vehicle spacing, the consideration of multi-lane structures, and the frequency of side-by-side occurrences are all aspects that affect the analysis. To this end, many studies have focused on the development of realistic traffic simulations (O'Connor and O'Brien, 2005; Cohen et. al, 2003; Zokaie et. al, 1991). However, such studies are time consuming and may not be easily transferred to structures of different span lengths, configurations, lanes, etc. In contrast, by measuring instead of modeling the live load response of a structure, such efforts are bypassed and quite possibly greater accuracy is obtained. This is the second main advantage of leveraging SHM. The third is passing from a general to a specific assessment of a structure. Codes and guidelines for both design and assessment must be generalized such that they are applicable across a wide variety of structures although some more recent codes have provisions allowing for a performance based design approach. The collection and use of structure specific data in a probabilistic analysis can consistently account for uncertainties at the local level and develop essentially what could be termed a bridge specific code (Enevoldsen, 2008). The last two advantages pertain to the value of increased information over time. Once a monitoring based live load distribution is characterized, it is possible not only to update an existing model but also to track changes as the structure ages. Such changes could either indicate an increase in the live loads placed upon the structure consistent with current trends in traffic or a decrease in the resistance capacity indicating damage. If the monitoring data is continuous, then it also becomes possible to provide a warning to decision makers when target threshold levels are breached.

5.3 Characterizing Monitoring Based EVDs and their use in a Reliability Analysis

The characterization of a monitoring-based distribution is sensitive to the amount of data available where more information correlates to greater accuracy. In some cases, the researcher or manager will be able to collect more data and in other cases only a limited data set may be available. Differences in the statistical characterization of distribution parameters can be addressed in terms of error, confidence, or uncertainty where more information decreases error, increases confidence, or reduces uncertainty. Throughout this study, an approach using uncertainty is developed. Melchers (1999) provides a listing and begins to quantify some of the common sources of uncertainty encountered in structural engineering problems. These include phenomenological (unforeseen events), decision, modeling, prediction, physical, and human factor sources of uncertainty. A detailed analysis or consideration of all sources of uncertainty is best suited to the development of a bottom-up model that seeks to predict the total amount of uncertainty present. However, in most cases, a monitoring-based approach will more closely resemble a top-down approach where the uncertainty is observed holistically instead of being modeled by parts. In these scenarios, Ang and Tang (2007) classification of uncertainty as either aleatory (data-based uncertainty associated with natural randomness) or epistemic (knowledge-based uncertainty associated with lack of information and imperfect models) is more appropriate. Using this approach, the aleatory uncertainty is the natural randomness of the process being observed, i.e. the true standard deviation of the monitoring-based live load. The epistemic uncertainty includes all factors that prevent the perfect characterization of this distribution (mean and standard deviation) and will likely be dominated by statistical uncertainty (amount of data) and model uncertainty (use of a best-fit distribution).

Due to the long service lives of bridges and the long return periods of extreme events they must withstand, it is impractical if not impossible to completely remove all epistemic uncertainty through an abundance of data, trials, or experiments. Instead, data collection programs must balance minimizing the epistemic uncertainty with the cost of obtaining additional data which, in turn, requires a method to quantify and account for the potential variability of the recorded point estimates based on the available amount of data. This is unique in that the random variable distribution parameters become random variables themselves. Accounting for this additional variability in a reliability analysis requires multiple iterations of the analysis where the parameters are randomly varied resulting in a distribution of the reliability index. Such a technique for the risk assessment of civil structures is developed and demonstrated by Ang (2007). In that work, the variability of random variable input parameters was based upon engineering judgment and expert opinion. Here, a statistical treatment of the data itself, along with the asymptotic behavior specific to the Gumbel distributions, will be used to quantify the variability of the monitoring based live load.

5.3.1 Observation of the transformation of a single known distribution

Method development begins with the investigation of an idealized simulation to quantify how quickly and how accurately the transformation of a Gumbel distribution can be identified via peak picking. The double exponential Type I Gumbel has a cumulative distribution function (CDF) and probability density function (PDF) defined, respectively, as

$$F_{Yn}(x) = \exp(-e^{-\alpha_n(x-u_n)}) \tag{5.4}$$

$$f_{Yn}(x) = \alpha_n e^{-\alpha_n(x-u_n)} \exp(-e^{-\alpha_n(x-u_n)}) \tag{5.5}$$

where n indicates the number of times the initial distribution X is sampled, α_n is the shape factor, and u_n is the characteristic value. In Messervey and Frangopol (2007b), a Gumbel distribution was fit to the results of the Gindy and Nassif (2006) weigh-in-motion study previously mentioned with the idea of developing a live load for assessment purposes based upon WIM data instead of the HS-20 truck. Although not specific to any particular bridge, the result is reflective of modern truck weights. The resulting parameters for the best fit Gumbel were a characteristic value of u_n = 156 kN and a shape factor of $\alpha = 0.015$ corresponding to an expected value of μ_X = 194.4 kN and standard deviation of σ_X = 85.5 kN. In the current study, this distribution is randomly sampled 300 times corresponding to an average daily truck volume of 300 trucks and the maximum value Y_n (Y_{300} if related to the sample size and Y_1 if related to time) is selected. This process is repeated to form a vector of maximum values Y_n which defines the observed extreme value distribution. The mean μ_{Yn} and standard deviation σ_{Yn} of this vector of maximum values are related to the Type I Gumbel EVD parameters as (Ang and Tang, 1984)

$$\alpha_n = \frac{\pi}{\sqrt{6}\sigma_{Yn}} \tag{5.6}$$

$$\mu_n = \mu_{Y_n} - \frac{\gamma}{\alpha_n} \tag{5.7}$$

where γ = 0.5772 is Euler's number. If the considered number of samples is infinitely large, the distribution obtained via "peak picking" will match the asymptotic transformation of the initial distribution defined as (Ang and Tang, 1984)

$$\mu_{Yn} = \mu_X + \frac{\ln(n)}{\alpha} = 194.4 + \frac{\ln(300)}{0.015} = 574.65kN \tag{5.8}$$

Specific to the Gumbel distribution, the standard deviation and shape factor are invariant and no equation is needed transform these quantities.

This concept of observing a transformed distribution from a known underlying distribution can be visualized in Figure 5.2b where the distribution on left side of this figure is being sampled, the distribution on the right is being observed via the "peak picking" of maximum values, and Equation 5.8 provides the theoretical result which enables an evaluation of the peak picking process. The simulation is repeated 1500 times for increasing lengths of the vector of observed maximum values Y_n. Each simulation provides a point estimate for μ_{Yn} and σ_{Yn}. Repeating the simulation allows the determination of the variability of these point estimates with respect to the number of observed maximum values. 1500 iterations of the simulation for each number of investigated maximum values were enough to ensure that the average of the point estimates (i.e., the mean of the mean and the mean of the standard deviation) converged to the correct values of μ_{Yn} = 574.65 *kN* and σ_{Yn} = 85.5 *kN*. As such, the standard deviation of the mean and the standard deviation of the standard deviation of the maximum values are determined for increasing sets of maximum values observed. Table 5.2 reports the results of this experiment. As expected, the consideration of more maximum values provides better parameter estimates (less variability of the result). Although a reasonable estimation of the mean maximum value μ_{Yn} is achieved rather quickly, the standard deviation of the maximum values σ_{Yn} requires more data. Minimum and maximum values of the parameters encountered in the simulation are reported in order to show the range of possible values and in particular to highlight the sensitivity of a point estimate of σ_{Yn} to a small number of observations. This is noteworthy because data monitoring sets of one or two weeks are far more common than monitoring data sets of 30, 60, or 90 days. The impact of such variability on a particular reliability analysis is case-by-case specific. However, it would be a mistake not to consider the variability of a point estimate at all.

Table 5.2. Simulation results describing the variability of monitoring-based parameters for a Type I Gumbel Extreme Value Distribution based on the number of maxium values observed.

Number of maximum values observed	5	10	15	30	50	100
Standard deviation of μ_{Yn} (kN)	38.1	26.8	21.7	15.8	12.0	8.5
Coefficient of variation using μ_{Yn} = 574.65 kN	0.066	0.047	0.038	0.028	0.021	0.015
Minimum/Maximum Observed μ_{Yn} (kN)	474.7 / 735.0	500.7 / 661.2	514.2 / 652.9	526.8 / 627.4	537.8 / 621.3	550.3 / 604.6
Standard deviation of σ_{Yn} (kN)	35.2	26.2	22.4	15.9	12.4	8.7
Coefficient of variation using σ_{Yn} = 85.5 kN	0.412	0.306	0.262	0.186	0.145	0.102
Minimum/Maximum Observed σ_{Yn} (kN)	4.8 / 291.2	29.3 / 212.7	34.7 / 178.1	41.1 / 152.2	50.8 / 128.1	57.0 / 113.6

Expanding the results of this particular simulation to a more generalized approach produces some interesting findings. First, comparing the results in the first and fourth rows of Table 5.2 reveals that, at least for considered case of a Gumbel distribution, the variability of both the mean and standard deviation parameters is approximately equal, that is

$$\sigma_{\mu_{Yn}} \approx \sigma_{\sigma_{Yn}} \tag{5.9}$$

Second, it is noted that the decrease in the variability of both parameters is proportional to the increase in the number of maximum values considered as predicted by the Central Limit Theorem using the standard deviation of the underlying distribution

$$\sigma_{\mu_{Yn}} = \frac{\sigma_X}{\sqrt{m}} \quad \text{and} \quad \sigma_{\sigma_{Yn}} = \frac{\sigma_X}{\sqrt{m}} \tag{5.10}$$

where m is the number of observations of the maximum value. For m = 10 and σ_X = 85.5 kN

$$\sigma_{\mu_{Yn}} = \sigma_{\sigma_{Yn}} = \frac{85.5\,kN}{\sqrt{10}} = 27.0\,kN \tag{5.11}$$

which is approximately equal to the simulated results for m = 10 in Table 5.2. Figure 5.3 and Figure 5.4 show the results of similar calculations for m = 5 to m = 100 and plots the coefficient of variation vs. the number of observed maximum values for μ_{Yn} and σ_{Yn}. Each plot consists of two curves, one simulated and the other predicted using Equation 5.10. The curves overlap nearly perfectly except for small values of m where small deviations are present. This result demonstrates that the Central Limit Theorem can be utilized to predict the decrease in variability with respect to the number of maximum values considered/available.

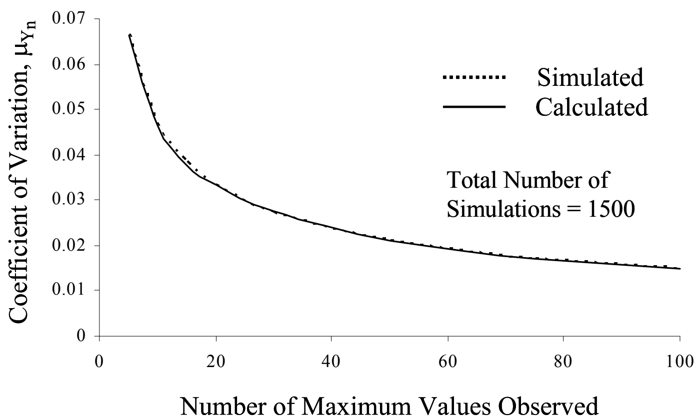


Figure 5.3. Coefficient of variation vs. the number of maximum values observed for the mean μ_{Yn}

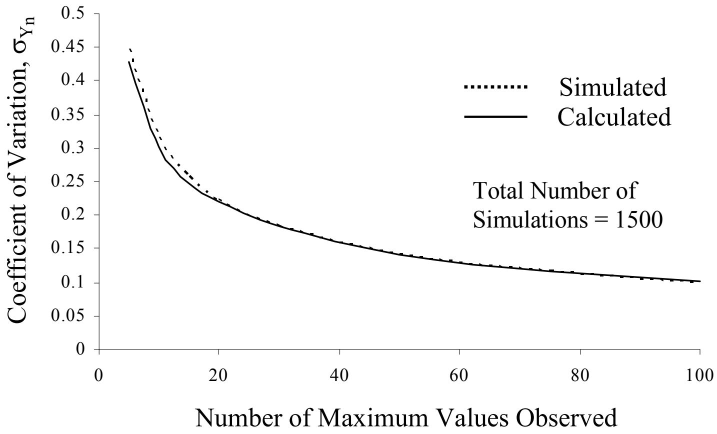


Figure 5.4. Coefficient of variation vs. the number of maximum values observed for the standard deviation σ_{Yn}

The last step in generalizing the approach is to address that the standard deviation of the underlying distribution will be unknown for monitoring applications. As such, it is necessary to assume that the point estimate for σ_{Yn} is reasonably accurate, i.e.

$$\sigma_{Yn} \approx \sigma_X \tag{5.12}$$

With this assumption, the variability of both Gumbel EVD parameters can be estimated directly from the monitoring data as

$$\sigma_{\mu_{Yn}} = \sigma_{\sigma_{Yn}} = \frac{\sigma_{Yn}}{\sqrt{m}} \tag{5.13}$$

The parameter variability estimations provided by Equation 5.13 allow for the treatment of parameter uncertainty within a reliability analysis. Additionally, the ability to predict how additional data reduces this variability can serve as a planning factor in the determination of how long to monitor a structure.

5.3.2 Observation of the transformation of a multiple distributions into a single EVD

The previous section demonstrated that the extreme value distribution for a sufficient number of n observations of an underlying distribution is both predictable (via transformation calculations) and observable (by selecting maximum values). However, characterizing the underlying distribution of the live loads upon a bridge structure is more complicated than the simulation of a single known distribution. Changes in daily traffic, side-by-side truck occurrences, and the effects of vehicle speeds, wind, and temperature quickly complicate the analysis. As a result, the monitored data reflects a much more uncertain phenomenon and the application of extreme statistics to this data must consider that the process is a convolution of potentially unknown distributions, each of them characterized by different and potentially varying sampling frequencies. For example, daily truck traffic may be 300 trucks today and 500 trucks tomorrow. Strong wind events may be fairly infrequent whereas temperature fluctuates daily and so on. For such a process, the transformation into an extreme value distribution for maximum values may be impossible to predict and may only be observable. Based on these observations, the possibility of measuring instead of modelling the live loads is highly desirable.

Such a scenario of in-service monitoring data involving multiple underlying distributions with non constant sampling frequencies raises several important questions. Do the maximum value descriptors converge to stable values in a reasonable amount of observations? Can the process still be modeled by an extreme value distribution? And lastly, what is the appropriate timeframe in which to observe and select the maximum values? For example, daily fluctuations in traffic may lead to high epistemic (model) uncertainty if a daily timeframe is used for the selection of maximum values because the process is not completely observed. Instead, weekly maximums or monthly maximums might be more appropriate by allowing short term traffic fluctuations to average out. Although a longer observation timeframe is generally more desirable, it must be balanced against the fact that it reduces the number of maximum values available to define the EVD using the same amount of data. For instance, 90 days of monitoring data provides 90 daily maximums vs. 12 weekly maximums, and 3 monthly maximums. Too few observations increases the uncertainty predicted by Equation 5.13 and depicted in Figures 5.3 and 5.4.

To begin answering these questions, three random processes are simulated as detailed in Table 5.3. Each random process has a different and random frequency of occurrence within each "day" of the simulation. Process 1 follows a Gamma distribution. Its frequency of occurrence each day is determined by a uniform random variable ranging between 400 and 1600. Hence, with equal probability, Process 1 occurs between 400 and 1600 times each day. Process 2 follows a Normal distribution. Its frequency of occurrence is controlled by a random variable with a probability of occurrence $p(s)$ = 0.05. As such, the normal distribution is either sampled or it is not sampled with an average occurrence (or return period) of one time every 20 days. Process 3 also follows a Normal distribution. This distribution is sampled exactly once per day.

Table 5.3. Simulation distribution types, parameters, and frequencies of occurrence.

Process 1 : Truck Load (kN)		*Process 2* : Wind Effect (kN)		*Process 3* : Temp. Effect (kN)	
Distribution	Frequency of Occurrence	Distribution	Frequency of Occurrence	Distribution	Frequency of Occurrence
Gamma	Uniform Distribution	Normal	Random	Normal	Once per day
$\alpha = 5.69$	$a = 400$	$\mu = 50$	$p(s) = 0.05$	$\mu = 0$	
$\beta = 35.83$	$b = 1600$	$\sigma = 10$		$\sigma = 20$	

The convolution of these three processes occurs daily within the simulation according to the following rules. Each day the maximum value from Process 1 is selected. If Process 2 occurs, this value is added directly to Process 1. Process 3 does occur each day and this observation is added directly to the summation of Processes 1 and 2. As such, the simulation and summation of these processes results in a highly random phenomenon that changes each day of the simulation.

This phenomenon is motivated by, but does not accurately model, the live-load demand on a generic member of a highway bridge where Process 1 represents the weight of daily truck crossings, Process 2 models an occasional wind effect, and Process 3 models daily thermal effects. The Gamma distribution for Process 1 is again fit to the Gindy and Nassif (2006) WIM study. The magnitude of the wind effect (Process 2) is small in proportion to the truck weight and always positive. The magnitude of the temperature effect (Process 3) is even smaller in proportion to the truck weight and can either be positive or negative. Of course, this scenario could be improved for any specific structure of interest. However, assuming a linear elastic behavior, it is reasonable to state the load effects of trucks, wind, and temperature on structural members can be superimposed. As such, the objective of the simulation is not to accurately model the live load demand upon any particular structure or member, but instead to model and capture the mathematical aspects of a process approximately as random in order to determine how long the process must be observed to define its characteristics.

The simulation is run for 45,000 days, the loads are simulated and combined as previously discussed, and 45,000 daily maximum values are generated. Such a long period is used only to be able to obtain and compare 1500 observations of daily, weekly, and monthly maximum data. Starting on the second day, the average, μ_{Yn}, and the standard deviation, σ_{Yn}, of the maximum load are calculated to investigate how many observations are required to converge on a particular value. The same process is repeated using the same daily data, but weekly and monthly maximums are selected. Hence, the parameters μ_{Y1}, μ_{Y7}, μ_{Y30} and σ_{Y1}, σ_{Y7}, σ_{Y30} (where 1, 7, and 30 denote one day, one week, and one month, respectively) are calculated which define the same extreme distribution for different observation timeframes (or number of instances sampled). Fig. 3 depicts the results of the simulation for 1,500 observations of each considered time interval (day, week, month). The observations are recorded on the abscissa, and magnitude of the mean load demand or standard deviation (in kN) is recorded on the ordinate. In each case, excellent convergence is generally achieved after 500 observations, but a sufficiently close convergence is observed to occur much sooner with a small margin of error. As expected with extreme values, longer timeframes (more samples) result in larger mean values.

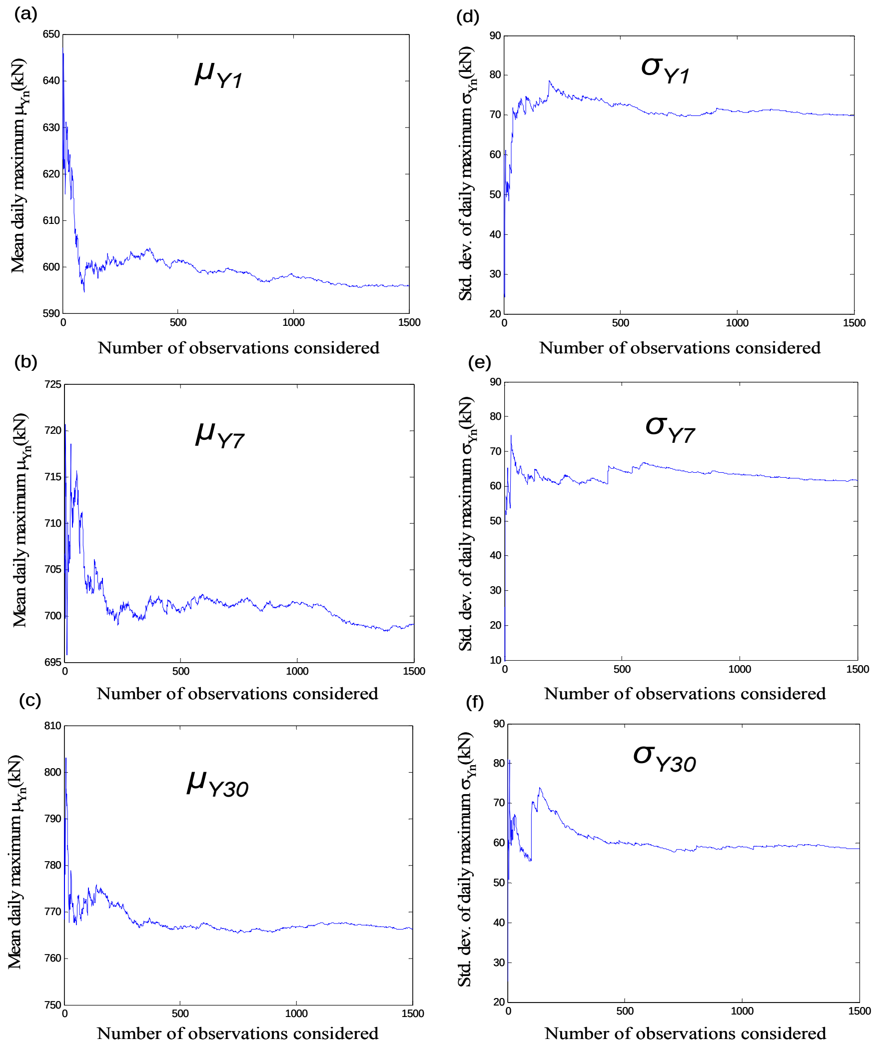


Figure 5.5. 1,500 observations of the mean of daily maxima, μ_{Yn}, in (a) daily (b) weekly and (c) monthly timeframes, and the standard deviation of daily maximums in (d) daily (e) weekly, and (f) monthly timeframes.

The average daily maximum converges to a value of 598 kN for the daily maximums, 699 kN for the weekly maximums, and 769 kN for the monthly maximums. With respect to the standard deviations, it is noted that longer timeframes decrease variability. The standard deviation of the daily maxima converges to a value of 70 kN, the weekly maxima to 62 kN and the monthly maxima to 59 kN. This decrease in standard deviation is correlated to the stability or maturity of the process being observed. Here, changes in daily traffic volumes increase the randomness of the daily maxima. Utilizing the same data, traffic volume fluctuations are less prevalent in the weekly and monthly observation timeframes leading to a lower standard deviation and more accurate characterization of the EVD. This can also described as reducing the epistemic (modeling) uncertainty to obtain the best possible characterization of the aleatory (natural) uncertainty.

Having demonstrated that the simulation results converge to stable values, it is desirable to investigate if an EVD is an appropriate model for this convolution of independent random processes. Figure 5.6 plots a histogram of the 45,000 daily maxima. The data dispays the characteristic shape of an EVD.

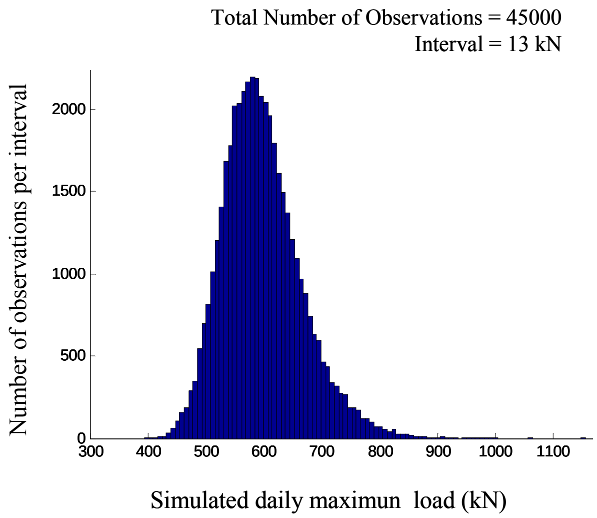


Figure 5.6. Histogram for the simulated daily maximum loads.

An empirical cumulative distribution function (ECDF) is created for the data which is shown in Figure 5.7. The best fit Type I, Type II, and Type III extreme value distribution CDFs are found by minimizing the sum squared error

(SSE) and are also plotted. Each EVD model provides a reasonable fit to the ECDF. Further investigating goodness of fit, the Type III (Weibull) fits the data nearly exactly with a slight deviation at the upper tail, the Type I (Gumbel) fits the data very well with a slight deviation at the lower tail, and the Type II (Fisher-Tippett) has slightly larger deviations at both tails.

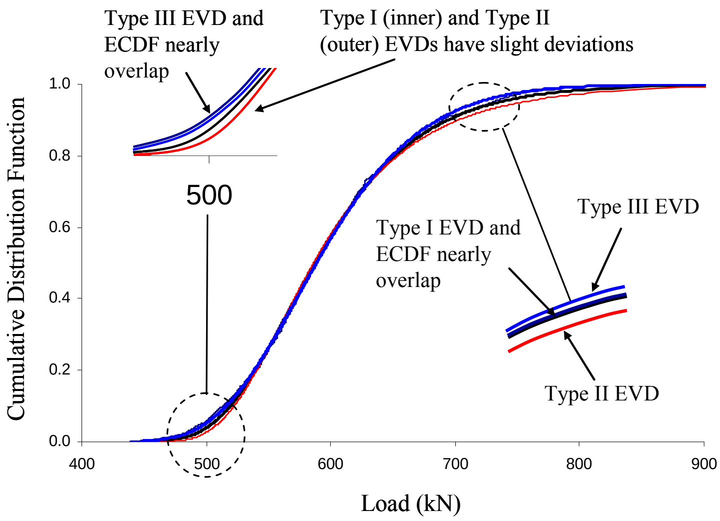


Figure 5.7. Simulation ECDF and the best fit EVD CDFs for the simulated daily maximum loads.

The Gumbel distribution is selected as the preferred model because of its previously discussed advantages. Next, the selection of the best possible observation timeframe is investigated and discussed. To make a comparison, the distributions must be transformed to a common reference timeframe. Because truck loads dominate the response of a highway bridge it is most appropriate to map the distribution defined by each observation timeframe to the 75 year design truck live load return period consistent with existing codes (Ghosn et. al, 2003; Ghosn and Moses, 1986). Using the mean and standard deviation obtained in Figure 5.5 for 1500 observations in a daily timeframe (e.g., μ_{Yn} = 598kN and σ_{Yn} = 70kN) the shape parameter of the daily extreme value distribution is calculated using Equation 6 as

$$\alpha_1 = \frac{\pi}{\sqrt{6}(70)} = 0.01833 \tag{5.14}$$

Equation 5.8 can then be used to transform the distribution of the daily maximums to the 75 year return period as

$$\mu_{Y75year} = 598kN + \frac{\ln(365.25\frac{day}{year} \times 75 years)}{.01833} = 1155.45kN \tag{5.15}$$

with the standard deviation and shape parameter remaining invariant. Table 5.4 reports these values together with the ones obtained when considering the weekly and monthly observation timeframes.

Table 5.4. Extreme value distribution (EVD) parameters characterized in different observation timeframes and transformed to 75 year EVDs.

EVD parameters	daily, Y_1 n = 1	75 year n = 27375	weekly, Y_7 n = 1	75 year n = 3900	monthly, Y_{30} n = 1	75 year n = 900
α	0.0183	0.0183	0.0207	0.0207	0.0217	0.0217
μ (kN)	598	1155	699	1099	769	1082
σ (kN)	70	70	62	62	59	59

The results show that each observed timeframe (daily, weekly, and monthly) maps to similar, but different 75-year live load distributions as depicted in Figure 5.8. Ideally, the observed distributions should be identical in shape and should successively shift to the right (larger mean values) on the abscissa. Instead, the transformed distributions should overlap (be the same distribution). For this simulation, there are some differences in shape among the observed distributions corresponding to the different observed standard deviations. For the transformed distributions, the weekly and monthly observation timeframes nearly overlap whereas the daily observation timeframe is shifted further to the right. From Equation 5.8, it is noted that the standard deviation is directly correlated to the magnitude of the transformation with higher standard deviations corresponding to larger shifts. For the application of monitoring highway bridges, higher standard deviations in part correspond to less monitoring information. Although generally desirable to minimize such variability, its inclusion (higher standard deviation) results in a conservative estimation of the live load (greater mean and standard deviation) when considered in a reliability analysis.

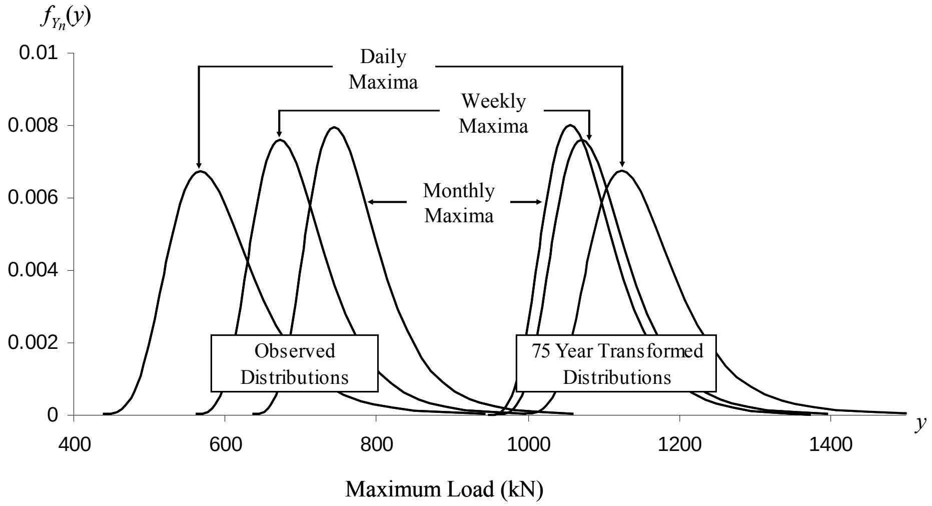


Figure 5.8. Simulation based observed daily, weekly, and monthly EVDs and their associated transformations to a 75 year EVD.

In itself, the results from this simulation or from Figure 5.8 cannot be utilized to state which observation timeframe is best suited for the reliability analysis of any particular bridge. Here, the amount of data was essentially unlimited as 1500 monthly observations correspond to an unrealistic monitoring period of 125 years. Furthermore, more data is not necessarily better. Although a longer observation timeframe does average out short term fluctuations in the data, it also implies a greater commitment of resources. Additionally, a desired outcome of such an approach is the investigation of changes in structural performance through distribution parameter changes. The selection of an observation timeframe and desired number of observations that span a period likely to undergo a change in performance would mask the ability to detect this change. More appropriate to bridge monitoring is the determination of an appropriate balance between selecting the observation period and number of observations of that period that provide reasonable results, and then repeating the process to search for trends in changes of performance. Separately, one may be constrained to a fixed or limited amount of data. In such cases, a method that optimizes the utility of the available data and which accounts for the uncertainty present is needed.

5.3.3 Two methods for the inclusion of live load parameter uncertainty in a reliability analysis

Two separate methods can be utilized to quantify the uncertainty associated with characterization of a monitoring based live load distribution and to incorporate this uncertainty in a reliability analysis. Either the random variable distribution parameters can themselves be treated as random variables or separate error terms can be added to the performance function. Equation 5.16 shows an approach where error terms are incorporated into the performance function and related to the live load (Messervey and Frangopol, 2008)

$$g(1) = R - L_D - (L_L + \varepsilon_{obs} + \varepsilon_{timeframe}) \tag{5.16}$$

where R is the resistance, L_D the dead load, L_L the monitoring-based EVD live load, ε_{obs} the error associated with the amount of data available, and $\varepsilon_{timeframe}$ the error associated with the selected observation timeframe. Two error terms are proposed instead of one because it is possible to conduct investigations to quantify uncertainty specific to both the observation timeframe and the amount of available data. Both error terms are modeled as normally distributed random variables. Each has a mean of zero indicating an equal likelihood of underestimating or overestimating the live load. The standard deviation of both types of error is calculated as the product of a coefficient and the mean value of the EVD. As such, the magnitude of the error is a function of the magnitude of the monitored observations. Both terms are calculated with respect to the observation timeframe utilized to characterize the EVD parameters (e.g. before transformation to a 75 year EVD). Table 5.5 and Table 5.6 provide a starting point for the estimation of two separate error coefficients, *a* and *b,* associated ε_{obs} and $\varepsilon_{timeframe}$ respectively. Coefficient values are estimated from the conducted simulation work, are preliminary estimates only, and should be regarded only as a proof of concept.

Table 5.5. Coefficient to determine the standard deviation of ε_{obs} as a function of the mean of the monitored extreme value distribution and amount of data considered

	Number of Observations					
	7	14	30	90	180	365
a	0.25	0.15	0.1	0.05	0.03	0.01

Table 5.6. Coefficient to determine the standard deviation of $\varepsilon_{timeframe}$ as a function of the mean of the monitored extreme value distribution and timeframe selected

	Selected Timeframe		
	Daily	Weekly	Monthly
b	0.06	0.03	0.01

As an example illustrating the use of these tables, Figure 5.5 is read at the 30 day mark for the daily observation timeframe representing a monitoring program that collects one month of information. After 30 days, the mean maximum value is approximately 620 kN and the standard deviation is approximately 65 kN. Estimating the error (uncertainty) associated with the daily observation timeframe results in the selection of a = 0.01 for 30 observations and b = 0.06 from Table 5.5 and Table 5.6. Applying these coefficients, ε_{obs} is normally distributed with parameters ~*N*(0, 62) kN where 620 x 0.1 = 62 kN for 30 days of data. Likewise, $\varepsilon_{timeframe}$ is normally distributed with parameters ~*N*(0, 37.2) where 620 x 0.06 = 37.2 kN for the daily observation timeframe. Transformation to the 75 year EVD is then conducted first using Equation 5.6 to calculate the shape factor

$$\alpha_n = \frac{\pi}{\sqrt{6}\sigma_{Yn}} = \frac{3.14}{\sqrt{6}(65)} = 0.01972 \qquad (5.17)$$

and then Equation 5.8 to conduct the transformation of the mean maximum value to the 75 year EVD

$$\mu_{Yn} = \mu_X + \frac{\ln(n)}{\alpha} = 620kN + \frac{\ln(27394)}{0.01972} = 1138.2kN \qquad (5.18)$$

The final distribution for use in a reliability analysis with respect to a 75 year safety assessment is Gumbel(1138.2, 65)kN with ε_{obs} = ~N(0, 62) kN and $\varepsilon_{timeframe}$ = ~N(0, 37.2).

The end result of employing this approach (Equation 5.15) is the calculation of a single value for the reliability index. With respect to a standard reliability analysis, the inclusion of error terms (additional uncertainty) results in a lower (more conservative) value of the reliability index. Instead, it might be desirable to calculate a distribution of the reliability index by considering the characterized monitoring based distribution parameters as random variables themselves as illustrated in Figure 5.9.

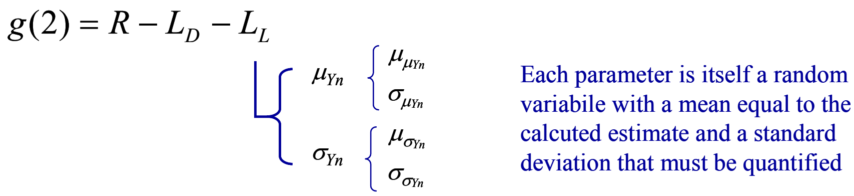


Figure 5.9. Performance function where the live load descriptors are in themselves random variables.

Using such an approach, the decision maker has a more detailed representation of the possible range of structural performance. Quantifying the variability of the mean and the variability of the standard deviation of a random variable can happen in two principle ways, it can be estimated or it can be calculated. In Ang (2007), the variability of random variable input parameters is based upon engineering judgment and expert opinion concerning the reliability of the levee system in New Orleans prior to Hurricane Katrina in 2005. By paring different storm intensities, storm surges, and other factors related to the system reliability, a distribution of the reliability index was created that provided a more complete assessment of risk with respect to levee failure. For monitoring data sets and the consideration of statistical error, it is possible to qualitatively estimate parameter uncertainty based off the amount of data collected. This is the purpose of equation 5.13 developed in the first simulation that demonstrated that the parameter uncertainty decreases proportional to the amount of data collected and can be estimated using the Central Limit Theorem. As an example of the application of Equation 5.13, the equation is applied again to the Figure 5.5 reading of μ_{Yn} = 620 *kN* and σ_{Yn} = 65 *kN* for 30 observations of daily maxima. Using this information

$$\sigma_{\mu_{Yn}} = \sigma_{\sigma_{Yn}} = \frac{65}{\sqrt{30}} = 11.87kN \tag{5.19}$$

Treated as a random variable, μ_{Yn} would be normally distributed centered at 620 *kN* with a standard deviation of 11.87 *kN*. The standard deviation as a random variable is also normally distributed, centered at 65 *kN* with a standard deviation of 11.87 *kN*. These characteristics are calculated in the observation timeframe of the data and are assumed not to amplify if transformed to another observation timeframe. For this example, the 75 year EVD with its parameters as random variables would have its mean centered at 1138.2 *kN* (Equation 5.18) with a standard deviation of the mean = 11.87 *kN* and a standard deviation of 65 *kN* with a standard deviation of the standard deviation = 11.87 *kN*. As such, the uncertainty associated with the characterization of the Type I Gumbel in the observation timeframe is assumed to be applicable to transformed distribution in any other timeframe.

To incorporate this information in a reliability analysis requires multiple iterations of the analysis. Essentially, one conducts a Monte Carlo simulation of the reliability analysis where first the parameters for the reliability analysis are simulated and then the reliability analysis is conducted. Each simulation results in one value of the reliability index. After a large number of simulations, a histogram of the reliability index is created. Figure 5.10 summarizes the process described in this section for the characterization of monitoring based distributions for use in a reliability analysis. This process is specific to and leverages the characteristics of the Type I Gumbel extreme value distribution.

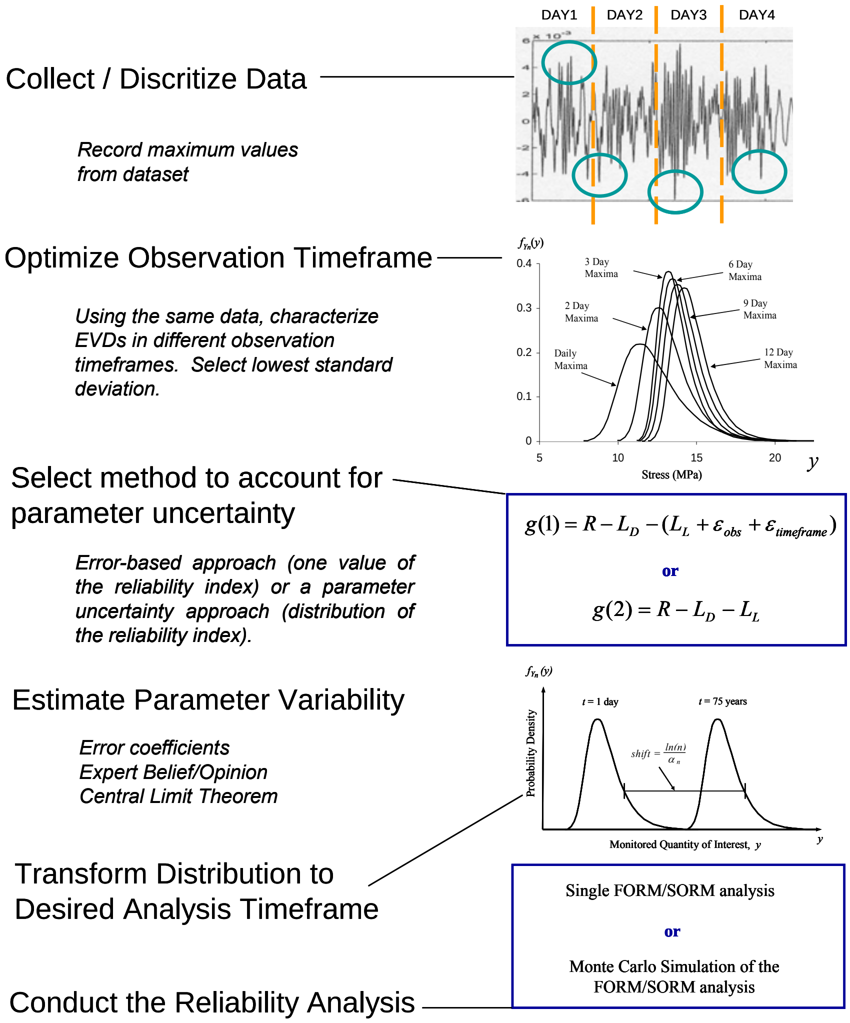


Figure 5.10. Process for the characterization of monitoring-based distributions for use in a reliability analysis.

5.4 Application

Bridge Overview and Monitoring Program

The Lehigh River Bridge SR-33 (Figure 5.11) was constructed in 2001 and is situated in Bethlehem, PA, USA. The bridge is a four-span continuous weathering steel deck truss with a main span of 181.05 *m*. The depth of the truss varies from 10.97 *m* (at midspans) to 21.95 *m* (over the supports). The structure is subjected to light to medium truck traffic.

Figure 5.11. Photograph of the main span of the SR33 Lehigh River Bridge (photo taken by Sunyong Kim on 8 January 2008).

The Lehigh River Bridge is unique because the reinforced concrete deck is not only composite with the longitudinal steel stringers and transverse floor beams, but also with the upper chord members of the truss through the use of shear studs connecting the upper chords directly to the bridge deck. This structure is the only composite truss in the State of Pennsylvania and possibly the United States (Connor and McCarthy, 2006). The main truss members (i.e., upper chords, lower chords and diagonals) are fabricated from structural steel plates into box or "H" shapes. The steel stringers, sway bracing, and cross bracing members are all rolled "W" shapes.

Monitoring of the Lehigh River Bridge was conducted during construction, for controlled load tests using test trucks, over time for temperature measurements, and for several short periods of in-service usage (Connor and McCarthy, 2006; Connor and Santosuosso, 2002). The objective of the study was to measure mechanical and thermal strains during construction and while in-service in order to better understand the performance of the structure, the composite truss-deck interaction, and to demonstrate the feasibility and value of monitoring activities during construction and while in service. Data is available from representative periods of time that include all seasons. Instrumentation and testing were conducted by personnel from Lehigh University's Center for Advanced Technology for Large Structural Systems (ATLSS). Complete descriptions of the bridge layout as well as the field and instrumentation programs are available in ATLSS reports prepared by Connor & Santosuosso (2002) and by Connor & McCarthy (2006).

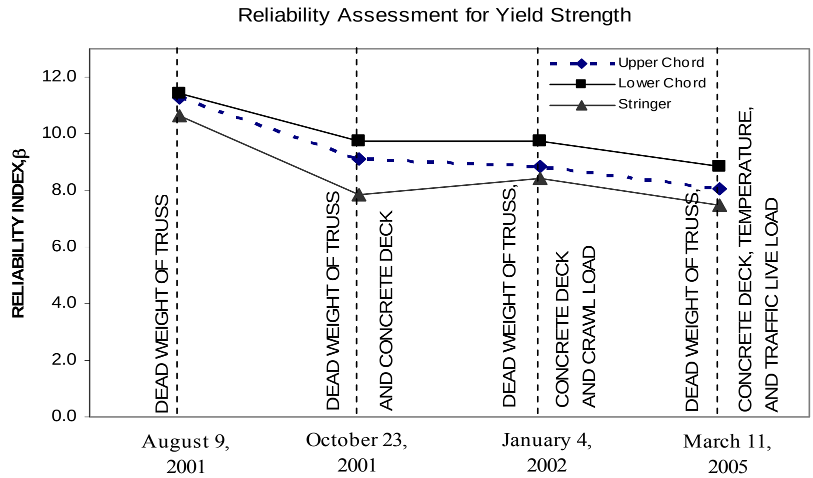


Figure 5.12. Reliability analysis of the SR33 Lehigh River Bridge at key construction and testing milestones (Adopted from Frangopol et al., 2008)

Frangopol et al. (2008) used data collected from this instrumentation program to assess the reliability of the truss upper chord, truss lower chord, and deck stringers at each construction or testing milestone. Sensors were located on member cross sections and from positions on the bridge that maximized strain responses. The end result of this work with respect to the reliability assessment of these members is reported in Frangopol et al. (2008) and determined that the structure had a high reliability during construction, for the controlled crawl load test, and for the one day of in-service live load monitoring as shown in Figure 5.12. The next logical step for the assessment of this structure is an extrapolation of the future reliability of the bridge based upon live-loads monitored over time.

Data Collection, Data Management, and Critical Member Selection

Periodic, in-service data is available from 24 sensors located on various members during dates that range from June 2004 to February 2005 (Connor and McCarthy, 2006). For each sensor, approximately 90 days of data are available. Measurements are trigger-based meaning that sensors were only activated when prescribed strain thresholds were exceeded (save power and reduce meaningless data). Two control units (one for each direction of traffic) were utilized to coordinate and log sensor data. Noise spikes (as shown in Figure 5.13) that are often associated with vibrating wire strain gauges were present in the data and were manually removed from each record for this analysis.

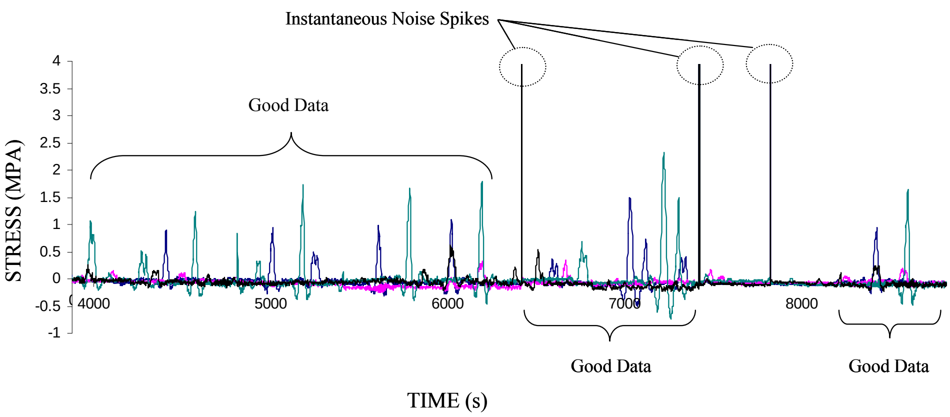


Figure 5.13 Stress response of four sensors for a particular segment of time

Because this application focuses specifically on the aspect of extreme values, it was not desirable to consider all 24 sensors due to the effort involved in manually managing and processing the data. Ideally, a data processing algorithm could be written and incorporated into the data collection program beforehand that would identify and log data of interest. However, this analysis occurred years after the data collection program and persistent noise spikes in the data made it impossible to process the data without human judgement. Figure 5.13 shows the stress response of 4 sensors for a particular segment of time. The spikes are identifiable because they are instantaneous in nature and they prevent the selection of maximum values without a visual check.

The selection of the most critical members for analysis was aided significantly by dynamic tests conducted and reported by Connor & McCarthy (2006) and by the reliability analysis conducted by Frangopol et al. (2008). The responses of a lower chord, upper chord, and two stringers to a series of vehicles travelling eastbound are shown in Figure 5.14 (adapted from Connor and McCarthy, 2006).

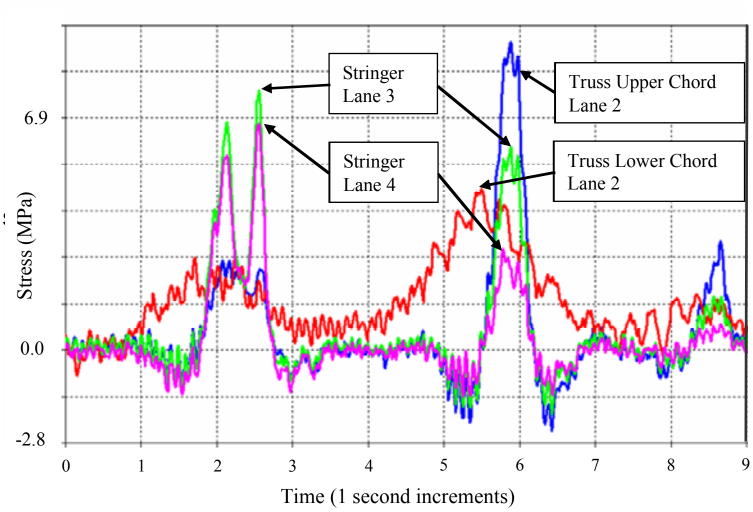


Figure 5.14. Structural responses of two stringers, the truss upper chord, and the truss lower chord to four separate vehicles traveling eastbound (adapted from Connor and McCarthy, 2006).

The global response of the lower chord is characterized by its early response to the load. Its response gradually increases as the load traverses the main river span and peaks when the truck is above the sensor. The upper chord and stringers show more abrupt responses when the load is directly above these members as these members primarily undergo local bending. Also, lane position can be inferred from this same figure. Stringers 3 and 4 have a significant response to the first two stress cycles, indicating that the vehicles are travelling in Lane 3, since these two stringers are directly beneath this lane of traffic. The next stress cycle indicates that the vehicle is positioned in Lane 2 as the upper and lower chords, located directly below Lane 2, have more significant responses than the stringers. These and similar dynamic tests reported in Connor and McCarthy (2006) consistently identify the upper truss chords and four (of nine) stringers as those having the most significant responses during traffic loading.

Sensor Selection, EVD parameter estimation, and optimization of the observation timeframe

The two upper truss chords, located above a support and at bridge midspan respectively, are selected as the critical members for this structure. Although the stringers have slightly lower reliability indexes (Frangopol et. al, 2008), the failure of one stringer does not typically lead to global failure of the structure due to load redistribution within the deck. In contrast, the failure of a truss component may result in a global collapse and as such these members are deemed more important. Figure 5.15 shows the structural scheme and the critical locations selected for the analysis in this paper. Two different locations are selected due to the composite nature of this particular truss. Although one may expect the upper truss chord to be in compression at midspan, local bending (with the deck) dominates the response. This local bending of the upper chord members is also of interest at midspan because the deck is thinner and the upper chord truss members also have smaller cross sections resulting in potentially larger stress demands.

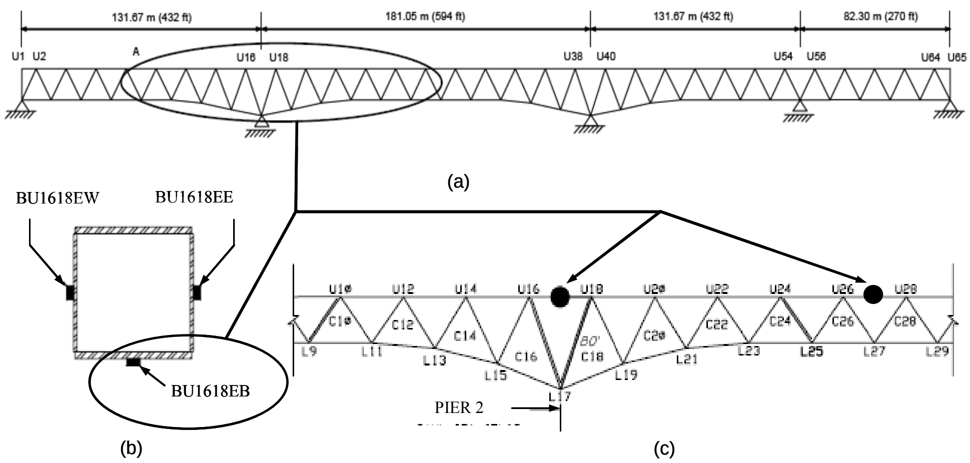


Figure 5.15. (a) Structural schematic of the bridge (b) sensor placement on members of interest, and (c) location of the members of interest selected for the reliability analysis.

Daily maximum stresses are computed from the measurements of four sensors centrally placed on the bottom flange of their respective upper chord truss members. Two sensors are located above the main support (one in each direction of traffic) and two sensors are located at the center of the main span of the bridge (again one in each direction of traffic). Each sensor records approximately 90 days of data. The number of observed days is not the same for all sensors due to the data being trigger-based, controller malfunction, and/or sensor malfunction. Table 5.7 shows the statistical descriptors of the daily maximum stresses for each of the four sensors. From the data, it appears that the eastbound lane experienced slightly greater stress demands and that the upper chord at bridge midspan is subjected to greater live-load stresses than the one above the main support. It is also observed that the bridge experiences very small live-load stresses compared to the average yield strength of 380 MPa for the M270 Grade 50W steel (Frangopol et. al, 2008).

Table 5.7: Daily maximum live-load stress descriptors for the upper truss chord at midspan and above main support in both directions of traffic

Descriptor	Span16-18 Over Support (Eastbound)	Span16-18 Over Support (Westbound)	Span26-28 Midspan (Eastbound)	Span26-28 Midspan (Westbound)
Number of days monitored	92	88	93	88
Average daily maximum stress, μ_{Yn} (MPa)	8.33	7.99	12.75	12.01
Std. dev. of the daily maxium stress, σ_{Yn} (MPa)	1.13	1.12	2.16	1.56
Maximum recorded daily maximum stress (MPa)	10.75	10.97	16.98	16.12
Minimum recorded daily maximum stress (MPa)	3.63	3.20	5.61	5.56

Using this data, Span 16-18 (Eastbound) and Span 26-28 (Eastbound) are selected for the reliability analysis. Both the midspan and the over support locations are considered due to differences in member sizes and the deck cross section affecting both the resistance capacity and the dead loads. Although the data in Table 4 could be utilized directly to characterize the daily EVDs for both sensor locations, it is first desirable to investigate if longer observation timeframes provide more accurate (less uncertain) characterizations of the EVDs. For this purpose, maxima are selected from the same data sets by picking the maximum value from timeframes of increasing length (e.g., every two days, every three days, and so on) thus creating new vectors of maximum values. Once each vector of maxima is established, the mean and standard deviation are computed, and Equations 5.6 and 5.7 are used to define the respective EVDs. The results from these calculations are shown in Figure 5.16 for the eastbound sensor at bridge midspan.

Ideally, each successive distribution should shift slightly to the right on the abscissa and no change in shape should be present. While the first aspect is observed as expected, a large change in shape between the 1 day, 2 day and 3 day maxima indicates the presence of routine short term fluctuations in the data. For the same data, the 3, 4, and 5 day distributions are nearly identical in shape indicating that the EVD is well defined by these timeframes for the available data. Because this analysis only had approximately 90 days of data, the standard deviations begin to increase for the 6 through 12 day observation timeframes as there are fewer and fewer maximums available to define the EVD distribution parameters.

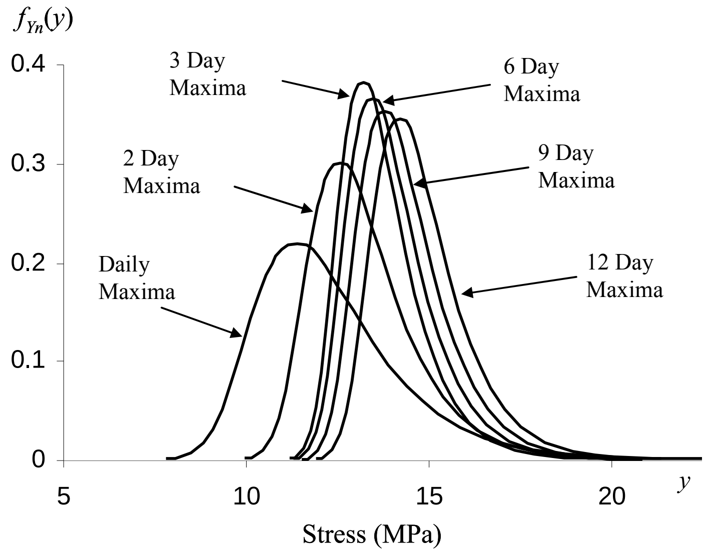


Figure 5.16 Optimization of the observation timeframe for 93 days of data for Span 26-28 (Eastbound)

Based on these results, the 3 day distribution is selected as the optimal timeframe from which to select the maximum values because it minimizes the standard deviation of the EVD and maximizes the number of available maximum value observations once a stable shape is obtained. Table 5.8 reports the monitoring based 3yr and 75yr Type I Gumbel EVD parameters.

Table 5.8. Type I Gumbel 3 year and 75 year EVD parameters

Sensor	Span16-18 Over Support (Eastbound)		Span 26-28 Midspan (Eastbound)	
Descriptor	3 Day EVD	75 Year EVD	3 Day EVD	75 Year EVD
Mean, μ_{Yn} (MPa)	9.13	14.00	14.26	23.03
Std. Dev., σ_{Yn} (MPa)	0.684	0.684	1.23	1.23
Charecteristic value, μ_n (MPa)	8.82	13.68	13.72	22.49
Shape factor, α	1.88	1.88	1.04	1.04

The impact of this choice (optimizing the observation timeframe and selecting the 3 day EVD instead of the 1 day EVD) is illustrated in Figure 5.17 which shows the transformation of both the 1 day and 3 day EVDs to a 75 year EVD using Equation 5.8. It is seen that a selection of the daily observation timeframe for this data would result in a significantly greater mean value and standard deviation for the 75 year EVD.

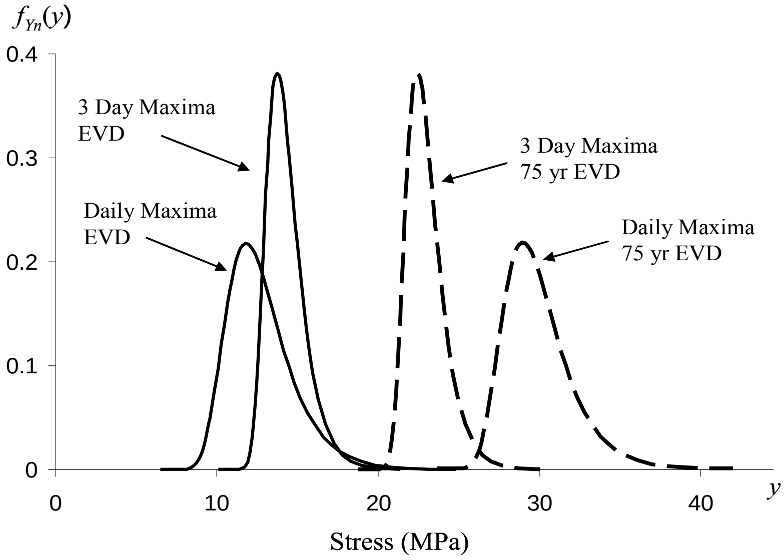


Figure 5.17. A comparison of the transformation of the same data to a 75 year EVD observed in two separate timeframes.

<u>*Estimation of Parameter Variability and Conduct of the Reliability Analysis*</u>

With the selection of a 3 day observation timeframe and the characterization of the 3 day EVD mean and standard deviation, the variability of each parameter is investigated. Although these particular 92 and 93 day datasets are best observed using 3 day maxima, neither distribution parameter reaches a stable value within the 90 days. This is illustrated by Figure 5.18 which, beginning second recorded maximum value (after 6 days of monitoring), shows the rolling mean and the rolling standard deviation for sensor 26-28 Eastbound.

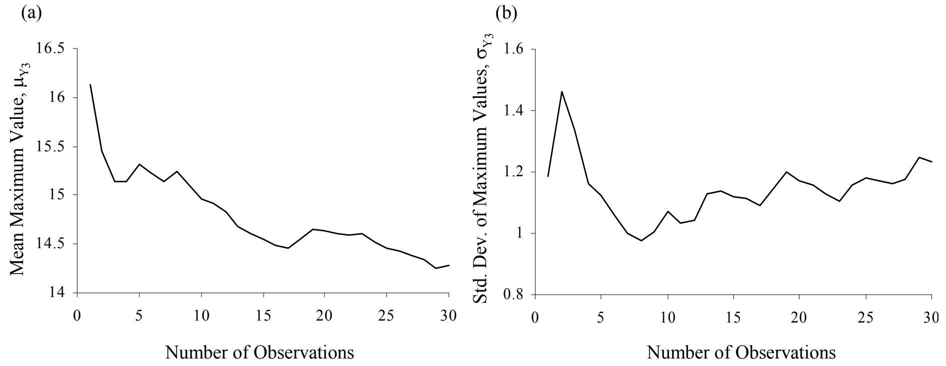


Figure 5.18. Beginning with the second observation, (a) the mean and (b) the standard deviation of the maximum values as each additional 3 day maximum is recorded.

Error based approach

Table 5.5 and Table 5.6 are utilized to select the coefficients for the error-based approach (Equation 5.16). From these tables, a = 0.1 for 30 data observations and b = 0.045 for the 3-day observation timeframe (interpolated). Using this information and sensor 26-28 Eastbound as an example, ε_{obs} is normally distributed with parameters ~N(0, 1.43) where 14.26 x 0.1 = 1.43 MPa for 30 data observations. Likewise, $\varepsilon_{timeframe}$ is normally distributed with parameters ~N(0, 0.642) where 14.26 x 0.045 = 0.642 MPa. Table 5.9 shows the random variable distributions, parameters, and sources utilized to conduct a FORM analysis for the performance function identified in Equation 5.16. All parameters are reported as stresses in MPa (linear elastic behavior has been assumed in this work). Also, each distribution is reported in terms of its mean and standard deviation.

Conducting the analysis, the reliability index for the upper truss chord above the support is β = 8.99 and for the upper chord at bridge midspan is β = 9.28. These results are consistent with the park and crawl tests conducted after construction (Figure 5.12) and the bridge maintains a high level of in-service safety. It is noted that this particular structure has an extremely low live to dead load ratio and that the monitoring stresses are also very small with relation to the yield stress of monitored members.

Table 5.9. Reliability analysis distributions, parameters, and sources (error-based approach)

Member	Random Variable	Distribution and Parameters (MPa)	Source
Span 26-28 Upper Chord Eastbound (Midspan)	R	Normal (380, 28)	Frangopol et al., (2008)
	L_D	Normal (92.7, 4.9)	Frangopol et al., 2008
	L_L	Gumbel (23.03, 1.23)	Monitoring data (75 yr EVD)
	ε_{obs}	Normal (0, 1.43)	Estimated
	$\varepsilon_{timeframe}$	Normal (0, 0.642)	Estimated
Span 16-18 Upper Chord Eastbound (Support)	R	Normal (380, 28)	Frangopol et al., 2008
	L_D	Normal (109, 5.7)	Frangopol et al., 2008
	L_L	Gumbel (14.0, 0.68)	Monitoring data (75 yr EVD)
	ε_{obs}	Normal (0, 0.913)	Estimated
	$\varepsilon_{timeframe}$	Normal (0, 0.411)	Estimated

Approach treating monitoring-based parameters as random variables

Treating the monitoring-based live load parameters as random variables, the variability of each parameter is estimated using Equation 5.13. Applying this equation, the variability of both the mean and the standard deviation of the 3 day EVD is

$$\text{Span 26-28:} \qquad \sigma_{\mu_{Yn}} = \sigma_{\sigma_{Yn}} = \frac{\sigma_{Yn}}{\sqrt{m}} = \frac{1.23}{\sqrt{31}} = 0.221MPa \tag{5.20}$$

$$\text{Span 16-18:} \qquad \sigma_{\mu_{Yn}} = \sigma_{\sigma_{Yn}} = \frac{\sigma_{Yn}}{\sqrt{m}} = \frac{0.684}{\sqrt{30}} = 0.124MPa \tag{5.21}$$

It is again noted that the magnitude of these deviations is extremely small and moreover with respect to member capacity. If instead one considers the coefficient of variation of the mean and standard deviation with respect to the estimated variability, they are approximately 2% for the mean and 17% for the standard deviation for both sensors. For this analysis Table 5.10 shows the 3 day EVDs, the 75 year EVDs, and the variability of the EVD mean and standard deviation parameters.

Table 5.10. Based on approximately 90 days of monitoring data, the 3 day EVD, the transformed 75 year EVD, and the variability of the EVD mean and standard deviation parameters

Sensor	Descriptor	3 Day EVD	75 Year EVD	Parameter Variability	
	Number of Observations	m = 31	n = 9131	m = 31	
Span 26-28 Eastbound sensor at bridge midspan	μ_Y (MPa)	14.26	23.03	mean	23.03
				standard deviation	0.221
	σ_Y (MPa)	1.23	1.23	mean	1.23
				std. deviation	0.221
	Number of Observations	m = 30	n = 9131	m = 30	
Span 16-18 Eastbound sensor above support	μ_Y (MPa)	9.13	14.00	mean	14.00
				standard deviation	0.124
	σ_Y (MPa)	0.684	0.684	mean	0.684
				std. deviation	0.124

The 75 year EVDs shown in Table 5.10 are now used for the reliability analysis of these members. Since the calculation of the reliability index requires the mean and standard deviation of the Type I EVD (one value for each parameter), incorporating the results of Table 5.10 into a reliability analysis requires multiple iterations of the analysis using each time different realizations of the EVD parameters. To do this, a Monte Carlo simulation of the reliability analysis is conducted that randomly changes the mean and standard deviation parameters according to the variability reported in Table 5.10 resulting in a distribution of the reliability index. Table 5.11 summarizes the parameters for the analysis. Elastic behaviour is assumed and each distribution is characterized by its mean and standard deviation.

Conducting the analysis, the mean reliability index for the upper truss chord at bridge midspan is $\beta = 9.297$ and for the upper chord above the support is $\beta = 8.994$. These results are also consistent with those of the park and crawl tests conducted after construction (Figure 5.12) and they indicate that the bridge maintains a high level of in-service safety.

Table 5.11. Reliability analysis distributions and parameters (parameter uncertainty approach)

Member	Random Variable	Distribution and Parameters (MPa)	Source
Span 26-28 Eastbound Upper Chord at Midspan	R	Normal (380, 28)	Frangopol et al., (2008)
	L_D	Normal (92.7, 4.9)	Frangopol et al., (2008)
	L_L	Gumbel (23.03, 1.23) *	Monitoring data (75 yr EVD)
Span 16-18 Eastbound Upper Chord at Support	R	Normal (380, 28)	Frangopol et al., (2008)
	L_D	Normal (109, 5.7)	Frangopol et al., (2008)
	L_L	Gumbel (14.0, 0.68) *	Monitoring data (75 yr EVD)

** These parameters are random variables themselves as indicated in Table 5.10*

Figure 5.19 depicts the distribution of the reliability indexes based on 2000 simulations of the analysis carried out for each member. Because this particular structure experiences small live load stresses relative to both its capacity and dead load, the reliability index is large in magnitude and the variability of the EVD parameters has little impact on the reliability index although a clear distribution is present. This result is not to be expected for all structures, and especially not for short span bridges. Regardless, the methodology provides a rational approach for the inclusion of monitoring data into a reliability analysis that considers both time effects and the treatment of the uncertainties inherent to any monitoring data set.

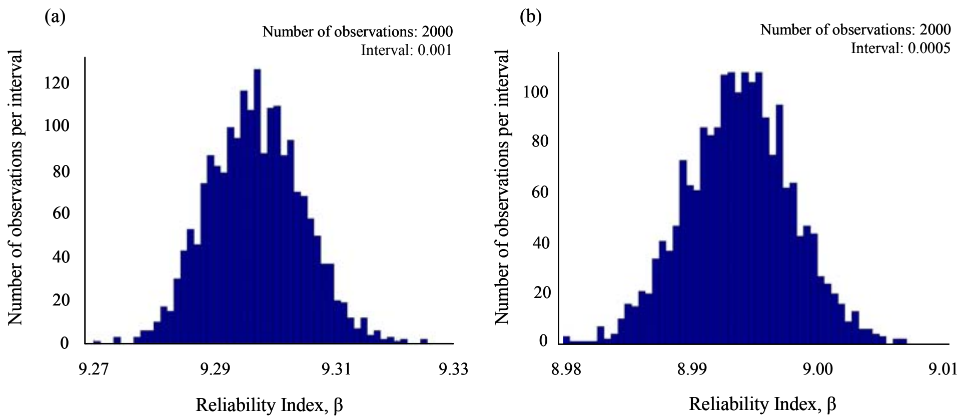


Figure 5.19. Distribution of the reliability index for the eastbound sensors located (a) at bridge midspan and (b) above the support.

5.5 Conclusions

The major findings obtained from Chapter 5 are summarized as follows:

1. Extreme value statistics can be applied to bridge monitoring data to characterize monitoring based live load distributions for use in a reliability analysis. Although the total live load demand is the effect of many processes that occur at different and varying frequencies, the end result (demand upon the structure) can be viewed holistically and an extreme value distribution characterized. The application of extreme value statistics in this manner is advantageous because it provides a simple and efficient data processing approach and prevents the difficult modeling of vehicle weights, speeds, configurations, side-by-side truck crossings, wind effects, temperature effects, etc. Furthermore, the asymptotic behavior of extreme value distributions provides a mechanism to incorporate time effects into the analysis. Once defined in any observation timeframe, a transformation can be utilized to relate the EVD to the desired return period consistent with code requirements.
2. The characterization of EVD parameters will always occur with less than perfect information. Because the live load on highway bridges is highly random and because monitoring based assessments will occur in short intervals with respect to the lifetime of the structure, it is necessary to optimize the timeframe from which maximum values are selected. This optimization must balance the benefit of using a longer observation timeframe that allows short-term fluctuations to average out against the disadvantage of having less maximum values available with which to characterize the distribution. The optimal timeframe can be obtained by creating the vectors of maximum values for timeframes of increasing length and be selecting the timeframe with the lowest standard deviation.
3. Once defined, EVD parameters are subject to certain degree of variability based upon how many point estimates were used for their characterization. It was demonstrated that the Central Limit Theorem can be utilized to determine the variability of the mean and standard deviation parameters of a Type I Gumbel EVD formed from the effects of separate random processes. This result enables the estimation of parameter variability directly from the number of maximum values in the data set and their standard deviation. Separately, coefficients were introduced to estimate this variability in terms of error. The introduced coefficients are preliminary in this study and need much further refinement.

4. The parameter variability of a monitoring based distribution can be addressed within a reliability analysis in two ways. If the distribution parameters are considered as random variables, multiple simulations of the analysis can be conducted in which the distribution parameters are randomly selected. For this approach, the end result is a distribution of the reliability index which can be utilized for maintenance and management decisions. If instead an error based approach is utilized, a more traditional reliability analysis is conducted with the addition of the error term (s) which results in one realization of the reliability index.
5. While the proposed approach to characterize monitoring-based distributions has a number of strengths, it also has some limitations. Because only maximum values are considered, a significant amount of information is discarded which likely eliminates a more detailed study of the underlying phenomenon and contributing sources of uncertainty. The method is best suited for a top-down analysis where simplified models of resistance and demand are employed to calculate structural safety or as a tool to specifically determine the live load distribution within a more detailed bottom-up analysis. The proposed approach may also prove useful in determining when more detailed inspections or analysis of the structure are necessary by providing in-service assessments of the reliability index over time. Future work on this method will investigate the development of metrics that indicate changes in structural performance over time based on changes in the EVD parameters.

Chapter 6

LIFETIME STRUCTURAL HEALTH MONITORING BASED ON SURVIVOR FUNCTIONS, HAZARD FUNCTIONS, AND COST

Abstract

This chapter presents different approaches to the time-dependent reliability problem. Beginning with basic reliability concepts and the need for structural reliability (as a subset of classical reliability) for the performance-based analysis of civil infrastructure, the differences, assumptions, and limitations for each approach are discussed. The motivation for this chapter is threefold. First and especially to the new researcher, it may not be clear what basic principles are being combined, what assumptions are being made, or what limitations are present in the provided model when reading the literature. It is possible to inappropriately combine principles from the different approaches, misinterpret the implications of the assumptions associated with each approach, or to not understand which model is best suited for a particular application. This drives the second motivation for the chapter which is to investigate if any particular

approaches are best suited for the inclusion of SHM and how monitoring can fit into each of the approaches. Lastly, the third motivating factor for this chapter is to promote the identification of what *adoptions in concert* (e.g. which common metrics and management guidelines) are required to implement, compare, and contrast SHM-enabled time dependent reliability analyses. An application is provided. This application includes risk and presents an approach to investigate the utility of monitoring in a prior analysis to provide an estimate of the monitoring benefit for use as a consideration for the design of the monitoring system.

6.1 Introduction

Reliability is often reported through the reliability index simply as a number, e.g. $\beta = 3.8$. Likewise, risk is typically reported with a dollar amount, e.g. \$230,000. Although such numbers can serve as a general comparison to a like analysis, they are not crisp and raise additional questions. Are these numbers cumulative or based on a point-in-time analysis? Are time effects considered and if so how? Are the values conditioned on past safe performance? Under what conditions is the analysis conducted and for what period of time? To fully understand the results of a reliability or risk analysis, these questions must be clearly addressed in the model description or aside the reported values.

The underlying concepts for reliability and lifetime characteristics are often introduced using actuary statistics. For example, if one can observe a large population of living organisms over their entire lifespan, then one can begin to relate quantities such as the probability of death at any particular time or within any particular interval for the population. Likewise, for any specific age one can estimate the percentage of the population that is no longer living or its complement, the percentage of the population still surviving. Instead, if an analysis conditions on past safe performance (the fact that a particular member of the population is still living at a particular time), then the future likelihood of failure (death) can be calculated for any future time or time interval.

These concepts can be used to define lifetime functions that describe the reliability of an item, member, system, or structure over time. These functions (in the order described in the preceding paragraph) are the probability density function of the time to failure $f(t)$, the cumulative distribution function of the time to failure $F(t)$, the survivor function $S(t)$, the hazard function $h(t)$, and the cumulative hazard function $H(t)$. Each function is completely defined in Section 6.2. The relationships defined by these functions are also termed lifetime characteristics.

The use of lifetime functions and the description of lifetime characteristics have been extended to and have proven useful in the field of mechanical engineering. However, instead of death (as compared to description of actuary statistics), a clear measure of acceptable performance must be specified and the conditions under which an experiment is performed become important. For example, the acceptable performance of a machine piston (e.g. the condition that it exhibits less than a 0.001 loss of diameter thickness due to wear) might be investigated with respect to 10000 operating hours at 5000 cycles per minute at a temperature of 200°C. For such an experiment, a change of any of the parameters (time, cycles/min, or temperature) results in a change in its reliability and the associated lifetime functions. Despite this sensitivity to operational and environmental conditions, reliability concepts are useful for mechanical engineering applications because the entire lifetime of machine components can often be observed and because the conditions can often be controlled across large numbers of experiments.

The extension of reliability concepts into civil engineering again increases the assumptions required and the problem complexity. For civil structures, acceptable performance is defined using a limit state. Although a limit state can be defined by structural collapse, rupture, overturning, etc., most often a limit state is used to define a threshold of safe performance (e.g. the onset of yielding, excessive deflections, or damage). Three primary challenges present themselves in collecting the statistical data required to define the performance of civil structures with respect to defined limit states. First, limit states may not be easily observable. Detecting such events such as the yielding of the outermost fiber, debonding of rebar within reinforced concrete, or the initiation of corrosion requires very specific and dedicated monitoring or testing regimens. To date, programs that support such databases are not fully developed. Second, the operational and environmental conditions are not controllable or consistent across the observation of any particular structure or especially across the observation of different structures. Loads (of all types), environmental stressors, and the aging process are all random. Moreover, each type (material and structural configuration) and length of structure will experience these conditions differently (e.g. short span structures and long span structures have inherently different responses to traffic loading). Comparatively, civil structures do not offer the same possibility for controlled experiments afforded to many mechanical engineering applications. Third, the lifetime of structures is long enough (in some cases centuries) and extreme load events and combinations of interest (e.g. flood, hurricane, accident, or overloaded truck) are infrequent and random enough that characterizing accurate lifetime characteristics via statistical observation is impractical if not impossible.

In response to these challenges, the field of structural reliability was developed to use probabilistic data to calculate and predict the probability of a limit state violation for engineered structures at any stage of their service life (Melchers, 1999). The result of such calculations is reported as a probability of failure, which is equivalent to the probability a limit state violation occurred. The reported results are dependent on the resistance and load models employed which are most often themselves functions of time for civil applications. This requires either that time effects are incorporated into the load and resistance terms enabling the evaluation of the integral in a time invariant manner, or the use of methods to evaluate the integral over time with the resistance and load terms remaining functions of time.

Although related, there are distinct differences between the actuary example provided, the mechanical engineering piston description, and that of structural reliability. In forming an analysis, it is important to understand and to clearly state how the probability of failure is obtained. Is it statistically observed? Are environmental conditions present? Is it based on expert opinion/belief? Is it calculated using structure-specific parameters? If it is indeed calculated, then particular attention must be placed upon correctly identifying time effects for both the resistance term(s) (typically decreasing in time) and for live loads (typically increasing in time). For example, the load term(s) in particular should be consistent with the methodology utilized for management decisions. It is possible to use a performance based live load that increases in time with the age of the structure and it is also possible to use a live load that is calibrated to a code requirement and held constant over time (e.g. a 75 year live load).

This chapter discusses several approaches for the construct of lifetime functions for use in a reliability-based life-cycle analysis for civil structures. Different modelling choices and their implications are demonstrated. After developing the lifetime functions in a classical sense, the extension to structural reliability concepts is presented. Advantages, disadvantages, and model limitations are illustrated to include the incorporation of risk in life-cycle calculations. The primary motivation for this investigation is that a critical understanding of each approach assists the development of monitoring strategies and the identification of common metrics (adoptions in concert) that enable the comparison of different modelling approaches and monitoring alternatives. The potential impact of SHM is discussed for each approach and the quantification of monitoring utility is demonstrated using life-cycle calculations. Lastly, a method to estimate the anticipated monetary benefit of SHM over the life of a structure and to use this estimation as a design constraint for the monitoring system is presented.

6.2 Classical Lifetime Functions

The time to failure of a component is defined as the time elapsing from the time the component is put into operation until it fails for the first time (Hoyland and Rausand 1994). This time to failure is uncertain and it is natural to interpret it as a random variable T (Hoyland and Rausand 1994). Statistical data collected for the service life of previously and currently used similar components can be compiled into histograms and frequency diagrams which are fitted into the best fit time to failure PDF distributions. It is this therefore the probability density function of the time to failure $f(t)$ which provides the link between available statistical data and predictive lifetime models (Okasha and Frangopol, 2008).

The Weibull distribution is often used in the aerospace industry, mechanical engineering, and manufacturing to model the time to failure probability density function (PDF) (Frangopol and Okasha, 2008). It has also been used in the field of structural engineering. One example is used in van Noortwijk and Klatter (2004) who used a Weibull distribution to model the time to failure of bridges based on a study of in-service bridges and demolished bridges in the Netherlands. The PDF of the Weibull distribution can be defined as (Leemis, 1995)

$$f(t_f) = \kappa\lambda(\lambda t)^{\kappa-1} e^{-(\lambda t)^{\kappa}} \qquad \text{for} \quad t, \kappa, \lambda > 0 \tag{6.1}$$

where λ is a scale parameter and κ is a shape parameter. Figure 6.1 shows the PDF of a Weibull distribution with the parameters $\lambda = 0.05$ and $\kappa = 2$.

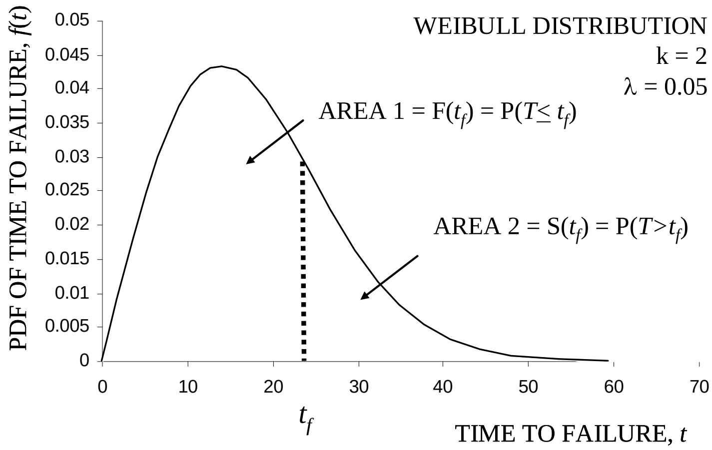


Figure 6.1. Geometric relationship between the PDF of the time to failure $f(t)$, the survivor function $S(t)$, and the cumulative probability of failure $F(t)$ (adapted from Frangopol and Okasha, 2008).

Reasonably, Figure 6.1 might apply to a bridge deck as most failures (in this figure) occur between years 10 and 25. This PDF would be developed from statistical observations of the performance of many bridge decks operating under many different environmental conditions. It is noted that the area under the PDF must be equal to one.

Figure 6.1 is the desired starting point for any lifetime analysis. Once defined, each of the other lifetime functions can be quickly derived from $f(t)$. One limitation of $f(t)$ as described above is that it is obtained from statistical observations. As such, the accuracy and applicability of the model will depend on whether or not the data collection process (type of structure, environmental conditions, and usage) is representative of the individual structure considered for analysis when using the model. Ideally, separate and uniquely defined $f(t)$ functions would be required for each type of bridge deck, operating under different types of environmental conditions, and undergoing different types of loading. Of course, this is not possible. The importance of structure type, environmental conditions, and usage across bridge components on these types of curves/functions is currently unknown.

Although there is room for interpretation, using statistical data to create $f(t)$ is closer to an empirical/qualitative approach than it is to analytical/quantitative approach. Using this method, SHM could improve the accuracy of the data collection process by better determining whether or not the failure condition of interest has occurred. However, this is perhaps a limited use of the potential of SHM as the goal is typically to develop a structure-specific data-driven approach (e.g. performance-based). The ability to update an empirical model using structure specific information would require the identification of structural data, environmental conditions, or loading data that could be correlated to the time to failure of structures exposed to similar conditions. Then, if provided (for example) 30 different $f(t)$ curves for bridge decks under different operating conditions, monitoring could direct the user to the most appropriate $f(t)$ curve. Currently, condition specific $f(t)$ curves are not available but data collection efforts that could support the construction of such functions are underway (FHWA, 2008).

Structural reliability calculations offer one possibility to address the challenges or limitations associated with a model based on statistical observation. The same lifetime function relationships that can be developed using Figure 6.1 are applicable (or adaptable) across time dependent structural reliability approaches. As such, they are developed and presented herein.

Once the time to failure PDF is defined, it can be utilized to answer basic probabilistic questions such as what is the probability of failure within the first 10 years, what is the probability of failure between years 10 and 20, and so on. Such questions are answered by integrating the PDF from the lower bound of interest to the upper bound of interest. The time to failure PDF can also be utilized to construct the other lifetime functions. The cumulative time probability of failure $F(t)$ is defined as (Leemis, 1995)

$$F(t_f) = P(T \leq t_f) = \int_0^{t_f} f(u)du \tag{6.2}$$

which captures the cumulative probability of failure up to any specified time of interest (and equal to 1 at the end of the assumed structural lifetime). Instead of using the probability of failure, it may be desirable to use its complement, the probability of survival. This is done using the survivor function $S(t)$ which represents the probability that an item is functioning at any time t, and can be defined as (Leemis, 1995)

$$S(t_f) = P(T \geq t_f) = \int_{t_f}^{\infty} f(u)du = 1 - F(t) \tag{6.3}$$

The survivor function is conceptually similar to the reliability profile or any other performance profile that shows the probability of safe performance over time. These profiles are important because they are typically utilized for the conduct and planning of maintenance and repair activities once a safe performance threshold is established. Using the same Weibull distribution characterized in Figure 6.1, Figure 6.2 shows both $F(t)$ and $S(t)$ over time.

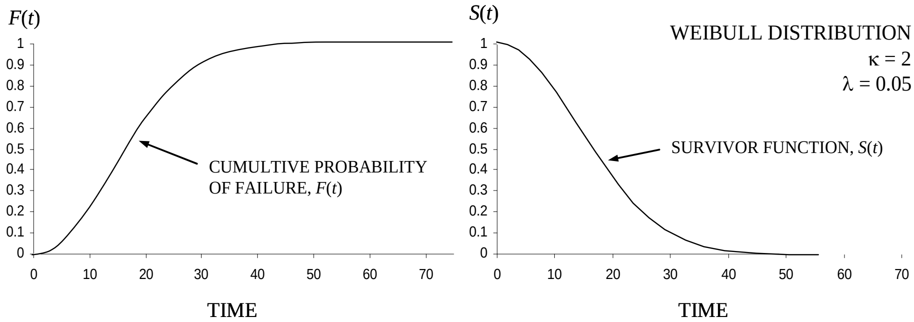


Figure 6.2. The cumulative probability of failure, F(t) and the survivor function, S(t) for a Weibull distribution with parameters κ = 2 and λ = 0.05.

In many cases it may be desirable to condition on past safe performance (e.g. the fact that failure has not occurred). The conditional survivor function demonstrates the effect of conditioning at one specific point in time and is defined as (Leemis, 1995)

$$S_{T|T\geq a}(t) = \frac{S(t)}{S(a)} \qquad \text{for} \quad t \geq a \tag{6.4}$$

Conditioning on past safe performance redistributes the future probability space such that the area under the PDF of $f(t)$ would again be equal to one, $F(t)$ would again start at 0, and $S(t)$ is reset to 1. Figure 6.3 illustrates the conditional survivor function for a = 15 assuming failure has not occurred prior to year 15. It is noted that conditioning (also termed scaling) does not change the general shape of the survivor function. Applied to civil structures, the idea of conditioning on past performance is very attractive as in-service structures are often assessed.

A conditional survivor function is specific to the point of time conditioning is applied. For example, conditioning on safe performance at year 16 (e.g. a = 16) in Figure 6.3 would result in a new and steeper profile. An investigation of conditioning on safe performance across time can be conducted using the hazard function. The hazard function expresses the conditional probability of failure in time $(t, t+dt)$, given that failure has not already occurred as (Leemis, 1995)

$$h(t) = -\frac{S'(t)}{S(t)} = \frac{f(t)}{S(t)} \qquad \text{for } t > 0 \qquad (6.5)$$

This function is often called the instantaneous failure rate. Similar to $f(t)$ its units are failures per unit time and its integration across a small time interval provides the probability of failure for that interval given no prior failure. Unlike $f(t)$ the hazard function must always be positive and non-zero and as such the area under all hazard functions is infinity.

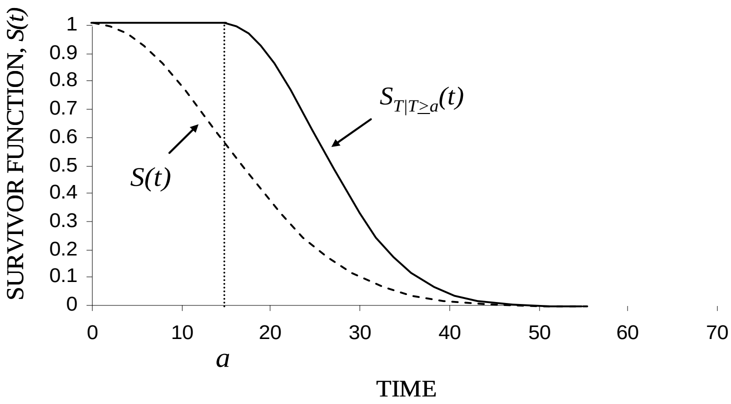


Figure 6.3. Conditional survivor function at year 15 for a Weibull distribution with parameters κ = 2 and λ = 0.05.

The cumulative hazard function $H(t)$ or integrated hazard function does just this and conducts the integration of $h(t)$ to capture the cumulative hazard as

$$H(t) = \int_0^t h(u)du \qquad \text{for } t \geq 0 \qquad (6.6)$$

The cumulative hazard is always increasing with an upper limit of infinity. With respect to life-cycle calculations, non cumulative hazard is typically utilized for risk calculations (e.g. to calculate the monetary value of the cost of failure for a desired time interval). Figure 6.4 shows the hazard function $h(t)$

and the cumulative hazard function $H(t)$ for the Weibull distribution shown in Figure 6.1. It is noted that although this particular $h(t)$ is linear, most are not, and also that the magnitude of the ordinate of $H(t)$ is large in comparison to the other lifetime functions.

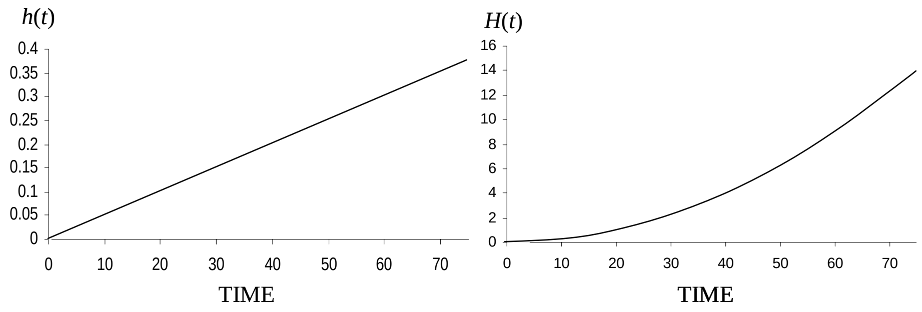


Figure 6.4. Hazard function h(t) and the cumulative hazard function H(t) for a Weibull distribution with parameters κ = 2 and λ = 0.05.

For the interested reader, Table 6.1 provides the equations and numerical results for the first 20 years of Figures 6.1 to 6.4.

Table 6.1. Lifetime functions numerical values for a Weibull distribution with κ = 0.05 and λ = 2.

t	$f(t)$	$F(t)$	$S(t)$	$h(t)$	$H(t)$	$S_{T\|T\geq 15}(t)$
0	0.0000	0.0000	1.0000	-	0	1
1	0.0050	0.0025	0.9975	0.0050	0.0025	1
2	0.0099	0.0100	0.9900	0.0100	0.0100	1
3	0.0147	0.0222	0.9778	0.0150	0.0225	1
4	0.0192	0.0392	0.9608	0.0200	0.0400	1
5	0.0235	0.0606	0.9394	0.0250	0.0625	1
6	0.0274	0.0861	0.9139	0.0300	0.0900	1
7	0.0310	0.1153	0.8847	0.0350	0.1225	1
8	0.0341	0.1479	0.8521	0.0400	0.1600	1
9	0.0368	0.1833	0.8167	0.0450	0.2025	1
10	0.0389	0.2212	0.7788	0.0500	0.2500	1
11	0.0406	0.2610	0.7390	0.0550	0.3025	1
12	0.0419	0.3023	0.6977	0.0600	0.3600	1
13	0.0426	0.3446	0.6554	0.0650	0.4225	1
14	0.0429	0.3874	0.6126	0.0700	0.4900	1
15	0.0427	0.4302	0.5698	0.0750	0.5625	1
16	0.0422	0.4727	0.5273	0.0800	0.6400	0.9871
17	0.0413	0.5145	0.4855	0.0850	0.7225	0.9658
18	0.0400	0.5551	0.4449	0.0900	0.8100	0.9369
19	0.0385	0.5944	0.4056	0.0950	0.9025	0.9016
20	0.0368	0.6321	0.3679	0.1000	1.0000	0.8609

6.3 Application of Lifetime Functions to Civil Structures

There remains a gap between the theoretical possibilities of working with a distribution as defined in Section 6.1 and the practical characterization of such a distribution and use for a civil structure. First, the characterization of such a distribution faces the challenges previously discussed (observability of limit states, changing operational/environmental conditions, and long lifespans). Another important question is to determine what exactly is being modeled and which distribution(s) are appropriate candidates for the model? Non cumulative hazard functions $h(t)$ are often utilized as an intuitive representation of the amount of risk associated an item at time t (Leemis, 1995). In mechanical engineering, machinery components often have a "bathtub" shaped hazard curve as shown in Figure 6.5a. There is an initial "burn in" period of high risk/hazard (A) where manufacturing defects result in failure or where components "wear in." This period is followed by a period of lower hazard associated with the anticipated normal use / function of the component (B). Toward the end of the component's planned life, the hazard increases due to old age, wear, fatigue, etc (C) (Leemis, 1995).

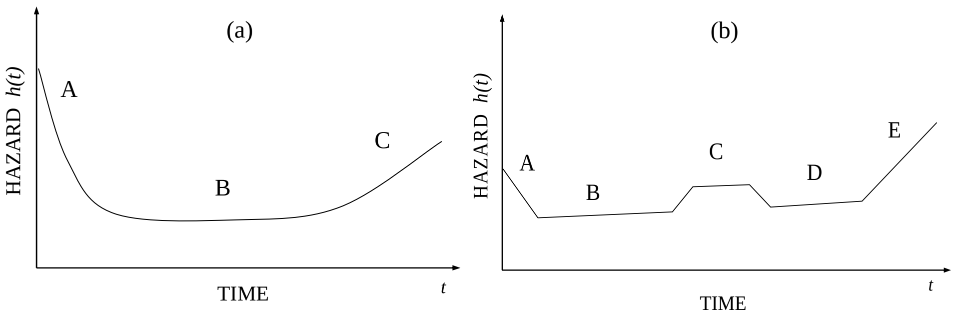


Figure 6.5. Hazard profiles: (a) for a typical machinery component (adopted from Leemis (1995) and (b) for the global performance of a civil structure.

A "bathtub" shape hazard profile also conceptually matches what is experienced/observed for civil structures as shown in Figure 6.5(b). A period of high hazard/risk occurs during construction (A) which is followed by a period of lower and steadily increasing hazard as the structure progresses through its early service life (B). Failure studies have revealed that material defects, construction errors, or design errors often result in failure as deterioration begins to affect the structure, typically around year 35 for highway bridges (Frangopol and Messervey, 2007c). Therefore, unlike a typical bathtub shaped curve, civil structures may have a period of heightened hazard at their midlife (C). This is followed by a period of slightly lower and increasing hazard (D) until the structure reaches old age at which point time the hazard increases more rapidly (E).

Figure 6.5(b) is deliberately not shown as a smooth curve because it may be impractical to model what is observed in reality with one continuous function. Instead, its characterization (hazard function $h(t)$) may be practically conducted using discrete intervals of time as shown in Figure 6.6(a). Working with a discrete model changes none of the relationships between the lifetime functions and the models simply become discrete instead of continuous. Figure 6.6(b) is utilized to notionally introduce the idea of using different distributions to characterize lifetime characteristics. This figure shows the modeling of $h(t)$ as three separate distributions. Such an approach lends itself to the study and characterization of each hazard, construction failure (A), failure at midlife due to defects (B), and failure due to routine usage and old age (C), separately.

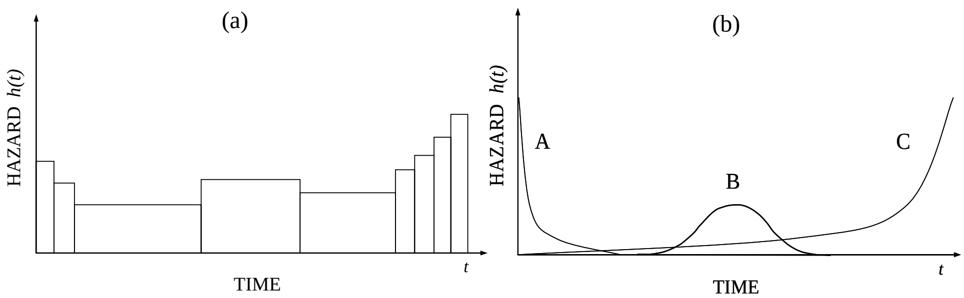


Figure 6.6. Hazard models (a) discrete and (b) using separate hazards.

Because the capacity of a structure and the loads that act upon it are functions of time, the probabilities of failure that result from structural reliability calculations are descriptive of the time interval considered.

6.4 The Construction of Time-Dependent Reliability Profiles

Recalling Equation 2.6, the basic reliability problem when the resistance and load are independent is

$$p_f = P(R - L < 0) = \iint_{R>L} f_R(r) f_L(l) drdl \tag{6.7}$$

The evaluation of the above convolution integral becomes considerably more challenging when one or both of the resistance or load terms are functions of time as

$$p_f(t) = P(R(t) - L(t) < 0) \tag{6.8}$$

If the instantaneous probability density functions $f_R(t)$ and $f_S(t)$ are known, the instantaneous probability of failure $p_f(t)$ can be obtained and integrated over time to find the cumulative probability of failure over time. If the resistance is considered invariant, an alternate solution to this problem is to instead transfer the integration to the load effect which is then assumed to be representative over the entire period as an extreme value distribution (Melchers, 1999). The reliability problem is then solved as a time invariant problem and the resulting probability of failure is cumulative and specific to the time (load effect) considered. One interpretation or use of this approach would be to assess the minimum lifetime safety by considering the maximum lifetime load and the minimum lifetime resistance as

$$p_f(T_L) = P(R(t_L)_{\min} - L(t_L)_{\max} < 0) \tag{6.9}$$

This scenario of minimum resistance and maximum load effects is shown in Figure 6.7. Because all parameters are treated as invariant with respect to time and the entire life of the structure is considered (for the time effects), the problem becomes equivalent to a time invariant reliability problem and the conditions present at the considered point in time (end of life) are assumed applicable to the entire life. Strictly applying Equation 6.9 only, there is no possibility to condition on past safe performance or to appropriately quantify risk in any interval of time smaller than the entire lifetime. Although this approach may be appropriate as a design benchmark or design check, it is not very appropriate for management decisions. Instead, it is necessary to predict structural performance over time in a time dependent manner.

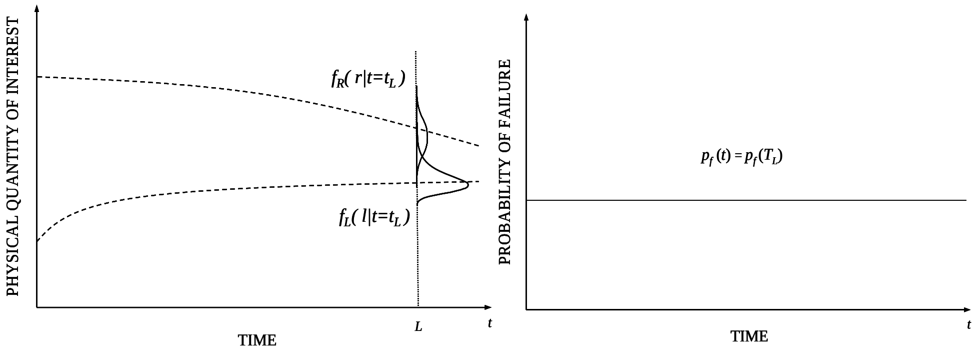


Figure 6.7. Modeling minimum lifetime safety as a time invariant reliability problem

Methods to conduct a time dependent reliability analysis are distinguished by whether the load and resistance terms are treated as continuous functions (instantaneously) or if their time effects are calculated specific to the point in time analyzed. Three approaches are briefly described herein. They are:

- The time discretized approach
- The point-in-time approach
- The cumulative-time approach

Time Discretized Approach: The time discretized approach evaluates reliability over time by considering small and discrete increments of time (with respect to the overall lifetime). For civil structures, one year intervals are typically selected (Melchers, 1999). All analysis random variables (load and resistance terms) are related to the selected time interval and the analysis is carried out resulting in a probability of failure that corresponds to and is specific to the length of time considered. A cumulative model can be constructed by summing the probability of failure for each time interval across time if statistical independence is assumed between the time intervals. The main advantage of the time discretized approach is its simplicity. The main disadvantage is the assumption of statistical independence between time intervals.

Point-in-time Approach: This cumulative time integrated approach is an adaptation of Equation 6.9 and the scenario presented in Figure 6.7. However, instead of considering the time effects at the end of the structure's lifetime only, they are considered successively at many points in time across the structure's lifetime. Intuitively, this can be thought of analyzing the entire lifetime of the structure many times as the structure ages. Each calculation provides the probability of failure specific to the point in time considered. For example, at $t = 30$, the degradation at year 30 is used for the resistance term and a 30 year EVD is used for the load effect. A time invariant calculation of the reliability is conducted and the resulting probability of failure represents the probability of failure at year 30. Figure 6.8 shows this process at three points during the structure's lifetime. Of course, more points in time are required for an effective analysis of the evolution of the failure probability over the life of the structure. Annual increments are likely appropriate. Each successive analysis provides $F(t)$ for that point in time. The survivor function $S(t)$ can be created directly as 1-F(t) at any point in time. By analyzing the change between intervals, $f(t)$ and $h(t)$ can be created. This change between intervals can also be utilized to quantify the risk particular to a certain interval or set of intervals.

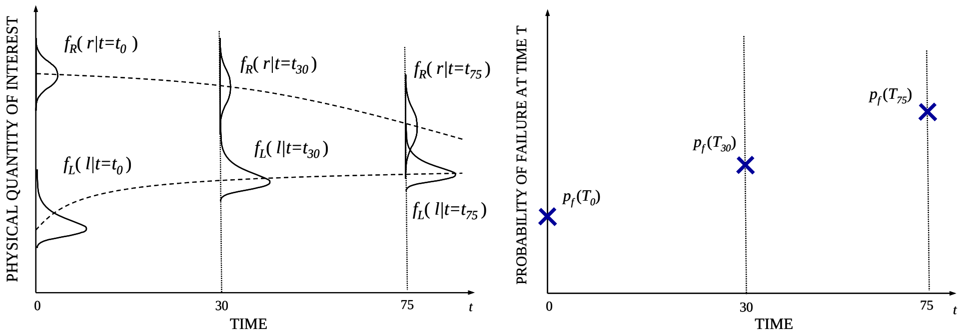


Figure 6.8. Point-in-time approach using three points of analysis

The main advantage of the point-in-time approach is that it allows a time invariant calculation of the probability of failure. Over time, loads and resistances can be changed, although the net effect of the change in these terms must result in an increase in the probability of failure (with respect to the last point in time analyzed). This is ensured if extreme value theory is utilized to account for the load effect. The main disadvantage of the approach is that it is inherently a discrete combination of multiple analyses. If employed, SHM can be utilized to characterize the live load effect for any considered lifetime as developed in Chapter 5. SHM can also be utilized in this approach to characterize or update the resistance terms or degradation process.

Cumulative-time approach: Stochastic process theory offers a continuous approach to the evaluation of the reliability problem by treating either or both of the load and resistance terms as continuous functions of time. Typically, a degradation function is used for the resistance and instead the load is treated as a stochastic process. For this reason, the approach is often referred to as an instantaneous approach because instead of transferring the load effects associated with a length of time through the use of an extreme value distribution, the approach considers the realization of dynamic loads as a stochastic process. The stochastic process may consider individual load pulses or may be modeled as a random function of time. Most often, a Poisson model is employed with a mean occurrence rate λ. Load intensities S_i can be assumed as identically distributed and statistically independent random pulses of constant amplitude described by the cumulative distribution function $F_S(s)$. For a component subjected to a single load, the cumulative probability of failure can be calculated as Mori and Ellingwood (1994)

$$F(t) = 1 - \int_0^\infty \exp\left[-\lambda t\left[1 - \frac{1}{t}\int_0^{t_L} F_s\{r \cdot g(\xi)\}d\xi\right]\right] f_{R_0}(r)dr \tag{6.10}$$

where R_0 is the initial resistance, $f_{R0}(r)$ is the probability density function of R_0, and $g(t) = E[G(t)]$ where $G(t)$ is the degradation function (Frangopol and Okasha, 2008). Equation 6.10 must be evaluated by Monte Carlo simulation for realistic deterioration mechanisms (Ciampoli and Ellingwood, 2002).

Applications using this approach for the conduct time dependent reliability analysis can be found in Melchers (1999), Mori and Ellingwood (1992), Enright and Frangopol (1999a) and Enright and Frangopol (1999b). The main advantage of this approach is that it is continuous. The main disadvantage is its complexity and computational effort. If employed, SHM can be utilized to update or better characterize the degradation function and to characterize or update the Poisson process utilized to model the load effect.

Comments on the three approaches and the construct in general Each approach provides the ability to analyze intervals within a structure's planned service life. This is necessary to optimize inspection planning, maintenance activities, repair actions, and to appropriately quantify risk. The *time discretized approach* is simple but approximate and may have very serious limitations in its application to civil structures. In contrast, the *point-in-time approach* directly defines $F(t)$. It is noted that there is a fundamental difference between the time-discretized approach which considers successive independent intervals of time as a series system and the point-in-time approach which analyzes the effect of increasing S and decreasing R within various points-in-time. Instead, the *cumulative time approach* offers a continuous construction of $F(t)$ by treating the resistance and load terms as functions of time. The approach is the most accurate, but also the most difficult to model and execute. The selection of a particular model will likely depend upon the desired accuracy, the available resources (computation effort) available to model the problem, and the assumptions the engineer or infrastructure manager desires to make.

6.5 Application

The application begun in Chapter 4 is continued here for the point-in-time approach. Figure 6.8 again shows the general scenario. A 12.2 meter short span bridge is subjected to deterioration over time which decreases the section modulus of a W690x125 beam with an increasing degree of uncertainty. The load is the average truck as determined in the Gindy and Nassif (2006) study which when placed at the position of maximum moment for this span results in a live load moment demand distribution assumed to be normally distributed with the parameters $N(167.5,\ 77.2)$ *kN-m*. The reliability investigation is conducted with respect to flexure which assumes elastic behaviour and uses the following performance function.

$$g(1) = f_y S - M_{DL} - M_{LL} \tag{6.11}$$

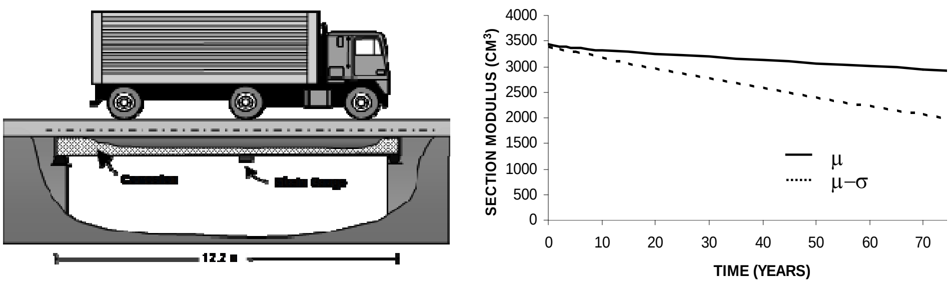


Figure 6.8. Application load scenario and beam section loss over time.

An average daily truck crossing rate of n = 300 is assumed. The appropriate live load effect for any point in time analysis is conducted using the extreme value distribution transformation equations (Equations 4.21-4.25) specific to the normal distribution (for this application). For example, at t = 1 year

$$n = (300 \text{ trucks/day})(365.25\text{days/year})(1 \text{ year}) = 109{,}575 \text{ trucks} \tag{6.11}$$

$$\alpha_n = \sqrt{2\ln(109{,}575)} = 4.82 \tag{6.12}$$

$$\mu_n = 4.81 - \frac{\ln[\ln(109575)] + \ln(4\pi)}{2(4.81)} = 4.29 \tag{6.13}$$

$$\mu_{Yn} = 77.2(4.29) + (167.5) + \frac{(.577216)(77.2)}{4.82} = 508.1kN - m \tag{6.14}$$

$$\sigma_{Yn} = \left(\frac{\pi}{\sqrt{6}}\right)\left(\frac{77.2}{4.82}\right) = 20.53kN - m \tag{6.15}$$

with the result being the 1 year Type I Gumbel EVD with the parameters μ_{Yn} = 508.1 *kN-m* and μ_{Yn} = 8.38 *kN-m*. This live load is used only for the analysis conducted the point in time t = 1 year. Changes in the live load for successive analyses reflect the increased number of trucks associated with length of time analyzed. The resistance for each analysis is calculated as demonstrated in Chapter 4 and as depicted in Figure 6.8. Table 6.2 reports the random variables, their descriptors, and sources utilized for the time dependent analysis.

Table 6.2. Random variables, descriptors, and sources

Random Variable	Distribution type. Mean, and Std. Deviation	Coefficient of Variation (COV)	Source
Yield Stress, f_y (MPa)	N[386, 42.5]	0.11	Nowak and Yamani (1995)
Elastic Section Modulus, S (cm^3)	Normal variable with time	variable with time	calculated
Dead Load Moment, M_{DL} (kN-m)	N[290, 14.5]	0.05	Nowak and Yamani (1995) for COV
Average Truck Live Load Moment, M_{LL} (kN-m)	N[167.5, 77.2]	0.46	Gindy and Nassif (2006)
Live Load Moment, M_{LL} (kN-m)	Gumbel variable with time	calculated	calculated

Reliability analysis software is utilized to evaluate the performance function shown in Equation 6.11 at successive one year intervals across the life of the structure for 75 years incorporating the appropriate time effects. Figure 6.9 shows the resulting cumulative failure probability CDF $F(t)$ and the associated survivor profile $S(t)$.

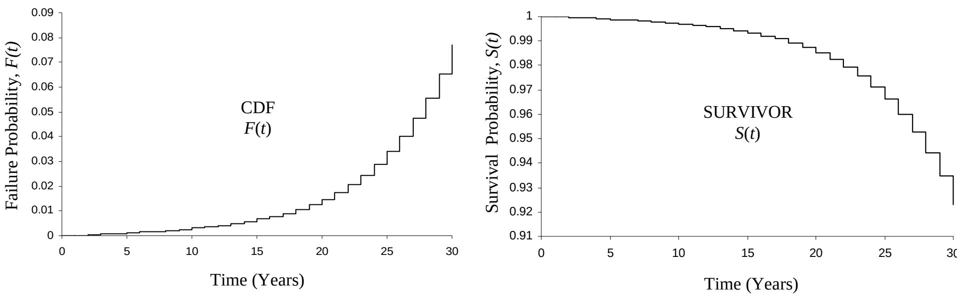


Figure 6.9. Failure probability $F(t)$ and the survivor function $S(t)$.

These profiles can be notionally related to the reliability index or safety margin using

$$p_f = \Phi(-\beta) \tag{6.16}$$

For the first 30 years, the reliability performance profile is shown in Figure 6.10. Assuming a minimum reliability threshold of $\beta = 2.0$, the profile crosses the threshold during year 28.

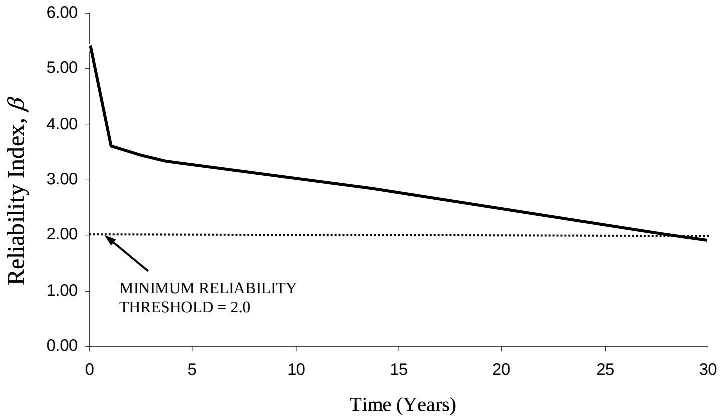


Figure 6.9. Time-dependent reliability profile for the first 30 years.

The results of this particular problem (hypothetical short span bridge) are dominated by the compounding uncertainty associated with future predictions of the section modulus and by the characterization of baseline live load distribution from which the time effects are calculated. SHM should therefore target these two parameters. Evaluation of the resistance over time can be conducting using proof load techniques (e.g. park tests) as discussed in Faber et al. (2000). Characterization of the live load distribution can be conducted using the techniques developed in Chapter 5. A monitoring based live load distribution would no longer be dependent on a non site-specific traffic study or an assumption regarding the average daily truck volume.

Prior Analysis to Estimate Monitoring Utility

The utility of monitoring can be estimated over a structures service life using life cycle calculations to compare different performance profiles. Distinct performance profiles can be obtained by making several assumptions regarding the anticipated benefit of monitoring. Conceptually, Figure 6.10 illustrates the anticipated result of the use of SHM and highlights four focal points which highlight reasons for the differences in the reliability profiles.

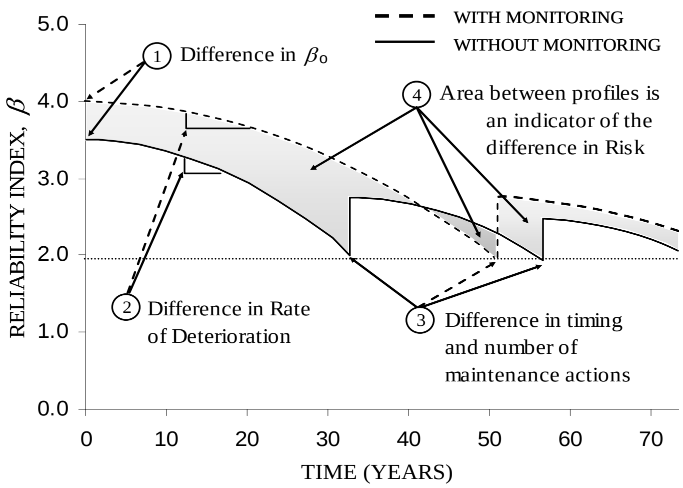


Figure 6.10. Anticipated differences in reliability profiles due to the inclusion of SHM.

Beginning with the initial reliability index, an increase in this parameter is anticipated with the incorporation of monitoring (Figure 6.10, (1)); of course, this is just an assumption, since the results of monitoring could also indicate a decrease in reliability. For the resistance parameters, a park or crawl test can be utilized to validate and update the initial input parameters. System effects not specifically modeled, load distribution patterns not foreseen, composite behavior between members, and even the contribution of uncracked concrete for tensile stresses will result in differences for these random variables with respect to what was originally anticipated. Once measured, Bayesian Updating can be utilized to combine monitored information with that used during design. Combined with the initial reliability index, the rate of deterioration determines when the first maintenance action is required. The second focal point identifies different deterioration rates. Deterioration processes are extremely random and it is anticipated that monitoring will reduce the uncertainty associated with deterioration parameters as shown in Figure 6.10(2). Once the shape of the reliability profile is established, inspection scheduling and maintenance actions can be optimized (Kong and Fragopol, 2005a). In Figure 6.10, maintenance is conducted whenever a minimum reliability threshold of 2.0 is reached. Consequently, the reliability profiles have a different number and timing of required maintenance actions (Figure 6.10, (3)). The fourth and last focal item identifies the difference in the reliability level between the profiles over time implying a difference in the life-cycle risk associated with each profile (Figure 6.10, (4)).

Estimating the utility of monitoring is demonstrated by extending the Chapter 6 application. Figure 6.11 shows the impact of removing uncertainty from the reliability analysis. Specifically, the standard deviation of the section modulus is reduced by 25%, 50% and treated quasi-deterministically (by assigning a very small standard deviation). No other parameters are changed.

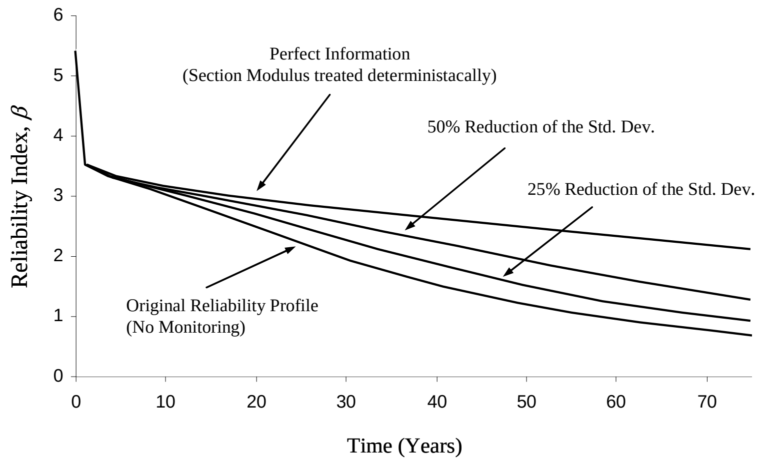


Figure 6.11. Effect of section modulus uncertainty on the reliability analysis.

The assumption is made that monitoring can achieve a 50% reduction of the section modulus uncertainty over time. Practically, this could be achieved through annual planned park tests on the structure. A reliability analysis is then conducted for both the non-monitoring profile and the 50% reduction of section modulus standard deviation profile with respect to a minimum reliability threshold of $\beta = 2.0$. Each time either profile reaches the minimum reliability threshold, the beam is notionally replaced and the deterioration process restarts. Live load effects are not restarted (nor interrupted) in the analysis. Each year the live load EVD is incremented by one additional year. Of interest, no change of mean values (representing a more accurate characterization of the random variables) is investigated nor does the monitoring profile begin with a higher initial reliability index. As such, the analysis is fairly conservative with respect to the anticipated benefit of monitoring.

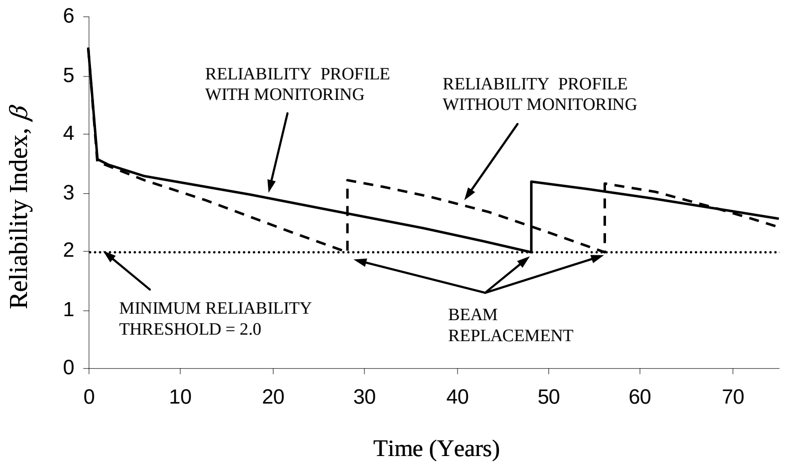


Figure 6.12. Application reliability profiles with and without monitoring.

Figure 6.12 shows the resulting reliability profiles with management actions over a 75 year service life. For the non monitoring profile, beam replacements are required at year 28 and at year 56. For the monitoring profile, one beam replacement is required at year 48. Recalling Equation 4.4

$$C_{ET}{}^{0} = C_{T}{}^{0} + C_{PM}{}^{0} + C_{INS}{}^{0} + C_{REP}{}^{0} + C_{F}{}^{0} + C_{MON} \qquad (4.4)$$

the change in repair costs and the change in the risk costs (cost of failure) are investigated in this application. Assuming an arbitrary beam replacement cost of \$200,000 the repair costs for the no monitoring and monitoring profiles respectively are

$$C_{REP} = \frac{\$200{,}000}{(1+.04)^{28}} + \frac{\$200{,}000}{(1+.04)^{56}} = \$88{,}937 \tag{6.17}$$

$$C_{REP}^{0} = \frac{\$200{,}000}{(1+.04)^{48}} = \$30{,}439 \tag{6.18}$$

The difference in risk costs is investigated by constructing the hazard profiles for both options over the service life using Equation 6.5. The results of these calculations are shown in Figure 6.13.

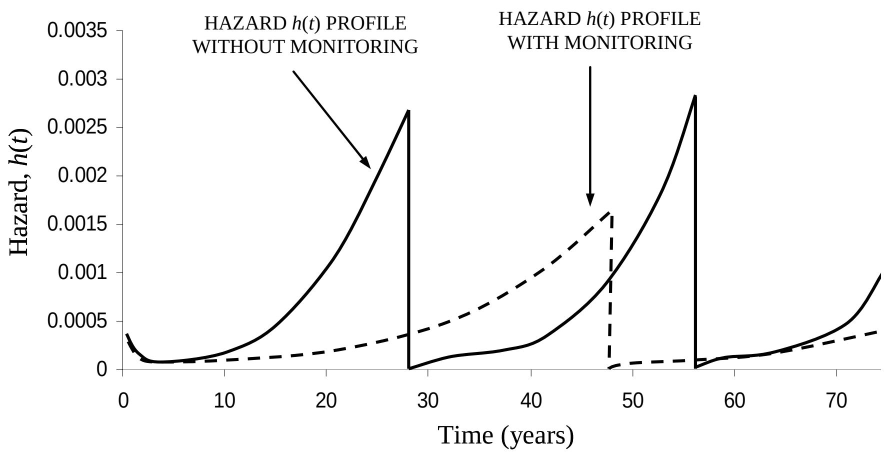


Figure 6.18. Hazard curves with and without monitoring.

Of interest, one cannot generalize that the monitoring profile has less risk. For example, at year 40, it is the monitoring profile that has higher failure rate. However, one can state that the cumulative risk is lower across the monitoring profile. This point is highlighted by Figure 6.19 which shows the cumulative hazard profiles with and without monitoring.

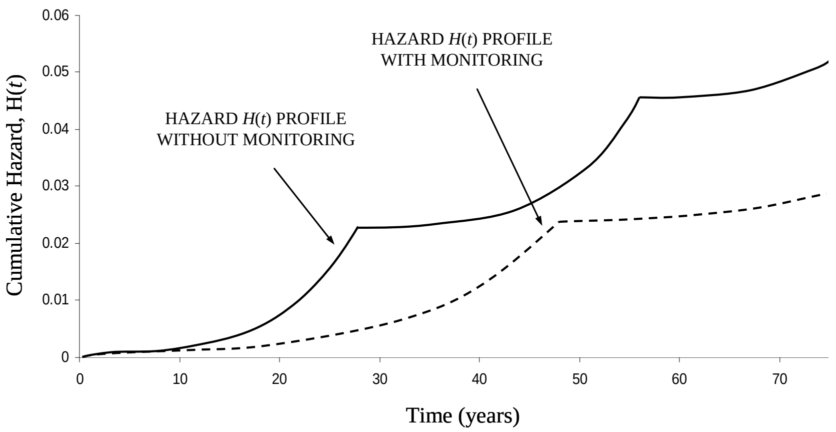


Figure 6.19. Cumulative hazard with and without monitoring.

The hazard profile $h(t)$ is most appropriate to calculate the cost of failure (risk cost) associated with each profile because the risk cost can be appropriately discounted when it occurs using net present value calculations. To make a comparison of the two profiles, a \$10,000,000 consequence of failure C and a discount rate of r = 4% are assumed. The choice of C is arbitrary, is reasonable for a small structure, and lacks a real world example for validation as conducted in Chapter 3 for a large scale structure (I35W failure). The choice for the discount rate is instead consistent with worldwide historical rates. The risk cost is calculated using $h(t)$ for each interval. For example, for year 20, the non-monitoring profile has a hazard of $h(20) = 0.001104$. Therefore the risk during year 20 is

$$Risk_{20} = C_{F20} = \$10{,}000{,}000 \times 0.001104 = \$11{,}040 \tag{6.19}$$

which is discounted to its net present value as

$$NPV = \frac{11{,}040}{(1+0.04)^{20}} = \$5{,}038 \tag{6.20}$$

This process is conducted for each interval (e.g. 75 times) and the results are summed for the 75 year service life. These calculations result in

$$C_F = \$136{,}586 \quad \text{and} \quad C_F^0 = \$66{,}637 \tag{6.21}$$

for the non monitoring and monitoring profiles respectively. As such, the utility of monitoring with respect to these two reliability profiles is calculated as

$$B_{MON} = C_{ET} - C_{ET}{}^0 = (\$88{,}937 + \$136{,}586) - (\$30{,}439 + \$66{,}637) = \$128{,}447 \tag{6.22}$$

This value of $128,447 can be utilized as a benchmark for the design and consideration of a monitoring system. For a bridge manager, a potential cost savings of $128,447 is attainable through the collection of more precise information for the section modulus over time. For the engineer designing a monitoring system, it can now be concluded that the system will be cost beneficial as long as the life-cycle cost does not exceed $128,447 and the system can indeed provide a 50% reduction of the section modulus standard deviation over time.

This analysis did not investigate changes in inspection costs, preventive maintenance actions, or the optimization of maintenance and replacement activities. The costs utilized (failure cost and beam replacement cost) were also reasonable, but arbitrary. However, this analysis did provide a methodology for the inclusion of monitoring in a time dependent reliability analysis and an estimation of the utility for SHM alternatives. The next critical step for such analysis and the consideration of more complex problems are guidelines (adoptions in concert) for the calculation of the consequence of failure, the structural lifetime to be considered, the discount rate, and the appropriate live load for use in the reliability analysis (e.g. performance based or calibrated against a specific return period). Lastly, it is also noted that although SHM has the capability to greatly improve the results of a reliability analysis through the reduction of parameter uncertainty, these benefits are only meaningful if the community as a whole adopts reliability and risk concepts for civil infrastructure assessment, performance prediction, and management.

6.6 Conclusions

The major findings obtained from Chapter 6 are summarized as follows:

1. Classical reliability concepts that define lifetime functions/characteristics can be extended to the assessment and performance prediction of civil infrastructure. In doing so, one must carefully specify if the model is based on statistical observation, expert opinion, or an analytical method.
2. The extension of classical reliability concepts to the analysis of civil infrastructure is marked by several challenges. These include long lifespans, constantly changing environmental conditions, and uncertain loading conditions. The challenges make if difficult to obtain lifetime characteristics through statistical observation. Structural reliability methods can provide an analytical approach to the characterization of lifetime characteristics. Such approaches are well suited for structure specific considerations and the inclusion of SHM data.
3. Civil structures are exposed to different hazards and different forms of risk. Typically an analytical approach (e.g. structural reliability) is limited to the prediction of a technical probability of failure. Including non technical probabilities of failure (e.g. human error) in reliability analyses is an open area of research. Although unanswered, an awareness of non technical probabilities of failure is appropriate.
4. Three different methods for the construction of a time dependent reliability profile were briefly reviewed, the time discretized approach, the point-in-time approach and the cumulative time approach. Advantages and limitations were discussed.
5. The point-in-time approach was demonstrated in an extension of the application started in Chapter 4. In addition, a method to estimate the utility of monitoring in a time dependent reliability analysis through the reduction of uncertainty was presented and demonstrated. In order to make the approach acceptable for comparison to other studies, the standardization of the type of reliability analysis and of the parameters that govern the analysis is required.

Chapter 7

CONCLUSIONS

7.1 Conclusions from the Investigation

Monitoring technologies provide both the opportunity and the obligation to take the next evolutionary step in the design and management of civil infrastructure. Data obtained through monitoring can be used not only to better understand existing structures, but the information can also be utilized to improve the design of future structures. This opportunity fortunately comes at a time of critical importance for civil infrastructure as current approaches may not be adequately accounting for safety or keeping up with the rate of new deficiencies. From this study, the following main conclusions are highlighted.

1. *Paradigm and/or Approach*: It is clear that for any future infrastructure management program, monitoring technologies will have a critical role. However, due to limited resources and potentially conflicting priorities or interests by different interested parties (owner, manager, researcher, user), the development, employment, and inclusion of SHM must occur within a paradigm appropriate for its consideration. This means reliability based assessment, life-cycle management, and risk must be considered when comparing monitoring alternatives. Both risk-based decision making and life-cycle management approaches are appropriate.

2. *Adoptions in Concert*: Because monitoring technologies enter this environment of limited resources amongst interested parties with potentially conflicting objectives, coordinated and synchronized actions (adoptions-in-concert) are necessary to facilitate synergistic and efficient solutions. Technologies must be adopted by and work within the programs utilized for asset management. In turn, asset management must be supported by and exist within the broader context of performance-based engineering. Particular attention is needed in the standardization of performance metrics and methodology requirements. These include the timespan for analysis (design life or warranty period), the requirement to include risk, guidelines for the calculation of the consequence of failure, minimum reliability thresholds, and discount rate. Through such adoptions in concert, different SHM design alternatives can be evaluated for comparison.
3. *Top-down design of monitoring programs:* SHM is most commonly utilized as a bottom-up response to an existing problem or defect. In contrast to this approach, there is both the need and the knowledge base to begin the planning and execution of the strategic employment of monitoring assets. At the national level, network level, and individual structural level, this means allocating monitoring resources to the most critical structures, for the most critical materials and failure modes, at the most critical locations, at the optimal point in time.
4. *Bottom-up design of monitoring solutions*: Once a structure, failure modes, and critical location are selected, SHM provides the capability for structure-specific performance-based design and assessment through the measurement of on site specific conditions and response data. The implication is that SHM enables the development and use of models that employ and produce quantitative data instead of qualitative information.
5. *Calculating the utility of monitoring solutions*: Several possibilities exist with respect to facilitating the continued development and adoption of monitoring technologies for the assessment, performance prediction, and management of civil structures. These include requirement by code or regulation, encouragement through advertising benefit or owner pride in the structure, economic savings through lower insurance rates against risk, or cost savings realized through more optimal inspection and management activities. The tool that the researcher can best control is to provide methods to estimate the utility of monitoring solutions in life-cycle calculations. By examining the effect of the reduction of uncertainty on any particular analysis and the templating of several likely outcome scenarios of how monitoring would change the performance profile over time, the

owner/manager can evaluate SHM alternatives on the basis of cost effectiveness.

6. *Characterization of monitoring-based live load distributions*: Live load effects are the result of many contributing factors which include vehicle weights, speeds, configurations, side-by-side truck crossings, wind effects, temperature effects and other types of loads. Furthermore, these loads and their effects are a function of time. Extreme value statistics can be applied to monitoring data to characterize the live load distribution with respect to a specific observation interval. The approach is simple and efficient because it makes use of only maximum values within the observation timeframe and the difficult modelling of all contributing factors to the live load and its effects on a structure is replaced with a site specific measurement of these effects. Furthermore, the asymptotic behaviour of extreme value distributions can be leveraged to transform the characterized live load distribution from the observation timeframe (typically short) to the code required return period for live loads (typically long).
7. *Treatment of parameter uncertainty*: Uncertainty is inherent to the collection and evaluation of monitoring data. Aside from technical accuracy of the monitoring instruments themselves, the quality and stability of the recorded information will always be a function of the amount of data collected, and the length of the successive intervals (observation timeframe) utilized to characterize the data. Two approaches for the treatment of this uncertainty were presented, one qualitative (error based approach) and one quantitative (based off the central limit theorem). The end result of these approaches is either a more conservative estimate of the reliability index (qualitative) or the creation of a distribution of the reliability index (quantitative) as different realizations of the live load mean and standard deviation are randomly considered.
8. *Classical reliability, structural reliability, and lifetime characteristics:* Because SHM enables a performance-based quantitative treatment of the time-dependent reliability problem, the basic principles governing reliability (both classical and structural approaches) can be revisited and considered in methodology development. Qualitative models (based on expert opinion or statistical observation) are convenient, but may be limited in their ability to conduct a structure specific analysis. In order to fully leverage SHM by incorporating structure specific loads, resistances, and their effects in a time dependent reliability analysis, several modeling approaches are available. They include a time discretized approach, the cumulative time integrated approach, and the use of stochastic process

theory. Each approach makes certain assumptions, produces a different result, and has advantages and limitations. It is not concluded that any approach is inherently better. It is instead concluded that the most appropriate approach depends on the analysis to be conducted, the required accuracy from the analysis, the time and computational effort available, and which assumptions the owner/manager/engineer desires to make.

9. *Documentation of the analysis:* Because of the breadth of the fields being combined (SHM, LCM, and Risk-based approaches) and the fact that each field is still being developed, a clear documentation of the methodology selected, assumptions, limitations, input parameters, and units is critical for work in this field. Comparisons of different approaches on the same example or test bed case studies will prove extremely useful in the future.

7.2 Areas for Continued Research

Based on the work conducted in this study, the following areas are highlighted for continued research.

1. *Collection and evaluation of long-term monitoring data*: Any researcher in this field will benefit greatly from access to long term monitoring data across different structures and it is expected that many existing challenges will be quickly solved and many new challenges will be quickly developed. In this regard, the long term bridge performance program is very promising.
2. *Investigation of stochastic process theory, time dependent reliability, and SHM*: Chapter 6 needs to be expanded to include the application of a stochastic approach to a common example for comparison with other methods. This approach may prove to be the most accurate and most appropriate for the investigation of civil structures although it may also prove to be the most complex.
3. *Time effects and Bayesian updating in a time dependent reliability analysis*: Typically, Bayesian updating is conducted when new information becomes available. A challenge with monitoring is that new information is always potentially available. As such, the question becomes at what frequency should updating occur in a time dependent reliability analysis for the embedded random variable parameters? The result is non trivial. If one updates each month as opposed to each year or every 10 years, the performance profile will be dramatically different (assuming there is indeed a difference between the assumed and monitored data). For the characterization of live loads, extreme value statistics provided a method to

calibrate monitoring information across time. Developing an approach for Bayesian updating that accomplishes this same task (e.g. a rational approach for the consideration of time effects) is needed. If this cannot be accomplished, then some rational guideline on the frequency of updating for bridge structures would be required based off the maturity and consistency of the monitored data.

4. *Further refinement of the basic principles:* For a time dependent reliability analysis, Chapter 6 raised some interesting questions that require further investigation. How do the approaches differ between several common examples? What accounts for these differences? What are the computational tradeoffs? Is any specific approach better suited for the inclusion of monitoring data?
5. *Making full use of previously conducted work and existing methods:* Once the construct of SHM-fed time dependent performance profiles with updating is firmly in place, existing work in the field can be leveraged. This includes the incorporation of system effects, the consideration and optimization of multiple maintenance/repair strategies, network analysis, and multiple performance criteria (cost and safety) multi-objective optimization.
6. *Further investigation of synergy between LCM and Risk-based decision making approaches*: The examples developed in this thesis focused mostly on the use of monitoring data to construct time dependent reliability profiles. Generally, this type of analysis is specific to estimating the probability of failure. Instead, risk-based decision making approaches are well suited to the consideration of additional hazards and exposures to include human error. Also, the use and ability of monitoring to reduce the likelihood of a human error related failure is an interesting topic of study. Such a study could include the reduction in failure probability as well as the monetary benefit of such a reduction.

References

Akgul, F., and Frangopol, D.M. 2005. Reliability-based prediction of the lifetime performance of existing bridges. *Proceedings of the 9th International Conference on Structural Safety and Reliability*, ICOSSAR'05, Rome, Italy, CD-ROM, 503-508.

Aktan, A. E., Ellingwood, B. R., Kehoe, B., 2007. Performance-Based Engineering of Constructed Systems. *Proceedings of ASCE Structures 2007*, Long Beach, CA.

Aktan, A.E., Chase, S., Inman, D. and Pines, D. 2001. Monitoring and Managing the Health of Infrastructure Systems, *Proceedings of the 2001 SPIE Conference on Health Monitoring of Highway Transportation Infrastructure*. Irvine, CA, USA.

Albrecht, P., and Naeemi, A., 1984. Performance of Weathering Steel in Bridges, NCHRP Report 272, Washington, DC.

American Association of State Highway and Transportation Officials (AASHTO). LRFD Bridge Design Specifications, 2nd ed., Washington, D.C., 2007.

American Association of State Highway and Transportation Officials (AASHTO) Highway Subcommittee on Bridges and Structures, 2005. Grand Challenges: A Strategic Plan. Available online at: http://www.transportation.org/?siteid=34

American Association of State Highway and Transportation Officials (AASHTO). Manual for Maintenance Inspection of Bridges, 1970.

Andersen T, Misund A., 1983. Pipeline reliability: an investigation of pipeline failure characteristics and analysis of pipeline failure rates for submarine and cross-country pipelines. *Journal of Petroleum Technology* 1983 **35**:709–717, http://www.osti.gov/energycitations/product.biblio.jsp?osti id=6192657.

Ang, A. H-S, 2007. An application of quantitative risk assessment in infrastructures engineering. *Proceedings of the Fourth Civil Engineering Conference in the Asian Region*, CECAR 4, Taipei, Taiwan, June 25-28, 2007 (invited paper); in

ASCE Tutorial & Workshop on Quantitative Risk Assessment, Taipei, Taiwan, June 25-28, 2007.

Ang, A.H-S., and DeLeon, D., 2005. Modeling and analysis of uncertainties for risk-informed decision in infrastructures engineering. *Structure and Infrastructure Engineering*, Taylor & Francis, **1**(1), 19-31.

Ang, A.H-S. and Tang, W.H. 2007, Probability Concepts in Engineering Planning and Design Volume II, 2nd ed., Wiley, New York.

Ang, A.H-S. and Tang, W.H. 1984. Probability Concepts in Engineering Planning and Design Volume II, John Wiley & Sons II, New York.

Ang, A. H-S. and Tang, W.H., 1975. Probability concepts in engineering planning and design: Vol. 1, basic principles. John Wiley & Sons, ISBN: 0-471-03526-2.

ASCE, Structural Health Monitoring Committee, 2000. Benchmark studies. Available online at http://cive.seas.wustl.edu/wusceel/asce.shm/benchmarks.htm (accessed June 19, 2007)

ASCE, 2005. Report card for America's Infrastructure, American Society of Civil Engineers, Reston, VA. Available online at www.asce.org/reportcard/2005/index.cfm (accessed 22 May 2007).

Associated Press, 2008. Report: Money fears might have led to bridge collapse. Available at the internet news portal CNN at http://edition.cnn.com/2008/US/05/21/bridge.collapse.ap/index.html

Beck, J. L. and Katafygiotis, L. S. (1998), "Updating models and their uncertainties: Bayesian statistical framework", *J. Eng. Mech.*, ASCE, 124(4), 455-461.

Benjamin, R.G. and Cornell, C.A., 1970. Probability, statics, and decisions for civil engineers. McGraw Hill, Inc. ISBN: 007-004549.

Bertrand A, Escoffier L. IFP, 1987. Databanks on offshore accidents. In *Reliability Data collection and Use of Risk and Availability Assessment*, Colombari V (ed). Springer-Verlag: Berlin.

BA 63/94 (1994). Inspection of highway structures. Design manual for roads and bridges. Vol. 3, Section 1, Part 5. Highways Agency, London, U.K.

BD 63/94 (1994). Inspection of highway structures. Design manual for roads and bridges. Vol. 3, Section 1, Part 4. Highways Agency, London, U.K.

Bijen, J., 2003. *Durability of Engineering Structures: Design, Repair and Maintenance*. Woodhead Publishing Limited, Abington Hall, Cambridge, England.

Blind H. The safety of dams. *Water Power and Dam Construction* 1983 **35**:17–21.

Brownjohn, J.M.W., Moyo, P., Omenzetter, P, & Chakraborty, S. 2003. Lessons from monitoring the performance of highway bridges. *Journal of Structural Control and Health Monitoring*, 12(3-4), 227-244.

Bucher, C., and Frangopol, D. M. 2006. Optimization of lifetime maintenance strategies for deteriorating structures considering probabilities of violating safety, condition, and cost thresholds. *Probabilistic Engineering Mechanics*, Elsevier, 21(1), 1-8.

Bucher, C., Huth, O. and Macke, M. (2003), "Accuracy of system identification in the presence of random fields", *Proceedings of the 9th International Conference on the Applications of Statistics and Probability* (ICASP 9).

Budelmann, H. and Hariri, K., 2006, A Structural Monitoring System for RC-/PC-Structures, Proceedings of the Fifth International Workshop on Life-Cycle Cost Analysis and Design of Civil Infrastructure Systems, Seoul, Korea; in *Life-Cycle Cost and Performance of Civil Infrastructure* (ISBN 13: 978-0-415-41356-5 (hbk)), Taylor & Francis Group plc, London, UK.

Bureau of Transportation Statistics (BTS), 2003. *Transportation Statistics Annual Report*, Report BTS. Department of Transportation: Washington, DC.

CALREL: Liu, P., Lin, H., & Der Kiureghian, A. 1989. CALREL User Manual. Structural Engineering Mechanics and Materials Report No. UCB/SEMM-89/18, University of California Berkeley.

Canadian Highway Bridge Design Code (CHBDC), 2006. Ministry of Transportation, Ontario, Canada.

Casas, J.R., Frangopol, D.M., and Nowak, A.S., eds. (2002). *Bridge Maintenance, Safety and Management*, Book (ISBN 84-95999-05-6, 540 pages) and CD-ROM (ISBN 84-89925-37-2), published by CIMNE, Barcelona, Spain.

Casciati, S., 2004. Damage detection and Localization in the Space of the Observed Variables. Ph.D. Dissertation. Department of Structural Mechanics, University of Pavia, Pavia, Italy.

Catbas FN, Susoy M, Frangopol DM., 2008. Structural health monitoring and reliability estimation: Long span truss bridge application with environmental monitoring data, *Engineering Structures*, Elsevier (in press).

Catbas, N.F., Zaurin, R., Frangopol, D.M., and Susoy, M., System Reliability-Based Structural Health Monitoring with FEM Simulation. *Proceedings SHMII-3*, Vancouver, B.C., Canada, 2007

CDOT, 1998. Pontis Bridge Inspection Coding Guide, Colorado Department of Transportation, Staff Bridge Branch, Denver, Colorado.

Cesare, M. Santamarina, J., Turkstra, C., and Vanmarcke, E., 1993. Risk-based bridge management. *Journal of Transportation Engineering*. ASCE, 119(5), pp 742-750.

Chan, T. H., Ni, Y. Q. and Ko, J. M. 1999. Neural network novelty filtering for anomaly detection of Tsing Ma bridge cables. *Structural Health Monitoring 2000*, Stanford University, Palo Alto, California, 430-439.

Cho, A. and Van-Hampton, T., 2008. Report: State DOT Ignored I-35W Bridge Recommendations. Engineering News Record available online at http://enr.construction.com/news/transportation/archives/080522.asp accessed 24 July, 2008.

Chong K.P., Carino N.J., and Washer G., 2003. Health monitoring of civil infrastructures. *Smart Materials and Structures*, **12**: pp 483-493.

Chryssanthopoulos, M.K., and Sterritt, G., 2002. Integration of deterioration modelling and reliability assessment for reinforced concrete bridge structures. ARANet Intl. Colloquium, Glasgow, July 2002, CD-ROM Proceedings (16 pages).

Ciampoli, M.; Ellingwood, B.R. 2002. Probabilistic methods for assessing current and future performance of concrete structures in nuclear power plants. *Materials and Structures*, 35, January-February, 2002, 3-14.

Cohen, H., Fu, G., Dekelbab, W., and Moses, F., 2003. Predicting Truck Load Spectra under Weight Limit Changes and its Application to Steel Bridge Fatigue Assessment. *Journal of Bridge Engineering*, ASCE 8(5), 312-322.

Connor, R.J., and McCarthy, J. R., 2006. Report on Field Measurements and Uncontrolled Load Testing of the Lehigh River Bridge (SR-33). Lehigh

University's Center for Advanced Technology for Large Structural Systems (ATLSS), ATLSS Phase II Final Report No. 06-12.

Connor, R.J., and Santosuosso, B. J., 2002. Field Measurements and Controlled Load Testing on the Lehigh River Bridge (SR-33). Lehigh University's Center for Advanced Technology for Large Structural Systems (ATLSS), ATLSS Report 02-07.

Corotis, R.B. 2003a. Socially relevant structural safety. Applications of statistics and probability in civil engineering. A der Kiureghian, S. Madanat, and J.M. Pestana, eds., 1, 15-24, Millpress, Rotterdam.

Corotis, R.B. 2003b. Risk and Uncertainty. Applications of statistics and probability in civil engineering. A der Kiureghian, S. Madanat, and J.M. Pestana, eds., 1, 15-24, Millpress, Rotterdam.

Cornell, C.A., 1967. Bounds on the Reliability of Structural Systems. Journal of the Structural Division, ASCE, 93(ST1): 171-200.

Corotis, R.B., 1996. Structural optimization: A lifetime project. Proceedings of the 7th IFIP WG 7.5 Conference on the Reliability and Optimization of Structural Sytems. D.M. Frangopol, R.B. Corotis, R. Rackwitz (eds.), pp 3-16.

Cruz, P.J.S., Frangopol, D.M., and Neves, L.C., 2006. Bridge Maintenance, Safety, Management, Life-Cycle Performance and Cost, Book (ISBN 0 415 40322 7, 1125 pages) and CD-ROM (ISBN 0 415 40325 1, 412 full length papers, 3484 pages), Taylor & Francis Group plc., London

CTV News Online, Engineer Links Overpass Collapse to Steel Bars, available online at http://www.ctv.ca/servlet/ArticleNews/story/CTVNews /20061002/overpasscollapse_causes_061002/20061002?hub=Specials&pr=showAll accessed 19 December, 2006.

Das, P.C., 1998b. Application of reliability analysis in bridge management. *Engineering Structures*, Vol. 20, No. 11, pp 957-959.

Das, P.C., 1996. Bridge management objectives and methodologies. Bridge management 3, Inspection, Assessment, and Repair. J.E. Harding, G.E.R. Parke, M.J. Ryall (eds.), University of Surrey, E & FN SPON London, pp 1-7.

Das P.C., 1994. Reliability analysis of bridges: past and potential applications. Bridge Assessment Management and Design. B.I.G. Barr, H.R. Evens, J.E. Harding (eds). Elsevier Science B.V.

Das, P.C., Frangopol, D.M., and Nowak, A.S., 1999. Current and Future Trends in Bridge Design, Construction, and Maintenance, The Institution of Civil Engineers, Thomas Telford (ISBN 0 7277 2841 5), London, 660 pages.

Dedman, B., 2008a. Late Bridge Inspections Put Public at Risk, MSNBC Online available at http://www.msnbc.msn.com/id/20998261/ accessed 24 July 2008

Dedman, B. 2008b. Feds let States Delay Inspections of Bad Bridges. MSNBC Online available at http://www.msnbc.msn.com/id/22300234/ accessed 24 July, 2008

Dedman, B. 2008c. Ga. Employee Faked Bridge Inspections, MSNBC Online available at http://www.msnbc.msn.com/id/23020686/ accessed 24 July, 2008

Dedman, B. 2007. I-35 bridge was rated among nation's worst. Available at the internet news portal MSNBC at http://www.msnbc.msn.com/id/20102713/ accessed 28 August, 2008.

El-Borgi, S., Choura, S., Ventura, C., Baccouch, M., and Cherif, F., 2004. Modal Identification and Model Updating of a Reinforced Concrete Bridge, *Smart Structures and Systems*, 1(1), 83-101.

Enevoldsen, I., 2008. Practical implementation of probability based assessment methods for bridges. *Proceedings of the Fourth International Conference on Bridge Maintenance and Safety*, Seoul, Korea, July 13-17, 2008, IABMAS'08 (Keynote).

Enright, M.P., and Frangopol, D.M., 1999a. Reliability-based condition assessment of deteriorating concrete bridges considering load redistribution. *Structural Safety*, Vol. 21, pp 159-195.

Enright, M.P., and Frangopol, D.M., 1999b. Condition prediction of deteriorating concrete bridges. *Journal of Structural Engineering*, ASCE, Vol. 125 (10), pp1118-1125.

Enright, M., Frangopol, D.M., Hearn, G., 1996. Degradation of Reinforced Concrete Structures Under Aggressive Conditions. Materials for the New Millennium, (Ken P. Chong, Editor), ASCE, New York, Vol. 2., 1996.

Estes, A.C. (1997). A System Reliability Approach to the Lifetime Optimization of Inspection and Repair of Highway Bridges. Ph.D. Dissertation, Department of Civil, Environmental and Architectural Engineering, University of Colorado at Boulder.

Estes, A. C., Frangopol, D. M., 2005a. Life-cycle evaluation and condition assessment of structures. Chapter 36 in *Structural Engineering Handbook*, 2nd Edition, W-F. Chen and E. M. Lui, eds., CRC Press: 36-1 to 36-51.

Estes, A. C., and Frangopol, D.M., 2005b. Reliability-based condition assessment, Chapter 2 in *Structural Condition Assessment*, R.T. Ratay, ed., John Wiley & Sons, Hoboken, New Jersey, 2005; 25-66.

Estes, A.C. & Frangopol, D.M., 2003. Updating Bridge Reliability Based on Bridge Management Systems Visual Inspection Results. *Bridge Engineering*, ASCE, 8(6), 374-382.

Estes, A. C., Frangopol, D. M., 1999. Repair optimization of highway bridges using a systems reliability approach. *Journal of Structural Engineering*, ASCE, 125(7), 766-775.

Esther, Bubley, 1946. New York harbor looking toward Manhattan from the footpath on Brooklyn Bridge (Photo). Available at Brooklyn Museum online at http://www.brooklynmuseum.org/research/digital-collections/brooklynbridge/photographs/full.php?imgNo=54.201.3 accessed 12 October, 2008.

EUROCODES, Basis of design and actions on structures, BS EN 1990:2002. British Standards Institution, London, United Kingdom, 2002

Faber, M.H., Reliability based assessment of existing structures, *Prog. Structural Engineering Materials*, 2000; 2, 247-253.

Faber MH, Val DV, Stewart MG, 2000. Proof load testing for bridge assessment and upgrading. *Engineering Structures*, **22**:1677–1689.

Farrar, C. R., Baker, W. E., Bell, T. M., Cone, K. M., Darling, T. W., Duffey, T. A., Eklund, A. and Migliori, A.(2004), “Dynamic characterization and damage detection in the I-40 Bridge over the Rio Grande”, Los Alamos National Laboratory Technical Report LA-12767-MS.

Federal Highway Administartion (FHWA), 2008. Long Term Bridge Performance (LTBP) program. Available online at http://www.tfhrc.gov/structur/ltbp.htm accessed 12 September, 2008.

Federal Highway Administration, National Bridge Inventory, available online at http://www.fhwa.dot. gov/bridge/nbi.htm (dated accessed May 2007).

Federal Highway Administration (FHWA) 2005. Bridge Preservation and Maintenance in Europe and South Africa. Report FHWA-PL-04-007. Washington, D.C., USA.

Frangopol, D. M. , 2007, Perspective from US Researchers on Bridge Long-Term Performance Program, FHWA/NSF Workshop on Future Directions for Long-Term Monitoring, Assessment, and Management, Las Vegas, Nevada, USA.

Frangopol, D.M., 2003. Preventive Maintenance Strategies for Bridge Groups – Analysis, Final Project Report to the Highways Agency, London, U.K., 139 pages.

Frangopol, D.M., 1999. Bridge Safety and Reliability, ASCE (ISBN 0-7844-0442-9), Reston, Virginia, USA, 244 pages.

Frangopol, D.M., 1998. A Probabilistic Model Based on Eight Random Variables for Preventive Maintenance of Bridges, Progress meeting on optimum maintenance strategies for different bridge types, The Highways Agency, London.

Frangopol, D.M., 1997. Application of life-cycle reliability-based criteria to bridge assessment and design. P.C. Das (ed.), Safety of Bridges. Thomas Telford, London, pp 151-157.

Frangopol, D.M., and Das, P.C., 1999. Management of bridge stocks based on future reliability and maintenance costs. Current and Future Trends in Bridge Design, Construction and Maintenance. P.C. Das, D.M. Frangopol and A.S. Nowak (eds.). Thomas Telford, London, pp 45-58.

Frangopol, D.M., Kong, J.S., and Gharaibeh, E.S., 2001. Reliability based life cycle management of highway bridges, *Journal of Computing in Civil Engineering*, ASCE 15(1), pp. 27-34.

Frangopol, D.M., Kong, J.S., and Garaibeh, E.S., 2000. Bridge management based on lifetime reliability and whole life costing: The next generation. Bridge

Management 4, M.J. Ryall, G.A.R. Parke, and J.E. Harding (eds.), Thomas Telford, London, pp 392-399.

Frangopol, D.M., Lin, K.Y., and Estes, A.C., 1997b. Reliability of reinforced concrete girders under corrosion attack. *Journal of Structural Engineering*, ASCE, Vol. 123, No. 3, pp 286-297.

Frangopol D.M., Liu M., 2007. Maintenance and management of civil infrastructure based on condition, safety, optimization, and life-cycle cost. *Structure and Infrastructure Engineering*, Taylor and Francis, **3**(1): pp 29-41.

Frangopol DM, Liu M., 2006. Life-cycle cost and performance of civil structures. *McGraw-Hill 2006 Yearbook of Science and Technology*. McGraw-Hill: NewYork, pp. 183–185 (invited article).

Frangopol, D.M., and Liu, M. 2005. Multi-objective optimization for performance based bridge network maintenance under uncertainty, *Proceedings of the 9th International Conference on Structural Safety and Reliability*, ICOSSAR'05, Rome, Italy, CD-ROM, 3599-3605.

Frangopol, D.M., and Messervey, T.B. 2009. Effect of SHM on reliability of bridges. Chapter 25 in *Monitoring Technologies for Bridge Management: State-of-the-Art*, A. A. Mufti and B. Bahkt, eds., Multi-Science Publishing Co., Ltd., England (invited chapter, submitted).

Frangopol, D.M., Messervey, T.B., 2008a. Maintenance principles for civil structures using SHM. *Encyclopedia of Structural Health Monitoring.* Ed. Christian Boller, Fu-Kuo Chang, and Yozo Fujino. John Wiley & Sons, Ltd (in press)

Frangopol, D.M., and Messervey, T.B., 2008b. Life-Cycle Cost and Performance Prediction: Role of Structural Health Monitoring. *Proceedings of the International Workshop on Frontier Technologies for Infrastructures Engineering.* 23-25 Oct 2008, Taipei, Taiwan.

Frangopol, D.M. and Messervey, T.B., 2008c. Use of Structural Health Monitoring for Improved Civil Infrastructure Management Under Uncertainty. *Proceedings of WG7.5 Reliability and Optimization of Structural Systems*. Toluca, Mexico, 6-9 August, 2008. (Keynote).

Frangopol, D.M., and Messervey, T.B., 2008d. Quantifying the Benefits of Smart Technologies in a Life-Cycle Context. *Proceedings of the 3rd International Conference on Smart Materials, Structures, and Systems CIMTEC08*. 8-13 June, 2008, Sicily, Italy.

Frangopol, D.M., and Messervey, T.B., 2007a. Lifetime oriented assessment and design optimization concepts under uncertainty: Role of structural health monitoring. *Lifetime-oriented Design Concepts, 2007*, Stangenberg, F., Bruhns, O.T., Hartmann, D., and Meschke. G., eds., Aedificatio Publishers Freiburg, 2007, 133-145 (keynote paper).

Frangopol, D.M., and Messervey, T., 2007b. Risk assessment for bridge decision making. *Proceedings of the Fourth Civil Engineering Conference in the Asian Region,* CECAR 4, Taipei, Taiwan, June 25-28, 2007 (invited paper); in *ASCE Tutorial & Workshop on Quantitative Risk Assessment*, Taipei, Taiwan, June 25-28, 2007, 37-42.

Frangopol, D.M., and Messervey, T., 2007c. Integrated life-cycle health monitoring, maintenance, management and cost of civil infrastructure. Proceedings of the International Symposium on Integrated Life-Cycle Design and Management of Infrastructures, Tongji University, Shanghai, China, May 16-18 (keynote paper); in *International Symposium on Integrated Life-cycle Design and Management of Infrastructure,* Lichu, F., Limin, S., and Zhi, S., eds., Tongji University Press, Shanghai, 2007, 216-218.

Frangopol, D.M., Strauss, A., and Kim, S., 2008. Bridge Reliability Assessment Based on Monitoring. *Journal of Bridge Engineering*, ASCE, 13(3), 258-270.

Fujino, Y, 2008. Development of a Practical Monitoring System of Urban Infrastructure toward Mitigation of Disaster and Accidents. *Proceedings of the 3rd International Conference on Smart Materials, Structures, and Systems*. 13-18 June, Acireale, Sicily, CIMTEC’08.

Fujino Y, Abe M., 2004. Structural health monitoring - current status and future. *Proceedings of the Second European Workshop on Structural Health Monitoring 2004*. DEStech Publications: Munich, pp. 3-10.

Furuta, H., Kameda.T., Nakahara, K., Takahashi, Y., and Frangopol, D. M. 2006. Optimal bridge maintenance planning using improved multi-objective genetic algorithm. *Structure and Infrastructure Engineering*, Taylor & Francis, **2**(1), 33-41.

Garcia, G. and Stubbs, N., 1997. Application and evaluation of classification algorithms to a finite element model of a three-dimensional truss structure for nondestructive damage detection. Smart Systems for Bridges, Structures, and Highways, *Proceedings of SPIE*, 3043, 205-216.

Ghosn, M., 2000. Development of Truck Weight Regulations Using Bridge Reliability Model, *Journal of Bridge Engineering,* 5(4): 293-303.

Ghosn, M., Moses, F., Wang, J., 2003. Design of Highway Bridges for Extreme Events. NCHRP TRB Report 489, Washington, D.C., U.S.A.

Ghosn, M., Moses, F., 1998. Redundancy in highway bridge superstructures. NCHRP TRB Report 406, Washington, D.C., U.S.A.

Ghosn, M., and Moses, F., 1986. Reliability calibration of a bridge design code. *Journal of Structural Engineering*, 112(4), 745–763.

Gindy, M. and Nassif, H. Effect of bridge live load based on 10 years of WIM data. *Proceedings of the Third International Conference on Bridge Maintenance and Safety*, Taylor & Francis, Porto, Portugal, 2006; 9 pages on CD-ROM.

Glaser, S.D., Li, H., Wang, M.L., Ou, J., and Lynch, J, 2007. Sensor technology innovation for the advancement of structural health monitoring: a strategic program of US-China research for the next decade. *Smart Structures and Systems*, 3(2), pp 221-244

Glisic, B. and Inaudi, D., 2007. *Fibre Optic Methods for Structural Health Monitoring.* John Wiley & Sons, LTD, England.

Hawk, H., and Small, E.P. 1998. The BRIDGIT Bridge Management System, Structural Engineering International (IABSE, Zurich, Switzerland), 8(4), 309-314.

Hearn, G., Frangopol, D.M., 1996. Segment-based reportingfor element level bridge inspection. *Proceedings of the 4th NSF National Workshop on Bridge Research in Progress*, Buffalo, NY, USA.

Hendawi, S., 1994. Structural System Reliability with Applications to Bridge Analysis, Design and Optimization. Ph.D. Dissertation, Department of Civil, Environmental and Architectural Engineering, University of Colorado at Boulder.

Holladay, S., George Washington Bridge (photo). Available online at http://www.flickr.com/search/?q=George+Washington+Bridge+Fort+Lee&page =10 accessed 12 October, 2008.

Hoyland, A. and Rausand, M., 1994. System Reliability Theory: Models and Statistical Methods. Wiley-Interscience publication, John Wiley & Sons, NY.

Inada, T., Shimamura, Y., Todoroki, A., Kobayashi, H. and Nakamura, H., 1999. Damage identification method for smart composite cantilever beams with piezoelectric materials. Structural Health Monitoring 2000, Stanford University, Palo Alto, California, 986-994.

Jardin, X., 2007. Minneapolis Bridge Collapse Blog Roundup. Located at http://www.boingboing.net/2007/08/02/minneapolis-bridge-c.html accessed 28 October, 2007.

Joint Task Committee on Maintenance Engineering, 2004. Infrastructure Maintenance Engineering, Japan Society of Civil Engineers. University of Tokyo Press, 2004 (in Japanese).

Kiremidjian, A.S., Sarabandi, P., Cheung, A., Cabrera, C., Nair, K.K., and Kiremidjian, G., 2008. Algorithm for identification of damage on bridge piers. Life-Cycle Civil Engineering: *Proceedings of the International Symposium on Life-Cycle Civil Engineering* (IALCCE'08), Varenna, Lake Como, Italy, June 10-14, 2008, pp. 990, ISBN: 9780415468572, CRC Press - Taylor & Francis Group, 935-940.

Klinzmann, C., Schnetgöke, R. and Hosser, D., 2006. A Framework for Reliability-Based System Assessment Based on Structural Health Monitoring, *Proceedings of the 3rd European Workshop on Structural Health Monitoring*, Granada, Spain.

Kong, J.S., and Frangopol, D.M., 2004. Cost-Reliability Interaction in Life-Cycle Cost Optimization of Deteriorating Structures, *Journal of Structural Engineering*, ASCE 130(11): 1704-1712.

Kong, J.S. and Frangopol, D.M., 2003. Evaluation of expected life-cycle maintenance cost of deteriorating structures. *Journal of Structural Engineering*, Vol. 129, ASCE, May 2003, pp 682-691.

Kong, J.S., and Frangopol, D.M., 2005a. Probabilistic optimization of aging structures considering maintenance and failure costs. *Journal of Structural Engineering*, ASCE, **131**(4), 600-616.

Kong, J.S., and Frangopol, D.M. 2005b. Sensitivity Analysis in Reliability-Based Lifetime Performance Prediction Using Simulation. *Journal of Materials in Civil Engineering*, ASCE, 17(3), 296-306.

LANL, 2003. *A Review of Structural Health Monitoring Literature: 1996-2001*, The Los Alamos National Laboratory Report LA 13976-MS, 2003. pp 1-307.

Lapin, L. L. (1990), Probability and Statistics for Modern Engineering, PWS-Kent, Boston.

Leemis, L.M., 1995. Reliability: Probabilistic Models and Statistical Methods, Prentice-Hall, Englewood Cliffs, N.J., USA.

Liu, M., and Frangopol, D.M. 2006a. Optimizing bridge network maintenance management under uncertainty with conflicting criteria: Life-cycle maintenance, failure, and user costs. *Journal of Structural Engineering*, ASCE, 132(11), 1835-1845.

Liu, M. and Frangopol, D.M., 2006b, Probability-Based Bridge Network Performance Evaluation, *Journal of Bridge Engineering*, ASCE, 11(5), 633-641.

Liu, M., and Frangopol, D.M., 2005. Time-dependent bridge network reliability: Novel approach. *Journal of Structural Engineering*, ASCE, 131(2), 329-337.

Liu, S.C., and Tomizuka, M., 2003, Vision and Strategy for Sensors and Smart Structures Technology Research, Proceedings of the 4th International Workshop on Structural Health Monitoring, Stanford, CA, September 15-17, 2003.

Loh, C. H. and Huang, C. C. 1999. Damage identification of multi-story steel frames using neural networks. Structural Health Monitoring 2000, Stanford University, Palo Alto, California, 390-399.

Lynch, J.P., 2007. An Overview of Wireless Structural Health Monitoring for Civil Structures. Philosophical Transactions of the Royal Society of London. *Series A, Mathematical and Physical Sciences*, The Royal Society, London, 365(1851):345-372.

Lynch, J.P., and Loh, K., 2005, A Summary Review of Wireless Sensors and Sensor Networks for Structural Health Monitoring, *Shock and Vibration Digest,* Sage Publications, 38(2), 91-128.

Madsen, H.L, Krensk, S., Lind, N.C., 1986. Methods of Structural Safety. Englewood Cliffs, NJ: Prentice-Hall Inc.

Marsh, P.S., and Frangopol, D.M. 2008. Reinforced concrete bridge deck reliability model incorporating temporal and spatial variations of probabilistic corrosion rate sensor data. *Reliability Engineering & System Safety*, Elsevier, 93(3), 394-409.

Masri, S. F., Smyth, A. W., Chassiakos, A. G., Caughey, T. K. and Hunter, N. F., 2000. Application of neural networks for detection of changes in nonlinear systems. *Engineering Mechanics*, (6), pp 666-676.

Matousek M, Schneider J., 1976. Untersuchungen zur Struktur des Sicherheitsproblems bei Bauwerken, (in German). Basel: BirkhaEuser, 1976.

Melchers. R.E., 1999. Structural Reliability Analysis and Prediction, 2d ed., Wiley, Chichester, UK.

Messervey, T.B., Frangopol, D.M., 2008. Probabilistic Treatment of Bridge Monitoring data and Associated Errors for Reliability Assessment and Prediction, *Proceedings, IALCCE08*, Como, Italy.

Messervey, T., and Frangopol, D.M., 2007a. A framework to incorporate structural health monitoring into reliability-based life-cycle bridge management models. Proceedings of the Fifth Computational Stochastic Mechanics Conference, Rhodos, Greece, June 21-23, 2006; in *Computational Stochastic Mechanics,* G. Deodatis and P.D. Spanos, eds., Millpress, Rotterdam, 2007, 463-469.

Messervey, T., and Frangopol, D.M. 2007b. "Bridge live load effects based on statistics of extremes using on-site load monitoring," *Proceedings of the 13th WG 7.5 Working Conference on Reliability and Optimization of Structural Systems,* Kobe, Japan. October 13-15, 2006; in *Reliability and Optimization of Structural Systems*: *Assessment, design, and life-cycle performance,* Frangopol, D.M., Kawatani, M., and C-W. Kim, eds., Taylor & Francis Group plc, London, 2007, 173-180.

Messervey, T., and Frangopol, D.M. 2007c. Updating the time-dependent reliability using load monitoring data and the statistics of extremes. Proceedings of the Fifth International Workshop on Life-Cycle Cost Analysis and Design of Civil Infrastructure Systems, Seoul, Korea, October 16-18, 2006;in *Life-Cycle Performance and Cost of Civil Infrastructure*, Cho, H-N., Frangopol, D.M., and Ang, A-H. S., eds., Taylor & Francis Group plc, London, 2007, 269-276.

Messervey, T. B., Frangopol, D. M., and Estes, A.C. 2006. Reliability-based life-cycle bridge management using structural health monitoring, *Proceedings of the Third International Conference on Bridge Maintenance and Safety*, Porto, Portugal, July 16-19, 2006, IABMAS'06.

Miclic, T.V., Chryssanthopoulos, M.K. and Baker, M.J., 1995. Reliability analysis for highway bridge deck assessment. *Structural Safety*, Vol 17, pp 135-150.

Moon, F.L. and Aktan, A.E., 2006. Structural Identification of Constructed Systems and the Impact of Epistemic Uncertainty, *Proceedings of the Third International Conference on Bridge Maintenance and Safety*, Taylor & Francis, Porto, Portugal, 2006., IABMAS'06, Taylor & Francis, 8 pages on CD-ROM.

Mori, Y.; Ellingwood, B.R., 1992. Reliability-based service -life assessment of aging concrete structures. ASCE, *Journal of Structural Engineering*, 119(5), 1600-1621.

Nair, K.K. and Kiremidjian, A.S., 2007. Time Series-Based Structural Damage Detection Algorithm Using Gaussian Mixtures Modeling. *Journal of Dynamic Systems, Measurement, and Control*, 129, 285–293.

Neves, L.C., Frangopol, D.M., and Cruz, P.J.S., 2006a. Lifetime multi-objective optimization of maintenance of existing steel structures. *Proceedings of the Sixth International Symposium on Steel Bridges, Prague*, Czech Republic.

Neves, L.A.C., Frangopol, D.M., and Cruz, P.J.S. 2006b. Probabilistic lifetime-oriented multi-objective optimization of bridge maintenance: single maintenance type. *Journal of Structural Engineering*, ASCE, 132(6), 991-1005.

Neves, L.A.C., Frangopol, D.M., and Petcherdchoo, A. 2006c. Probabilistic lifetime-oriented multi-objective optimization of bridge maintenance:

combination of maintenance types. Journal of Structural Engineering, ASCE, 132(11), 1821-1834.

Neves, L.C., Petcherdchoo, A., and Frangopol, D.M. 2005. Probabilistic lifetime-oriented maintenance optimization of structures, *Proceedings of the 9th International Conference on Structural Safety and Reliability*, ICOSSAR'05, Rome, Italy, CD-ROM, 1465-1471.

Neves, L.C. and Frangopol, D. M. 2004. Condition, safety, and cost profiles for deteriorating structures with emphasis on bridges, *Reliability Engineering and System Safety*, Vol. 89, pp. 185-198.

Nowak, A.S., 1993. Live load model for highway bridges. *Structural Safety*, 13(1–2): 53–66.

Nowak, A.S. and Yamani, A.S. (1995). A reliability analysis for girder bridges. *Structural Engineering Review*, 7(13), 251-256.

O'Connor, A., and O'Brien, E.J., 2005. Traffic load modeling and factors influencing the accuracy of predicted extremes. *Canadian Journal of Civil Engineering*, 32, pp. 270-278.

Peil, U., 2003. Life-Cycle Prolongation of Civil Engineering Structures via Monitoring, Proceedings of the 4th International Workshop on Structural Health Monitoring, DEStech Publications, Inc.: 64-78. Stanford, CA, U.S.A.

Petcherdchoo, A., Neves, L.C., and Frangopol, D.M., 2004. Combinations of Probabilistic Maintenance Actions for Minimum Life-Cycle Cost of Deteriorating Bridges. *Proceedings of the second International Conference on Bridge Maintenance, Safety, Management, and Cost*, IABMAS'04, Tokyo, Japan.

Podoba, Matthew, J., 2007. Minneapolis Bridge Collapse Victims cannot get Financial Help for Expenses. Featured at http://wordpress.com/tag/i35-bridge-collapse/ accessed 28 Oct 2007.

PROBAN-2: Example Manual, Report No. 89-2025, A.S Veritas Research, Hovik, Norway, August, 1989

Rackwitz, R., 2004. Life quality index revisited. *Structural Safety*, 26 (2004) pp 443-451.

Rackwitz, R., Schrupp, R., 1985. Quality control, proof testing, and structural reliability. *Structural Safety*, 2, 239-244.

Rafiq MI., 2005. Health Monitoring in Proactive Reliability Management of Deteriorating Concrete Bridges. Doctoral Theses, University of Surrey.

RELSYS: Estes AC, Frangopol DM. RELSYS: A computer program for structural system reliability analysis. *Structural Engineering Mechanics 1998*; 6(8):901–919.

Roberts, J.E., and Shepard, R, 2002. Bridge Management for the 21st Century. *Proceedings from the First International Conference on Bridge Maintenance, Safety, and Management, IABMAS'02,* Barcelona, Spain.

Ruotolo, R. and Surace, C. 1997. Damage assessment of multi-cracked beams using combinatorial optimization. Structural Damage Assessment Using Advanced Signal Processing Procedures, *Proceedings of DAMAS '97,* University of Sheffield, UK, 77-86.

Scott RL, Gallaher RB., 1981. Review of safety-related events at nuclear power plants as reported in 1979. *Nuclear Safety* **22**(4):505–515.

Small, E.P., and Cooper, J., 1998a, Bridge Management Software Programs, *TR News*, (194), 10-11.

Small, E.P., and Cooper, J., 1998b, Condition of the Nation's Highway Bridges. A Look at the Post, Present, and Future, *TR News*, (194), 3-8.

Sohn, H., Farrar, C. R., Hunter, N. S. and Worden, K., 2001. Structural health monitoring using statistical pattern recognition techniques. *ASME Journal of Dynamic Systems, Measurement and Control*, 123(4), 706-711.

Sohn, H., Czarnecki, J. J. and Farrar, C. R., 2000. Structural health monitoring using statistical process control. *Structural Engineering*, 126(11), 1356-1363.

Sohn, H. and Law, K. L. 1997. A Bayesian probabilistic approach for structure damage detection, *Earthq. Eng. Struct. Dyn.*, 26(12), 1259-1281.

Sterritt, G., 2000. Probabilistic procedures for lifetime management of reinforced concrete highway bridges. Department of Civil and Environmental Engineering, University of London, Imperial college of Sciences, Technology and Medicine.

Stewart, M.G., Melchers, R.E., 1997. Probabilistic Risk Assessment of Engineering Systems, Chapman & Hall, London.

STRUREL Vesion 6.1, Theoretical, Technical and Users Manual. Munich: RCP-GmbH. 1998.

Susoy, M., Catbas, N., and Frangopol, D.M., 2007. SHM development using system reliability. Proceedings of the Tenth International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP 10, Tokyo, Japan. July 31-August 3, 2007; in Applications of Statistics and Probability in Civil Engineering, Kanda, J., Takada, T., and Furuta, H., eds., Taylor & Francis Group plc, London, 2007, 79-80.

Thoft-Christensen, P., 1998. Assessment of the reliability profiles for concrete bridges. *Engineering Structures*, Vol. 20, No. 11, pp 1004-1009.

Thoft-Christensen, P., 1993. Reliability-based expert systems for optimal maintenance of concrete bridges. Proceedings of ASCE Structural Congress 93, California.

Thoft-Christensen, P., Jensen, F.M., Middleton, C.R. and Blackmore, A., 1996. Assessment of the reliability of concrete slab bridges. Proceedings of the 7th IFIP WG 7.5 Working Conference on the Reliability and Optimization of Structural Systems. D.M. Frangopol, R.B. Corotis, R. Rackwitz (eds.), pp 321-328.

Thoft-Christensen, P. and Hansen, H.I., 1993. Optimal strategy for maintenance of concrete bridges using expert systems. *Proceedings ICOSSAR '93*, Innsbruck, pp 939-946.

Thoft-Christensen, P. and Baker, M., 1982. Structural Reliability Theory and its Applications, Springer Verlag, New York, ISBN: 0387117318.

Thompson, P.D., Small, E.P., Johnson, M., and Marshall, A.R. (1998), The Pontis Bridge Management System, *Structural Engineering International* (IABSE, Zurich, Switzerland), 8(4), 303-308.

Tolliver D., 1994. Highway Impact Assessment: Techniques and Procedures for Transportation Planners and Managers. Quorum Books: Westport, CT.

U.S. Army Corps of Engineers: USACE, 1992. Reliability Assessment of Navigation Structures, ETL 1110-2-532. Corps of Engineers Engineering and Design Division. Department of the Army, Washington D.C.

Val, D.V., Stewart, M.G., and Melchers, R.E., 2000. Life-cycle performance of RC bridges: probabilistic approach. *Computer-Aided Civil Infrastructure Engineering*, Vol. 15, pp 14-25.

Val, D.V., Stewart, M.G., and Melchers, R.E., 1998. Effect of reinforcement corrosion on the reliability of highway bridges. *Engineering Structures*, Vol. 20, No. 11, pp 1010-1019.

Watanabe, E., Frangopol, D.M., and Utsunomiya, T., 2004. Bridge Maintenance, Safety, Management and Cost, Book (ISBN 90-5809-680-7, 1016 pages) and CD-ROM (ISBN 04-1536-336-X, 347 full length papers), A.A. Balkema, Swets & Zeitlinger B.V., Lisse, The Netherlands.

Wikipedia, 2008a. Northeast Blackout of 2003. Available online at http://en.wikipedia.org/wiki/2003_North_America_blackout accessed 12 October, 2008.

Wikipedia, 2008b. Hurricane Katrina. Available online at http://en.wikipedia.org/wiki/Hurricane_katrina accessed 12 October, 2008.

Worden, K. and Lane, A. J., 2001. Damage identification using support vector machines. *Smart Material Structures*, 10, 540-547.

Val, D.V., Bljuger, F. and Yankelevsky, D., 1997. Reliability evaluation in nonlinear analysis of reinforced concrete structures. *Structural Safety*, Vol. 19, No. 2, pp 203-217.

Zokaie, T., Imbsen, R.A., and Osterkamp, T.A., 1991. Distribution of Wheel Loads on Highway Bridges, Transportation Research Record 1290, 119-126, Washington D.C., U.S.A.