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Stambaugh, Karl

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On Ship Structure Risk and Total Ownership Cost Management Assisted by Prognostic Hull Structure Monitoring

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by

Karl Allen STAMBAUGH

Bachelor of Science and Engineering, Naval Architecture and Marine Engineering
University of Michigan
Born in York, Pennsylvania, United States of America

This dissertation has been approved by the promotors.
Composition of the doctoral committee:

Rector Magnificus, chairperson
Prof. Dr. Ir. M.L. Kaminski Delft University of Technology, promotor

Promotors
Prof. Dr. Ir. M.L. Kaminski Delft University of Technology, promotor
Prof. Dr. B. Ayyub - University of Maryland USA, co-promotor
Dr. Ir. C. Walters - Delft University of Technology, co-promotor

Independent members:
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Prof. Dr. Ir. J. Maljaars - Eindhoven University of Technology
Prof. Dr. Ir. P. van Gelder - Delft University of Technology
Prof. ir. H. Hopman - Delft University of Technology

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CONTENTS

SUMMARY

Ships must perform their missions with a high degree of reliability to maximize availability through their service life. The ultimate safety of the hull structure is time-dependent with degradation caused by the operational environment. Achieving the fore mentioned reliability and mission availability requirements are complicated because ships operate in random seaways producing random loading on the hull structure. The subsequent strength degradation also involves random processes including the material properties themselves. Furthermore, the models used to estimate the loading and responses are not perfect and result in additional randomness and related uncertainty. The potential Risks involved are very high, given the combination of uncertainties and high value of the assets, crews, and related resources. The primary research questions posed by this dissertation include; 1) what approaches are needed to make Risk informed decisions in Ship Structure Life Cycle Management (SSLCM) and, 2) how can Hull Structural Monitoring (HSM) be used effectively to support these decisions? This dissertation addresses these research questions by building on the fundamentals of hull structural loading and failure mechanisms on both component and systems-levels that are unique to ship structure. This fundamental research includes a correlation analysis of the system loading to support new definitions of ship structural system response. This new definition of structural system response provides insights into definitions of serviceability failure, reserve strength, and redundancy. Following the structural systems definition development, this dissertation proposes a Risk and Total Ownership Cost (TOC) trade-space perspective for making informed decisions and managing both Risk and costs associated with SSLCM and fundamental characterization of Risk and uncertainty. The development of Risk-TOC approach provides tangible and relatable benefits for understanding uncertainty in Risk terms required to make informed decisions. The Risk-TOC approach provides a more informed perspective than prior proposals for Decision Theory-based Optimal Inspection approaches with assumptions and parameters that do not fully quantify the uncertainties involved in the SSLCM processes. The Risk-TOC approach also provides a quantitative means for assessing the consequences of different failure modes (i.e., fatigue cracking and corrosion). The Risk-TOC approach provides a quantified basis for comparing Risk and costs given the magnitude of resources at Risk by monetizing uncertainty. In this manner, the Risk - TOC approach provides a framework for fundamental definitions, including monetized uncertainty, analysis of alternatives (AoAs), Return on Investment (*RoI*), and Value of Information (*VoI*). The benefits of prognostic HSM are presented in the context of reduction of uncertainty in the SSLCM processes; thereby, reducing Risk and TOC with favorable *RoI* and *VoI*. The Risk-TOC approach is verified as demonstrated in example applications involving a US Coast Guard Cutter. A discussion is provided on the implications of the Risk-TOC approach on SSLCM and sustainability. Conclusions and recommendations are presented for further development of the Risk-TOC approach for SSLCM.

SAMENVATTING

Schepen moeten hun missies uitvoeren met een hoge mate van betrouwbaarheid om de beschikbaarheid gedurende hun levensduur te maximaliseren. De ultieme veiligheid van de rompstructuur is tijdsafhankelijk met degradatie veroorzaakt door de operationele omgeving. Het bereiken van de bovengenoemde betrouwbaarheid en missiebeschikbaarheidseisen is gecompliceerd omdat schepen in willekeurige zeewegen opereren en willekeurige lading op de rompstructuur produceren. De daaropvolgende sterktedegradatie omvat ook willekeurige processen met inbegrip van de materiaaleigenschappen zelf. Bovendien zijn de modellen die worden gebruikt om de belasting en reacties te schatten niet perfect en resulteren ze in extra willekeurigheid en gerelateerde onzekerheid. De potentiële risico's zijn zeer hoog, gezien de combinatie van onzekerheid, hoge waarde van de activa, bemanningen en gerelateerde middelen. De primaire onderzoeksvragen van dit proefschrift zijn; 1) welke benaderingen zijn nodig om risico-geïnformeerde beslissingen te nemen in Ship Structure Life Cycle Management (SSLCM) en, 2) hoe kan Hull Structural Monitoring (HSM) effectief worden gebruikt om de geïnformeerde beslissingen te ondersteunen?

Dit proefschrift behandelt deze onderzoeksvragen door voort te bouwen op de basisprincipes van structurele laad- en faalmechanismen van de romp op zowel component- als systeemniveau's die uniek zijn voor de scheepsstructuur. Dit fundamentele onderzoek omvat een correlatieanalyse van de systeembelasting ter ondersteuning van nieuwe definities van structurele systeemreacties van schepen. Deze nieuwe definitie van structurele systeemrespons biedt inzicht in definities van falen van bruikbaarheid, reservesterkte en redundantie. In navolging van de ontwikkeling van de structurele systeemdefinitie, stelt dit proefschrift een perspectief voor de risico- en totale eigendomskosten (TOC) voor het nemen van geïnformeerde beslissingen en het beheren van zowel risico als kosten in verband met SSLCM en fundamentele karakterisering van risico en onzekerheid. De ontwikkeling van de Risk-TOC-aanpak biedt tastbare en herkenbare voordelen voor het begrijpen van onzekerheid in risicotermen die nodig zijn om een weloverwogen beslissing te nemen. De Risk-TOC-benadering biedt een beter geïnformeerd perspectief dan eerdere voorstellen voor op besluittheorie gebaseerde Optimal Inspection-benaderingen met aannames en parameters die de onzekerheden bij de SSLCM-processen niet volledig kwantificeren. De Risk-TOC-benadering biedt ook een kwantitatief middel voor het beoordelen van de gevolgen van verschillende faalwijzen (d.w.z. vermoeidheidsscheuren en corrosie). De Risk-TOC-benadering biedt een gekwantificeerde vergelijkingsbasis gezien de omvang van de risicomiddelen door onzekerheid te gelde te maken. Op deze manier biedt de Risk - TOC-benadering een kader voor fundamentele definities, waaronder monetaire onzekerheid, analyse van alternatieven (AoA's), Return on Investment (RoI) en Value of Information (VoI). De voordelen van prognostische HSM worden gepresenteerd in de context van vermindering van onzekerheid in de SSLCM-processen; waardoor het risico en de TOC worden verlaagd met gunstige RoI en VoI. De

Risk-TOC-aanpak wordt geverifieerd zoals aangetoond in voorbeeldtoepassingen met een US Coast Guard-cutter. Er wordt een discussie gegeven over de implicaties van de Risk-TOC-benadering voor SSLCM en duurzaamheid. Conclusies en aanbevelingen worden gepresenteerd voor de verdere ontwikkeling van de Risk-TOC-aanpak voor SSLCM.

PROLOG

I began working for the US Coast Guard when they were starting a major surface fleet recapitalization. This ambitious undertaking produced many challenges in acquiring new cutters and extending the service life of the legacy fleet. The challenges in structural design and service life evaluations involved decisions relating to hull structural degradation from both fatigue and corrosion. The analysis tools used in the early design and analysis processes were assumed to be conservative but were limited in their ability to fully quantify the uncertainties and related Risks associated with the decisions being made. I was familiar with the significant amount of work conducted on structural reliability by the US Navy in the area of structural response, including the works by Hess, Ayyub, and many more referenced in the Bibliography. The Hull Structural Monitoring (HSM) work by Principal Advisor Professor Kaminski and I provided insights into the uncertainties on the load side of the reliability analysis. I found the structural reliability provided a valuable approach to address the totality of combined uncertainties in the structural analysis processes. In the course of this work, it became clear that the systems analysis definitions required further consideration along with the approaches for evaluating the decisions to be made affecting the safety, availability, and cost that are of significant impact to the US Coast Guard. As part of the decision processes, HSM was (and still is) used to collect hull structural response data to verify the analysis approaches and provide invaluable information on the operational environment. The HSM efforts provided valuable insights into reducing the uncertainties in the analysis processes and provide information for updating the structural reliability based forecasts. However, there appeared to be a need for a quantitative framework for making decisions on uncertainties, substantial expenditures, and Risks involved.

The research for this investigation began with ideas and intentions to investigate Risk-Based Inspection (RBI) guided by prognostic HSM and reliability-based maintenance. However, in reviewing prior research in the context of Ship Structure Life Cycle Maintenance (SSLCM), it became clear the fundamentals definitions of ship structural systems and the uncertainty components of Risk required further quantification. This fundamental work was also needed in order to clarify the differences between the concepts and prior approaches being proposed for ship structure life cycle management. The results of the investigative research conducted on Risk Analysis and Management in many industries provided insights that were useful in developing a new fundamental approach for SSLCM. During this review, it also became clear that the decision processes in ship structure lifecycle management involves trade-offs between Risk and Total Ownership Cost (TOC). This understanding became the underlying foundation for the development and verification of the Risk-TOC approach. Risk and TOC analysis involves considerable effort to quantify related uncertainties required for decision-making; however, the Risk-TOC provides a framework for adding additional complexity where it is useful and data available to support further development. The results of the investigation into the intricacies of the Risk-TOC as a decisional approach are presented in this dissertation.

The further motivations for the development of the Risk-TOC process include the initiation of further discussions, development of the related processes, and the eventual implementation of the approach for continued SSLCM decisions faced in the US Coast Guard (in general and my coworkers in specific), US Navy, Valid JIP members, and beyond to commercial applications.

Karl Stambaugh Naval Architect, May 2020

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One of the many advantages of completing a Doctoral degree is having the privilege of working with numerous influential people that have contributed to the knowledge base that has gone into this work. Many mentors and associates in my career have had advanced degrees in the field of ship hydrodynamics and structures, beginning with professors at The University of Michigan followed by Drs. Paul Van Matter and Julio Giannotti, who provided my first professional opportunity as a Naval Architect. This first employment experience involved seakeeping model tests providing insights into the randomness of the sea environment and resulting loads on the ship hull and structure. This included meeting Dr. Owen Hughes and working with his structural analysis and optimization program that would later be known as MAESTRO that continues to be influential in my knowledge of ship structural design and analysis. This employment experience included numerous Ship Structures Committee (SSC) research projects, first under the guidance of Drs. Van Matter and Giannotti and later as Principle Investigator. Further opportunities included work with experts in the field of fatigue and fracture with Professor Stan Rolfe, Dr. Alan Pense, Professor Bill Munse, and Dr. Frederick Lawrence. This experience was followed by employment with the US Coast Guard Naval Engineering and continued work with experts in the field of event statistics with Dr. Ross Leadbetter and Dr. Igor Rychlik. Additional efforts included advanced topics related to ship structure loading, fatigue, reliability, and monitoring, working with Dr. Bilal Ayyub, Dr. Mirek Kaminski, Dr. Ingo Drummen, Dr. Goute Strohag, Dr. Henk den Besten, Dr. Len Rogers, Dr. Paul Hess, (Dr student) Remco Hageman and many others in the Cooperative Research Ships and Valid Joint Industry Projects. The influence of these associates and mentors is greatly appreciated

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1.0 INTRODUCTION

Ships must perform their missions with a high degree of reliability to maximize availability and safety through their service life. The long-term hull structure reliability and ultimate safety is time-dependent with degradation caused by the operational environment. Current practices by ship structural designers, maintenance planners, and operators are based on fixed design parameters that are prescriptive and more reactive than proactive in providing the required system availability and safety. However, the prescriptive and deterministic answers do not convey the true nature of the quantified uncertainties associated with Risk or provide a basis for formulating Risk avoidance or mitigation strategies. To this end, uncertainty matters in decisions involving large complex structural systems and major financial expenditures associated with ships. Uncertainty quantification is essential in understanding and managing Risk in ship structure.

Achieving the system safety requirements and availability are complicated because ships operate in stochastically, non-stationary random seaways resulting in long-term processes producing highly random loading on the hull structure. The subsequent strength degradation and material properties are both stochastically random. Furthermore, the models used to simulate and estimate the loading and responses are not perfect and subject to a type of randomness associated with their accuracy. Given the random processes and related uncertainties associated with the Ship Structure Lifecycle Management (SSLCM), the related Risks; and therefore, costs involved are significant. However, ship structural design has evolved to be prescriptive rule-based on structural engineering principles, for the most part, derived from empirical factors based on experience. This approach has produced a damage tolerant structure with empirical safety factors that are not fully characterized in quantified Risk terms. More recently, analytical approaches have been developed and applied based on physics-based hydrodynamic predictions of the hull loads, and high-fidelity Finite Element Analysis; however, failures have resulted because of unquantified uncertainties in the processes. There is a significant need to correlate the new analytically based approaches with the uncertainties and Risks that have been included empirically in the prescriptive rules.

Although structural reliability approaches have been developed to characterize the uncertainty in structural systems and applied in other industries, the technology transfer has not been fully realized for ship structures or framed in an applicable decision-making process. Research on ship maintenance management includes Optimal Inspection strategies to detect fatigue cracks and update the structural reliability when the cracks are found and repaired. This approach relies on finding fatigue cracks and determining an updated level of reliability after the repairs are made. This approach also includes the effects of the repair quality on reliability updating. However, Optimal Inspection approaches based on finding fatigue cracks in the structure are not cost-effective for complex ship structures in the context of Total Ownership Costs and quantified Risk as described in more detail herein. Furthermore, Optimal Inspection approaches are based on many assumptions that are not applicable to SSLCM as will be explained in later Chapters of this dissertation.

The SSLCM involves significant resources due to the enormity and complexity of the structure. Decisions made regarding SSLCM have a high impact value on these financial numbers and system performance in terms of availability. It follows that a more systematic approach to decision making will provide valuable insights into SSLCM with a high return on investment and reduced Risk exposure. The approach for Risk and Total Ownership Costs (TOC) presented in this dissertation applies to most any quantifiable mitigation scenario because it is a fundamental framework for making high impact decisions with significant economic implications.

1.1 Problem Statement and Proposed Solution

In this dissertation, the Risk-TOC approach was developed by examining the decision process and data required to make informed decisions. A new approach is proposed that applies specifically to SSLCM decisions evaluated in a Risk-TOC trade-off space. The underlying data and decision experience provided a unique opportunity to investigate the Risk-TOC trade-space decisional approach. In particular, the proposed Risk-TOC approach is verified using real data from full scale measurements (Stambaugh *et. al.,* 2014b and 2019) and related decisions as evidence in verification.

Example decisions influencing safety and major expenditures in SSLCM include:

1) Designing ship structure to prescriptive rules based on experience and empirically derived algorithms without explicitly considering the biases and uncertainties involved,
2) Appling Spectral Fatigue Analysis (SFA) in the design stage or not,
3) Increasing strength by making modifications as a result of observed progressive failures (generally buckling, corrosion and fatigue cracking),
4) Remaining Useful Life (RUL), End of Service Life (EOSL), and Service Life Extension Program (SLEP), and,
5) Prognostic Hull Structure Monitoring (HSM) to provide design process feedback and reduce uncertainty and risk exposure in SSLCM decisions.

These influential decisions involve the management of uncertainties, as an integral component of Risk, in the life cycle of the structural system with significant costs involved. For example, to repair fatigue cracks, the costs of Emergency Drydocking (EDD) and associated loss of availability of the asset-related costs can easily be in millions of dollars. The high cost of repair in EDD may result in early EOSL without adequate time to plan for replacement leading to higher long-term maintenance costs. EOSL (typically an economic decision) with adequate plans in place for timely asset replacement. The concepts of structural degradation and degrading structural reliability seem intuitively similar, and they are; however, dealing with the results is less intuitively obvious to a Decision Maker without a quantified frame of reference.

Because the SSLCM decision processes are not fully quantified in deterministic terms, the research question addressed in this dissertation is, given uncertainties in process and modeling of current state and future outcomes:

> How should ship structural designers and maintainers make objective decisions affecting SSLCM on system and subsystems levels required to achieve positive outcomes in safety at an affordable cost?

This question and related decisions have implications influencing TOC and Risk in SSLCM. Therefore, the proposed fundamental assumption of this dissertation is that SSLCM decisions are made in quantifiable terms in the Risk-TOC trade-off space.

The proposed solution is to:

> Develop a systems reliability approach and a Risk-TOC trade-space, with supporting technologies identified that will inform Decision Makers on positive outcomes in terms of economics and safety of ship structures.

The Risk-TOC approach provides a framework to evaluate and manage the trade-offs required to meet short term and long-term cost and safety objectives of the Decision Makers. This proposed solution begins by revisiting the systems level failure definitions and related structural system reliability, defining fundamentals of uncertainty contributing to Risk, further definition of the Risk-TOC trade-space, and supporting options the Decision Makers might consider in effecting SSLCM to achieve positive outcomes.

This dissertation combines theory, literature review, analysis of test data, and applications to clarify the subtleties, implications, and distinctions between uncertainty, Risk, and related ambiguities. New approaches are proposed to test the predictions of theory in the context of real applications. A literature review is included throughout the dissertation to support the development of the Risk-TOC approach and its verification. This dissertation includes both statistically-based Risk estimates and economics applied to SSLCM.

Supporting research includes an investigation into component level correlations of ship structural loading and the response and how that influences the system reliability estimate. This correlation has significant implications on the system's reliability analysis and failure predictions. Additionally, Bayesian Hyper Parameters (BHPs) are proposed for structural reliability and uncertainty propagation in a Bayesian Model Averaging (BMA) setting and demonstration of the benefits of prognostic HSM in uncertainty reduction.

This dissertation provides fundamental discussions on uncertainty, Risk, and Risk Analysis as a background and to contrast with the basics of prior proposed approaches. The inclusion of the fundamentals of quantifying uncertainty as it relates to Risk is intended to be useful to ship structural designers in general and the Naval Architects of the US Coast Guard in specific who may wish to understand, consider, and apply the approach. The fundamental approach descriptions are also intended to be useful in any further development of the approach by others who wish to build on this research.

1.2 Research Contributions

In the process of investigating the overall problems and critical decisions associated with SSLCM, it became clear that there are numerous fundamentally different definitions and approaches being proposed by others to solve this challenging problem. The concepts of structural reliability and Risk are not new in general as applied in other industries; however, their basic assumptions and fundamentals do not align with the realities of SSLCM. These prior approaches have been developed and proposed for many industries and applied in others. For example, Optimal Inspection approaches have been proposed for transfer to ship structures. However, these proposals have not considered the fundamental differences between fixed structures and ships. Many of the underlying assumptions are not applicable to ship structure from a philosophical and fundamental viewpoint, as will be discussed in greater detail in this dissertation.

Most (arguably all) of the prior approaches based on Decision Theory and Optimal Inspection were developed by researches working in the civil and offshore structures and then proposed similar approaches for ship structures. Of these approaches, basic definitions and assumptions related to the number of welded structural details, amount of structural redundancy, definition of failure, and related consequences do not apply to the ship structure. In the initial stage of this investigation, it became clear there was a need to review the fundamental definitions, assumptions, and details of the approaches associated with Risk assessments, including the definition of Risk to establish a sound foundation for a new approach for SSLCM.

This dissertation began with an investigation into the basic structural principles that define the fundamentals of the development of a new set of approaches for ship structural Risk management and sustainable lifecycle. The systems reliability and Risk-TOC framework proposed herein provides a basis for evaluating the assumptions required for application to ship structure Risk Analysis and decisions. The verification by examples demonstrates the efficacy of the Risk-TOC approach.

The resulting research and original work, which makes significant contributions to the field of knowledge presented in this dissertation include:

- Fundamental understanding is proposed and demonstrated that there is strong evidence the hull loading is highly correlated, and the ship's structural system response is statistically independent initially. The definition of the ship's structural system is examined, a new system's reliability perspective is proposed, and demonstrated. This new understanding includes:

  - Ship structure forms an integral network of load-carrying members and is a structural system with thousands of welded structural details, panels, grillages, where failures progress with increasing time dependent correlations. The implications of the structural configuration and failure processes are more involved than simple series or parallel system failure definitions.

  - Ship structural loading is highly correlated in primary structure, providing a basis for the estimation of the structural system behavior. The characteristics of the welded structural geometry and material response produce independence of welded structural details as demonstrated by the random characteristics of material properties, buckling, yielding, and fatigue life test data. This combination of correlated loading and time dependent response has a significant influence on system characterization.

  - The system-level structural fatigue and buckling failures are both cumulative and progressive events with potentially catastrophic results. The cumulative probabilities of the complex ship structural system are unique compared to other types of structures and have a fundamental influence on the management of failure probability and consequences.

  - Analysis of component load and failure correlation hypothesis and experimental verification is a foundation for an in-depth understanding of the systems failure process. This first phase of the research formed a basis for the development of the systems reliability definitions, implications of system failures, and formulation of the new Risk-TOC decision model proposed.

- Identification of fundamental differences between prior proposed Decision Theory-based approaches and the Risk-TOC are relevant to Risk Management of a large number of probabilistic based uncertainties. The prior definitions and details of implementation do not apply to ship structures; therefore, new definitions are presented herein along with their verification using a realistic case-studies.

- New definitions are proposed for ship structure systems failure, serviceability failure, and redundancy based on the time dependent failure processes and correlations that are modeled as a Markov process, all applicable to ship structures.

- A new approach is proposed for systems reliability based on system failure, and related correlations proposed and demonstrated. The new reliability updating approach is applicable to the systems level with a large number of structural components.

- New fundamental definitions are proposed for the Risk-TOC trade-space, and demonstrated, including expected TOC required to mitigate expected loss, Value at Risk measures, information entropy-based Risk measures, Value of Information (VoI), and Return on Investment (RoI) for evaluating investment alternatives in SSLCM.

- A new application of Bayesian Hyper Parameters (BHP) in a Bayesian Model Averaging (BMA) setting is proposed and demonstrated in uncertainty propagation associated with prognostic HSM in Risk Management approaches for ship structures. The approach verification is shown by using case study data.

- A new approach is proposed for inspection scheduling related to encountered wave heights and measured responses using Risk informed prognostic HSM.

- A new approach is proposed and demonstrated for estimating the fatigue crack growth from initiation through life to fracture failure given uncertainties associated with the application of both S-N and F-M based approaches, especially related to initial flaw size, weld geometries, and residual stresses in ship structural details included in S-N and F-M fatigue test data. The SN+FM Total Life approach is the combination of two ideas resulting in something new and useful in Risk Analysis and similar applications

- A discussion Chapter is provided to introduce new insights gained from the application of the Risk-TOC approach.

Risk concepts have been developed for many types of structures; however, they are based on assumptions applicable specifically to the type of structure and often differ significantly from ship structure. These prior approaches and related assumptions (proposed for bridges, offshore structures, pressure vessels, and aircraft) are examined for how they do and don't apply to ship structures, including SSLCM decisions and associated Risk.

The Sections of this dissertation on structural reliability provided background references to prior work used as a foundation to build the Risk-TOC approach. The prior work on structural reliability is presented for completeness rather than a specific recommendation of an approach. It is entirely possible to use other structural reliability approaches (preferably with appropriate verification) in the Risk-TOC assessments.

The Risk and TOC trade-space presented in this dissertation is a paradigm shift in SSLCM approach evaluations. The new perspectives presented relate to Risk Analysis, and Risk Management approaches and represents a fundamental shift in approach as compared to previous research on the topic of SSLCM, including RUL and EOSL decisions. The Risk-

TOC approach forms a framework for assessing new Risk Mitigation approaches in SSLCM, including the efficacy of prior proposed approaches.

1.3 Dissertation Overview

The overview of this dissertation begins with this Introduction, followed by Chapter 2.0, providing a background on the definition problem, systems-level failure definitions, and structural reliability updating. Chapter 3.0 provides a review of prior proposed approaches for SSLCM. Chapter 4.0 provides fundamental definitions needed to understand the Risk-TOC approach. Chapter 5.0 presents the definitions and development of the Risk-TOC approach. Chapter 6.0 provides example applications of the Risk-TOC approach for verification. Chapter 7.0 presents a discussion on results and implications for future applications and development. Chapters 8.0 and 9.0 are Conclusions and Recommendations, respectively. Appendices are included with more in-depth discussions on A) the fundamental work on loading correlation, B) the origins of Bayesian perspective and implications in Risk Management approaches, and C) a new SN+FM Total Life approach is proposed for total life fatigue crack growth prediction.

Figure 1.1 shows the overview and organization diagram of this dissertation.

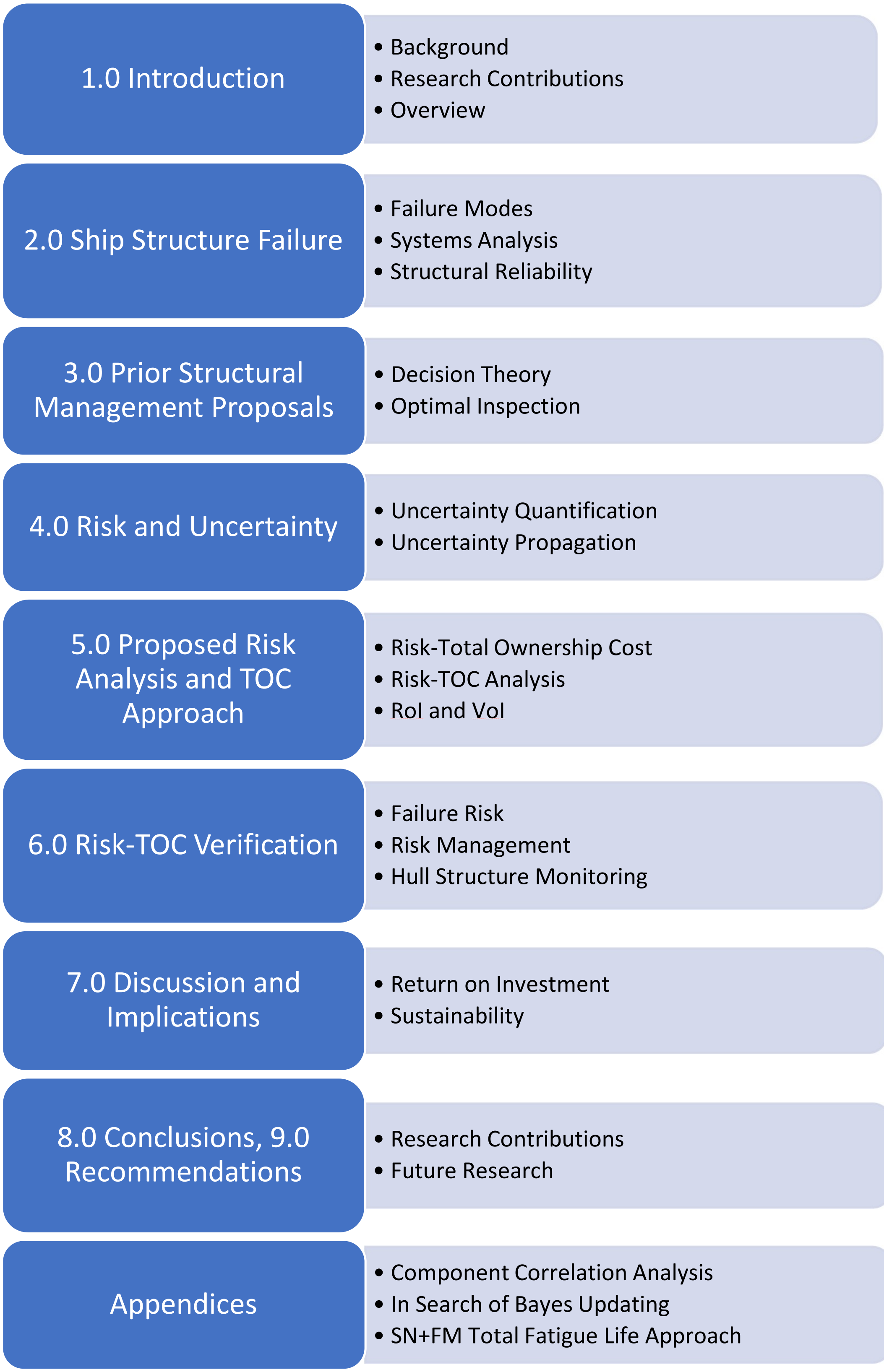

Figure 1.1 – Risk-TOC Dissertation Overview

2.0 SHIP STRUCTURE FAILURE

Problem Formulation

A Risk-based approach is proposed for Ship Structure Life Cycle Management (SSLCM) reflecting the significant costs and Risks associated with ship hull structure degradation, primarily from cyclic fatigue loading and structural wastage in a corrosive environment. The background research and problem formulation are presented in this Section of the dissertation. A summary of ship structure failure modes is presented in Sections 2.1. The foundational work on ship structural systems used to estimate probabilities of failure as the approach for aggregating probabilities associated with uncertainties in ship structure degradation are presented in Section 2.2. Section 2.3 presents prior approaches for estimating component-level structural reliability and a new approach for estimating system-level structural reliability, and Section 2.4 presents a discussion on the implications of system-level failure management.

2.1 Ship Structure Failure Modes

In order to define Risk in ship structure, it is necessary to consider the structural failure modes. There are several possible failure modes in ship structures, including yielding, buckling, fatigue, fracture, and corrosion. Both fatigue and corrosion degrade structural strength over time and pose a significant threat and cost to mitigate their destructive effects.

2.1.1 Fatigue and Fracture

Fatigue is the progressive and permanent structural change that occurs in a material subjected to repeated or fluctuating strains at nominal stresses that have maximum values less than the static yield strength of the global material. Fatigue may lead to the emergence of cracks and cause fracture after a sufficient number of fluctuations. In the process of fatigue failure in an originally intact metal, microcracks arise, coalesce or grow to macro-cracks that propagate until the fracture toughness of the material is exceeded and final fracture will occur.

Ship structural fatigue occurs as a result of cyclic loading, primarily in welded structural details. The fatigue damage progresses from an initial flaw in the structure and continues to grow as it experiences various levels of cyclic loading. Fatigue cracking initiation, through-thickness cracking, and crack growth all characterize the progression. However, if not considered in the design or adequately detected and repaired, fatigue cracking can lead to significant economic failure if fatigue cracking is widespread, and repair efforts are needed to prevent it from reaching the ultimate limit state with its associated high Risk and consequences.

Given a ship hull form and structural design, the following are the major elements of a fatigue life assessment of that design and the concerns associated with each element. They include:

1. Environment and operational profile – is highly dependent upon the relevance of the operational profile and associated environmental data used to develop the environmental loads.

2. Ship data and hydrostatic loading – requires careful attention as proper modeling and scaling of mass, buoyancy, and stiffness distributions are needed to draw proper conclusions from comparing results of numerical calculations, model testing, and full-scale measurements.

3. Hull Girder Hydrodynamic Loading – is the area of uncertainty due to complex physics, dynamics and random nature of wave action, and linear relations used in modeling.

4. Structural Response– FEA modeling assumes an ideal structure without geometric and fabrication imperfections. The focus of the approach is on the nominal stresses where specific types of geometric stress concentrations are included in the S-N data.

5. Fatigue Life Calculation - The application of S-N data and the cumulative damage approach process is relatively well established for bridges and other large civil structures; however, there are uncertainties associated with the process and systems approach discussed later in this dissertation. Also, the use of design or characteristic curves, as illustrated in Figure 2.2, are used with fatigue response presented on a logarithmic scale obscures the magnitude of this uncertainty.

The construction quality, tolerances, and imperfections, such as misalignments are very important aspects of structural fatigue life but not included as part of this validation study. Their uncertainties in the context of structural reliability analysis are documented by Hess *et. al.,* (2002a, 2002b, 2003, and 2015), Collette (2018), and Ayyub *et. al*., (2014).

In current practice, fatigue failure in component testing is defined as a through-thickness crack, as observed in the welded structural details. A fatigue crack can spend years growing prior to becoming a visible or through-thickness crack. As a practical matter, fatigue cracks located in the shell structure often leak as they extend beyond this through-thickness definition and are detected. In general, the initial through-thickness cracks are not a cause for concern in ultimate strength (see Dexter *et. al.,* 2000); however, at this stage, they can begin to grow very quickly and then become a greater Risk of more significant failure. Stable fatigue crack growth progresses relatively quickly if not found and repaired. The probability of more severe failure by fast fracture increases rapidly as the crack length increases. The critical nature associated with large cracks should never be underestimated because of the potential consequences of rapidly growing fractures.

There are several computational approaches for estimating the cumulative fatigue damage analysis, including cumulative damage summation and fracture mechanics-based, crack propagation approaches.

In a Spectral Fatigue Analysis (SFA), fatigue damage is calculated by comparing the predicted cyclic stress loading history to the experimentally based cyclic loading history, known as Stress-Number of Cycles (S-N), required to produce fatigue cracking in welded details. This approach is known as the Palmgren-Miner (Miner 1945) cumulative damage summation approach. In the Palmgren-Miner approach, the ratio of stress load cycles used to calculate the total number for the service life of the structure to stress to failure (defined as a through-thickness fatigue crack) is summed over the range of cycles and fatigue life is consumed when this ratio equals one. Damage ratio values greater than one indicate a shorter fatigue life as represented by the number of cycles calculated for the service life of the structural detail in question.

The SFA and S-N approaches are based on the fundamental definitions that the encountered wave loading is statistically stationary and independent for periods on the order of one-half hour for unique combinations of wave environment, ship speed, and heading. The results of the independent definition provide a basis for estimating the structural response to the loading for the specified conditions, then summing the probabilities over a convolution integral over the probabilities of the wave, speed, and heading occurrences.

Sikora *et al.* (1983) and Sieve *et al.* (2000) provide examples of fatigue loading estimates and data sets used by naval ship designers. These fatigue design approaches and data sets have been used in the fatigue evaluations of numerous design and sustainment decisions for US Coast Guard surface assets.

The SFA and S-N curve approaches (Sieve *et. al.,* 2000) are useful in design applications where the Miner's cumulative damage summation equals one, and the probability of failure is 2.3% of a through-thickness fatigue crack as the characteristic design curve. While appropriate for design as the current state of practice, the time-varying probability of failure is of interest to calculate the time-varying Risk.

Fatigue in ship structures is the result of cyclic loading on a structure resulting in cracking on a micro-scale progressing to large cracks. Modern materials are generally selected, so cracks grow in a stable manner; however, it is the responsibility of the ship structural designer and maintainer to make decisions that minimize the possibility that fatigue cracks will grow to a size where they result in a fast-growing fracture.

Fracture in ships has been documented by Stambaugh *et. al.,* (1987) and, more recently, by the Ship Structures Committee (www.shipstructurecomittee.org). A significant amount of research has been conducted on fracture toughness of ship steels by the Ship Structures Committee and other research institutions. However, the majority of this work has been to determine a lower bound on material properties, and little is provided on the statistical quantification of the material properties for use in reliability and Risk Analysis. The approaches used for fracture analysis determine a lower bound on material toughness for design and few have addressed Risk as defined by the probability of failure time consequences in Life Cycle Management (LCM) applications

Rolfe *et. al.,* (1993) is one of the early works that has looked at the fracture mechanics of the critical crack length *KIc* and estimated the stress loading history to calculate the critical crack length as 380mm (15") using a deterministic *KIc* and an empirically based maximum load. The critical stress intensity factor was chosen as a lower bound and not quantified statistically. The calculations indicated it will take a through-thickness crack five years to grow to reach the 380mm length. They also concluded that a 380mm crack will be detected before reaching this length; however, they did indicate that the probability of detection data was non-existent and needed further development. While interesting as an early benchmark for critical crack length, no consideration is given for the specifics of the structural geometry or probability of failure or consequences of Risk. The work by Rolfe *et. al.,* (1993) provides interesting information on the crack transition from an elliptical shape to through-thickness for use in stress intensity calculations.

Dexter *et. al.,* (2004) investigated large stable cracks growing through plating and framing typical of ship structure; however, he did not consider the probability of detection or full statistical characterization of the load and strength parameters for ships. Similarly, Ayala-Uraga *et. al.,* (2007) investigated the impact of long cracks in FPSOs, including the effects of high mean stress and estimated Probability of Brittle Fracture (*PfBF*) higher than 10^{-2}. They did not address the probability of detection or the Risks associated with this high *PfBF*.

Sumpter *et. al.,* (2004) investigated the probability of fracture in ships based on historical data and a statistically based calculation of load vs. resistance but did not describe the details of the *Pf* calculation. They estimated a probability of failure (*Pf*) of 10^{-4} for a 250mm crack. No Probability of Detection (*PoD*) was considered in the analysis.

Fast fracture can be brittle or exhibit ductility. However, results are often catastrophic at worst and expensive to repair at best, as investigated by Stambaugh *et. al.,* (1987). Fracture in ships has been investigated more recently by Sumpter *et. al.,* (2004) and Ayala-Uraga, *et. al.,* (2007) for FPSO's.

The prescriptive design approaches used for ship structures are based on years of success and failures with a probability of fracture in the 10-4 range, as discussed by Sumpter *et. al.,* (2004). The prescriptive design approach includes material specifications with adequate toughness for most common applications. The difficulty arises when a proposed ship will operate in conditions (both loading and temperature) that are outside of the empirically based prescriptive approach. Current first principles approaches do not include Risk Analysis of fracture specifically; rather, they rely on empirically derived material toughness properties that have been acceptable historically (Sumpter *et. al.*, 2004).

Fracture remains the proverbial elephant in the room for other Decision Theory and Optimal Inspection Risk-based approaches as the ultimate failure Risk with significant consequences. In commercial applications, ships are insured (Risk transfer). Naval vessels are typically self-insured by the country owning the vessels (Risk acceptance). The potential consequences extend beyond the cost of the asset replacement and include loss of life and political fallout with major financial implications. Therefore, the Risk approach discussed in this dissertation is of significant value in minimizing TOC and Risk for SSLCM, as will be presented in the following Chapters.

Appendix C contains a discussion on the S-N and F-M approaches for estimation of total life from crack initiation to fracture. This total life approach is used in estimating Risk in the examples presented in Chapter 6.0 of this dissertation.

2.1.2 Corrosion

Corrosion is the degradation of a material by chemical or electrochemical reaction with its environment. Corrosion reduces the component thickness, either uniformly or locally. The corrosion phenomenon is a response of metallic material exposed to a corrosive environment that includes a large number of parameters typically present in a corrosive environment. The variety of chemical and physical variables of environments and materials leads to a large number of types and appearance of corrosion (Melchers 2007, Geddes *et. al.,* 1999, and Cronvall 2011).

Corrosion can manifest itself in several forms, and there are generally accepted categories of corrosion based on the appearance and electrochemical processes. The types of corrosion include (but are not limited to):

- uniform,
- pitting,
- galvanic (two-metal) corrosion,
- crevice corrosion,
- intergranular corrosion,

The most common types of corrosion in ship structure include uniform corrosion and local groove and pitting corrosions.

Uniform corrosion refers to a uniform attack over surfaces of the material and results in thinning of the material. Uniform corrosion rates vary with fluid oxygen content, temperature, and many other environmental parameters (Melchers 2007, Geddes *et. al.,* 1999) for more on the various physical parameters that play a major role in the physical process).

Local corrosion occurs in areas of non-homogeneities at the metal surface, and in local differences in the electrochemical reactivity of the environment, the creation of local electrolytic cells results in local corrosion degradation. Localized corrosion includes pitting, groove, and crevice corrosion. Local corrosions are commonly caused by the breakdown of a passive film coating (i.e., paint) on metal in local areas. Crevice corrosion results from local environmental conditions in the restricted region of a crevice being different and more aggressive than the global environment.

Intergranular corrosion is produced by a difference in electronic potential across various grain boundaries often formed by aging or heat affected material properties. This type of corrosion often occurred in aluminum structure exposed to long term exposures to sunlight and resulting heat input to the exposed aluminum structure.

Corrosion rate estimates are typically physics-based or probabilistic based. The former requires knowledge of the material and environmental factors (including but not limited to chemical, biological) both past and future (Melchers 2007). The latter requires historical knowledge of the corrosion rate (Lampe 2018). Both approaches involve data-intensive requirements; however, the probabilistic approach is generally used to evaluate corrosion rates due to the complexities of the physics-based approach requiring complete knowledge of a large number of variables over time.

Although corrosion is not explicitly a failure mode in itself, the wastage of structure (i.e., thickness reductions) can lead to a reduction in structural capacity in both yielding and buckling modes of failure. The interactions of corrosion and buckling modes of structural failure are very complex, and while progressive failure to discrete instantaneous loading has been investigated, progressive failure spatially in the structure and temporally in a random environment have not been fully addressed in the current research.

Corrosion inspections are predominantly visual supplemented with Ultrasonic Thickness (UT) measurements, typically of the hull shell plating. While this has proven successful empirically generally, *PoD* statistics for corrosion inspections in ships have not been quantified for Risk-based assessments. Published UT measurements and related statistics are typically used to determine average values and not fully characterize the extremes (see Luque *et. al.,* 2014).

Although the effects of corrosion have a significant influence on the hull girder structural failure, it does not constitute a hull structural failure independently without accelerating one of the other failure modes. However, serviceability can be affected significantly as local corrosion causes loss of watertight integrity or sinking as a worst-case.

Corrosion degrades the strength of a structure and depends on many factors, as discussed by Ayyub *et al.* (2014). Corrosion reduces the section modulus of the hull of a vessel by thinning the thickness of primary structural members. It reduces the ability of the structure to resist externally induced bending moment.

Unlike fatigue cracks, uniform corrosion wastage is easier to observe visually as coatings breakdown. Generally, widespread corrosion is detected before it degrades structural integrity from progressive, serviceability failure to ultimate failure. Although corrosion is pervasive in ship structure in relatively small areas, on average, it is managed successfully for the majority of structure with coatings and periodic inspections. There are, however, isolated problematic areas in the structure where corrosion can become severe and, in cases, go undetected as noted by Melcher *et. al.,* (2007). In the extreme, the severe undetected corrosion may penetrate the entire structure and compromise watertight integrity, if not outright degradation of global hull strength. This isolated undetected corrosion is especially problematic in naval ships with interior thermal insulation on the primary structural envelop, and also in machinery and dense piping spaces with constraints for adequate inspections. A literature search on *PoD* for corrosion in ship structures produced no references with verified approaches, most being proposed without relevant data for verification. The Risk to hull structural integrity increases significantly as corrosion wastage goes undetected, and progressive failure occurs under modest loading.

According to Ayyub *et al.,* (2014), several models of uniform corrosion growth have been suggested by Orisamolu *et al.,* (1999) and Paik *et al.* (1998), Akpan *et al.,* (2002), and more recently Luque *et. al.,* (2014). In the presence of corrosion, the ultimate strength (S_u) of a structural member is given by

$$S_u(t) = \begin{cases} S_{u0} & t \le t_r \\ c(t)S_{u0} & t > t_r \end{cases} \tag{1}$$

where S_u = ultimate strength of a structural component; t_r is the life of coating (years) as a threshold time; t is the age of the vessel (years), S_{u0} is the initial ultimate strength of a structural component at t is equal to zero; $c(t)$ is a strength reduction factor accounting for corrosion of dimensionless nature in the range [0, 1], a model that may take the following form:

$$c(t) = 1 - a_1 a_2 (t - t_r)^b \tag{2}$$

where a_1 is the annual thickness reduction factor for general corrosion, a_2 is a strength reduction factor per unit value of a_1, and b is a model coefficient to account for trend nonlinearity, commonly taken as one.

2.1.3 Buckling and Yielding

For the most part, the strength of ship structural components (for example, hull girder, stiffened panel, unstiffened panel, and details) are calculated using algorithms developed with empirical relations, which do not necessarily reflect the global interactions of the ship structural system being analyzed, especially for the ultimate strength. If the global interactions of the ship system and progressive damage are ignored, potentially high-Risk failure modes corresponding to lower energy (serviceability failure), pre-collapse structural response effects may be missing from the design evaluation, resulting in a non-conservative design. The ability to assess the hull girder bending load at the onset of damage, or first failure, as well as ultimate collapse, is accomplished on a ship hull structure section using computer codes such as ALPS (Hughes *et. al.,* 2010) and ULSTR (Adamchak 1982). The point of initial failure can be predicted with these codes and compared to the ultimate bending resistance. The degree of separation between initial failure and ultimate collapse is an indicator of the reserve strength and provides a measure of safety. In this example, the target reliability associated with the onset of failure must be less than that for collapse as shown in Figure 2.1

Application of Non-Linear Finite Element Analysis (NL-FEA) is used to evaluate the ULS and contributions of progressive failure and the hull loading required to produce this loading, as presented by Sheinberg *et al.* (2011). The results of the NL-FEA capture local and global response with similar results illustrated in Figure 2.1. Key assumptions on initial imperfections are important, and considerable computational time is required for this analysis. However, this is often justified in making large scale sustainment and service life decisions of investments in capital assets such as ships.

2.1.3.1 Structural Buckling

Although structural buckling is well developed and applied in design, the impact of corrosion reduces the strength of structure buckling capacity, both locally in individual structural members, but globally if the corrosion wastage or progressive failure has progressed due to successive overloads. Paik *et. al.,* (2002), Guedes-Scores *et.al,* (1999) have written extensively on this topic.

2.1.3.2 Structural Yielding

Similar to buckling, yielding analysis as an ultimate failure mode is well developed for design, but less understood is experiencing severe corrosion wastage. Paik *et. al.,* (2002), Guedes-Scores (1988), and Hess (2003) have written extensively on this topic.

2.1.4 Structural Limit States

To assess ship structural failure, designers analyze the limit state functions of that ship. The most commonly used limit states include the Ultimate Limit State (ULS), and to a lesser extent Service Limit State (SLS). The SLS deals with the assessment of conditions under which the vessel can still perform its main duties even though some functionality may be impaired. The failure process can occur progressively from mechanisms such as yielding, plate buckling, and fatigue in the material. These failures often occur locally and in isolated areas with little notice. However, the seemingly minor failures will accumulate over time and reduce the overall strength of the hull structure and increase the potential for serious, if not catastrophic failure.

2.1.4.1 Serviceability Limit State

A frequently used definition of serviceability failure has been the onset of yielding or local buckling in the structural material. The structural response under consideration is the stress, which is then compared to the nominal yield strength, buckling, or cracking as derived from component material testing. The idea of the loaded structure experiencing the onset of plastic deformations or rapid crack growth, or fraction thereof is useful as precursor failures, and related probabilities are used to support the remaining strength assessments. This approach provides a valuable perspective as prior events relative to structural performance associated with higher energy collapse mechanisms such as buckling or fracture discuss later for ultimate limit states. Progressive damage resulting from consecutive near overloads (stresses producing permanent deformations and strength reductions) weaken the structure such that the collapse strength is markedly less than originally assumed in local panel strength evaluations. Defining serviceability failure as the onset of inelastic behavior is intended to provide a margin between safe and more uncertain, higher energy failures, with much higher consequences. Further definition of serviceability failure is presented next.

Many of the component level hull structural failures are local to individual panel stiffener failure modes, panel failure modes, grillage failure modes, and global hull girder failure modes. These failures often occur individually, often with minor consequences in hull structure ultimate strength; however, as the failures progress, they become significant from a cumulative effect of overloads or in rare circumstances, from one single ultimate overload. In practice, the failure of the components occurs from smaller, more probable loadings than compared to the lower probability of a single load required to collapse the hull girder. The implication on serviceability and ultimate strength must be assessed on their probability of occurrence and the associated consequences of failure. This sequence of failure occurs along a continuum of the failure curve of bending moment vs. curvature, as illustrated in Figure 2.1 In the case of buckling failure, the hull structure acts in the elastic range for low hull loading effects. Figure 2.1 shows an example load and hull curvature (global deformation) that is representative of typical hull girder response to various levels of loading and progressive failure of individual structural components in the system produce the appearance of ductile failure in the progressive failure range. As loading increases, a few individual components may fail with minimal effect, and the hull girder may still behave for the most part, in the elastic range. However, as the component level failure increases when the ship encounters more severe conditions, the cumulative effects increase component level failures in a progressive manner. This progressive failure reduces the hull girder capacity.

In the Figure 2.1 illustration, the proposed serviceability limit is at the end of the elastic range, and ultimate capacity at the maximum loading the hull can withstand. In practice, the end of the elastic range is difficult to isolate; however, the probability of failure and the consequences of damage incurred in the early inelastic range can be evaluated. The question becomes, how much progressive failure is too much, and what is the Risk of failure? If the structure has sufficient reserve capacity between the elastic range and ultimate capacity, the range of serviceability can be extended, but not without understanding the Risk and costs of doing so.

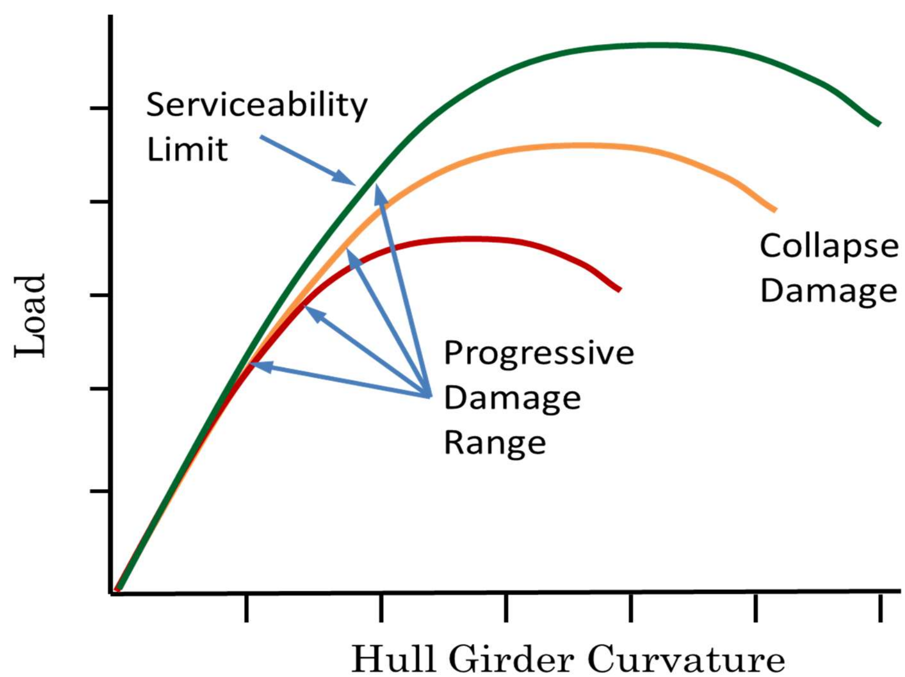

Figure 2.1 – Illustration of load and hull curvature showing transitions from serviceability limit state to ultimate failure limit state

Serviceability limit states are in the linear range for buckling prior to ULS. As a practical matter, if a component failure reduces the hull strength in any region above the elastic range, it should be repaired to reduce the effects of progressive failure on ultimate strength. If not repaired, further damage will become more extensive and more expensive to repair.

Of these failure modes, fatigue and corrosion are progressive as a function of time, generally a period of years, depending on the quality of design in the former and maintenance in the latter. Buckling and yielding are generally related to overloads from environmental induced loading; however, they can be progressive over time. Brittle or fast fracture is an event, given the presence of a critical size fatigue crack. This event happens very fast, potentially at the speed of sound in the case of brittle fracture. Brittle fracture in ship structure often makes a loud sound or bang when it occurs.

The time-varying effects of fatigue and corrosion are addressed here because of the associated lifecycle maintenance costs. Brittle fracture is important because of the high value of consequence when it occurs.

2.1.4.2 Ultimate Limit State

Ultimate strength, as described by Hess (2003), Hughes *et. al.,* (2010), and Piak *et. al.,* (2002) is summarized here and adapted within a format needed to consider the failure progression of SLS and its relationship to ULS.

The ultimate failure is the point at which a structural member is unable to continue to carry an additional load. Analytical approaches used to evaluate a structure either predict a response due to loading (for example, stress or displacement) or predict the ultimate strength (for example, collapse strength). To predict an ultimate failure, the designer may either choose a simple model that gives only the collapse or buckling strength or a more complex model, which shows the progression to the ultimate collapse and beyond (post-buckling regime). On a local component level, the simpler model provides a threshold between serviceability and failure. The complex global hull girder structure, the progression from no damage to the ultimate collapse over time because lower loading magnitudes will occur more frequently than the ultimate collapse ultimate load. More detail on the modeling of these global approaches is discussed in Hughes *et al*., (2010) and Benson (2011).

As ships age, they experience progressive degradation by corrosion, fatigue, buckling, and current repair criteria are not based on a direct analysis approach. In the case of uniform corrosion, 25% wastage is often used as a practical limiting criteria, and there is even less guidance on acceptable fatigue cracking limits for plate or supporting structure.

In the past, ship structure design has focused almost entirely on the ULS with Hess (2003) and Paik *et.al,* (2003) being exceptions. However, current economic realities have placed more emphasis on SLS, and this is an area where further research on reserve strength and its degradation will be beneficial in assessing Risk in SSLCM. Failure mode definitions based on time-dependent reliability levels will be beneficial in the SSLCM decision process.

Table 2.1 Hull Structure Failure Modes

Failure Mode	Serviceability		Ultimate		Variable State
	Failure	Limit State	Failure	Limit State	
Yielding	Local members deformations	Yield strength	Hull girder collapse	Gross material failure	Maximum local stress
Buckling	Local member deformations	Onset of nonlinearity in bending moment to curvature plot	Hull girder collapse	Maximum bending resistance	Maximum local and global stress
Cracking	Local fatigue crack in the structure	Through thickness	Hull girder separation	Fracture in the hull girder	Stress load history

In summary, Table 2-1 from Stambaugh *et. al.,* (2014a) provides an overview of the definitions of structural failure and considerations involved.

2.2 Structural Component and Systems Performance

Why is this important?

Reliability analysis of a complex system with a large number of components must include consideration for the correlation of structural components in the system loading, independence of their response capacity, and dependencies of the system elements as they degrade in strength during the ship's service life.

A new fundamental understanding is proposed for ship structural systems considering correlations of components in spatial and temporal terms. This new systems-level understanding is based on an analysis of full-scale measured strain data in a ship structure and inspection of system response test data.

2.2.1 Structural Component Level Performance

What is it? How is it Calculated? How is it Used?

In the context of complex structural system reliability, the interactions of structural components must be considered in how they 1) correlate within the total system response based on their relative performance, and 2) as they relate to one another as time progresses, and weakening occurs by failure mode (e.g., fatigue and corrosion). In ship structural systems analysis, both loading and response must be evaluated based on their correlations, independencies, and interdependencies, both spatially and temporally.

In systems analysis, in general, the concept of independence and dependence are used to define the relationship between two events as used in probability theory. For example, events A and B are called perfectly dependent if the occurrence of A results in the occurrence of B and vice versa, (i.e., the conditional probabilities $P(A|B)=1$ and the $P(B|A)=1$; where | means "given"). On the other extreme, A and B are independent means $P(A|B)=P(A)$ and $P(B|A)=P(B)$. In the context of the relationship of component failure, the performance of two details represents perfectly independent failure (or survival) events to indicate that if one occurs, the other will not occur.

2.2.2 Prior Definitions of Structural Systems Performance

The reliability of civil structural systems is assessed based on the assumption that it is composed of components that are functioning either in series, parallel, or a combination. These definitions are implied in system failure definitions for the civil structures are briefly stated as:

> Series – components linked together in a manner that if one fails, the system fails or is no longer functional.
>
> Parallel – components are working together in a manner that if one fails, the other components will continue to function; therefore, the system continues to function completely or partially.

A system of individual components may be a combination of series and parallel. There are combinations of the series and parallel system depending on the structural configuration.

The concepts of series and parallel system are used frequently in civil structures made up of identifiable independent (i.e., in truss configurations) components as in a simple bridge span with multiple girders, bridge structure with truss elements, steel beam buildings or offshore structures of individual, interconnected, tubular members. Many civil and offshore structures are constructed with individual structural members that are physically independent structural elements conforming to series or parallel definitions of systems reliability.

These concepts of series and parallel have been proposed for ship structure as described by Hecht *et. al.,* (2004), Frangapol *et. al.,* (2012) and Garbatov *et. al.,* (2002) and numerous others. However, from a viewpoint of failure in ship structures, the structural system is neither in series, parallel, nor a simple hybrid of both. Ship structure is a complex system of components and welded geometric details undergoing a correlated loading exposure with different magnitudes depending on location. In this case, the structural components have correlated loading and are independent in structural response capacity, at least initially. These concepts are very useful in providing insights as to the overall system's useful life from initial local component failures to the failure of the entire system.

Welded ship structure consists of structural shapes and plates welded to form **a** structural monocoque system. Failure of the system results in a catastrophic event if the structural failure is not prevented by sound structural design, material properties for safe life or rigorous inspection, and redundancy in the case of fail-safe design. In the case of one continuously welded shell structure, progressive failure at multiple sites will likely progress until the failure locations aggregate to weaken the structure and collapses by local buckling or in the case of subsequent fractures initiating from fatigue cracks depending on the failure mode[1].

In summary, at the system level, ship structural elements do not follow series or parallel models. From a failure perspective, be it fatigue, fracture, buckling, or yielding in a ship structural system, the failure is progressive either progressive over time from multiple events or instantaneously and possibly catastrophic. From a catastrophic failure perspective, there is no structural redundancy from independent load paths in modern welded ships. However, there is reserve strength in the hull girder structure, and its importance cannot be understated in assessing local damage, progressive failure, and ultimate collapse failures. Reserve strength will be discussed again in Chapter 7.0

2.2.3 Ship Structural System Performance

In the context of a structural system, correlation means the system components are experiencing similar stress experiences, and there is a high amount of autocorrelation between them.

The measured amount of correlation in the structural component details is determined by conducting a correlation analysis of the measured loading response from a full-scale instrumentation program. A correlation analysis of full-scale measured strain in ship structures is presented in Appendix A.

The correlation analysis presented in Appendix A indicates the loading experienced by ship structural components are highly correlated. In terms of hull girder bending, the structural components are sharing the same general hull girder load spectrum in different magnitudes depending on location in the hull girder and component local stress concentrations form geometry and weld configuration.

---

[1] Prior to WWII, ships were riveted together in longitudinal strakes along with the longitudinal and transverse supporting structure forming multiple independent load paths of a redundant parallel system, from a fracture failure perspective. During WWII, ship hull structure began being built by welding all of structure together as a faster way to build ships; however, the resulting completely welded ships were far less tolerant of fatigue cracks, often initiating in the joining welds. More on the impact of the transition from riveted to all welded structure is documented in SSC research.

There are other types of local loading, including bow and side wave impacts that have their correlation effects that are addressed next in the systems analysis discussion.

2.2.3.1 System Loading of Ship Structural Components

System reliability and capacity are evaluated for any group of components that are correlated on the hull structure loading side of the reliability analysis.

The significant amount of loading correlation between hull structural components means they are sharing the same general hull girder load spectrum. Differences in the resulting stress loading spectrum are scaled based on location and hull girder structure and correlated with relative stress magnitude. The differences in the loading spectrum are primarily scaled based on location and hull girder structure, not the spectrum itself. This scaling approach is used where the hull girder loading is scaled depending on location and structure determined typically by FEA. The stress spectrum is not perfectly correlated do to the phasing of horizontal and torsional bending induced stresses; however, the correlation analysis presented in Appendix A indicates a very high amount of correlation in the primary hull girder structure of an instrumented ship (Stambaugh *et. al.,* 2014b).

The finding associated with loading correlation implies that each component can be grouped according to the component geometry, stress spectrum and stress magnitude experienced. Each fully correlated component group is represented according to the loading for that group. Therefore, the aggregated statistical uncertainties of response will represent the total uncertainty for that group of structural components. In an ideal situation, where all structural component details are designed with the same strength (e.g., fatigue life), there is one massive group. This idealized example is not the general practice due to the preference for uniformity of structural components and details for construction cost considerations, producing a variety of correlated structural detail groupings.

Sources of component independency on the system response side can be attributed to variations in weld detail configurations and structural geometry and type of welded structural detail fatigue category on the response side that are correlated into groupings and used in fatigue design (ABS 2017, Sieve *et al.,* 2000). The following definitions are proposed based on the inspection of fatigue response in welded structural details.

Structural material response to loading is random due to variations in properties, and the resulting failures are independent based on fatigue test data examples illustrated in Figure 2.2. There are correlations to be found in fatigue test data from variables in weld geometry, quality (flaws), residual stress. Implications of the independence of material response within correlated groupings form one of the underlying assumptions associated with the S-N fatigue design approach and the use of typical geometric and welded detail configurations.

2.2.3.2 System Response of Ship Structural Components

The structural response characteristics have significant implications in system analysis, as described in the dissertation.

In the context of ship structural system analysis, the definition(s) of system failure depends on the mode of failure and degradation over time. While most modes of failure are initially independent and are isolated, they become more dependent and correlated as both the damage and loading increase depending on the failure mode. The spatial and temporal probabilities of failure also change as failure progresses and or load increases.

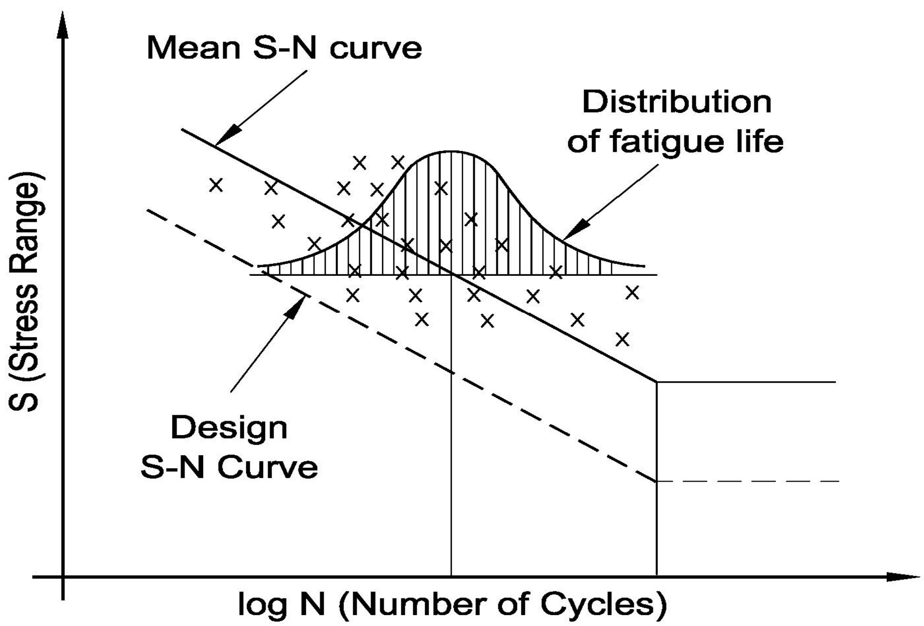

Figure 2.2 - Illustration of characteristic design curve and test data (redrawn from Hughes *et. al.,* 2010)

Ship structural details respond independently on a systems-level, as noted by the data associated with S-N curves for specific category characteristics. The scatter illustrated in Figure 2.2 is characteristic of the statistical variance of life (number of cycles to failure) in the fatigue response of structural details given a detail configuration and level of stress in the structural detail. The structural response from the material properties and fabrication procedures are generally correlated; however, they are highly independent in response within each correlated grouping (i.e., fatigue class or category), as can be seen in fatigue test data sets (e.g., ABS 2017 and Sieve *et. al.,* 2000). From a fatigue material response perspective, failures for a given applied load, are statistically independent for a given fatigue category. This material response is a fundamental stochastic characteristic of the S-N test data and transfers to the as-built structure. This combination of correlated stress loading and independent failure of welded details is discussed later in the context of their influence on the system reliability.

In ship structure, system complexity, failure processes, and failure interactions are spatial and temporal that may be modeled as Markov processes. Quantifying the failure processes and related structural reliability in a stochastic loading involves more complex approaches, including the Markov process approach, as suggested by Ebeling (2010) and Lassen *et. al.,* (2015) as examples. An application of the Markov process modeling of system failure is presented in Chapters 5.0 and 6.0 of this dissertation.

2.2.4 Systems Failure Definitions and Implications

Given the evaluation and related discussion on component and systems structural reliability as correlated on the loading side and independent on the response side, there are cases when the system is undergoing large amounts of component failures and then combine to reduce the overall hull girder strength collectively. The interactions of progressive damage modes become interrelated, result in complex interactions as strength degrades, and require analysis on a systems level. In continuous complex ship structure, failures are independent until they aggregate and begin to correlate, weaken the structure collectively, and produce progressive damage to the system. For example, in ship structures, component failures by fatigue and corrosion wastage degradation experience correlated loading and subsequently fail in combined patterns as in progressive failure as they correlate and aggregate and weaken the hull structure on the strength response side.

Fatigue and corrosion structural degradation effects are similarly independent up to a time when the aggregated weakening effects become significant, and progressive failure begins. In this case of advanced progressive failure, it is prudent not to push the limits beyond serviceability because the aggregated progressive failure increases the probability of failure in collapse modes, and consequences of major damage may occur, resulting in very high Risk, as shown in later Chapters.

A long transition of structural weakening is typically the case for fatigue failures, at least initially as fatigue cracks grow in the subcritical sizes. The fatigue cracks do not typically correlate in failure dependency or load shedding in subcritical sizes. However, as fatigue cracks transition to larger sizes, any single fatigue crack that is loaded sufficiently, could conceivably, transition into brittle fracture. This type of sudden failure is more likely to occur before large numbers of fatigue cracks occurring and reducing strength collectively and globally. Although this collective weakening is not aggregated spatially due to loading interactions, there is temporal aggregation reducing the reliability of the system as independent components degrade in strength toward their respective potentials to become fracture initiation sites as described in a later example.

In a worst-case scenario, fatigue cracks can reach a critical size in a short time between serviceability and catastrophic failure; therefore, their criticality should be considered in a structural Risk Analysis.

Corrosion wastage in ship structures is more likely to experience temporally aggregated effects of weakened structure, and progressive failure becomes rapid among spatially correlated weakened areas over time.

The implications of the proposed approach presented herein for estimating the total systems approach to fatigue failure is relatively simple; however, they are profound in estimating the Risk associated with options for dealing with estimated fatigue failures in a structure with a large number of structural components and welded connection details. The proposed systems evaluation approach is based on the findings from the hull structural loading correlation analysis (Appendix A), and the ship structural system is continuously welded structure has no redundancy from fatigue and fracture failure, as discussed in the next Section. From a systems perspective, when a fracture occurs, a very large area of the structure fails almost instantaneously with potentially catastrophic consequences.

Based on the discussion and the implications for systems failure, a proposed technical definition of serviceability failure is the local component failures are "purely" independent of each other, at least initially. Progressive failure begins as component failures become correlated. As degradation progresses, aggregated effects increase and failure modes interact spatially and temporally, at which time structural response transitions from severe progressive failure to ultimate collapse failure. By this definition of serviceability failure, the aggregation of failures spatially and temporally is also a quantitative estimate of progressive failure as failures transition from isolated and independent to correlated failures with combined effects of weakening the structure. In other words, failures are independent initially, and as they become correlated (if not detected and repaired) in aggregated failure modes as they transition from isolated serviceability failures to more severe progressive failures with potentially catastrophic consequences, see Figure 2.1. Thus, serviceability and progressive failure definitions match our intuitive decision to repair prior to the progressive aggregation of failures as the component failures correlate and result in significant degradation of the structural system.

The transition for independent to correlated failures is also key in the definition of reserve strength, both instantaneous and time-dependent transition. This serviceability failure definition matches our intuitive decision to repair prior to the progressive failure of aggregated failures as interactive correlations develop, and the combined effects significantly weaken the structure. In this context, Markov processes are useful, as discussed later in this dissertation.

These findings based on observations in measurements of structural system response have a significant influence on Risk Analysis and Risk Management approaches (i.e., fail-safe and safe life).

> **Fail-Safe** approaches involve managing failures in a redundant structure where the failure of one component is independent of any other structural element in failure consequences — commonly used in civil, offshore, and aircraft structures.
>
> **Safe life** is an approach where precursor, serviceability, or early progressive failures can be detected and repaired in a timely manner. This approach is common in pressure vessels and piping structures.

Related to this proposed definition of serviceability failure is the concept of reserve strength is the amount of strength between component level (serviceability) failure and ultimate strength of the system, in terms of buckling collapse, massive yielding or fracture is a proposed definition of reserve strength. This definition of reserve strength is in contrast to redundancy associated with civil structures with multiple independent load paths and structural members. The latter definition of redundancy is not part of the all-welded ship structural system.

2.3 Ship Structural Reliability

Reliability theory was adapted to larger complex systems (see Ebeling 2010) using component testing and, on occasion, full-scale destructive testing in large quantity production applications. Reliability theory is used extensively in the mass production industries where products are produced repetitively on a scale large enough to characterize failure statistics with some level of acceptable confidence. Product reliability relies on objective probabilities, and failure statistics in contrast to component structural reliability analysis is based on relative or even subjective probabilities. This approach is rarely used in large complex structural systems where failure consequences are less tolerable and less frequent. Many industries rely on component testing for fatigue and buckling failure, for example, and apply the derived statistical probabilistic response to similar components in (assumed) similar applications. Safety margins are often used in this context.

In reliability estimating, a basic instantaneous event reliability estimate is possible if the distributions for both the load (stress) and the strength both follow a known probability distribution (Normal in this case), then the reliability (R) of a component (Ebeling 2010) can be determined by the following equation:

$$R = 1 - P(Z) \tag{3}$$

Where:

$$Z = \frac{\mu_x - \mu_y}{\sqrt{S'^2_x + S'^2_y}} \tag{4}$$

Where μ and s' are mean and standard deviations of the Load (x) and Response (y) functions. The probability of failure *P(Z)* can be determined from a Z table or a statistical text (i.e., Walpole *et. al.,* 2014). While this interference approach is useful when the normal distribution is applicable, there are more complex application that require a more detailed approach to determine structural reliability.

The adaptation of the component test and analysis approach to reliability analysis has developed for applications based on a large number of statistical samples, component testing, and direct analysis tools with known biases and uncertainties that must be accounted for as described later in this dissertation. Similarly, the systems analysis approach must consider the correlations and dependencies of components, as discussed previously.

Numerous approaches that have been developed to calculate structural reliability analysis (SRA) for bridges (Frangapol *et. al.,* 2004), offshore structures (Melchers 1999), and ships (Mansour *et. al.,* 1997, and Ayyub *et. al.,* 2000, 2002 and 2014) as examples. Each proposed reliability approach has its strengths and weaknesses for the intended application and generally range in accuracy and complexity.

Ship SRA is a more complex problem than in fixed structures because they involve environmental and structural variables that are more complex. One approach proposed by Ayyub *et. al.,* (2014) included developments from the prior work in this area of ship structural reliability and used by this investigator to develop the probability of fatigue failure estimates and determine related Risk in Chapter 6.0. The fatigue reliability approach was built upon prior work on structural reliability and provides a foundation for further development, verification, and refinement of the complexities associated with fatigue in ship structure discussed in this dissertation. The response side component structural component level reliability approach used herein builds on a significant amount of work by, Hess *et. al.,* (2002a), Hess *et. al.,* (2002b), and Hess (2003). The fatigue reliability approach provides an excellent foundation for verification of analytical tools and quantifying the uncertainties using hull structure monitoring programs (Stambaugh *et. al.,* 2014b, 2019 and Hageman *et. al.,* 2014 and 2019).

2.3.1 Ship Structural Reliability – Component Level

A described by Ayyub *et. al.,* (2014), the reliability of ship structural components is defined as the probability of it maintaining its ability to fulfill its design purpose for a given time period under specified environmental and operational conditions. In this approach, calculating time-dependent reliabilities are calculated for stiffened panels in a particular region of interest of the ship.

The instantaneous reliability may be obtained based on the limit state defined in Equation 5. The instantaneous failure probability at time t is defined by:

$$P_f(t) = \int f\big(x(t)\big)dx \tag{5}$$

Where $f\big(x(t)\big)$ is the joint probability density function of the basic random variables defining strength and loading random variables at time t.

In the presence of degradation mechanisms such as fatigue, the strength $S_u(t)$ is a decreasing function of time, according to Equation. 4; therefore, the probability of failure is also a function of time. By varying the time period t from zero to an expected service life, the decreasing values of ultimate strength $S_u(t)$ can be estimated.

Several methods for analytical time-dependent reliability assessment are available. In these methods, significant loads as a sequence of events can be described by a Poisson process with a mean occurrence rate, random intensity, and duration. According to Ayyub *et. al.,* (2014), the performance function (Z) of a component or system at any instant of time (t) can be defined as:

$$Z(t) = S(t) - L(t) \tag{6}$$

where $R(t)$ is the strength at time t, and $L(t)$ is the load at time t, as shown in Figure 2.3. The instantaneous probability of failure at time t can then are defined as the probability of $S(t)$ less than $L(t)$; however, this instantaneous probability treatment does not recognize what has previously happened to the component or system from start of its life to the present represented by time t. Ship designers are usually interested in the first occurrence of L exceeding S, not the instantaneous occurrence, requiring the imposition of a condition on the probability of L exceeding S of being the first time in its life. This conditional probability concept is the basis for computing what is termed time-dependent reliability and estimated using the reliability function $Z(t)$.

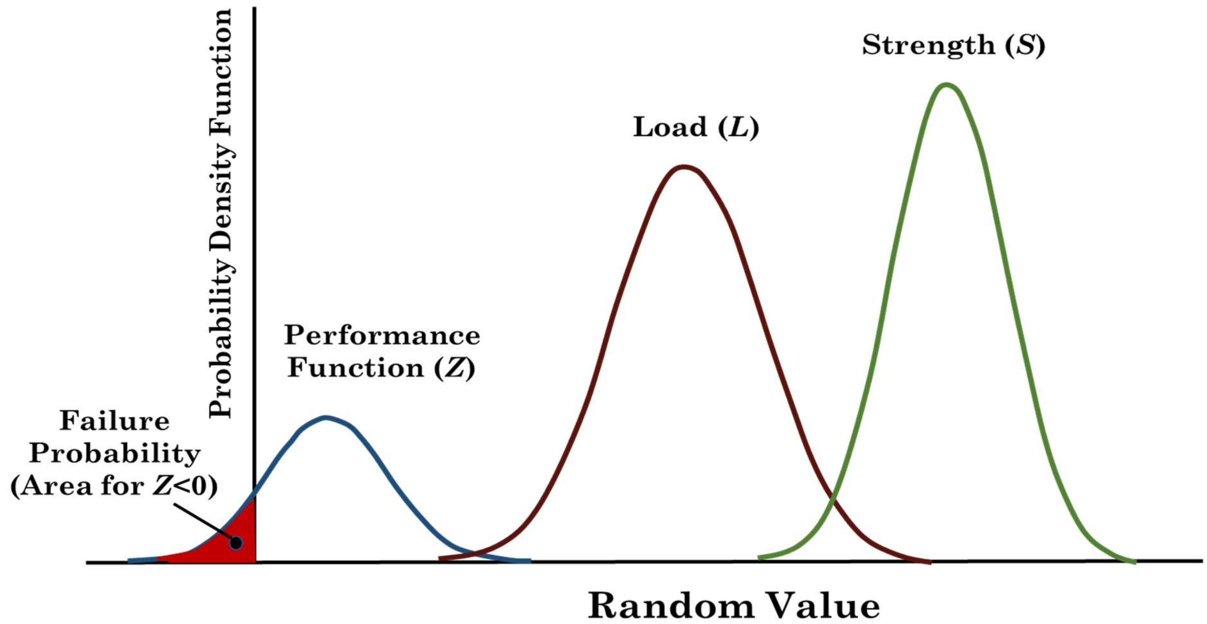

Figure 2.3 – Illustration of fatigue reliability calculation (Redrawn from Ayyub *et. al.,* 2014)

A limit state performance function related to ship loading can be expressed in consistent units as follows:

$$g(t) = S_u(t) - L_{sw}(t) - L_w(t) \tag{7}$$

Where S_u is the strength of a stiffened panel random variable accounting for relevant uncertainties; L_{sw} is still-water loading random variable accounting for modeling uncertainty in still water; L_w is wave loading random variable accounting for modeling uncertainty, nonlinearities, and dynamic effects.

With the knowledge of the loading bias and coefficient of variation obtained from measured data described by Hageman *et. al.,* (2014), and the uncertainties of the S-N diagram from Ayyub *et. al.,* (2014) illustrated in Figure 2.2, it is possible to make a time-dependent reliability prediction for various details in the ship structure. The reliability calculation approach uses a Monti Carlo approach to solve the time-varying limit state. The fatigue calculation results shown in Figure 2.4 include Stress Concentration Factors (SCFs) related to the local structural geometry for the various fatigue sensitive locations, were obtained from FEA described by Drummen *et. al.,* (2014). Sieve *et. al.,* (2000) describe the AASHTO fatigue categories and their application to fatigue design of naval ship structures. The fatigue reliability calculation discussed here is also based on Miner's (1945) damage summation and the P_f is time-varying reflecting the variance of the fatigue test data and other uncertainties included in the analysis instead of a fixed P_f (i.e., 2.3% characteristic design curve illustrated in Figure 2.2). In the test data sets used for these fatigue calculations, failure is defined as a visible or through-thickness crack (***tt***$_c$) is present. More on the significance of $\boldsymbol{tt_c}$ and associated Risk is discussed in Chapter 6.0 and Appendix C of this dissertation.

The time span for fatigue failure is considerable for the lower probability of failure group of correlated structural details shown in Figure 2.4. In this example, the fatigue life is dominated by the magnitude of Stress Concentration Factor (SCF) with fatigue damage being proportional to stress range to the third power. The uncertainty in the fatigue response is dominated by the variance in material test data, as illustrated in Figure 2.2 The fatigue reliability calculation is based on the component level failure and needs to be extended to the failure of the system, as discussed next.

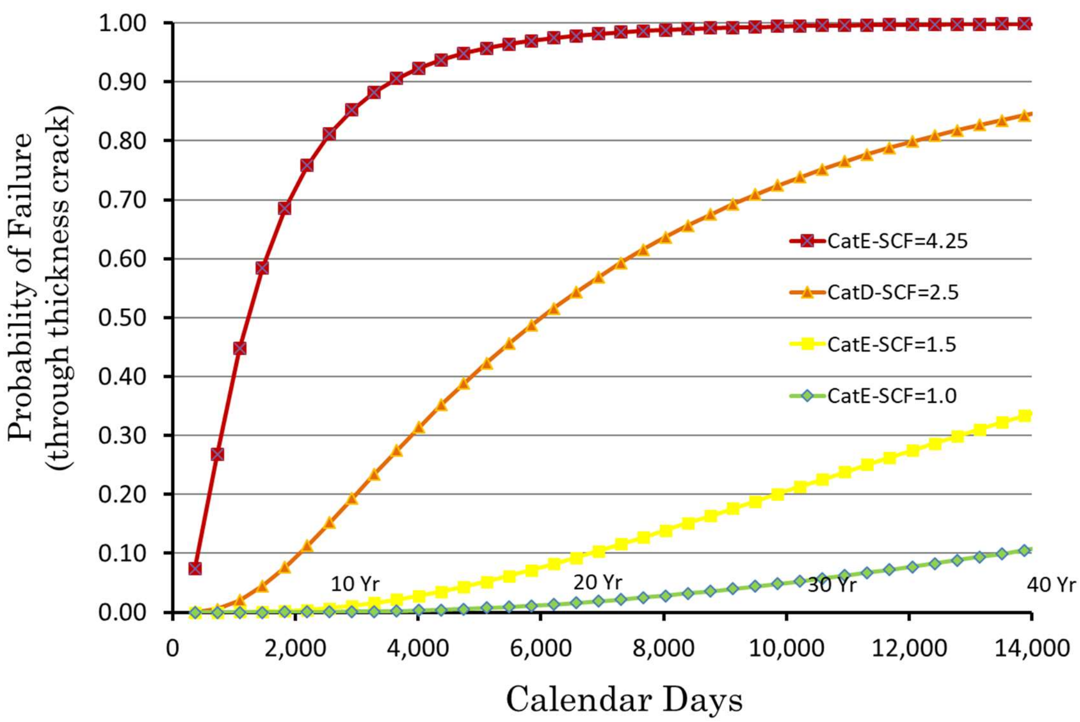

Figure 2.4 – Example fatigue failure (*ttc*) estimate for critical details in a ship hull structure with correlated groupings according to stress concentration factors and fatigue categories

The resulting component reliability as a function of probability of failure is:

$$R_c = 1- (Pf_c) \tag{8}$$

2.3.2 Structural Reliability – System Level

Based on the results of the correlation analysis discussed previously, the ship structure as a system is correlated among loading groups, including weld configurations associated with welded fatigue life data, the fatigue response is highly independent as characterized by the scatter of fatigue test data over number of cycles and time to failure as the cycles are applied over time. The independent nature of the fatigue response data requires that reliability of the system consider both the correlations that can be utilized to reduce the number of reliability calculations needing to be performed (although it is possible to accomplish for every detail) and more importantly, consider the time-varying influence of the fatigue response. In this manner, probability of failure and reliability can be estimated, and then correlated groups are summed at time intervals to produce the expected number of details that will fail in a given time period. This process is repeated over the service life and beyond. The total number of details represents an important consideration the proposed systems approach.

The probability of system failures (continuing here with the ***ttc*** failure definition) for the correlated groups is then multiplied by the number of details in that group and summed the number of probable failed details is summed for a specific time period. The expected number failed details at time T is estimated from:

$$N_{df}(T) = \sum_{i}^{n}((Pf_{c(i)}(T)\ \cdot\ (N_{d(i)}(T)) \tag{9}$$

Where:

N_{df} = Expected number of component details that have failed (visible through thickness crack)

Pf_c = Probability of failure for the correlated group of details and,

N_d = Number of details in the correlated group

i is equal to 1 to n and n is equal to the total number of details in the system being considered. T is a specific time interval in the structural life.

The system probability of fatigue ***ttc*** failures then calculated as:

$$Pf_s(T) = ((N_{df}(T)/N_{dt}(T)) \tag{10}$$

Where:

Pf_s = the system probability of ***ttc*** failures and,

N_{dt} = the total number of structural details considered in the system.

These system level definitions are used in the example shown in Figure 2.4, the probability of ***ttc*** failures is calculated for classes of details and loading combinations. The results of the component level probability of fatigue failures are shown in Figure 2.4. The cumulative probability of system failures over time is shown in Figure 2.4 for the highest correlated groupings of fatigue stress levels and types of details. The classes and loading combinations are obtained from an FEA model and relative stress concentration factors from wave loading on the FEA model. The probability of ***ttc*** failures was calculated for 12 correlated groups and the four groups with the highest probability of failure are shown in Figure 2.4. Given this information on the probability of failure and the number of details in each group as a function of time, it is possible to estimate the number of details expected to fail at any given time.

From the correlation and systems definitions, it follows that cumulative probabilities for the structural system can be grouped by stress and weld detail configuration in the context of the SFA and S-N approach. Construction practices (i.e., weld and construction quality) are not correlated because they are highly random and statistically independent (i.e., as in producing randomness of response in fatigue testing). The correlation of structural details based on the characteristic load facilitates the addition of failure probabilities for the correlated groupings and is then added for time intervals to produce histograms of details with ***ttc*** failures as shown in Figure 2.5 The results shown in Figure 2.5 are for a systems reliability calculation based on the cumulative number of details that are expected to fail at a given time period T according to the systems reliability example shown in Figure 2.4, where failure defined as a through-thickness crack.

This discussion and related equations are proposed as an alternate hypothesis to the series and parallel definitions of systems reliability as it relates to the expected number of failures shown in Figure 2.5 that were derived from the probability of failure estimates presented in Figure 2.4. The expected number of ***ttc*** failures shown in Figure 2.5 represents the cumulative expected failures up to the time interval T indicated in Figure 2.5. In the example shown in Figure 2.5, fatigue failures are calculated for intervals of five years. The number intervals are calculated for five-year increments of the planning horizon.

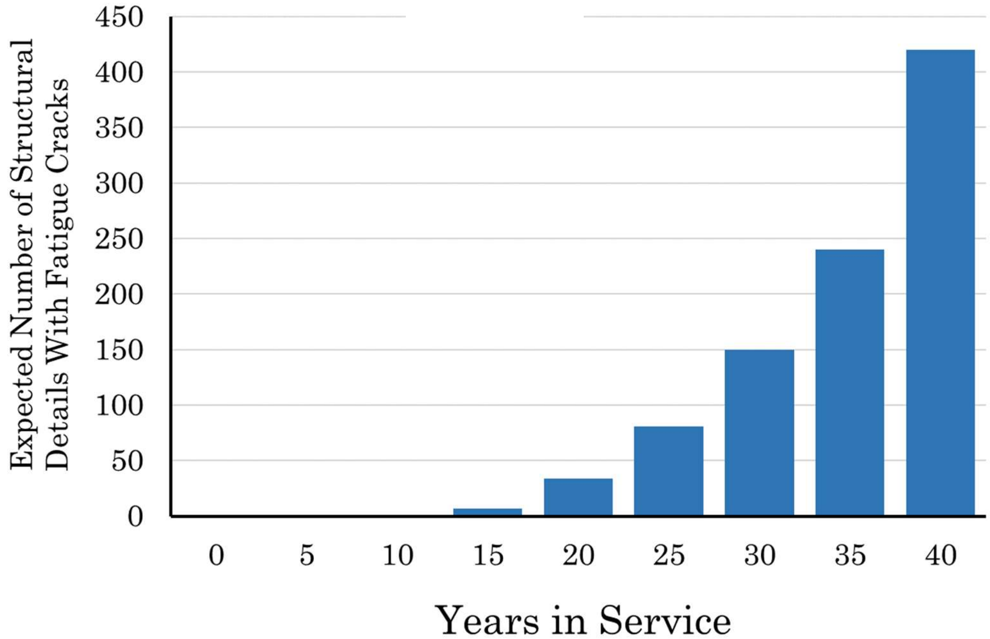

Figure 2.5 - Expected number of ship hull structural details with *ttc* fatigue cracks

The addition of cumulative probabilities of failure, whether fatigue or corrosion, is a relatively new approach with others (Temple *et. al.,* 2013, Kong *et. al.,* 2013) proposing this approach for fatigue failure predictions for ship structures. However, the implications of these ***ttc*** fatigue failures are not fully realized and addressed in terms of probability of detection, ultimate failures if they grow undetected, and related Risks. The number of ***ttc*** failures shown in Figure 2.5 are used for further Risk-TOC Analysis in Chapter 6.0 where the implications of the number of fatigue cracks, and the probability that they will grow undetected to critical fracture size, are addressed in context of Risk Analysis applicable to ship structural systems.

The discussion on systems failure and updating that follows here provides a new perspective for reliability updating for a number of ***ttc*** fatigue failures. The results of this reliability updating are used highlight the need for Risk Analysis in SSLCM.

In the correlated-independent systems analysis for a large number of component structural details in the system, reliability updating is estimated by changing the expected number of failed component details by subtracting the number of repaired component details. In this systems reliability example, one repaired component detail with a ***ttc*** fatigue failure does not change the probability of failure of the other components in the system group. The updating must reflect the reliability of the total number of component details considered in the system.

In this system reliability example, the number of component details failed at time T equals the sum of the product of the probability of failure for each correlated group and the net difference between the total number of component details in a specific group c (not number failed) minus the number of component details repaired illustrated as:

$$N_{du}(T) = \sum_{i}^{n} (Pf_{c(i)}(T) \cdot (N_{dc(i)}(T) - N_{dr(i)}(T))) \tag{11}$$

The probability of systems failure is then the number of failed component details divided by the total number of component details at time T calculated as in equation 10.

The probability of systems failure with updating is then the number of failed component details divided by the total number of details at time T.

$$Pf_{su}(T) = \left(\frac{N_{du}(T)}{N_{dt}(T)}\right) \tag{12}$$

The probability of systems failure is then either probability of failure with or (V) without repair as follows:

$$Pf_S(T) = ((Pf_s\,(T) \vee (Pf_{su}(T)) \tag{13}$$

The total system reliability without repair at time interval T is then written as:

$$R_S(T) = (1 - Pf_S(T)) \tag{14}$$

The total system updated reliability with repair at time interval T can be written as:

$$R_{Su}(T) = (1 - Pf_{Su}(T)) \tag{15}$$

After a component detail in the system has been repaired, the component reliability updates to a reliability of one (assuming the repair is 100% effective) at time T, and degradation begins again moving forward in time. The remaining system reliability is updated based on the remaining number of component details not repaired for the correlated groups.

2.3.3 Proposed Systems Reliability Example

An example of the proposed systems reliability approach is presented next. Figure 2.6 shows the results of the time-varying reliability estimates for more than 1200 structural details in the primary hull girder. In this format, the system's reliability or Pf calculation is straight forward. The number of component details repaired by rewelding can be subtracted from the total and transposed to a new start date, essentially shifted to the right, and added to the other component details at the respective timeframes. Similarly, if the component details are redesigned and structure modified, the new estimates are shifted in time based on the given repair date and summed as before. The number of component details with ***ttc*** fatigue failures at any given time can be multiplied by one minus the Probability of Detection (*1-PoD*) to determine the number of fatigue cracks that could potentially go undetected and continue to grow undetected. Additional discussion on the implications of the undetected cracks is provided in later examples in Chapter 6.0 as they grow beyond ***ttc*** to larger faster growing fatigue cracks with potentially catastrophic failure resulting.

This systems approach is applicable to the addition of correlated groups of cumulative density functions and the number of components therein for other locations such as bow impact loading or local side shell loading that is not load correlated but is time-correlated with an associated probability of failure as a function of time. Table 2.2 provides a simple example of how systems updating is estimated for a specific time period *T*.

Table 2.2 – Example fatigue reliability updating with correlation and a large number of structural details

Without Repairs				With Repairs		
N Critical Details	Probability of Failure	Expected N Failures		N Critical Details Less Repair	Probability of Failure	Expected N Failures
1	0.99	1.0		0.0	0.99	0.0
5	0.5	2.5		2.5	0.5	1.3
20	0.1	2.0		18.0	0.1	1.8
200	0.01	2.0		198.0	0.01	2.0
	Sum	7.5			Weighted Sum	5.0
	N total details	1200			N total details	1200
	Pfs	0.006242			Pfsu	0.0042
	Rs =	0.993758			Rsu =	0.9958

Figure 2.6 shows the results of an example systems reliability calculation based on the number of component details that are expected to have failures, given the systems reliability example shown in Figure 2.5, where failure defined as a through-thickness crack (***ttc***). Where *Pfs* is the System's Probability of Failure, *Pfu* is the updated system's probability of failure, *Rs* is the System's Reliability, and *Rsu* is the updates system reliability as shown in equations 11 through 15. In this example, the Sum is a summation of the probability-weighted or expected number of components with ***ttc*** failures in the system.

In Figure 2.6, the lowest red solid line is the estimated reliability given no intervention, also known as the "Do-Nothing" option. This option represents reliability given survived component details in the system, including component details that fail for the second time after having been repaired years earlier. The solid blue line represents the updating of reliability given the component details with ***ttc*** fatigue failures have been found and repaired. The estimated number of failed details (~30) in 20 years has little effect on overall systems reliability because this number of failures is small relative to the total (~1200). In a ship structure, there are thousands of structural details, and even 1200 is a select subset.

This example uses a systems reliability approach based on *Pf* being a combination of correlated details on the load side and independent failure on the response side of the evaluation. This systems approach is in contract to many Optimal Inspection approaches proposed for ship structures where reliability calculations are erroneously based on series or parallel models, and one or few details in the system and results show near 100% reliability after one or few repairs. The systems failure is more complex than simple series or parallel models for systems reliability described previously.

The assumptions in this illustrative example also include:

- 1200 critical details in the primary hull structure that have an increasing *Pf* of through-thickness cracking throughout the 35year time period,
- 100% effective *PoD*, and
- 100% effective repair.

These assumptions are optimistic but useful to show the total system reliability in contrast to proposed Optimal Inspection approaches based on assumed components in series for systems reliability estimates. In reality, *PoD* will not be 100% and given the large number of cracks expected to be growing, and there will likely be fatigue cracks that are not detected, leading to a high probability that one will reach a critical length producing a high-Risk situation that will be shown in a later example in Chapter 6.0.

In looking at Figure 2.6, an interesting observation includes the limited effects of repair of structural details on reliability initially (i.e., at 20 years) relative to the total number of structural details in the system (approx. 1%). In later years (i.e., 30-40), the increased effect of repairs is much greater because there are a significant number of component details with ***ttc*** fatigue failures that are being repaired (see Figure 2.6), on the order of 25% or more.

In this systems reliability analysis example, significant updating doesn't occur until major numbers of structural fatigue cracks are repaired. Conversely, the updating of a few cracks has minimal effects on system reliability. Both conclusions are intuitive given the number of structural details in ships. The intuitive hypothesis is confirmed with this quantified example based on a large number of structural details in ships.

The results shown in Figures 2.5 and 2.6 imply the number of fatigue cracks estimated to occur over time will impact on LCC and Risk-based decisions. It becomes clear that the number of failures associated with fatigue cracking, for example, are expected to become expensive to repair, increasing LCC (and TOC described later) and increases the Risk of a severe if not catastrophic failure.

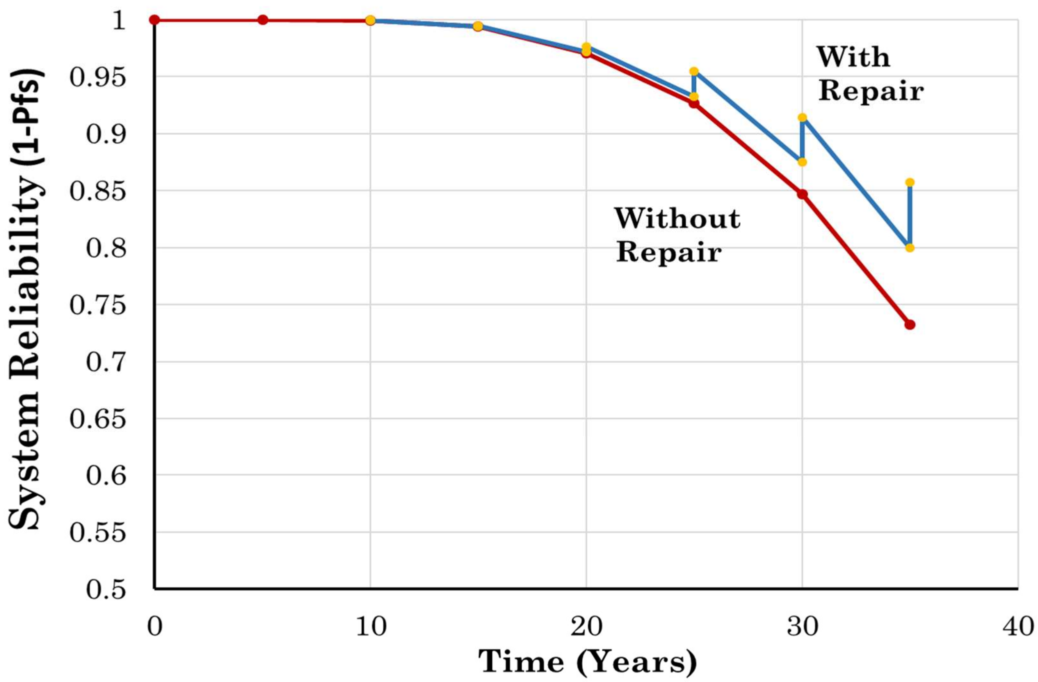

Figure 2.6 – Example ship structure fatigue system reliability with updating

2.4 Ship Structural Reliability and Lifecycle Related Issues

Given the challenges associated with fatigue crack failures in component structural details when there are thousands of component structural details in the primary hull girder structural system, the lifecycle Risk related considerations include:

- Implications if the fatigue cracks are not found until they become large or more typically leak water from the outside or fuel from the inside of the ship,
- Repair costs are difficult to predict with any certainty given random failures at high rates (i.e., EDDs are cost drivers, but how many should be anticipated) and associated non-budgeted costs,
- Randomly occurring failures have a significant impact on Operational Availability (Ao), and

- There is no system-level redundancy (e.g., independent load carrying paths) in ship structures. A brittle fracture will travel through the structure until either the load is reduced or it reaches material tough enough to arrest the fracture (or combination of both). In either case, the consequences are potentially catastrophic. The probability of brittle fracture is a significant part of a Risk Analysis when combined with the value of the asset.

These issues and the related Risks associated with ship structures provide the motivation to look for alternate Risk mitigation strategies including the application of SFA and HSM as proactive measures. Further evaluation of the impact of these observations and hypothesis provides the insights and guidance for conducting a Risk Analysis and evaluating Risk mitigation approaches for SSLCM.

While this dissertation builds on the basic structural reliability approach to quantify basic stochastic uncertainties in the processes involved, the new work takes a fundamental look at the overall system based on analysis of the correlated loading and a fundamentally new approach for Risk assessment that differs from all Optimal Inspection approaches based on Decision Theory as proposed for other types of structures as described next.

3.0 PRIOR STRUCTURAL MANAGEMENT APPROACHES

One approach often proposed (arguably the only approach proposed) to manage structural LCM decisions is through Optimal Inspection, including its relative Risk Based Inspection. The Optimal Inspection and Risk Based Inspection approaches are based on Decision Theory. These Decision Theory based Optimal Inspection, approaches are proposed for civil and offshore structures for LCM.

The literature on Optimal Inspection of civil structures and similar proposals for ship structures is far to large to summarize here [2]. Briefly, the Decision Theory based Optimal Inspection approaches assume that fatigue cracks are found according to a fixed pre-calculated optimal schedule, repaired to extend the service life, and form a basis to determine the future reliability of the structure.

The Decision Theory based Optimal Inspection approaches are based on specific assumptions and implementation details that are in contrast to Risk Analysis in a broader sense. Therefore, a more detailed discussion on Decision Theory is presented to provide the reference for contrasting Decision Theory and Risk Analysis based approaches proposed in this dissertation for Ship Structural Life Cycle Management (SSLCM).

3.1 Decision Theory Basics

Making a decision involves alternatives, preferences, and knowledge of the nature of the processes involved in the outcomes. If there are no alternatives, there are no choices and a decision is not necessary. Similarly, if there are no preferences, a decision doesn't matter.

In Decision Theory, the Decision Maker faces a choice among several likely alternatives. Each alternative may result in one of several possible outcomes, but which outcome will occur is uncertain at the time of decision making. Decision Theory represents the possible outcomes in the decision alternatives by discrete probabilities.

In Decision Theory, discrete probabilities are used to characterize the likelihood of outcomes when such data is available. In the context of decisions, the likelihood of outcomes may vary from the seat of the pants gut feelings to probabilities.

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[2] [Examples of the many references on Optimal Inspection based approaches include; Madsen *et. al.,* (1991), Hecht (2003), Straub *et. al.,* (2005), Sorensen *et. al.,* (2008), Frangopol *et. al.,* (2012)]. A summary of the literature on the application of Decision Theory-based Optimal Inspection approaches for Structure Life Cycle Management (SLCM) and Structural Health Monitoring (SHM) is provided by Xing *et. al.,* (2017). This literature will be referred to as Decision Theory-based Optimal Inspection approaches herein].

In terms of the probable outcomes in Decision Theory and Decision Trees, the summation of probabilities must equal one. As a consequence, in Decision Theory, the Decision Maker computes expected values across outcomes using the probabilities as weights, and these expected values are comparable to the single estimate of expected outcomes of a decision. The product of the probabilities and economic outcomes forms an Expected Value *E(V)*. Decision Theory also involves calculating the expected consequences of uncertain decisions formulated as discrete probabilities of possible events or outcomes in the future and inferred Expected Utility *E(U)* based on weighted preferences of the Decision Maker. This approach to quantifying Decision Maker's Risk preferences was first attributed to Pascal in the 17th century.

Typically, the probabilities used in Decision Theory are developed based on assumptions and limited data sets that are often subjective estimates. Increasing knowledge about the nature of the outcome is intended to reduce the uncertainty associated with the expected value *E(V)* of the outcome. The ability of the test or the results of data collection to reduce uncertainty is known as the Value of Information (*VoI*). In this case, the value of the information is positive if the *E(V)* is reduced. These topics are discussed next for the context of prior approaches proposed for SSLCM.

3.2 Decision Theory Based Approaches for Optimal Inspection

Origins of modern Decision Theory proposed for civil (i.e., offshore and bridge applications of Optimal Inspection) can be traced to the theories proposed by Von Neumann *et. al.,* (1947), and includes utility theory. Later, the decision analysis presented by Raiffa *et. al.,* (1961), provided a more formal mechanism for taking into account the preferences, judgments, and limited amounts of objective information of the Decision Maker(s).

The definitions used in Decision Theory proposals for LCCM are interpreted differently than in Risk Analysis proposed here.

For example, in fatigue reliability applications, failure is often deterministic crack length plus additional simplifying assumptions (i.e., one or few details, all cracks are found and repaired) for structural reliability applications.

In Decision Theory based LCM approaches, discrete probabilities and Risk are typically defined as one of the following:

- *E($\$C_{failure}$) defined as Expected Value of costs to repair failed structure,*
- *E($Cs) defined as Expected Value serviceability costs to be mitigated by a theoretical optimal inspection approach.*

In prior proposed structural Risk approaches based on Decision Theory (see footnote 2 for references) *E(V)* and *E(U)* are equated to Risk. In the Decision Theory based approaches, expected repair costs (termed Risk as the product of the probability of failure and the cost to repair the failure, typically welding fatigue cracks) are minimized based on an Optimal Inspection periodicity.

In the Utility based extension of Decision Theory analysis, the Risk for each activity is stated to be:

$$Risk_{DT} = E[U] = \sum_{i}^{n} P_{(i)} C_{(i)} \tag{16}$$

Where $Risk_{DT}$ is equal to *E(U)*, P_i is the i^{th} branching probability, and C_i the cost of the event of branch *i.* in a Decision Tree based analysis. The i^{th} branch refers to decision options or choices and *i* relates to the independent number of decision options. The *E(U)* is a modified version of *E(V)* reflecting the preferences of the Decision Maker(s) as described previously. In Decision Theory, Utility Theory and Prospect Theory, the utility is a relative measure based on the Decision Maker's preference and is knowledge biased with no quantitative value. In Utility theory, the utility is a subjective, relative measure used to establish the Risk tolerance relative to individual preferences.

In using Decision Trees as part of a Decision Analysis, the Decision Maker(s) must estimate the probabilities of the outcomes at chance nodes, and are best suited for decisions that can be assessed by either using discrete probabilities based on past data or collecting new data if Expected Values of the Decision Theory based results imply that it will be beneficial to do so based on a Value of Information analysis. See Raiffa *et. al.,* (1961), and North (1968) for more on the application of Decision Trees used as part of the Decision Theory approach.

In summary, Decision Theory is used for discrete probabilities of decision outcomes. In Decision Theory, a Decision Tree provides an assessment tool to determine the expected outcome and courses of action, provided discrete probabilities are known that fully characterize the uncertainties of the decision, which they typically do not for complex structures.

3.3 Limitations of Decision Theory and Optimal Inspection based Approaches for Complex Systems

In the next two Sections, Decision Theory and Optimal Inspection based approaches for Structural LCM are discussed along with their limitations for complex structural systems found in ship structure and SSLCM applications are presented next.

3.3.1 Contrasting Decision Theory and Risk Analysis

The Decision Theory proposed by Raiffa *et. al.,* (1961) is applied as the basis of Optimal Inspection approaches to Structural LCM. This approach is very insightful for relatively simple decision problems; however, it varies from Risk Analysis in very fundamental definitions. Decision Theory proponents equate the expected utility from the Decision Theory approach as the product of a probability and a consequence to Risk, which is not a full evaluation of either the probabilities or consequences of the more complex processes of structural management of large complex structural systems.

The definition of "Risk" used in Decision Theory based Optimal Inspection approaches is a very narrowly founded where, for example, P_i is typically limited to the probability of occurrence of "a" (single) fatigue crack, and similarly C_i consequence is limited to the repair costs without any subsequent consequences if the crack is not detected and repaired.

While most Decision Theory based approaches are useful in their settings, for financial and economic investments, they do not fully represent the context of uncertainties and consequences in Risk Analysis in general and the SSLCM setting in specific.

Fundamental differences between Decision Theory and Risk Analysis based approaches include:

- In Decision Theory, Risk is when discrete probabilities are assumed to be known with some certainty. However, in most examples, subjective probabilities are used, that is, unsubstantiated (guesses, educated or otherwise) probabilities.
- Decision Theory based definitions of Risk and Uncertainty assume discrete probabilities (lotteries) vs. more stochastic based ranges of uncertainty.
- In Decision Theory, uncertainty is defined as an outcome with "known" probabilities and Risk is defined as an outcome with known probabilities. This is in contrast to Risk Analysis where uncertainties are characterized by a range of probabilities.
- In Decision Theory, correlations in parameters are not explicitly considered in Decision Theory based approaches.

In the Utility theory based extensions of Decision Theory, *E(U)*, is classically defined on the basis of a user's preference associated with an expected outcome. There is a specific distinction between *E(V)* and *E(U)*. The former is a function of the calculated probabilities and the latter includes the Decision Maker's preferences on uncertainty from a personal relative scale. Expected Utility is often mistakenly used to indicate a true value as compared to a relative personal value and is often used as a decision criterion in offshore and civil applications of the Optimal Inspection approach. This definition is in contrast to the more general definition of Risk as the product of a probability of occurrence of a catastrophic event with an undesirable cost of consequences without unbiased user-defined utilities. Furthermore, for the Decision Theory and Utility Theory based, Optimal

Inspection approaches, the expected value occurrence of serviceability failure, not the Risk of a catastrophic failure. In Risk Analysis of large complex ship structures, the results are typically more complex probabilities, not representable by simple discrete probabilities and related *E(V)* and *E(U)*. The implications of the range of uncertainty is completely ignored and is the first type of "Flaw of Averages" discussed by Savage (2012) and Hubbard (2009) as compared to a thorough Risk Analysis of a complex structural system and considering the full range of uncertainties involved to the extent possible.

Decision Theory and Utility Theory are useful for initial thought and conceptual development of the problem along with a decision tree of decision options and scenarios; however, the uncertainties known to the Decision Maker must be fully captured in the Risk Analysis to make a valid quantified decision. Decision Theory is useful for conceptualizing the decision framework; however, not in solving the problems involving more varied and complex uncertainties to be quantified in SSLCM.

3.3.2 Limitations of Optimal Inspection Approaches for Complex Structural Systems

There are numerous assumptions associated with Decision Theory based Optimal Inspection approaches. The Optimal Inspection techniques proposed for Life Cycle Management (LCM) of civil and offshore structures originated in aerospace industries and transferred to offshore structures by Madsen *et. al.,* (1991), Straub *et. al.,* (2006), and Xing *et. al.,* (2017). These approaches are based on Decision Theory with assumptions related to offshore structures.

An illustration of a proposed Optimal Inspection approach is shown in Figure 3.1 to illustrate the assumptions in this process.

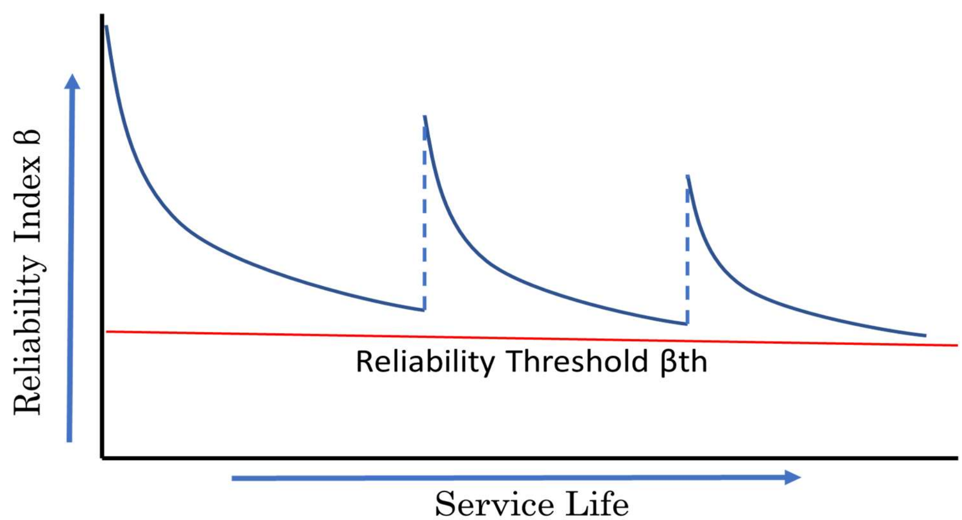

Figure 3.1 – Illustration of Optimal Inspection and reliability updating

In this example of the Optimal Inspection approach, reliability is updated for the details that have been detected, assuming the details are rewelded and removed from the number of failures moving forward. A minimum reliability threshold is illustrated in this example, and the inspection interval is determined so that, given a *PoD*, the fatigue cracks will be found and either repaired or not depending on their criticality relative to the limiting reliability target. The reliability targets are determined based on comparable structures and prior reliability validation efforts for a particular type of structure. In applications of the Optimal Inspection approach, a deterministic crack size is often chosen as a limiting failure criterion. Examples of Optimal Inspection approaches proposed for LCM of ship structures are summarized in Table 3.1.

3.3.2.1 Finding Fatigue Cracks in Ship Structure

The effectiveness of structural inspection is an important input parameter in Optimal Inspection approaches. A quantitative measure of inspection effectiveness is needed in order to calculate the reduction in Risk associated with inspection. The reliability of Non-Destructive Testing (NDT) techniques is usually quantified in terms of the *PoD* of various deterministic flaw sizes.

Table 3.1- Summary of Example Optimal Inspection Approaches Proposed for Ship Structure

Source	Limiting Criteria	Critical Crack Definition	Systems Definition	System Availability	System Failure
Ayyub (2002)	Pf =10e-3	20mm	Component	Discussed	Component repair cost
Li (2007)	ß = 3.95	Not given	Not given	Not given	$0.3M
Hecht (2004)	ß = discrete	Not given	Nfailed/Ntotal (Ntotal not given)	Discussed	$500M
Garbatov (2011)	ß = variable	Frame or plate component	Component Series	Not given	Component repair cost
Soliman (2015)	Lifecycle cost	50mm	Component	Not given	$0.1M

The probability of fatigue crack detection is typically presented in the form of *PoD* functions (Melchers 1999, Shinozuka, 1989), which describe the detection probability as a function of the flaw size, e.g., flaw depth or length. However, the construction of a *PoD* function requires a considerable amount of data before statistical confidence is achieved. In the case of NDT methods, it is often expensive and time-consuming to produce such a large amount of data. In the Optimal Inspection approaches, NDT is typically assumed to be over 90%

effective in finding cracks and that all details can be inspected and are found and repaired. Furthermore, the highly effective *PoD* data does not exist for ship structures; therefore, *PoDs* have been proposed for ship structures based on applications in other industries and structures and completely different structural systems with a limited amount of consideration for the practicalities of their application to ship structures.

The practicalities (i.e., high costs) of achieving highly effective *PoD* is very limited for military ships (due to the coverage of insulation on the interior of the weather decks and side shell down to the turn of the bilge) and many types of commercial ships due to the vast number of details present in the hull structural primary strength girder. The ship structure of commercial ships is difficult to inspect due to trade schedules. In tankers, inspections are often conducted in ballast tanks while underway in rafts. These are very poor conditions at best, given the *PoD* reported by Shinozuka (1989) under ideal conditions in Dry Dock.

In one example of applying visual inspection to commercial ship structures, Shinozuka, (1989). This data collection effort took several weeks of survey time to accumulated and results in limited quantity for objective statistics. In the context of SSLCM, *PoD* statistics for various NDT approaches are not quantified for Optimal Inspection applications. *PoD* statistics from other industries and applications should be used with caution on their ability to be applied in a quantified way needed for Optimal Inspection and on the scope of thousands of structural details in ship structure.

Quantitative estimates of the inspection capability and costs are essential for a realistic Optimal Inspection; however, these practical costs have not been quantified for SSLCM and are likely to be unrealistically high for SSLCM applications.

3.3.2.2 Issues with NOT Finding Fatigue Cracks in Complex Structures

The number of expected fatigue cracks for five-year increments is shown in Figure 2-5 for an example ship design. In this case example, the number of failures increases significantly in the 20 to 25 year time periods to 50 and 125 fatigue failures, respectively. The time-varying accumulation of numerous failed details becomes significant and unmanageable in repair cost and related time out of service. This increasing number of failures over time raises many very important questions about the consequences of the number of fatigue cracks including:

- What is the cost to repair the fatigue cracks, apriori?
    - How many of the cracks are easy to repair dockside?
    - Can any of the cracks wait to be repaired in a scheduled drydocking (DD), and what are the Risks of this deferred maintenance?
    - How many of the cracks will require emergency drydocking (EDD)?

    - What is the impact on operational availability (Ao)?
- What is the impact of fatigue failures on current and future maintenance costs and budgets?
- What happens if any of the cracks go undetected?

The last question implies an unknown amount of Risk, which in turn generates more questions.

- What are the (quantified) Risks associated with large cracks?
    - What are the practical aspects of executing the NDT as compared to the theoretical applicant of *PoD* approaches?
    - What is the probability of a severe failure from a large number of fatigue cracks, i.e., brittle fracture (*PfBF*)?
    - What are the consequences of brittle fracture (and $ at Risk)?
- How do we mitigate the Risks, and at what cost?

Given the uncertainties and potentially high Risk implied by these questions, the last question of Risk mitigation is often answered qualitatively, resulting in an End of Service Life (EOSL) decision because the repair costs are out of control (exceeding budgets) and loss of the assett if the ship is taken out of service. This dissertation presents a Risk-TOC framework to facilitate quantified information for answering these questions and making informed decisions.

In the Decision Theory based Optimal Inspection approaches, the reliability estimates and updating are conducted assuming one or a few details. However, there are thousands of welded details in ship structure. While there are correlations among details (see Appendix A and Kaminski *et. al.,* 2010), these correlations are not considered in the proposed Decision Theory based approaches for Optimal inspection and LCM. The Decision Theory and Optimal Inspection approaches do not consider the significant number of structural details in ship structure or the influence on the uncertainty in the fatigue process (i.e., scatter in S-N data) on system failure definitions. Optimal Inspection may be useful in reliability updating for one or a small set of structural details; however, a systems approach is required for more complex systems with thousands of structural details.

3.4 Summary of Prior DT, OI and RBI Based Approaches

The Optimal Inspection approaches proposed for ship structure summarized in Table 3.1 typically include the following: [*with comments by the investigator based on the discussion herein*]

1) Inspection approaches assume well-defined *PoD* characterized in stochastic terms that apply to the ship application. [*None of the inspection approaches have been calibrated for the ship structural in-service application, nor has PoD and sampling processes been quantified for the NDT used in ship construction for that matter. The*

cost-effectiveness for the proposed high-quality NDT does not appear to be realistic for ship applications given the size of the structure, number of component details and meters of welds involved. The complex system does not lend itself to isolated inspections as illustrated in the structural system reliability discussion].

2) Inspection approaches and inspection intervals are determined so that limiting criteria are not exceeded. In most cases, limiting criteria are based on component failure within a system in terms of either a target reliability (β) or a deterministic fatigue crack length (anywhere between through-thickness to through the structural member). The limiting criteria are assumed to be conservative relative to the critical fatigue crack length. [*The limiting crack size is chosen deterministically. The reliability targets have been transferred from other types of structures. The fracture hazard and possible system loss is not evaluated explicitly in stochastic terms for a comprehensive Risk Analysis*].

3) The analysis is most often conducted on the component level. System level analysis inherently assumes redundant structure with multiple independent load carrying paths and a parallel system with the associated component first failure definition. [*These assumptions are not applicable to ship structural systems. Reliability degradation, updating, and Risk are not fully addressed on a system level resulting in optimistic results*].

4) Repairs are made to the fatigue cracks when found or left to grow if the limiting criteria are not met. [*The Risk of the growing cracks is not fully evaluated in light of ship loading magnitudes, related random nature, and resulting growth rates, i.e. encountering a severe storm with an actively growing crack*].

5) An optimization process is typically conducted to identify the most cost-effective trade-off between inspection types and inspection intervals to minimize the inspection and repair related costs at a deterministic limit of reliability or critical crack size. [*The Risk of total system loss is not explicitly considered because inspection approaches and intervals are established so that the limiting deterministic criteria are not exceeded. By definition, the optimization of inspection processes does not consider LCM alternatives, including other proactive actions*].

6) The optimization process is typically based on a Decision Theory and Utility Theory (tree) approaches with calculated expected values E(V) or expected utilities E(U) for the decision options/tree branches). [*Neither E(V) nor E(U) reflect the true Risk (i.e., uncertainty) in a ship structural system and encountered loading. The probabilities used in Decision Theory do not reflect the temporal processes involved in ship structural loading and resulting fatigue crack growth rates that are the highest Risk to the system*].

Moan and Fricke (2018) discuss the limitations of Optimal Inspection approaches in real structural applications and the need for additional Risk mitigation factors. According to Moan;

"*Hence, to manage the Risk associated with failure modes involving cracks, it is necessary to adopt a broader Risk Management approach*".

Moan goes on to state;

"The choice of mitigation approach clearly depends on the character of the crack growth and fracture, and hence the environmental conditions, structural layout, etc. Moreover, a balance between Risk reduction and expenditure is required."

This dissertation provides a proposal for achieving these objectives. Faced with uncertainties and associated Risk, and to summarize the complex pertinent questions, how does the structural engineer and analyst make actionable decisions based on estimated economic impact, at what Risk and what are the related uncertainties.

To address these highly relevant questions and issues presented above, the structural designer must make decisions that involve significant Risks (i.e., uncertainties of failures and significant cost implications) in complex systems in ship structure. There are several alternatives they might consider in making the decisions to manage cost and Risk over the lifecycle of the ship structure. The proposed Risk Analysis approach provides a means of quantifying probabilities to facilitate decisions systematically. However, there are conflicting definitions in the literature on what constitutes Risk Analysis that requires a closer examination.

Given the assumptions, limitations, and challenges of the Decision Theory based Optimal Inspection approaches, it is necessary to investigate alternative approaches applicable to SSLCM. The new approach must consider the fundamental considerations in the decision process firmly based on the systems analysis, failure modes, and cost considerations associated with SSLCM. This problem statement forms the basis for the research investigation into this dissertation. The following Section provides a baseline of fundamental definitions that apply to SSLCM decisions.

Although Optimal Inspection approaches have limitations, it is at least theoretically possible to develop the inspection technologies, including novel approaches (i.e., Acoustic Emission). However, there is a proposed benefit in evaluating these approaches within a Risk and TOC trade-space, including their contributions to uncertainty reduction, along with other proactive alternatives as discussed herein.

There are also proposals for Risk Based Inspections using onboard measurements (Kaminski *et. al*, (2010), Tammer *et. al.,* (2013), and Hageman, *et al.,* (2016) that make intuitive sense given the limitations of Optimal Inspection discussed, especially related to actual encountered loading and measured system response. However, there are systems considerations that need to be considered as described in Chapter 2.0 and examples in Chapter 6.0

Many of the approached proposed for Optimal Inspection of fatigue cracking failure also include corrosion failure. This is a natural extension of the process with generally higher *PoD* for visual inspection of corrosion vs. fatigue cracks, which is why it is a common approach in practice today; however, *PoD* for corrosion has not been quantified for ship structure applications. There are many aspects of this approach related to corrosion failure that remain to be quantified including the *PoD* statistics and implications of progressive failure with corroded structure required to quantify the associated system failure and Risk.

4.0 RISK AND UNCERTAINTY

In looking at the fundamental assumptions of prior Decision Theory based structural life cycle management approaches, it became clear that it was necessary to investigate the fundamental definitions of Risk and uncertainty that are relevant to Risk Analysis and understanding uncertainty quantification in broader stochastic terms. Simply stated, the terms Risk and uncertainty refer to perceptions about the occurrence of alternative future events, in which current assumptions might not hold. The quantified definitions of both uncertainty and Risk are central to understanding the actions required to reduce or minimize both in complex structural systems with a very wide variety of stochastic processes found in the life cycle decisions and management of ships in general and structure in specific. Therefore, the review of the definitions of uncertainty and Risk is presented here to clarify these terms and how to understand them and their impact on SSLCM decisions with major cost implications. The following Sections present the results of this fundamental investigation into uncertainty and how it relates to Risk for effective SSLCM decisions.

4.1 Why Uncertainty Matters

The definitions of Risk and uncertainty vary from very broad to specific quantitative terms that depend on a specific application even within the technical communities of Decision Theory and Risk Analysis. The discussion on uncertainty is presented here to clarify the definition as it relates to fundamental foundations of Risk quantification, management, and communication.

Risk perspectives depend on the amount of knowledge individuals, groups of individuals and society have to make a decision and their reactions when faced with uncertainty. In each Risk setting, these individuals and groups of individuals may have no, little, or much information to make the decision and this makes a significant difference in the individual or groups view as does the consequences of the decision and are also related to the amount of information required to make an informed decision. Therefore, in the two extremes, when faced with a decision, if there are no uncertainties (all is certain or deterministic), there is no Risk. Similarly, if there are no consequences to an event or decision, there is no Risk. In between complete certainty and complete ignorance, the characterization of the uncertainty has a direct influence on Risk as proposed in this dissertation.

A useful general definition of Risk follows that it is a characteristic of a situation, action, or event in which:

- A number of outcomes are possible
- The specifics of a particular outcome that will occur are uncertain
- At least one of the possible outcomes is undesirable

In simple terms:

$$Risk = U^{*}C \tag{17}$$

Where U = Uncertainty and C = Consequences of a decision on outcomes or event, typically an undesirable outcome, although some include possible good outcomes as an alternative opportunity, a term typically used in financial market assessments. In this context of Risk definition, quantifying uncertainty is a fundamental aspect associated with understanding the definition of Risk and its applications.

The lengthy discussion presented on the topic of uncertainty provides a foundation for the understanding and communication of its integral component of Risk. A review of Risk definitions is provided to show the contrast between Decision Theory (used in Optimal Inspection based LCM approaches) and those used in Risk Analysis.

The manner that individuals, collective groups of individuals, or societies make decisions given uncertainties about an event or possible outcome varies from intuitive feel too sophisticated analysis and testing efforts and everything in between. In any given Risk scenario and alternatives, there are varying degrees of uncertainty. Humans have evolved learning based on experiences that become engrained as normative of our personal and collective experiences. The normative set of what is safe or unsafe is a reference set of data as prior experience. Experiences that are outside of the normative experiences are conditioned to pique our interest as a minimum and set up a fight or flight awareness to reflexive response if the observations are deemed significantly outside of the normative status quo.

Thus, fear of the unknown outside the normative experience heavily influences decisions and is a major consideration, instinctively or cognitively, by those who need to make a decision and take action. Most humans dislike the absence of certainty and are conditioned fundamentally (in DNA) to react to the uncertainty in instinctive ways (flight or fight) in the absence of real actionable information to make an informed decision. These inherent feelings of fear of the unknown are fundamental to understanding how we benefit from Risk Analysis for guidance and how we respond in making decisions.

Brown (2010) presents a researched viewpoint on how we view uncertainty with innate (gut) intuition.

"Intuition is not independent of any reasoning process. In fact, psychologists believe that intuition is a rapid-fire, unconscious associating process-like a mental puzzle. The brain makes an observation with existing memories, knowledge, and experiences. Once it puts together a series of matches, we get a "gut" [feel] on what we've observed.

Sometimes our intuition or our gut tells us what we need to know; other times it actually steers us to fact-finding and reasoning. As it turns out, intuition may be the quiet voice within, but that voice is not limited to one message. Sometimes our intuition whispers, Follow your instincts. Other times it shouts, You need to check this out, we don't have enough information."

This discussion on intuition by Dr. Brown, as it relates to uncertainty and decision making, reflects an individual's experience and related personality, and resources (time and money) to obtain information to reduce uncertainty. Obtaining information and knowledge is intended to reduce uncertainty in making decisions. One of the key elements of this dissertation and research, in general, is to provide a verifiable framework for presenting information on uncertainty, Risk, and a systematic decision process that, in some ways, mimics our natural ability to make decisions, only in a more quantified way. While those making decisions on major investments such as ship structure, and ship design and management in general, have considerably more experience than most people making daily intuitive based decisions, the basic process is similar in that quantified information is useful as a basis for making high-value decisions rather than relying solely on intuition. The quantified Risk-TOC process becomes supporting information to intuitional guidance for acceptable Risk. This dissertation provides fundamental definitions and a framework for making decisions based on quantification of Risk, its underlying uncertainty, and consequences. Understanding the fundamental human response to Risk and related aspects facilitates the communication of Risk and uncertainty in a manner that is intuitive to Decision Makers.

Weisberg (2014) also describes this inherent, instinctive response to uncertainty;

"…, imagine that you are sitting comfortably and reading this book, suddenly, you hear a very loud bang. Instantaneously, your startle response kicks in, precipitating a number of programmed reflexive reactions. Your senses are oriented to determine the source of that disturbance, and your body is ready for "Fight of Flight. During the eons, when hominids were evolving, these extreme reactions were highly adaptive. In a sense, the noise was interpreted to mean there was a high "probability" (or likelihood) of danger." and action is required to minimize, mitigate or avoid unwanted consequences.

These experiences outside of the normative learned knowledge and emotional, instinctive response base typically requires us to "pay closer attention" to the situation and instinctively collect more information through our heightened senses and then go back to what we were doing if the data collected warrants an all-clear decision. We typically need additional observations because there is a perceived deviation from the normal experience creating uncertainty in the overall situation. While not everyone has the same reaction to this uncertainty, it does provide awareness when we do pay attention to our inner questioning of an unfamiliar situation. This uncertainty that peaks our awareness is the underpinnings of the uncertainties associated with a Risk Analysis and its interpretation presented in this dissertation. Given the importance of uncertainty as a major component of Risk, it is beneficial to understand uncertainty, its sources, and definitions. This understanding of uncertainty will help in defining, understanding, and communicating Risk.

4.2 Definition of Uncertainty in Risk Analysis

Webster's Dictionary defines uncertainty as doubt or the opposite of certain. If events are certain, the likelihood that events or outcomes will occur is certain; therefore, there is no Risk. Uncertainty may take many forms from near certainty to no knowledge or information, including ignorance that we do not know anything about a future event or decision.

4.2.1 What We Know and Don't Know

…in this world nothing can be said to be ***certain****, except death and taxes.* Benjamin Franklin 1789

The decision in Risk Analysis fall between two extreme cases depending on the degree of knowledge we have about the outcome of an event and our actions. We may have little or a lot of information or any amount in-between. A range of knowledge may be described as:

Complete Ignorance – (Unknown-Unknowns) - as in chaotic events, rare events, and black swans

Ambiguity- (Confusing Known-Unknowns) unknown probabilities or conflicting probabilities, fuzzy data

Partial Knowledge – (Known – Unknowns) - Quantifying aleatory and epistemic uncertainties with relative probabilities (variant being Unknown to us individually but Known by others)

Full Knowledge – (Known-Knowns) – Deterministic System with no uncertainty, (arguably, there is no such a thing as full knowledge in complex systems)

In fundamental terms in the context of decision making, the Decision Maker must face the fact that there is uncertainty and then proceed to characterize the uncertainty to decide to collect more information or perform other actions required to characterize the uncertainty.

According to Males (2002), uncertainty exists because of:

- Natural Variability: Nature is random (at our level of view) and is also known as aleatory uncertainty.

- Knowledge Gaps: Lack of knowledge, time or resources. Our knowledge, models, analysis techniques and data are not perfect. Our estimates of parameters and limitations of theory for models are not exact and are also known as epistemic uncertainty.

According to Weisberg (2014);

"By reducing all problems to matters of prediction, we are willfully ignoring ambiguity, Consequently, we tend to devalue the expert's role in resolving ambiguity because it cannot be measured objectively"

"Suppose, however, that we are dealing with a situation that is fraught with ambiguity. Is predictive skill a valid standard for assessing expertise? In such a context, it may be difficult or impossible to represent our uncertainty as a mathematical probability. Forcing the expert to frame his uncertainty so precisely may be artificial. Before this uncertainty can be placed on a numerical scale, it would be necessary to substantially resolve the ambiguity. The ability to resolve ambiguity productively is a much a hallmark of expertise as the ability to analyze preexisting data.

The conceptual definitions of uncertainty presented herein are used to support decisions based on modeling and quantification in scientific and engineering quantities. In engineering and science, uncertainty is quantified by the application of statistical principals of an event or event processes. Uncertainty theories are also used where the information is not available in sufficient quantities to quantify stochastically. In these cases, fuzzy logic and similar approaches are used. Ayyub (2006) presents an overview of managing uncertainties, including ignorance, ambiguity, and fuzzy logic-based approaches. Ignorance is not having any knowledge or ideas about an event or process. Induction is often used to infer the unknown from the known as originally proposed by Bayes (see Appendix B).

4.2.2 Stochastic Uncertainty in Science and Engineering

In the context of uncertainties and Risk in engineering systems, the general classification is divided into two categories: Aleatory and Epistemic uncertainties. There are various descriptions of Aleatory and Epistemic uncertainties presented in the literature, including (Messec 2015, Ayyub 2006, Limbourg 2004, and Collette 2018).

The descriptions of Aleatory and Epistemic uncertainties are summarized here with examples applicable to the uncertainties associated with Risk Analysis.

1) Aleatory uncertainty refers to the inherent variability or randomness that exists in a physical process or physical characteristics of the system. The inherent randomness of events and modeling variables are perceived as inherently random and are treated to be non-deterministic in nature. The uncertainty, in this case, is attributed to the physical world because it cannot be reduced or eliminated by enhancing the underlying

knowledge base. Examples of this type of uncertainty include strength properties of steel and structural wave loading of offshore structures and ships. Aleatory uncertainty of a quantity can often be distinguished from other types of uncertainty by its characterization as a random value with "known" (inferred or implied) statistical distribution. The exact value will change but is expected to follow the distribution. This randomness is a characteristic of the physical world as in material properties and wave loading on a fixed or floating structure. Aleatory uncertainty is typically not reducible and is characterized in random process terms.

2) Epistemic uncertainty is present as the result of a lack of complete knowledge or modeling of knowledge about a random process in many physical systems. In this case, the magnitude could be reduced as a result of enhancing the state of knowledge by expending resources. Sometimes, this uncertainty cannot be reduced due to resource limitations, technological infeasibility. Epistemic uncertainties are unknowns in the modeling of a system or process reducible with more information or data. The modeling uncertainty may be caused by insufficient data needed to develop the model, over-simplification of a complex process (i.e., seakeeping and structural loads are produced by a random seaway and modeling the loading and response to the required accuracy requires more time and resources than may available) typically because of lack of information or data or general lack of complete knowledge about the system or process. The former is known-unknowns, the latter is unknown-unknowns or a type of ignorance. Epistemic uncertainty is not an inherent property of the system. A gain of information about the system or environmental factors can lead to a reduction of epistemic uncertainty (i.e., by improved modeling). Before we do this, we don't have enough information to assume any possible model without neglecting that reality may be misrepresented. Hence, epistemic uncertainty is our inability to model reality, with exact precision. Epistemic uncertainties are generally not reducible at any given time; however, they may be reduced with additional information or new models. Epistemic uncertainty is often ignored, and some arbitrary distribution over the uncertain value stated as "the best/most realistic/most intuitive". In many cases, the modeling error may be known and compensated for, as is done in reliability-based approaches (Stambaugh *et. al.,* 2014b and Hageman *et. al.,* 2019).

An example epistemic uncertainty includes fatigue analysis used in design standards and guidelines, and aleatory uncertainties include test data from specimens subjected to cyclic loading with considerable uncertainty in response. Another example of epistemic uncertainty includes the cumulative damage summation to compare fatigue loading to the structural damage response. The variability in the test data from material and physical geometric properties produces aleatory uncertainty, while the damage modeling of the fatigue damage process produces epistemic uncertainty associated with the data scatter. Both examples have considerable inherent uncertainties related to the complex physical and material properties of the system. These characteristics of uncertainties are inherent in the processes and models and are fundamental components of the underlying uncertainties associated with Risk.

Deterministic decisions related to events and outcomes associated with complex structures are rare due to the inherent aleatory and epistemic nature of the various stochastic processes involved. Deterministic quantities (i.e., 30 FL) require the user to interpret or ignore the reality of the random nature of the environment ships operate and the randomness of the structure's capacity to withstand the demand of the numerous uncertainties in SSLCM.

4.3 Quantifying Uncertainty with Probabilities

The following discussions on fundamental definitions of uncertainty are intended to be useful if not necessary in understanding uncertainty quantification, propagation, and mitigation associated with Risk Management. In the context of Risk Analysis, probabilities are used to characterize aleatory and epistemic uncertainties in mathematical terms. Probability is a measure of the likelihood of something happening, and statistics are numerical measures that summarize and describe larger amounts of information. A discussion on quantifying uncertainty is presented next to clarify how the uncertainty component of Risk is quantified, when information exists to do so, and enable efficient communication on Risk among Decision Makers.

4.3.1 A Brief History of Probabilities for Context

According to the history of probability and statistics provided by Wiesberg (2014), it was in the mid-1600s when Pascal developed mathematical definitions for the games of chance (odds ratio of a fixed data set) and equated them to mathematical definitions of probabilities. Prior to that time, the word probabilities had been used to characterize the collection of evidence of observations in qualitative and subjective terms without any formal justifications or counting. In the new context of games of chance, probabilities were calculated frequencies of outcomes with a known reference class of total observations (i.e., a roll of two dice, there are a fixed number of outcomes for the total in each possible roll). Laplace and others developed the mathematical definitions of probabilities of chance and further developed them into relative frequencies independent of any reference class. These relative frequencies were then applied to other empirically random observations without context or full resolution of ambiguities of a total reference population with limited amounts of data for complex systems also requirements for contextual reference class to fully resolve the ambiguity of this disconnect the data sets reference class. Bayes and Laplace provided additional context to a reference class of random data and is unfortunately defined by many as subjective probabilities even though the conditional information may be fully quantified based on past observed experience or prior information.

The point being made here is that probabilities are very insightful in characterizing uncertainties associated with observations in random processes; however, the contextual information, prior experience, conclusions about the observations, and decisions regarding uncertainty should also be considered in a larger perspective to reach informed decisions about uncertainties associated with Risk.

4.3.2 Interpreting Probabilities

Probability is a measure of the likelihood of something happening, and statistics are numerical measures that summarize and describe larger amounts of information. Although in most practical problems the probabilities will have some amount of aleatory and epistemic uncertainties or even some amount of subjectivity, these probabilities must still conform to the underlying axioms of probability theory, including the Kolmogorov axioms (Kolmogorov, 1956), restated here as follows:

1) The probability of an event occurring must be non-negative,

2) The probability of an event which is certain to occur is 1,

3 The probabilities of two or more mutually exclusive independent events ($p(A \cap B)=0$) can be added, i.e. $p(A \cup B) = p(A) + p(B)$,

4) The probability that two or more independent events will occur together in succession is the product of all the individual probabilities, i.e., $p(A \cap B) = p(A) \cdot p(B)$ (joint probability),

5) The conditional probability of event A, given event B, is defined by $p(A \mid B) = p(A \cap B)/p(B)$ on condition $p(B) \neq 0$; if A and B are independent, $p(A \mid B) = p(A)$.

The first two axioms imply that the probability of an event occurring must be at least zero and no greater than 1.

The following approaches describe the interpretation of probabilities:

- Repeatable experiments (tossing a die, flipping a coin) generate *odds/chance* probabilities.
- The probabilities may involve *relative* probabilities to particular outcomes in terms of limited experiments or information available.
- Where there is a lack of exact experiments or only limited understanding of the process from prior experience, subjective probabilities are assigned. According to the subjective view, the probability of an outcome represents the Decision Maker's degree of belief that the outcome will occur and bounds of possible outcomes as examples.

The following Sections describe the approaches to quantifying uncertainties with the information available in probabilistic terms.

4.3.2.1 Classical Probabilities

In classical statistics, the probability of an event occurring is defined as the number of outcomes that lead to the event divided by the total number of possible outcomes given a fixed, known reference set. This is referred to as a point estimate of probability and can be used to describe, for example, the chance that a coin toss will result in heads or tails, or the probability of throwing a two with a pair of dice or selecting a particular card from a card deck. For classical probabilities from a known set, the probability of drawing a Jack out of a standard deck of 52 cards is 4/52 = 0.0769 according to the classical approach for characterizing probabilities with a fixed, known reference set (i.e., the total number of possible outcomes is known prior to the trials or experiments).

4.3.2.2 Relative Frequency Probabilities

The frequentist view of probability defines the probability of an event's occurring in a particular trial as the frequency with which it occurs in a long sequence of similar trials. More precisely, the probability is the value to which the long-run frequency converges as the number of trials increases, at least that is how the frequentists have developed modern statistical approaches. In scientific and engineering applications, long-run frequentists probability measures are rare, and this is the case for ship structural analysis. Therefore, in most, if not all, scientific and engineering, uncertainty is characterized in terms of relative probabilities or relative frequencies often without due consideration to a true reference class for their application.

Other names for relative probabilities include relative frequencies, experimental probabilities, and objective probabilities. Relative probabilities are essentially the number of times an outcome occurs during an experiment divided by the total number of times the experiment is conducted. There are two types of relative probabilities including those with:

1) Measurements from tests and trials and statistical characteristics are statistically "significant."
2) Measurements from tests and trials that are not statistically "significant" or lack of knowledge about the reference set.

The first type of measurements are typically defined as experiments repeated often enough to develop confidence the results are "significant" as defined by Fisher (1992) This type of probabilities are often called objective probabilities and are associated with medical trials and product reliability where long-run tests or trials are conducted to develop volumes of statistical data to be quantified as "significant"

The second type of measurement is very common in the shipping industry. For example, fatigue test data is developed from other industries for specific applications and applied to ship structures (i.e., Sieve *et. al.,* 2000 and ABS 2017). This approach has not fully verified in ship structures, especially for the more complex geometries of ship structural details and their specific loading profile (i.e., the fatigue tests are constant amplitude and the ship loading is random and non-linear). This finding relates to the phenomena being measured, the reference class that is not known, and there are conditional probabilities and ambiguities not considered.

4.3.2.3 Subjective Probabilities

Because different people may have different information related to an event (i.e., different reference set basis), and the same people may acquire new information as time progresses, there is strictly no such thing as 'the' probability of an event in using relative probabilities. Different people or one person at different times may legitimately assign different probabilities to the same event.

Similarly, when there is limited or no relevant statistical population (i.e., failure statistics), it is not possible to obtain an objective or relative frequency probabilities. For problems that are not similar enough data to derive classical or relative frequency approaches, subjective probabilities are used. Subjective probabilities include relevant probabilities from experience and opinions of possible outcomes.

Subjective probabilities include**:**

1) Prior probabilities are data from another, but similar source, i.e., fatigue test data used in other industries and wave heights used in fatigue calculations
2) Conditional and marginal probabilities, i.e., Joint pdf of Hs and Tp used in Spectral Fatigue Analysis (SFA)
3) Guesstimates, i.e., Small sample data from a similar application, Best Estimates of ranges perceived possible (Guesstimates), or Expert Opinion

According to Males (2002) and Gedig, *et. al.,* (2006), a subjective probability of an event involves a degree of belief or likelihood that a person has that it will occur, given all the relevant information currently known to that person. A subjective probability is an expression of an individual's degree of belief that a particular event will occur and may also be based on conditional probabilities. Subjective probabilities vary from individual to individual, even when they have access to the same information. Therefore, a subjective probability is a function not only of the event but of the state of information, including the perspective of the observer and limits that may be associated with the perspective. This statement is especially important in interpreting relative probabilities and assessing the legitimacy of the reference set.

For practical applications, the probabilities used to characterize and quantify uncertainty may be relative frequencies from a set of experiments (e.g., fatigue life testing under some specified loading that may or may not represent actual loading), which becomes prior knowledge in subjective probabilistic based definitions.

Although purely objective probabilities are desirable, testing and experiments in large complex structural systems is expensive to conduct to achieve a representative sample for a specific application and are rarely repeatable. In ship structural applications, it is not economically practical to make new components, test them 1,000 times, and measure the frequency with which it succeeds—as is typical in aircraft and nuclear industries. In many industries, objective probabilities are of limited application in decision problems because there are infinite possibilities and uncertainties involved in the problems (i.e., the reference class is difficult if not impossible to determine).

For scientific and engineering applications, the probabilities used to characterize and quantify uncertainty may be relative frequencies from a specific set of experiments or in engineering applications of material test data (e.g., fatigue life testing under some specified loading that may or may not represent actual loading) which becomes prior knowledge in subjective probabilistic based definitions. Successful scientific research and engineering should also include both quantitative and qualitative judgment on the researcher to propose creative hypotheses and contextualize the data analysis and their place in a reference class setting.

The subjective conditional and marginal probabilities are combined using a Bayes approach to use prior and conditional knowledge and probabilities as a starting or reference perspective and updating the priors based on new data as it is obtained. These definitions are important in how Risk and its uncertainty are quantified and communicated.

According to Taghavifard *et. al.*, (2009)

"Purely subjective probabilities are used extensively in decision analysis for several reasons. In many cases, they represent the best information available to the decision maker. When using subjective probabilities, it is beneficial to perform sensitivity studies to understand how the outcomes of a decision model changes in response to the chosen probability value. Often, sensitivity analysis indicates that major changes can be made to probabilities in decision models before affecting the recommended course of action. Finally, a systematic method is available in Bayes' Theorem to test and refine the hypothesis suggested by a subjective or [conditional] probability as more information becomes available."

4.3.2.4 Summary of Interpreting Probabilities

In summary, it is preferable to work with objective relative frequency probabilities; however, this is not always possible. In using relative frequency probabilities, there are always questions about the population being examined or the model being used. These uncertainties are typically either aleatory in nature or epistemic in modeling, as discussed later. Often in practice, subsystem and component testing is performed, or analytical constructs are proposed. The experimental sample size of a data set is 1) estimated to be, 2) thought to be, 3) assumed to be, 4) hoped to be representative of the population, or similar application.

According to Wiesberg (2014), in understanding the uncertainty as a component of Risk,

"*Uncertainty is characterized by the amount of information and quality of that information. Uncertainty with complete ignorance refers to those situations in which no assumptions can be made about the probabilities of alternative outcomes under different states of nature*".

Uncertainty with stochastic information on a random process is categorized as objective, relative, or subjective probabilities to possible outcomes. The objective, relative and subjective probabilities may be based on test data in the former two cases or personal knowledge, intuition, or experience in the latter subjective case. The process of decision making under conditions of uncertainty is effectively the same as decision making under Risk because uncertainty is a component of Risk. Uncertainty with complete ignorance requires alternative approaches to the decision-making process including gathering more information.

Extensive testing and research are often applied in the nuclear and aerospace industries due to both magnitudes of Risk (consequences) and economies involves. However, in the marine industry, Risk based approaches that consider the broader range of uncertainties involved are still developing, and incentives are reduced do to perceived Risk (by complying with class rules), Risk transfer (to insurance companies), and short-term perspectives on the economics of profit. In structural engineering, most decision problems concern unique events or one-off decisions. Often, there are limited amounts of data on the failures of the entire system in the public domain (see Stambaugh *et. al.,* 1987 and SSC website). When no data exists ranges of possibilities and opinions are the only information available. In cases of limited information, fuzzy set theory of probabilities may apply as discussed previously; however, additional research is required to formulate them into a quantified approach for Risk Analysis and decision making

Probabilities range in quality (or confidence) depending on the amount of data available and are often included as either objective or subjective depending on the context and amount of data. As Savage (1971) suggested, *"when we have little data, we are Bayesianists, and as we acquire large amounts of data, we become frequentists. For the most part, we are in the middle ground of partial data and relative frequencies not enough to be objective frequentists"*, but not fully subjective guessing implied by the extreme view of Bayesianists. Bayes' interpretation of probabilities provides a valuable perspective for relative frequencies and can be updated as proposed by Reverend Bayes and presented by Reverend Price (1763).

Given the valuable insights into probabilities attributed to Bayes and the more strictly defined modern interpretations, a more in-depth discussion about what Bayes "said" and didn't "say" related to prior knowledge, updating given new evidence, and how the perspective has evolved to the version(s) we know today is presented in Appendix B. This discussion may be helpful to others in search of Bayes' philosophy and its relevance in understanding the context of relative and subjective probabilities and their influence on uncertainty and Risk.

The main point here is that in uncertainty quantification, the degree of certainty varies among Decision Makers depending upon how much knowledge each one has about the same problem. This also reflects the differences in the perception of solutions by everyone involved in the decision process. This awareness of uncertainty becomes even more acute in decisions with significant financial implications. Probabilities are useful in quantifying uncertainties in an event or outcome and form a common reference frame for Decision Makers.

Figure 4.1 presents A schematic relationship of the uncertainties discussed here in the context of Risk definitions.

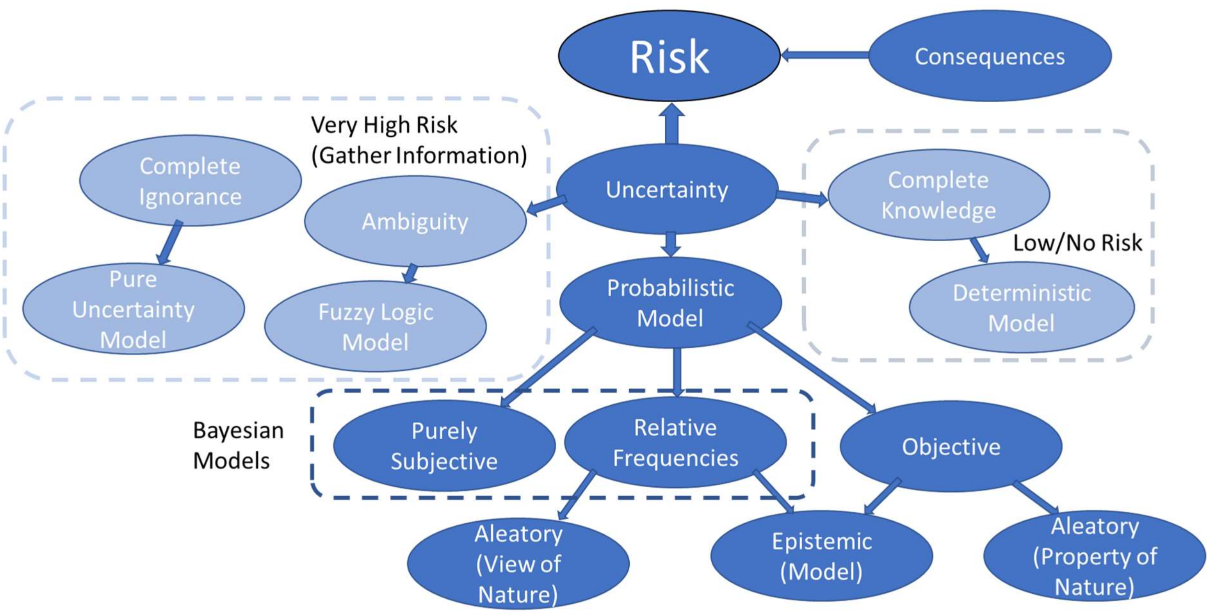

Figure 4.1 – Types of uncertainties contributing to Risk

4.3.3 Interpreting a Range of Uncertainty Using Probabilities

A range of outcomes for a future event includes two extremes. One extreme on this scale is deterministic certainty (P = 1 or 0). The opposite extreme is pure uncertainty (i.e., 50/50 chance and a uniform probability distribution). Between these two extremes are problems with varying amounts of information to characterize uncertainty and make a fully informed decision.

Figure 4.2 shows examples of both discrete and continuous probabilities varying in degrees of uncertainty to certainty of the probability.   For example, 4.2(a) the discrete probabilities A, B, C with equal values indicating all are equally likely to occur with maximum uncertainty. Example 4.2(b) shows a slightly higher level of probability, and example 4.2(c) would seem to indicate B is by far the most likely and more certainty in choosing that option if it related to a decision process. Similarly, the examples of 4.2(d) is a uniform distribution of probabilities with equally likely probabilities and no clear choice, maximizing uncertainty, followers by example 4.2(e) appearing to have a useful mean value and 4.2(f) showing a high probability with narrow distribution of probabilities and more certainty in making a decision, over example 4.2(e) with wider range of probabilities. Assuming examples 4.2(e) and 4.2(f) follow a normal statistical distribution, example 4.2(f) will have a much smaller standard of deviation indicating a narrower range of probabilities and again, an indicator of the amount of certainty we might have in the mean value of the continuous distribution. Although these concepts are fundamental in statistical analysis, they are crucial in understanding and characterize the uncertainty (estimated by probabilities) in Risk Analysis and decision making, as presented in this dissertation.

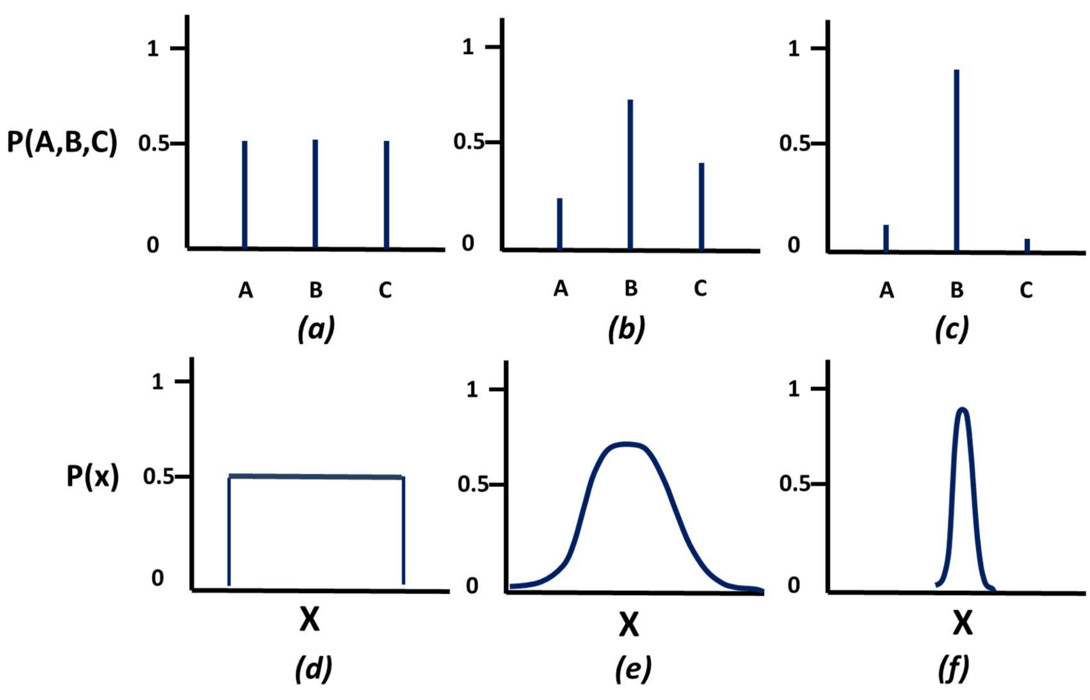

Figure 4.2 - Illustration of quantifying of ranges of uncertainty in terms of discrete and continuous probabilities (Redrawn in part from Arsham, 2019**)**

The implication of the characterization of uncertainty is important in understanding risk, information, and decision making. The uncertainty characterized by a uniform distribution of probabilities reflects the maximum amount of uncertainty. The flat uniform distribution of probabilities has the largest uncertainty (i.e., all outcomes are equally likely); therefore, the largest Risk. In such a case, the quality of information is at its lowest level. In statistical terms, the quality of information and variation are inversely related. Specifically, the larger the variation in data implies lower quality data (i.e., information). The more centralized probabilities (and smaller variance) reflect a higher amount of certainty available to calculate Risk and make informed decisions. It follows that the more information we have to characterize the uncertainty with probabilities and reduce its variance or dispersion, the more confidence the Decision Maker will have in the decision. Gathering the information in terms of data collection or experiments are intended to reduce the uncertainties in a process or observations of a process. Concepts of initial uncertainty (Bayes and Jaynes prior distributions), information gain (Shannon Information Entropy), and information updating are discussed in more detail in later Chapters of this dissertation for further understanding of this topic on quantifying uncertainty as a fundamental part of Risk.

When a range of possibilities exists for an outcome, then the estimates of probabilities are expressed as either a discrete probabilities, histograms, or continuous curve known as a probability distribution. Certain shapes of distributions occur frequently and are useful in many circumstances because they describe many phenomena quite well. The Gaussian or Normal Distribution (the bell-shaped curve) is an example of a probability distribution. Statistical distributions are characterized by parametric measures. Typical measures are the mean and the standard deviation. Such measures are called the parameters of the distribution. Confidence intervals (or Confidence bounds, Confidence limits) describe a range of certainty about estimates (e.g., 95 percent certainty) that the *E(V)* of a distribution of data or outcomes lies between the values of X and Y. Standard deviation and confidence interval are ways to describe the dispersion of the data set with variations discussed above. The larger the standard deviation and the range of confidence level (e.g., 95 percent), the less certainty there is about an estimate as described by Walpole *et. al.,* (2012).

5.0 PROPOSED RISK ANALYSIS AND TOC APPROACH

Risk and uncertainty definitions often vary depending on the discipline, including Decision Theory and Risk Analysis. This chapter presents a summary of Risk definitions common in the Risk Analysis and Management disciplines and how these definitions are applicable to Risk communication in SSLCM.

5.1 Risk Overview

Risk Analysis is a technique for identifying, characterizing, quantifying, and evaluating hazards. It is widely used to support resource allocation decisions. The estimation of probability or frequency of hazard occurrence depends greatly on the reliability of the system components, the system as a whole, and human-system interactions. There are two major parts of quantified Risk Analysis:

- Determination of the probability of an undesirable event (typically failure).
- Evaluation of the consequence of the hazardous event.

According to Ayyub (2003),

"*Risks to a system may result from its interaction with natural hazards, its aging and degradation, or from human and organizational factors. Consequently, Risk can be classified as either voluntary or involuntary, depending on whether or not the events leading to the Risk are under the control of the Risk. Society generally accepts a higher level of voluntary Risk than involuntary. The losses associated with events may be classified as either reversible or irreversible, depending on whether the loss is of property or human life, respectively. Choosing the target Risk level should minimize total expected costs over the service life of the structure and for dealing with a design for which failure results in economic losses and consequences.*"

In general, there is a wide range of Risk Analysis methods and related theories. However, in quantified engineering based Risk assessments, the likelihood of an event is expressed in terms of probability, P_i, of that event. Consequence, C_i, is a measure of the impacts of an event. This can be in the form of mission loss, cargo damage, number of injuries, number of fatalities, environmental, political, and societal damages (Ayyub 2003). The results of Risk estimation are then used to interpret the various contributors to Risk, which are compared, ranked, and placed in perspective. The Risk assessment for an individual Risk, R_i, and the total Risk, R, can be obtained by applying the following two equations (Ebeling 2010, Ayyub 2003, Moderes 2006):

$$Risk_{(i)} = P_{(i)} * C_{(i)} \qquad (18)$$

for a possible event, i in a system with N Risk identities and the Total Risk is,

$$Risk_{Total} = \sum_{i=1}^{N} P_{(i)} * C_{(i)} \tag{19}$$

for all possible events n in a system at a specific time T.

Although this is the fundamental equation for quantifying Risk, the Risk Managers and Decision Makers may consider a number of other Risk processes depending on the application.

In the prior discussions on Decision Theory (Chapter 3), concepts of *E(V)*, *E(U)*, and Risk are interchanged as equal concepts. In contrast to Decision Theory discussed previously, Risk Analysis involves the quality, quantity, and subjectivity of the information are factors in the Decision Maker's choice of mitigation approaches, as discussed by Yoe (2000). With probabilistic approaches to Risk assessment, the Risk estimates are not limited to an Expected Value *E(V)* or Expected Utility *E(U)* and must also provide a sense of the range of possible outcomes across events and alternatives. Simulation-based Risk Analysis involves being able to assess a range of uncertainty parameters, probability distributions (where known), and time-based continuous stochastic processes. In Risk Analysis, probabilistic information and distributions are often used to capture all known outcomes for a set of scenarios or options to make an informed decision based on their estimated benefit. Risk Analysis provides complete assessments of Risk because it is based upon a range of probabilistic information for each scenario (rather than a single E(V) or discrete outcomes). The output from a Risk Analysis takes the form of quantified ranges of measures representing a range of uncertainty associated with the scenario outcomes. Risk and related quantified effectiveness of Risk mitigation strategies are defined here in a much different way than in Decision and Utility Theories.

Risk in engineering applications presented in the literature (see Yoe 2000 and Ayyub 2003) define quantified Risk as:

$$Risk = P_f * C_{failure} \tag{20}$$

In contrast to Decision and Utility Theories, Risk is characterized by the product of stochastic uncertainty (i.e., probability of failure *Pf)* and the potential for unwanted consequences ($C_{failure}$) associated with the failure outcome. Quantifying Risk in terms of probabilities and uncertainty reduction becomes relatable to the definitions, as discussed previously. Risk defined in this manner is easy to communicate, an essential part of any Risk Analysis.

According to Yoe (2000) and DHS guidance (2011), Risk management actions include acceptance, avoidance, control, and transfer. In ship structures, Risk Management includes acceptance and, to a lesser extent Risk control. Approaches for Risk avoidance by proactive measures have relied on prescriptive rules and experience. The ability to quantify the time-dependent degradation, serviceability, ultimate failure, and their associated costs provides an approach for determining EOSL and proactive measures that save on long term TOC as discussed in the following Chapters.

Target Risk levels are useful to evaluate acceptable Risk; however, they should not used as the sole objective for decision making. Risk involves evaluating both the probability of failure and consequences. In this trade-off, the selected probability of failure level is determined on a structural component and global level.

Occurrence probabilities (which can be annual) and consequences can be plotted as acceptable failure probability limits. An example set of Risk limits is presented by Tammer *et. al.,* (2013) and shown in Table 5.1.

Table 5.1 - Example of annual Risk Assessment criteria

Frequency Category	Range	Severity level	Severity M Euro	Consequence Range			
				Environment Range (1000 bbl)	Personnel onsite Range [#people]	Personnel external Range [#people]	Personnel range additional criteria [#people]
Likely	$>10^{-2}$	Moderate	0.2	<0.01	-	-	-
Unlikely	10^{-2}-10^{-3}	Serious	0.2 - 2	0.01 - 1	1 - 99	1-9	-
Very unlikely	10^{-3}-10^{-4}	Major	2 - 10	1 - 20	100 – 499 [1]	10-99 [-]	<500
Extremely unlikely	10^{-4}-10^{-5}	Catastrophic	10 - 100	20 - 200	500 – 999 [2-5]	100-999 [1]	<1000
Remote	$<10^{-5}$	Disastrous	>100	>200	>999 [>5]	>999 [>2]	>1000

In Table 5.1, the number between closed brackets […] denotes the number of fatalities corresponding to the defined consequence level.

5.2 Quantifying Risk as part of the Risk-TOC Approach

When assessing and evaluating uncertainties associated with an event, Risk is broadly defined as the potential for loss as a result of a system failure. This Risk can be measured as a pair of factors, one being the probability of occurrence of an event and the other being the possible outcome or consequence associated with the event's occurrence. The probabilities provide a relative measure and safety factor between serviceability and catastrophic failure.

In Risk Analysis proposed here for SSLCM, Risk of system loss ($Risk_{Loss}$) is defined as the sum of the product of the probability of failure (Pf) and cost of consequences of failure ($\$C_{Failure}$) written as:

$$Risk_{Loss} = \sum_{i}^{n} Pf_{(i)} * \$C_{Failure\ (i)} \tag{21}$$

The Risk of loss and consequences of failure are defined in terms of a system loss (ultimate limit state failure of the hull girder) and include monetary, human, environmental, and political costs of major significance. Risk of loss includes the cost of a significant or catastrophic failure that includes significant financial loss from non-availability for service, or loss of the asset and crew at the extreme. This is not intended to be the cost of a fatigue crack repair as in most (if not arguably all) Decision Theory based approaches, as discussed in Chapter 3.0.

The Risk of failure and loss terms considerations include probability of failure, cost of Ao, cost of asset loss, and the invaluable loss of people (the extreme end of the Risk exposure spectrum) as shown in Figure 5.1 Specific applications have unique considerations in consequences such as the magnitude of asset availability loss, repair magnitude, and loss of life (e.g., one, most, or all crew) provide a range of consequences with preferences on Risk associated with each. The failure consequences also depend on the failure mode. For example, severe corrosion damage may involve lower consequence costs than a brittle fracture in considering a range of physical damage, human lives, environmental or political implications. This range of consequences provides an approach for quantifying a consequence utility function associated with the system rather than predetermined or arbitrary utilities from the literature on Utility Theory as described previously. Additional discussion on this aspect of Risk consequences is presented in Chapter 6.0 examples.

Although not specifically addressing human error (and often related black swans Hajikazemi *et. al.,* 2015) in this dissertation, extending Risk-TOC to include this is certainly possible. Suffice to propose that working through a systematic Risk Analysis will identify key failure events and associated lead to Risk elements that will reduce human error occurrences with mitigations and contingencies in place to reduce the Risk exposure.

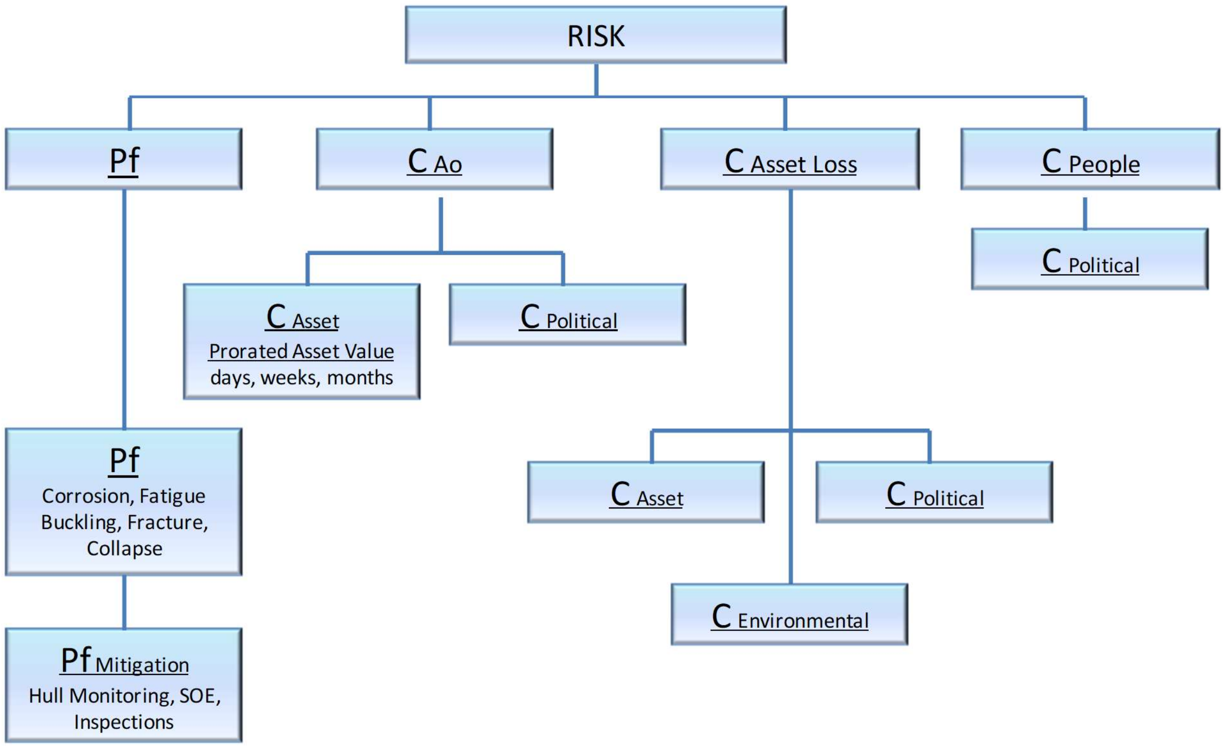

Figure 5.1 – Naval ship structure Risk considerations

5.3 Quantifying TOC as part of the Risk-TOC Approach

Total Ownership Cost (TOC) definitions are presented next along with the uncertainties associated with TOC.

5.3.1 Total Ownership Cost

Structural LCC and TOC models have been proposed by Temple *et. al.*, (2013), Frangopol *et al.* (2012), Hecht (2004), Gratos (2005 and 2009), US Navy (2012), USCG (2002) and the US Government Accountability Office (GAO 2009).

In TOC, the Total Ownership Costs are defined as:

$$TOC = \sum \$C_{LCC}\ (R\&D,\ Design,\ Acquisition,\ Operation,\ Support,\ Disposal) \tag{22}$$

$$+\sum \$Cpm\ (preventative\ maintenance)$$
$$+\sum Pf * \$Csr\ (serviceability\ failure\ repair)$$
$$+\sum Pf * \$Cna\ (non\text{-}availability)$$

Including the cost of serviceability failure in TOC, is a new approach relative to any other Optimal Inspection approach where this quantity is used as a Risk quantity. Serviceability failure is not the ultimate Risk in terms of failure and consequences (e.g., brittle fracture) but does have a significant effect on TOC. Total Ownership Cost also includes the costs of Risk avoidance, mitigation, transfer, contingency, or sharing actions, typically part of Life Cycle Costs.

The LCC, largest component of TOC, is defined by the US Government Auditing Office, GAO (2009) as;

"*life-cycle cost estimate that provides an exhaustive and structured accounting of all resources and associated cost elements required to develop, produce, deploy, and sustain a particular program. The life cycle can be thought of as a "cradle to grave" approach to managing a program throughout its useful life. This approach entails identifying all cost elements that pertain to the program from initial concept all the way through operations, support, and disposal. An LCC encompasses all past (or sunk), present, and future costs for every aspect of the program, regardless of funding source. LCC estimates enhance decision making, especially in early planning and concept formulation of acquisition. Design trade-off studies conducted in this period can be evaluated on a total cost basis, as well as on the performance and technical basis. An LCC estimate can support budgetary decisions, key decision points, milestone reviews, and investment decisions. The LCC usually becomes the program's budget baseline. Using the LCC to determine the budget helps to ensure that all costs are fully accounted for so that resources are adequate to support the program. DOD identifies four phases that an LCC must address: research and development, procurement and investment, operations and support, and disposal. Civilian agencies may refer to the first two as development, modernization, and enhancement and may include in them acquisition planning and funding. Similarly, civilian agencies may refer to operations and support as "steady state" and include them in operations and maintenance activities. Although these terms mean essentially the same thing, they can differ from agency to agency.*"

In the Risk-TOC approach proposed in this dissertation, expected maintenance costs are included in Total Ownership Costs, and the Risk failure of the structure is defined in more severe catastrophic terms in contrast to prior Decision Theory based approaches discussed in Chapter 3.0

Temple and Collette (2013) present the total lifetime maintenance cost for a ship, C_T, as the sum of four different values:

$$C_T = C_F + C_C + C_S + C_{FR} \tag{23}$$

In the equation:

C_F is the costs due to fatigue damage,

C_C is the total cost due to corrosion damage,

C_S is the costs associated with maintenance, and

C_{FR} is the total costs charged for the method used to perform any repairs (i.e., maintenance done at drydock versus that done while pier side).

Each of these costs is the sum of the corresponding yearly costs over the service life of the vessel.

Another cost to consider in TOC is the cost of lost Operational Availability (Ao) if the ship is not able to perform its intended service or C_{na} for Costs of non-availability. All ships have expected levels of operational availability (Ao), and there are costs associated with maintaining the required levels of availability. Downtime for dockside repairs extended dry-docking (if that is when damage is discovered), or emergency dry docking all have a significant impact on this availability and Operation and Maintenance (OM) cost. Time out of service can be related to the cost of the availability of the asset. These are lost opportunity costs and may be estimated by the true lost costs in profit for a commercial ship or societal benefit in the case of a military ship. Alternately, this cost can be estimated based on willingness to pay bases on the ship's value and service life in days to arrive at a daily rate for Ao. For example, a ship valued at $500M and a 30-year target service life results in approximately $50K/day loss in opportunity costs if the ship is not able to operate. This cost is additional to repair costs. Another model of asset availability includes constructed costs (i.e., crew and support costs) and lost opportunity costs (i.e., cost implications of missions not conducted of cargo not transported). Other economic and societal costs may also be impacted. Additional costs and associated consequences occur if other assets are not able to fill in if there is a significant gap in asset availability.

For a Risk and TOC based evaluation of service life, the ability or inability of being able to execute a Service Life Extension Program (SLEP) is included in the TOC definition. A SLEP has the potential to return significant cost savings when compared to a recapitalization of an asset if the condition of the existing hull structure is sound. Inclusion of SLEP cost savings should be considered in TOC on equally extended timeframes; however, this has not been discussed in the TOC context by prior approaches. Both Ao and SLEP additions to TOC are quantified as a function of time and are considered herein as TOC+ implying an extended definition of TOC.

TOC elements proposed for a Risk-TOC analysis are summarized in Figure 5.2

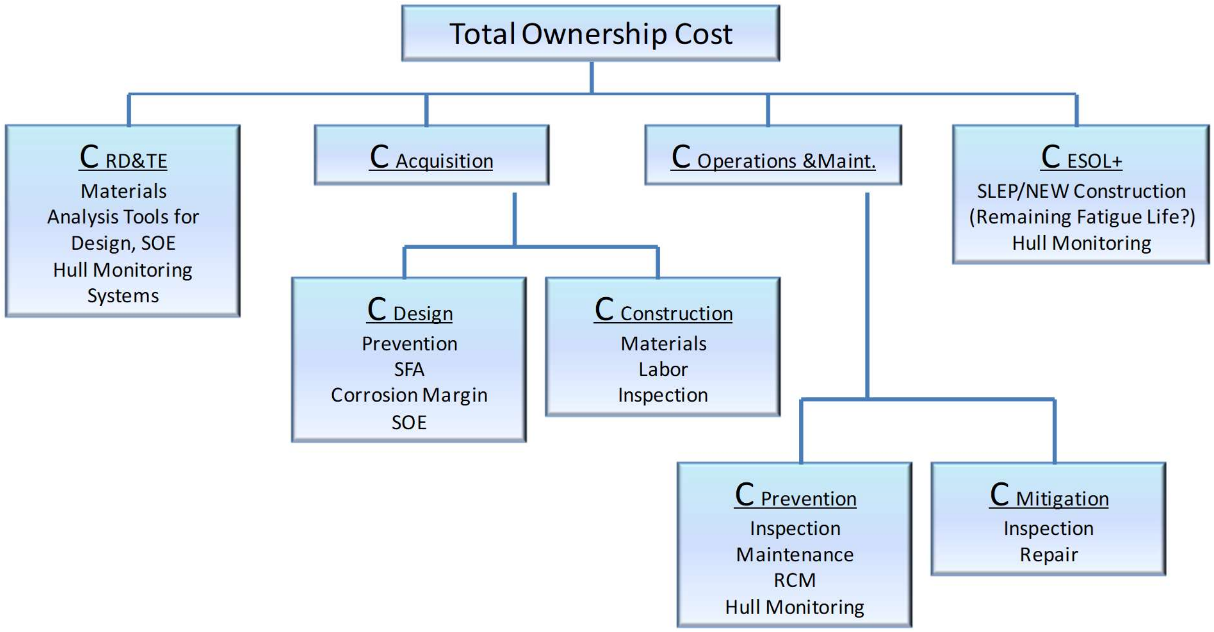

Figure 5.2 - Naval ship Total Ownership Cost considerations

5.3.2 Uncertainties in SSLCM Cost Estimates

The uncertainties associated with cost estimates have been considered in ship construction by Brown (2009) and many others in terms of financial Risk approaches, including Savage (2012), Hubbard (2009), and the GAO (2009). Full implementation of the Risk Analysis includes the statistical evaluation of the cost uncertainties.

As described by Yoe (2000),

"traditional single point cost estimates are made without considering the full range of uncertainties associated with the estimate. When the estimating process is complete, the only certainty that can be assigned to a single point cost value is that it is going to be wrong. The actual single point cost estimate will either be higher or lower than the estimated value. The single-point estimate is a single value that does not include all that is known or uncertain about the costs of complex structural systems operating over a life span of decades. Engineers and Risk Analysts must interpret and analyze information in order to get to a single number with significant loss of information about the uncertainty of the estimate, leaving the estimate's true value subject to interpretation by others without critical reference information. One of the critical differences of single-point cost estimates is that they do not address or provide all that is known about a cost estimate required to make an informed decision."

Probabilistic based cost estimates provide useful information than a single-point estimate. Probabilistic based estimates can reveal best and worst-case scenarios and characterize the variation in possible cost outcomes and Risk exposure as determined by the appropriate Risk measures.

In summary, traditional single point cost estimates are less reliable for decision making as those based on probabilistic (Risk based) methods that attempt to quantify uncertainty.

The sources of uncertainty in the cost analysis depend on the complexities of the system being modeled. Generally, variables in a complex cost model should be considered as uncertain in a stochastic context. The typical sources of uncertainty in cost estimates often relate to the quality and quality of cost data because ships are not built in sufficient numbers of the same type. The modeling of uncertainties is also often limited to simple regression models with basic characteristic parameters associated with weight, power, and volume of the ship.

The analysis of uncertainties in cost modeling should also consider correlations in the uncertainties of the Risk calculation given the interrelationships of the cost estimation process by functional groupings and their physical characteristics. Typically, cost estimating parameters are utilized to estimate the singular components of a ship's total cost estimate and repair. If cost elements rely on the same parameter (for example, weld costs based on the length or weight of the structure), they are parametrically correlated. In this example, a change in the weight value leads to a change in both cost estimates. This is called implicit or functional correlation, as it is introduced through the cost model itself. For example, there are often situations where cost elements are related by other direct parameters. This will be the case if the components are made from the same material or share common pricing factors and trends in the same manner and proportion. Without accounting for correlation, combining distributions for multiple parameters will result in an unrealistically high variance of the final estimates of the range of uncertainty, typically characterized by the variance of the stochastic outcomes.

Assuming suitable statistical distributions are found to model the uncertainty in cost estimate components, (derived, simulated, or assumed) for all uncertain input variables, the analyst’s next task is to use a Monte Carlo simulation-based approach in order to estimate the distribution of the total results.

Further examples of the uncertainties associated with costs and modeling are presented by Brown (2008, 2009), Kirkwooda *et. al.,* (2015), Bakhshi *et. al.,* (2015), Duffey, *et. al.,* (1999), and Neumann (2015).

5.3.3 Expected TOC

In the context of cost Risk Analysis, proposed definitions of TOC and related uncertainties in the estimate are defined as the Expected TOC, written as *E(TOC*), and related terms identifying the range of uncertainty in the estimate. In Risk Analysis, TOC, and *E(TOC)* are used to characterize and quantify the range of uncertainty in TOC estimates similar to $E(Risk_{\alpha})$ as described in Risk measures.

5.3.4 Economics Based Definitions

TOC estimates are subject to financial considerations of resource allocations with unique variations and even applicability depending on the application of short-term profit-taking or long-term sustainment. An overview of the financial terms and approaches commonly proposed for forecasting and hindcasting costs are presented here.

5.3.4.1 Net Present Value

Major investments with future outcome projections are often evaluated by their Net Present Value (*NPV*). This method can be used to compare results to alternative investments in Risk mitigation and cost avoidance strategies. Although Risk Analysis in SSLCM is not a classical investment, the *NPV* may be defined as the sum of all present values of cash outflows and costs avoided discounted to a fixed point of time.

Several structural life-cycle management-based approaches advocate *NPV* (Hecht, *et. al.,* 2003, Risia *et. al.,* 2018, Kirkwooda *et. al.,* 2015) in cost-benefit assessments. A review of these *NPV* based approaches follows.

Net Present Value (*NPV*) is defined as the value of all future cash flows (positive and negative) over the entire life of an investment discounted to the present minus the initial investment. *NPV* analysis is used extensively across finance and accounting for determining the value of a business, investment security, capital project, new venture, cost reduction program, and anything that involves cash flow.

$$NPV = \sum_{t=1}^{T} \frac{C_{(t)}}{(1+\xi)_{(t)}} - C_{(o)} \qquad (24)$$

Where C_t is the total of cash flows, C_o is the initial investment, and ξ is the effective discount rate at time t.

The effective Net Discount Rate is equal to:

$$\xi_{net} = \left[\frac{1+d}{1+i}\right] - 1 \qquad (25)$$

$\zeta = \{(1 + \textit{Discount Rate})/(1 + \textit{Inflation Rate})\} - 1$

d= Discount Rate

i= Inflation Rate

From extension of the basic definition of *NPV* definition to ship structural applications, discounting and aggregation of expected annual maintenance costs over total time *T* yields their estimated present as:

$$E(TOC)_{NPV} = \sum_{t=1}^{T} \frac{E(TOC)_{(t)}}{(1+\xi)_{(t)}} - E(TOC)_{(0)} \tag{26}$$

Because the choice of effective discount rate ξ affects E(TOC) over time with some uncertainty, this parameter is typically part of a sensitivity analysis considering additional possibilities of discount values.

Costs from planned and unplanned maintenance and availability costs are integrated into TOC. In Risk Analysis context, $E(TOC)_{NPVn}$ is the stream of equal expected annual expenditures necessary to repair/replace the structure in question, and t is the time in years up to the reference life *T* of the structure. Each component of *E(TOC)* must be evaluated as continuous (i.e., annual costs of crew, fuel, and maintenance) or discrete (i.e. midlife overhaul, service life extension, and disposal) expenditures or savings in these expenditures and associated *NPV* calculation approach.

Furthermore, *NPV* is a frequently used method for evaluating investment opportunities; however, it does have some drawbacks that include sensitivity to discount rate changes over time and does not consider the Risks associated with these uncertainties.

At the time of this writing (2020), the inflation rate is 2.44%, and the discount rate is 3.0% producing an effective discount rate of 0.55%, not very helpful or useful given future uncertainty in these numbers. There will likely be other applications with a more useful discount rate to apply. In the TOC examples presented, all costs are current-year estimates. The sheer magnitude of investments involved and the natural *RoI* of the fatigue process produce more significant *RoI* implications without *NPV* analysis, and uncertainties in current year monies are sufficient to evaluate the Risk and benefits of Risk reduction scenarios. See Kirkwooda *et. al.,* (2015) for additional discussion on the *NPV* and *RoI* topics.

Although a naval ship is not a classical equity-type investment made to earn financial profits (naval ships do not generate financial revenues), and in the absence of better methods, *NPV* can be applied in this context to cover inflation or alternate funding requirements. The present value of money is often considered in large financial decisions that involve expenditures over a length of time, typically of many years or even decades, as applicable for SSLCM. Risk Analysis of alternatives investment strategies and magnitude of payback may be an important consideration to the Decision Makers. Although the discount rate is most often used for *NPV* estimates, the Decision Maker(s) may have other investment opportunities that pay higher returns and costs adjusted accordingly.

5.3.4.2 Return on Investment Formulations

Although *NPV* is one approach for assessing the valuation of cash flows to present value typically applied in financial investment opportunities, the Return on Investment (*RoI*) is another approach for evaluating the alternative, independent scenarios.

Risk Analysis is not trivial to implement because of the stochastic nature of the problem. The Risk-TOC approach proposed here-in was developed to include stochastic modeling for major elements of TOC and associated *RoI* analysis that can be used to assess Risk Management alternatives and technology insertion. The important considerations for *RoI* in Risk Analysis include:

- Decision Makers and technology providers need business cases that demonstrate the economic value of their technology,
- These are "cost avoidance" business cases, which are not simple in *NPV* terms and require the calculation of *RoIs*,
- Generally, prior proposed life-cycle cost models do not address the capability to calculate the stochastic *RoIs* needed to produce business cases as proposed in this dissertation.

As described by Bakhshi *et. al.,* (2015), cost savings, avoided cost, and opportunity cost are relative terms. They have meaning only when comparing one outcome to another.

The three terms, "**cost savings**," "**avoided cost**," and "**opportunity cost**" can play an essential role in business planning, budgeting, and decision support. In the context of the Risk-TOC approach presented here for public governmental applications, the *RoI* of Risk mitigation strategies are based on cost avoidance, rather than money gained; however, in commercial applications, reductions in both Risk and TOC represent opportunities for long term profits in constrained freight rates or possibilities to increase profits through freight rate reductions and increased competitiveness.

These relative costs only exist when comparing one cost outcome to another. Typically, the magnitudes represent differences between relative outcome values. In the context of cost analysis, three cost concepts include:

- Cost scenarios **are** expenses not incurred or cost not already being paid,

- Avoided **cost** is also a cost-saving, but the reference is to a charge not yet incurred,

- Opportunity **cost** is a foregone gain that follows from choosing one outcome over another

According to Risia *et. al.,* (2018),

"like other cash flow metrics, RoI takes an investment view of the cash flow streams that follow from a decision and action. Each of these metrics compares likely returns to the likely costs in a unique way and, as a result, each sends a message of its own about the cash flow stream."

Risk reduction is typically relative to the initial "Do-Nothing" baseline scenario for calculating the Risk for no mitigation options implemented. The *RoI* may also be calculated for competing Risk reduction scenarios (i.e., different hull structure monitoring approaches). The *RoI* calculation also provides a basis for the value of information and the expected value of the cost reduction or cost avoidance for the Risk mitigation actions (see Bakhshi *et. al* . 2015). In SSLCM, the benefit is cost avoidance vs. profit as used in Risk Analysis in financial industries and applications.

The output of the Risk-TOC analysis is the TOC of the system, and the Risk associated with each given scenario is evaluated based on *RoI* for implementation of technologies based on the merits of the methodologies, as discussed later. In simple terms, Return on Investment (*RoI*) is calculated as the benefit-cost ratio of an investment:

$$RoI = Benefit\ (of\ cost\ avoidance)/Cost$$

where the benefit (Risk or costs avoided) of implementing a Risk mitigation strategy S_i is the difference between the *NPV* of *E(TOC)* of the baseline (S_0) and intervention (S_i) scenarios, respectively.

In the context of E(TOC), RoI is calculated as,

$$RoI = \frac{E(TOC)_{S0} - E(TOC)_{Si}}{Cost\ of\ Investment_0} \quad (27)$$

Where:

$E(TOC)_{So}$ = Expected Total Ownership Cost for Risk mitigation scenario (o) at time T

$E(TOC)_{Si}$ = Expected Total Ownership Cost for Risk mitigation scenario (i) at time T

As in *TOC* analysis, the costs of S_i include not only initial implementation cost but also ongoing maintenance and availability costs:

The payback period (when $RoI_T = 1$) is the time necessary for intervention *RoI* to reach unity. This is the point at which the *NPV* of the cumulative costs of the intervention. The *RoI* is less than unity if the *NPV* of implementation costs of the intervention exceeds the reduction the intervention produces in the *NPV* of expected annual losses and Risks.

Relative *NPV* in *RoI* analysis is calculated as:

$$RoI_{NPV}, t = \frac{E(TOC)_{NPVSo}, (t) - E(TOC)_{NPVSi}, (t)}{Cost\ of\ Investment_0} \tag{28}$$

Where the *NPV* of *E(TOC)* is calculated as in Equation 26.

In the Risk-TOC application, the cost of the investment is equal to the cost of implementing the new technology or management approach in the present time.

In evaluating the range of uncertainty on TOC, the *E(TOC)* may also be accompanied by a conditional TOC as in *E(TOC)* and evaluated through to present value as described above. In this approach, both the expected and contingency costs are addressed for each Risk mitigation scenario being considered.

5.4 Quantifying Uncertainties in Risk Analysis

Beyond Expected Value and Expected Utility

Decision making based Expected Value, defined as expected loss, falls under the category of the "Flaw of Averages" (see Savage 2012). The approach recommended by Savage is to look at the user-defined worst case(s) based on the Decision Maker's Risk limits and not the weighted average Expected Value when there is an expected range of uncertainty to consider. The approach to consider a range of uncertain outcomes beyond Expected Value is another major difference between Decision Theory and its expected value and utilities (often referred to as Risk).

The selection of a probability of failure for Risk Analysis depends on the application and Risks involved and the decisions to be made. Risk Analysts and Decision Makers typically evaluate the costs of multiple alternative scenarios. Questions related to the evaluation of scenarios include:

- What quantities and variables in Risk and TOC are uncertain?

- What are the average costs, and what are their variances?

- What are the contingency costs that can be estimated based on the range of unacceptable values and their probabilities?

According to Males (2002):

"If [full dimensions of] Risk is [are] explicitly taken into account, [the] added dimensions describing the [range of] uncertainty [in the quantified Risk] must be included. The uncertainty measures can be incorporated within each criterion, or separated out as separate criteria. Certain decision-making tools and techniques can make use of mathematical distributions associated with criteria, allowing the uncertainty measures to be handled directly, while others require that the uncertainty measures be considered separately, as distinct criteria." Further to Males, "The former approach is preferred. At minimum, the expected value… [and] the uncertainty in that value, is measured [estimated] as a criterion for all alternatives [of Risk mitigation options]". [emphasis added by the investigator].

Therefore, Risk Analysis should include consideration of the range of uncertainty within expectations of the Decision Maker in choosing options to mitigate Risk. In Risk Management, Risk Analyst and Decision Makers need to determine a measure of Risk. Three types of Risk measures commonly used in actuarial, financial, and engineering applications include Mean-Variance, Value at Risk, Conditional Value at Risk, and Information Entropy measures.

5.4.1 Mean - Variance (in Uncertainty Characterizations)

The magnitude and dispersion of uncertainty in Risk may be estimated based on the mean and variance of the dependent variables of interest if there is enough information to calculate the variance. Variance denotes the data dispersion through the whole distribution without differentiating the left or right tails.

For example, two statistical distributions are illustrated in Figure 5.3 for Risk-TOC Scenarios A and B with different means and variances. Risk-TOC Scenario A has a mean cost M_A with a narrow distribution of potential costs because it is a well-known design with time-tested technology. Risk-TOC Scenario B represents a newer untested Scenario, although it has a slightly lower mean cost M_B, it has the potential to cost more or less than Risk-TOC Scenario A because the variance or uncertainty is greater due to further development and testing costs. The range of uncertainty in Risk-TOC scenarios may be greater due to a number of sources of uncertainties (i.e., aleatory, epistemic or new design and technologies considered.

Risk exposure can be reduced in more than one way. The variance or dispersion of the distribution of Risk-TOC Scenario costs could be reduced by gathering additional information. Risk and TOC uncertainty (i.e., Risk exposure) may be reduced by a more accurate baseline Risk-TOC scenario estimate. One estimate that is higher than the current mean or average of the probabilities or uncertainty may be better because the range of uncertainty in Risk-TOC Scenario might not be less.

With the key sources of uncertainty in Risk-TOC scenario identified, the Risk Analysts are able to review a list of key inputs and trying to identify ways to affect those inputs favorably by reducing uncertainty and related Risk, generally by acquiring additional information.

Developing the relationship of Mean-Variance among options or scenarios is the basis of Portfolio Theory as popularized by Markowitz (1952 and 1959). The Mean-Variance of scenarios or options being considered for decision making is illustrated as dots in Figure 5.4 In Portfolio Theory, the optimum value of Mean-Variance is related to ones that exceed the discount rate of return. In Risk Analysis, the decision criterion is not as clear, but certainly insightful on a range of Risk options to consider.

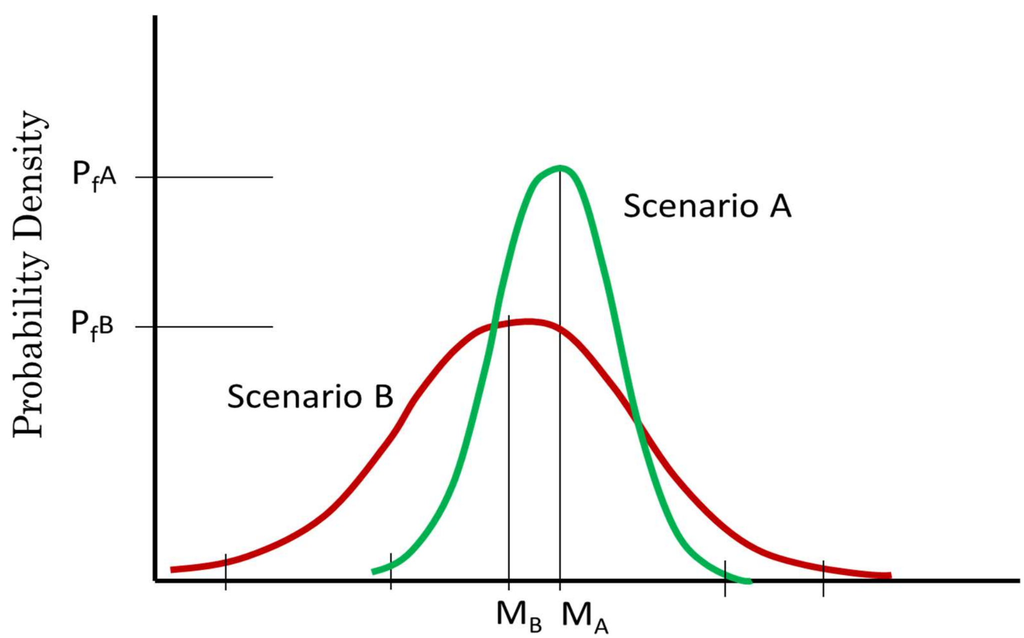

Figure 5.3 – Illustration of two ranges of uncertainty in continuous distributions

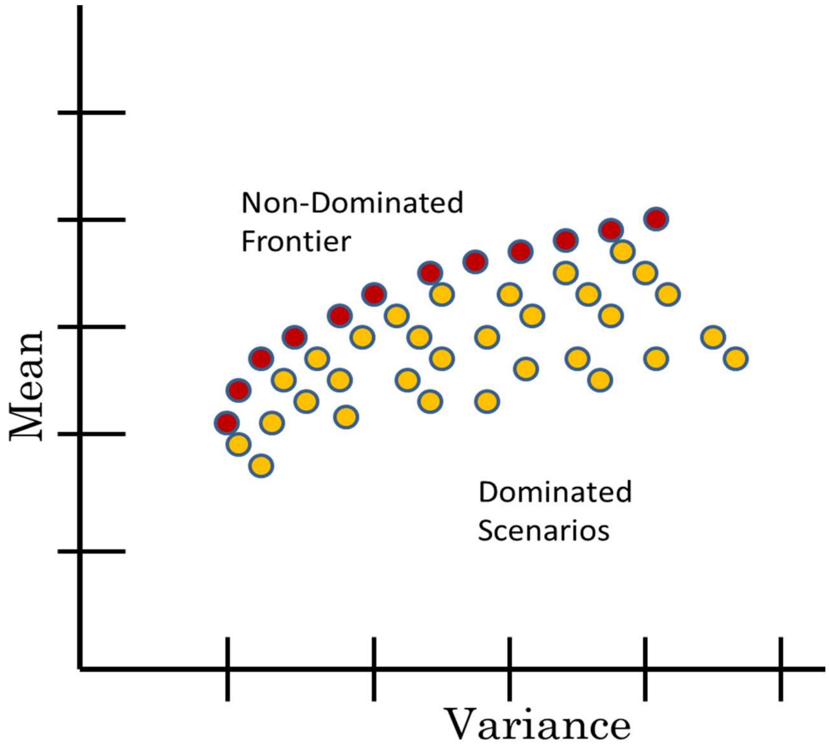

Figure 5.4 – Illustration of Mean-Variance comparison to find optimum in the non-dominated frontier

5.4.2 Value at Risk Measures

Measures of Risk, beyond expected value, are used to quantify the uncertainty associated with events that are relatively rare but still have significant consequences of producing high Risk. This is known as tail Risk and tail moment-based decision criteria because the low probabilities occur in the tail of the probability distribution (if known) or relative frequencies of a data set. The two most common variations of these tail measures include Value at Risk and Conditional Value at Risk. There are a number of variations of these Risk measures found in the literature, (see Anderson *et., al.,* 2014, Glasserman, *et. al.,* 2013, Krokhmala*, et. al*., 2011, and Sarykalin *et al.* 2008), and the two most common types, useful in the Risk-TOC application, are summarized next.

Value at Risk, $VaR_{\alpha}(X)$ is a lower frequency or percentile α of the random variable X. The definition of α varies in the literature and involves a specific probability frequency, and Confidence Interval $CI\ (\alpha)$ is defined here as frequency percentile, typically CI, as a probability frequency. The value of α of 5% is commonly chosen based on the standard significance bounds of CI when CI is *95%.* However, α may be chosen or optimized based on the specifics of the Risk, amount of information available, and the tail of the frequency distribution is known with confidence. A similar measure for α could include a basis as multiples of standard deviations (i.e., 2σ) based on sensitivity to resulting Risk and also subject to optimization if sufficient information is known about the uncertainties involved. The value of a may also be investigated to determine system sensitivity to outliers at values greater than three standard deviations as discussed by Walpole, *et. al.,* (2012) and Soe (2006).

One limitation of the *VaR* measure is that it does not reflect the Risk of scenario probabilities exceeding *VaR*. This property can be both good and bad, depending upon the Decision Makers' objectives. For example, assessing relative Risk or maximum Risk if the tails are sufficiently well defined. The indifference of *VaR* to extreme tails may be quite an undesirable property, allowing to take high unmanageable Risks.

Another measure of Risk is conditional Value-at-Risk *(CVaR).* Conditional Value-at-Risk *CVaRa(X)* equals the conditional expectation of *X* subject to the integration of *X(a)* ≥ *VaRa(X)* with frequency of *X* at *a, CVaR* accounts for losses exceeding *VaR*. In other words, Conditional Value at Risk *(CVaR)* is defined as the average value of the highest $1 - a$ proportion of the distribution of the sample set. As in *VaR*, the parameter a here is usually referred to as the confidence level or confidence interval.

Risk Management with *CVaR* functions can be done quite efficiently if the distribution tail information is known sufficiently. *CVaR* can be optimized, while *VaR* is relatively difficult to optimize, but is a consistent relative measure. *CVaR* provides an adequate picture of Risks reflected in extreme tails. This is a very important property if the extreme tail losses are correctly estimated. Conversely, *CVaR* may have a relatively poor performance compared with *VaR* if data or distribution tails are not modeled correctly.

According to Tian (2008):

" VaR is a tail Risk measurement which is widely applied in quantitative Risk management for many types of Risk. It is the "maximum" possible loss over a specified period at a given confidence level. However, VaR does not give any information about the severity of the loss by which it is exceeded. In contrast, another tail measure, CVaR, designates the magnitude of the tail "events" (Risk) by calculating the expected loss that exceeds the VaR. Moreover, compared with VaR, CVaR and expected shortfall are coherent measures which satisfy the properties of monotonicity, sub-additivity, homogeneity, and transitional invariance".

It is possible to calculate the Confidence Interval (*CI*) in the probabilistic range of uncertainty and determine if the results will produce higher values at Risk and a look at the best and worst-case scenario of Risk. With this information, the Decision Maker can then decide if the Value at Risk is too high and plan accordingly (i.e., avoid or mitigate with contingency).

5.4.3 Information Entropy and Risk

Although the use of Mean-Variance and Value at Risk measures are useful approaches in characterization of uncertainty and cost trade-offs for a limited number of example values, more systematic approaches generalized over a large number of Risk and TOC scenarios will be beneficial. The use of information entropy and cross-Entropy are proposed based on the formulations developed by research in the area of information theory as a Risk measure.

A brief overview of Entropy and information Entropy according to Ormos *et. al.,* (2014) includes,

"Entropy is a mathematically-defined quantity that is generally used for characterizing the probability of outcomes in a system that is undergoing a process. It was originally introduced in thermodynamics by Rudolf Clausius to measure the ratio of transferred heat through a reversible process in an isolated system. In statistical mechanics the interpretation of entropy is the measure of uncertainty about the system that remains after observing its macroscopic properties (pressure, temperature or volume). The application of entropy in this perspective was introduced by Ludwig Boltzmann. He defined the configuration entropy as the diversity of specific ways in which the components of the system may be arranged. He found a strong relationship between the thermodynamic and the statistical aspects of entropy: the formulae for thermodynamic entropy and configuration entropy only differ in the so-called Boltzmann constant. There is an important application of entropy in information theory as well, and this is often called Shannon entropy… The information entropy quantifies the expected value of the information in a stochastic process… The more unpredictable (uncertain) a message provided by the system process is, the greater the expected value of the information is contained in the message. Consequently, greater uncertainty in the messages of the system means higher entropy."

5.4.3.1 Information Entropy Formulations

According to Shannon (1948), Information Entropy (SIE) is defined as:

$$H(X) = -\sum_{i}^{n} p_{(i)}\, log_2 p_{(i)} \tag{29}$$

SIE will reach its maximum value of $H(X) = log_2\, n$ for the uniform distribution, while the minimum of 0 is attained for a distribution where one of the probabilities pi is 1 and the rest are 0. In other words, high (low) levels of Entropy are obtained for probability distributions with high (low) levels of uncertainty.

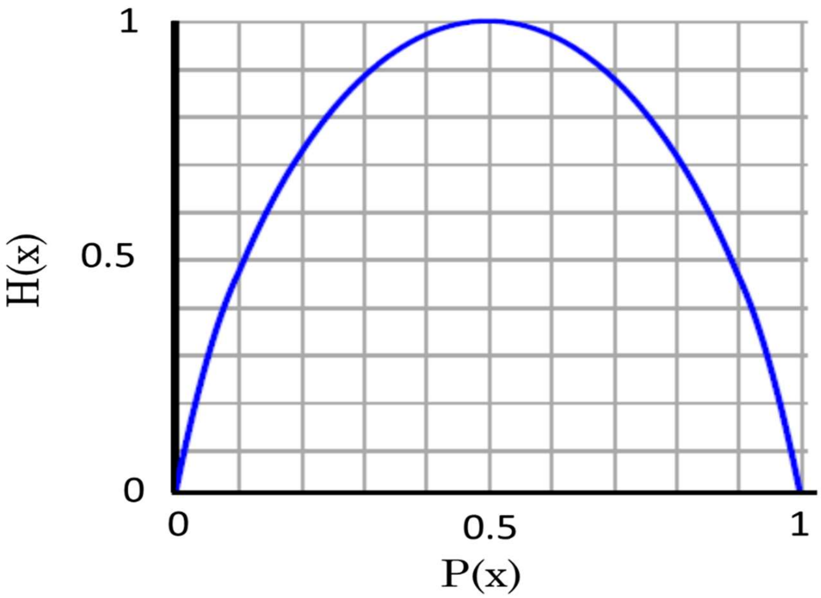

Figure 5.5 – Illustration of Information Entropy for a simple binary system

In Figure 5.5, information Entropy *H(X)* of a fair coin flip is shown versus *Pr (X= 1)*, where *X = 1* represents a result of heads measured in Shannons or bits. In this example, the information Entropy is at most 1 bit, and to communicate the outcome of a fair coin flip (2 possible values) will require an average of at most 1 bit.

Relative entropy, also known as the Kullback-Leibler (1951) divergence between two probability distributions on a random variable, is a measure of the distance between them. Formally, given two probabilities distributions p(x) and q(x) over a discrete random variable X, the relative entropy is defined as follows:

$$D(X)_N = \sum_{i}^{n} p_{(i)}(x)\, log_2 \frac{p_{(i)}(x)}{q_{(i)}(x)} \tag{30}$$

Joint entropy (Learned-Miller (2013), Cover *et. al.,* (1991), and Abbas (2006)) is the entropy of a joint probability distribution or a multi-valued random variable. If *P(E,C)* defines the joint probability distribution, then we write that their joint entropy is:

$$H(E,C) = -\sum_{e}^{E}\sum_{c}^{C} p_{(e,c)}\, log_2 p_{(e,c)} \tag{31}$$

Joint Entropy is essentially SIE in a computation over all possible pairs of the two random variables.

Joint information entropy is useful to infer uncertainty in the combinations of Risk-TOC uncertainties in each Risk scenario. This joint Entropy assumes the independence of variable arguments.

5.4.3.2 Information Entropy Risk Measures

Entropy can be proposed in the area of Risk management, as described in Bowden (2007), Pele (2017), and Traian (2017).

According to Bowden (2007),

"*Information Entropy [In Risk Analysis] is a more general measure of uncertainty than the mean-variance or distribution tail measures. [This is because] the entropy is related to higher-order moments of a distribution, unlike the variance or distribution tail measures, so it could be a better measure of uncertainty. Both measures of entropy and the variance reflect concentration but use different metrics; while the variance measures the concentration around the mean, the entropy measures the dispersion of the density irrespective of the location of the concentration. The entropy of a distribution function is strongly related to its tails and this feature is more important for distributions with heavy tails or with an infinite second-order moment [where] an estimator of variance is [not defined].*" [Additions by the author]

Information Entropy characterizes the uncertainty as a measure the dispersion of a random variable. In this particular case, it characterizes the uncertainty in structural failure probability. The main goal of this approach is to apply entropy as a Risk measure for Risk related uncertainty. In Risk Analysis, SIE reduction relates to uncertainty reduction in a similar manner as standard deviation reduction. SIE provides a measure for quantifying the reduction in uncertainty in;

- (Expected) Total information Entropy, and
- Conditional (Expected) information Entropy at Risk

As with *C(V@R)*, the conditional *E(V)* of SIE relates to the distribution above an exceedance value in the uncertainty in the distribution tail. SIE is not sensitive to the distribution definition. These definitions are analogous to the tail measures described previously with SIE being introduced to quantify the information gain or loss in the data.

Kullback-Leibler (1951) divergence type of relative entropy may be used in characterizing the difference in information entropy in Risk reduction alternatives.

Entropy is well suited to large complex systems analysis of Risk and TOC as the analysis progress toward automation of the calculations, and more Risk scenarios are considered along with the ranges of uncertainty. The *SIE* will likely become useful for aggregating the Risks from larger sets of variables with continuous distributions of uncertainties in multi-variable space. In this case, Joint Entropy will likely be useful in characterizing the uncertainty in a Risk scenario and relative differences.

5.4.4 Summary of Risk Measures

Estimating Risk scenarios and contingencies is another way to manage the range Risk exposure. The Risk and TOC estimates can be established using the baseline cost plus a contingency that achieves the desired level of total cost required to mitigate Risk exposure. In this manner, the Risk and TOC Analysis are not based upon overly conservatively deterministic cost estimates, and the Decision Maker is then aware of the quantified range of Risk exposure beyond *E(V)* and *E(U)*.

In understanding the range of Risk exposure, improving the quality information is always desirable. This includes improvements in the quality and quantity of the data upon which the Risk-TOC Scenario estimates are based. There is no guarantee that more data will reduce the probability of any event; however, if the data collection is structured in a way to provide information related to uncertainty reduction, it will be useful and quantifiable in *VoI* terms. The point being made is that for high Risk and uncertainty, the value of information gain is assessed based on the amount of uncertainty reduction even if it is a relative basis.

In summary, the various approaches to evaluating the range of Risk exposure include:

- Mean-Variance
  - Based on Portfolio Theory
  - Assumes Normal Distribution
  - No information about extremes/tails
- Value at Risk and Conditional Value at Risk
  - *VaR* based on exceedance of a discrete value of importance
  - Provides no information above the limit
  - *CVaR* based on a discrete range of values above a discrete value
  - Characterized the distribution tail is best if that information is available
- Information Entropy and Conditional Information Entropy
  - Expected Entropy is a characteristic a range of uncertainty in the total distribution
  - *CiEVaR* based on a discrete range of values above a discrete value
  - Not sensitive to distribution type
  - Best approach for characterizing extremes
  - Joint Entropy for multivariant distributions

Figure 5.6 shows the progression of $V@R_{\alpha}$ at frequency of α, $CV@R_{\alpha}$ with α as a lower integration bounds, and similar information Entropy based integration quantities.

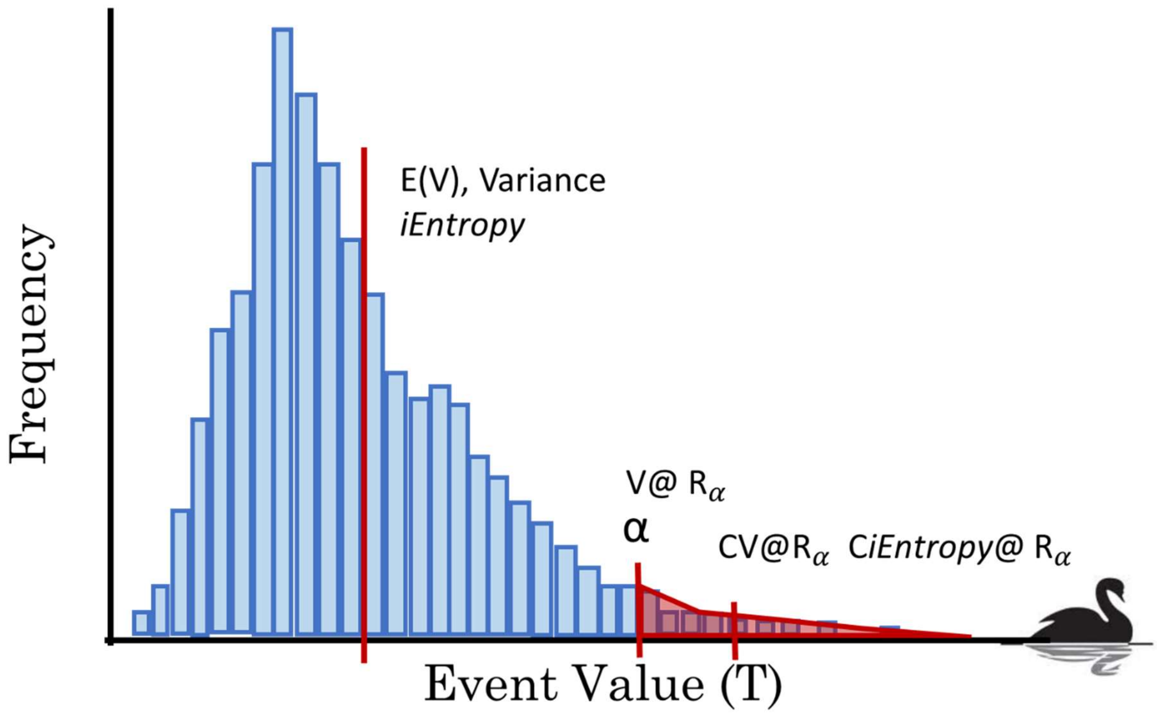

Figure 5.6 - Illustration of Risk Measures

Figure 5.6 shows the outer limits of these bounds and illustrates their relationship to the outlier, rare, and black swan type events. See Hajikazemi (2015) for more discussion on Black Swans.

As the number of scenarios, alternatives, and CoAs increase in complexity and uncertainties accumulate, information entropy theory becomes a more attractive approach for characterizing uncertainty and changes in uncertainty associated with Risk. The initial expected information entropy provides a reference for maximum ignorance in terms of Jaynes (1957) and Jeffery (1961). The SIE theory provides a means of characterizing the amount of "surprise" associated with uncertainty putting more emphasis on the tails of distributions and their associated relationship with extremes and outliers falling into the category of surprise.

One of the benefits of the *VaR* based methods is that the incomplete knowledge of distributions is very common, especially the information about the low probability of failure in the tail of the forecast probabilities. Rare events may occur only one or two times in a lifetime, leaving little room to learn from experience. However, in many cases, extreme events contribute to the Risks. The extreme events, no matter how rare, could have a profound impact on Risk beyond E(V) and E(U), resulting in complete surprise and vastly underprepared for the events that aren't really that rare. This dichotomy is also known as the "Flaw of Averages" (Savage 2012) discussed throughout this dissertation.

5.5 Uncertainty Propagation and Markov Processes

Understanding and quantifying uncertainty in stochastic terms is a process that also transitions through time. This propagation of uncertainty over time is a forecast that must be evaluated with objective approaches and understanding of the extent of uncertainty as it propagates over time. Ship structural reliability estimates are a means of propagating Risk and its uncertainties. A knowledge-based sensitivity analysis with likelihood estimates as ensembles is one approach to propagating the uncertainties via an ensemble of structural reliability estimates. The Markov process is also a useful approach in propagating Risk and uncertainty over time. Both ensemble averaging and Markov processes are discussed next as they will later be applied in the context of Risk Analysis.

5.5.1 Bayesian Model Averaging and Forecasting Uncertainty

Structural reliability estimates are used to forecast uncertainty and are also used for probabilistic based analysis. The full range of reliability forecasts, given various scenarios of input variables, provides an indication of the total uncertainty in the range of structural reliability forecasts and related parameters may be considered as equally weighted. Another approach is to weight each reliability forecast with a prior statistical weighting based on prior knowledge or as a sensitivity of prior information on the critical parameters as a function of a future time T. The weighting of forecast parameters is also known as Bayesian Model Averaging (BMA) and is used in both environmental and financial applications. See Lee *et. al.,* (2017), Sloughter *et. al.,* (2010), Kang *et. al.,* (2016), Wright (2003), Hamill (2010) and Shackelford (2017) for more in the various applications of BMA.

5.5.1.1 Bayesian Model Averaging

According to an Oracle White Paper (2006)

"The Bayesian [Model Averaging] approach combines the results of individual models. Each model is evaluated, and each model in turn tests a number of subsets of system and user-supplied causal factors (price is almost invariably a causal factor). All combinations of models and subsets of causal factors are assigned weights indicating their relevance. Every combination contributes to the final forecast according to its weighting. The reconciliation procedure ensures that the results meet the necessary constraint of the relationship.

The Bayesian [Model Averaging] technique uses a methodology that can be described by the following equation: "

$$F = w_1 f_1 + w_2 f_2 + w_n f_n \tag{32}$$

Where F is the final forecast where:

f_1 refers to the forecast using model ***1***

f_2 refers to the forecast using model ***2***

f_n refers to the forecast using model n, and w_i is a weight given to model i

and $\sum w_n = 1$

In a Bayesian setting, this becomes:

$$F(i,n) = \frac{p(f_{(i)}|w_{(i)}) \cdot p(f_{(i)})}{\sum_i^n p(f_{(i)}|w_{(i)}) \cdot p(f_{(i)})} \tag{33}$$

The value assigned for weight takes into account the residuals or the difference between the forecasted data in this example. When determining the weight value, the model accuracy is typically used as a weighting factor. This weighting factor may have Bayesian implications and the weighting approach used accordingly.

5.5.1.2 Forecasting Uncertainty

A practical approach for forecasting uncertainty is to use Bayesian Hyper Parameters (BHP) or Hyper-Priors with Latin-Hypercube sampling approach (see Modarres 2006, and Loucks *et. al.,* 2005). The proposed approach for forecasting uncertainties quantified in structural reliability consists of Bayesian estimates of expected weighted hyperparameters (BHPs) associated with the ensemble of reliability estimates. This type of forecasting is BMA with BHPs. In the context of Risk Analysis, the goal is to determine the Risk sensitivity and quantify its reduction according to the influence of changes in the BHPs and their reflection in the information gain and reduction of forecast uncertainty.

The proposed approach given the range of primary factors driving uncertainty is to make a prediction for a range of the parameters in combinations in a Latin-Hypercube sampling format and use weighted probabilities for each possible combination of outcomes in the Latin-Hypercube. This will in effect, provide a BHP based probability of failure at any specified time. The probabilities are updated either a-priori for what-if propositions about the evidence or as the time progresses with measured data. The prior probabilities are based on prior knowledge where available.

An important consideration in the development of the hyper-parameters is their statistical independence. The BHPs of environment, weld quality, and stress prediction are statistically independent parameters. This statistical independence is essential for statically sound uncertainty propagation and its quantification. However, if the hyper-parameters are in fact, correlated, this must be considered in their combination to retain the appropriate statistically base uncertainty propagation.

In forecasting structural reliability or probability of failure to be more specific, the primary forecast hyperparameters include operational wave environment the ship will operate in, the quality of the analytical prediction of loading, and the initial quality of welding at the time of construction. Initially (i.e., in design), none of these three major parameters are known with certainty; however, there may be relevant evidence from similar applications or other prior knowledge that may be useful to guide the uncertainty analysis, narrow the range of uncertainty in the forecast, or perhaps provide insights in "what-if" scenarios.

Wave Environment, Design wave environment is assumed to dominate the prediction so is weighted most highly at the beginning of the design life; however, may have some considerations for prior information if known. As time progresses, this information becomes clearer if measurements are made, and the weighted probability can be adjusted accordingly.

Construction and Weld Quality, is not known at the time of construction with any quantified certainty so that we may assume a wide range of possibilities. As time progresses, it becomes increasingly clear if the weld quality is an issue based on the number of cracks that may or may not have appeared early in the service life. This is somewhat correlated with stress application; however, they are considered qualitatively independent in applications where loading is near design values.

Stress Prediction, accuracy is reported to be in the 20% to 30% range (i.e., CoV) for most analytical hydrodynamic predictive techniques (see Stambaugh *et. al.,* 2014b, Colette 2018, and Hegeman *et. al.,* 2019). The knowledge regarding stress experienced by the ship is assumed to improve in the future as measured data, and that information is used for validation of load and stress predictions. Eventually, measured knowledge replaces predictions with measured data assumed here to be in the 5% to 10% CoV range near the EOSL.

Although the various parametric forecasts used in the BHP predictions represent likelihood estimates, the weighted probabilities are not specifically conditional probabilities framed in the published Bayes equation (see eq. 33 and Appendix B) and used in many examples as specific conditional probabilities, they do represent the prior knowledge used to update the parametric predictions so do follow the general intent of the Bayesian inference approach where we update our probabilistic forecast based on prior probabilities in a BMA approach.

In this application of BHPs, discrete probabilities represent the prior knowledge of weighted probabilities. Although it is possible to develop statistical distributions of the BHP prior probabilities, at this time there is insufficient information to do so; therefore, limited justification for doing so based on limited data in terms of bias, scatter, and lack of knowledge about the statistical distribution. However, the discrete probabilities represent real prior information to the extent that makes them useful in a forecast.

The BHPs may be chosen based on the knowledge of the Risk Analyst or Decision Makers. When prior knowledge is limited, the uniform distribution may be used in Bayesian (1763) perspective of uniform ignorance, maximum ignorance according to Jeffery (1957), or maximum information entropy as ascribed by Jaynes (1961).

In the Risk-TOC application, this forecast approach intends to illustrate the impact of hull structure monitoring approaches in reducing uncertainty in probability of failure forecasts and resulting reduction in Risk over a range of time intervals.

5.5.2 Markov Processes and Uncertainty Propagation

Continuing the discussion on systems reliability, serviceability, and progressive failures in Section 5.5, propagating structural reliability on a systems-level over time involves a Markov process.

According to Modarres (2006) and Ebeling (2010), a Markov process is a process that transitions from one state to another, and each state has the properties of independent probabilities. A Markov process is a sequence or chain of events if:

1) The outcome of each event is one of a set of discrete states,
2) The outcome of an event depends only on the present state, and not on any past states.

The probabilities from one state to another are called transition probabilities. The transition process can remain in the state it is in, and this occurs with an initial probability. Typically, an initial probability distribution specifies the starting state. Usually, this is done by specifying a particular state as the starting state. This process is typically defined as an initial state of probabilities and is multiplied by a transitional set of probabilities for each possibility in the transition state.

The Markov process is used in an example in Chapter 6.0 of this dissertation to determine the probability of crack growth over time given the ***ttc*** fatigue cracks shown in Figure 2.5 that are predicted to grow through a transition in crack length as described by Lassen *et. al.,* (2017), and the associated probability of detection. The final product is the time-based probability where the fatigue cracks will grow undetected and potentially grow large enough to result in a brittle fracture. Progressive failure and correlation of corrosion component failures may also be modeled as a Markovian process as described in general by Ayyub (2003) presenting an application in ship hull structural coating and corrosion. This transition process is also associated with correlated progressive failures as they combine to transform total system failure. Du *et. al.,* (2017) propose examples of alternative approaches for reliability of complex structures with multi-parameter correlations.

5.6 Proposed Risk-TOC Approach

The proposed Risk-TOC concept develops from the understanding that there is a trade-off between Risk and the cost to mitigate that Risk that influences SSLCM. Furthermore, the decision process in SSLCM is unique as compared to prior proposals based on financial and economic based decision processes. A new perspective is proposed here that relates specifically to SSLCM.

The Risk-TOC approach is an overarching and intended for the evaluation of Risk and TOC in a framework to facilitate the assessment of all alternatives on a comparable Risk-TOC basis and quantified decision process. The proposed Risk-TOC approach is a systematic method for evaluating all aspects of SSLCM depending on the information available to implement the approach.

5.6.1 Risk-TOC Considerations and Implications

Risk Analysis in SSLCM and related mitigations decisions involve trade-offs in Risk and TOC. All else being equal (i.e., actions and interventions) maintenance elements of TOC typically increases with service life just as does Risk when structural degradation progresses from the effects of fatigue and corrosion. The varying time effects on TOC include possible serviceability failure and related loss of availability when excessive maintenance is required. Often, interventions are required to reduce both Risk and TOC in SSLCM. The definition of TOC itself implies a total lifecycle perspective. The Risk-TOC approach proposal presented here is that SSLCM is managed over time; therefore, so are both Risk and TOC. This implies that Risk and TOC are evaluated at specific time intervals to evaluate different Risk and TOC mitigation strategies and Risk_T and TOC_T where T is a specific time in the SSLCM planning horizon.

Examples of key points in time T and related implications include:

1) Years where Risk mitigation by repairing failures exceed available maintenance budgets,
2) Years to major events such as EOSL,
3) 40 years with SLEP at 30 years or,
4) 30 years with new construction (instead of SLEP)

In these cases, both Risk_T and TOC_T will be very different at 40 years, given what happened at 30 years as a mitigation strategy. For example, if a ship is in service for 30 years and anew ship is built at 30 to replace it, Risk_T will go down if the right mitigation strategy is used (i.e., SFA). In this case, TOC_T will increase over the time period by the cost of the ship and related acquisition costs. However, if the ship's service life can be extended based on the improved design (with SFA) and quantified information to confirm this (HSM), the TOC will be reduced significantly, essentially prorating the extended life and the cost of a new ship saved. This analysis is then repeated for additional years to determine when TOC is projected to be at least equal to the costs incurred and saved by replacement or Risk has risen to unacceptable levels.

In principle, TOC is not limited to the costs associated with ship structure, but holistic total costs incurred by the owner over a period of time as described previously. This may include more than one ship's life or not. In practice, the TOC evaluations may be made as a net increase considering all the costs that change in a SSLCM setting.

5.6.2 Risk-TOC Trade-Space

The Risk-TOC approach is proposed in a fundamentally different way in the details of its execution than prior Cost-Benefit based approaches. Although there are similarities with Cost-Benefit analysis, the executable definitions for development and decisions are fundamentally different being related to Risk Analysis rather than the more common Decision Theory based approaches.

5.6.2.1 Prior Cost-Benefit Trade-Space Models

Cost-Benefit trade-space models have been proposed to highlight cost-effective options and decisions concerning Risk. In this context, Risk avoidance and related cost saving in management are counted as benefits. The following discussion presents the results of a brief literature review revealed prior examples of Cost-Benefit analysis proposed to compare Risk mitigation scenarios. They are presented here to highlight the underlying differences between the prior approaches and the Risk-TOC approach proposed in this dissertation.

According to Ayyub *et. al.*, (2000 & 2003), Cost-Benefit analysis is proposed for Risk management, where economic efficiency is used to determine the most effective means of expending resources. This process compares the costs and benefits to determine the optimal value. For example, the proposed cost of mitigation and cost of loss are balanced, and Risk equilibrium is found at their intersection is illustrated in Figure 5.7 This optimal value occurs when costs to control Risk are equal to the Risk cost due to the consequence (loss). In the Cost-Benefit trade-off illustration, proactive maintenance costs and cost of reactive repair are compared as dependent variables of a performance function. In this illustrative example, the more money that is spent on maintenance, the less money will be spent on repair costs. Although illustrative, the concept lacks clarity on the constituents of total costs (including serviceability failure) and a decision process in considering Risk mitigation alternatives.

This illustrated example works well for simple discrete component systems where parameters such as Mean Time Between Failure (MTBF) are well established for component failures. However, this simple approach is difficult to apply to more complex systems or comparisons of alternative Risk mitigation scenarios.

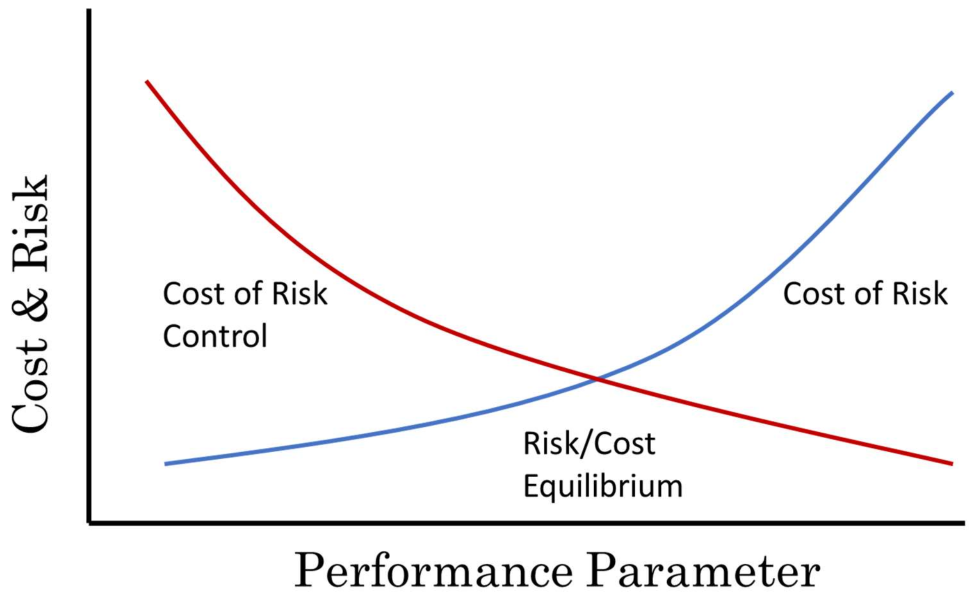

Figure 5.7 - Illustrative example of Cost-Benefit trade-space in Risk Analysis proposed by Ayyub (2000 and 2003)

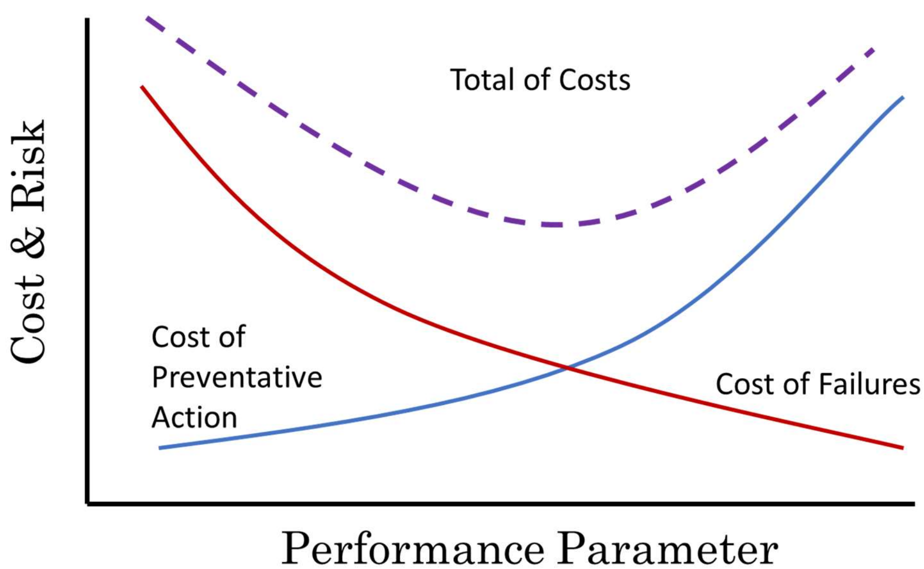

Figure 5.8 - Illustrative example of Cost-Benefit trade-space in Risk Analysis proposed by Modarres **(2006), Saydam (2013), Ebeling (2010) and similar in Hecht (2004), Straub *et. a*l (2005)**

Hecht *et. al.,* (2004) provides an illustrative example of Cost-Benefit analysis as in Figure 5.8, where the Total Ownership Costs are compared against a maintenance "effectiveness" parameter based on an undefined probability trade-space. The illustration and related discussion by Hecht *et. al.,* (2004) state the basic premise is Risk Analysis; however, they relate the Risk of failure to maintenance effectiveness, which is defined as a quantity between 0 and 1. Hecht and others do not include the probability or consequences of failure in specific terms. In this example, maintenance costs, inspection costs, and Risk of loss are all added together as Total Ownership Cost for a given Risk control scenario. In this example, a loss is the economic cost of repair and not system loss. The Risk of system loss is low due to the overly optimistic assumptions associated with Optimal Inspection approaches considered in the approach.

Straub *et. al.,* (2005) present a similar conceptual process to represent a Risk based optimal inspection where expected costs are traded against reliability with design, maintenance, and inspection as an opposing orthogonal axis. It is not clear, in the proposed concepts for trade-space, why design and inspection are not included in the expected total costs and total life cycle cost in overall systems approach to Risk assessment.

More recently, Spackova *et. al.,* (2015) defined a Cost-Benefit trade-space for flood control that does trade-off invested cost against Risk for control scenarios; however, the decision process is more specific to individual mitigation strategies and not overall system optimization. In this example, the benefits and decision processes are more in line with financial investment settings where Risk is loss of money, not assets, and people as consequences. The decision process is very different when there is more than money to be considered as Risk exposure.

In these illustrative examples, the total cost as the objective function is useful for illustrative purposes, as shown in Figures 5.7 and 5.8; however, in complex systems, the scenarios involve subsystem variables, and there are opportunities for optimization within each scenario. The Risk-TOC approach is suitable for sub-scenario optimization and a systematic comparison of alternative scenarios, as discussed next.

5.6.2.2 Proposed Risk-TOC Trade-Space Model

In the context of the Risk-TOC approach proposed for SSLCM, the terms Cost-Benefit do not reflect the quantities of the application being considered and are not explicitly applicable to SSLCM. In the works cited, the definitions of both cost and Risk are based on Decision Theory definitions of expected value and related expected utilities. The definitions of the Cost-Benefit analysis are carried over from financial and economic settings based on Decision Theory. In these settings, invested costs are compared to expected gain or loss of financial investment and a positive gain is a benefit, and negative benefit is a financial Risk. As noted previously in this dissertation, the Expected Value and related Decision Maker's preferences (and Expected Utilities) do not reflect the full extent of uncertainties and, therefore, Risks that might occur in the future.

According to Messac (2015),

"*one of the [defining] features of multi-objective optimization is that the solution to the problem is generally not unique as different trade-off levels may be desirable with each tradeoff yielding a different solution. A set of solutions called a Pareto Optimal Solutions form the complete solution set [of decision alternatives] of the optimized problem.*

If we define the trade space of each objective function or alternative independently, ignoring the other objective set, we will obtain the point that corresponds to the minimum of the objective being minimized. The minimum of each independent set points are called Pareto optimal solutions and non-dominated solutions. By definition, Pareto optimal solutions are those for which any improvement in one objective will result in a worsening of at least one other objective. That is a trade-off will take place. "

In developing the Risk-TOC trade-space, there are discrete scenarios for Risk mitigation strategies where sufficient data is known for each scenario at this time. In this case, the optimum is simply the scenario that provided the best trade-off between Risk and TOC as shown in the Risk-TOC plot examples (see Figure 5.9). Where numerous scenarios are to be evaluated in parametric terms and related insights, evaluating the optimum Risk mitigation strategy becomes more complex. In the more complex cases, multi-objective optimization and Pareto Frontier type optimization may be useful, especially in parametric sensitivity type analysis.

The proposal here is that each scenario has an underlying Pareto frontier based on local sensitivities within the scenario, as illustrated in Figure 5.9 In Risk-TOC, the scenarios form a Pareto Frontier on a scenario and overall systems level as illustrated in Figures 5.9 and 5.10

Risk Analysis calculations are used to develop the Risk-TOC trade-space. $E(TOC_a)$ (i.e., maintenance and inspection) as part of $E(TOC_a)_T$ and are compared to $E(Risk_a)_T$ (Loss) for various alternatives one may consider in SSLCM.

In the conceptual Risk Analysis trade-space shown in Figures 5.9 and 5.10, the illustrative Risk scenarios are points, leading to the observation that the full collection of possible scenarios would represent a non-dominated Pareto frontier (see Messac (2015) for general approaches). The Risk-TOC trade-space analysis provides a view of Risk and Cost consequences needed to compare and assess alternative Risk mitigation strategies required to facilitate decision making on the appropriate scenarios or CoAs.

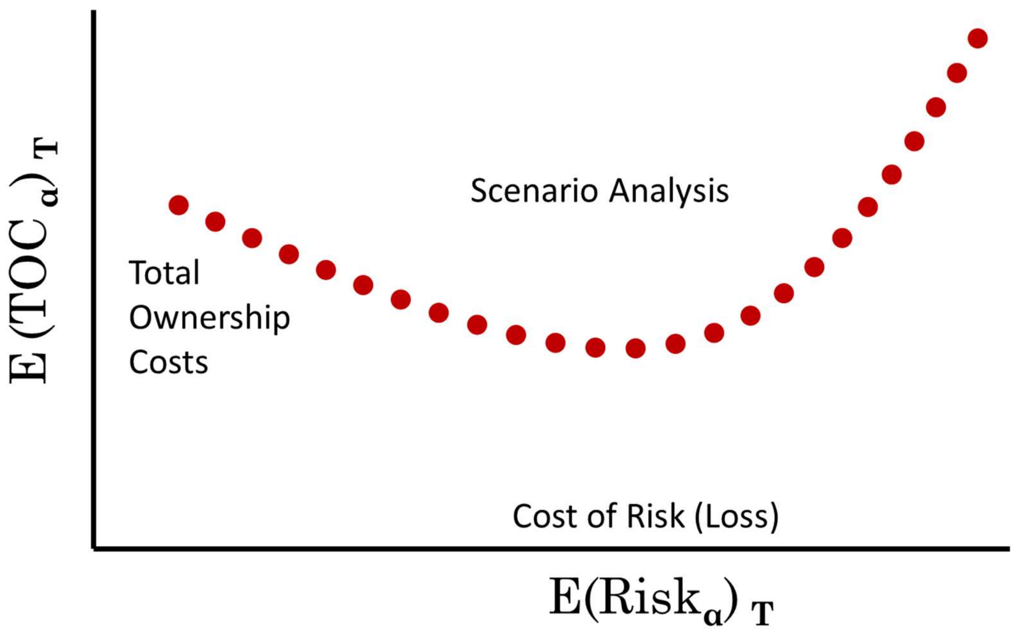

Figure 5.9 Illustration of the proposed Risk-TOC trade-space for subsystem scenario analysis

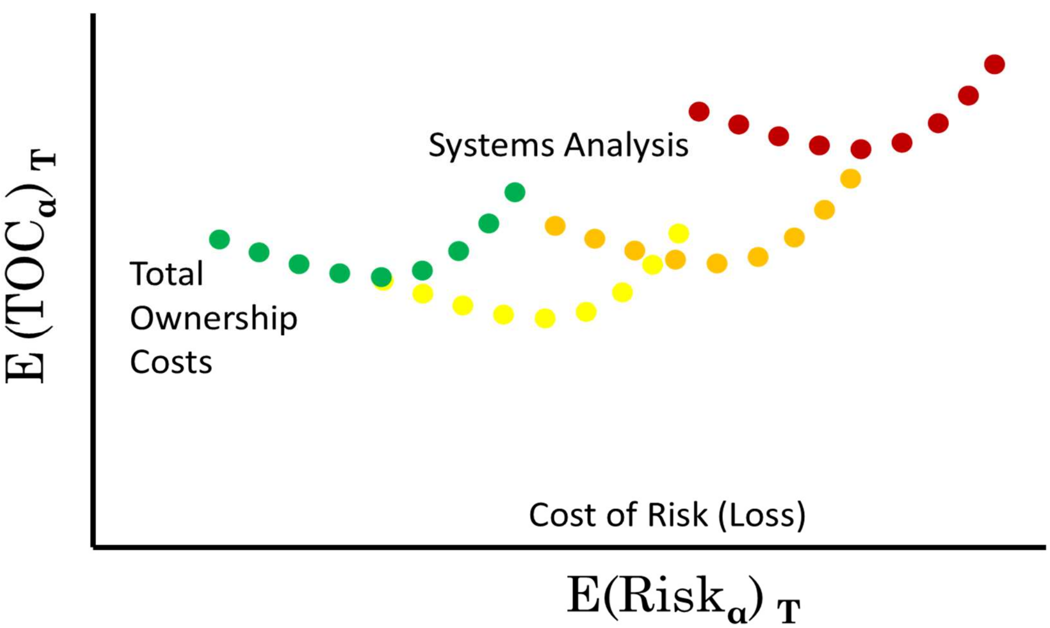

Figure 5.10 Illustration of the proposed Risk-TOC trade-space- systems Risk Analysis

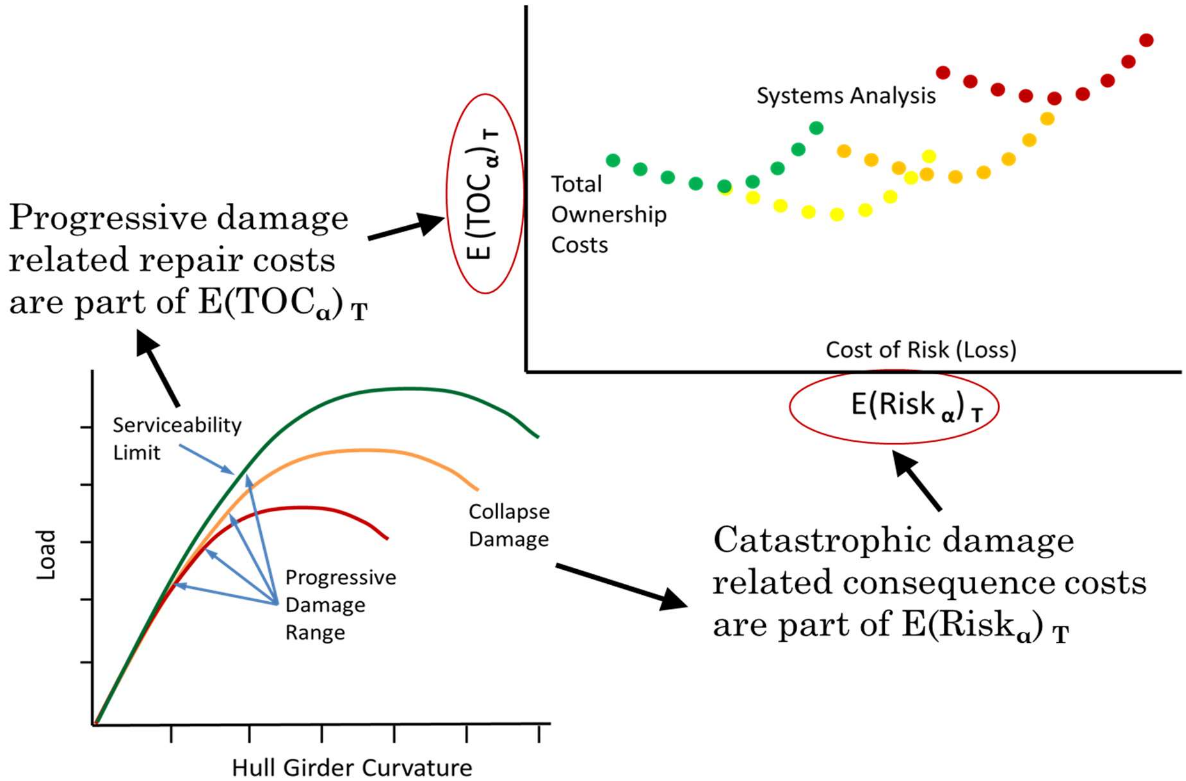

Figure 5.11 - Relationship of serviceability failure and ultimate failures as part of TOC and Risk respectively

Figure 5.11 shows the relationship of serviceability failure and ultimate failures as part of TOC and Risk respectively and the inclusion in the Risk-TOC trade-space. This is a proposed definition of how to quantify serviceability and ultimate failure in a Risk-based approach. Decision Theory based approaches typically include serviceability failures and their repair cost as consequences in Risk and do not consider the ultimate failure option because all serviceability failures are assumed to be found and repaired resulting in a low probability of system failure if considered at all.

There are cases where total system performance parameters are important in the overall total system life cycle. Total system performance includes mission effectiveness for military ships. Profit and freight rates are examples of performance objectives for commercial ships. These systems parameters are affected by an increase in weight of structure and implications on payload and cargo capacity or increase in fuel needed to maintain a design speed. The aspects of performance that are included in TOC proposed, including fuel consumption, so double counting should be avoided in the Risk-TOC analysis. By definition, the minimum weight objective must be met within the Risk-TOC minimum objectives to provide the best trade-off in system safety and cost-effectiveness while meeting performance objectives. More discussion on the aspects of performance objectives are discussed later in this dissertation in the examples in Chapter 6.0, Discussion in Chapter 7.0, and Recommendations in Chapter 9.0.

5.6.3 Risk-TOC Decision Measures

In SSLCM, Risks and costs are being trade-off instead of benefits and costs. This is a fundamental difference in definitions of the Risk-TOC approach as compared to Decision Theory based approaches. In contract to E(U) in Decision Theory, the Decision Makers should consider the less likely but higher consequence implications. This decision process should include an evaluation of the uncertainties in the specific Risk scenario or set of scenarios. In the decision process, Decision Makers should evaluate a number of options for quantifying probabilistic uncertainties of the system. Specifically, Decision Makers should consider Value at Risk ($V@R_{\alpha}$) and Conditional Value at Risk ($CV@R_{\alpha}$) or similar information Entropy measures.

Anderson *et. al.,* (2014) assessed Risk in terms of maximum expected values such as $V@R_{\alpha}$ and $CV@R_{\alpha}$.

Where:

> α is a prescribed limit, typically confidence interval (CI) of the data or distribution if known.
>
> $CVaR_{\alpha}$ = average value of the highest $1\text{-}\alpha$ proportion of the distribution.

As $\alpha \Rightarrow 1$, the $CVaR_{\alpha}$ approaches minimax criteria, *MnMx*. In applications where the exact distribution is not known, the α values are estimated by simulation. With conditional constraints, the $CVaR_{\alpha}$ may be written as *MnCnMx*, according to Anderson *et. al.,* (2014).

In statistical analysis, a 90% to 95% range of *CI* is used to differentiate between extreme event probabilities and more common expected event probabilities. The Decision Makers may also conduct a sensitivity analysis on this value to determine its impact on outcomes of the Risk calculation and $E(VaR_{\alpha})$. Ultimately in the Risk Analysis context, α values are chosen to align with the Decision Maker's Risk preferences and consequences at Risk (i.e. loss of ship and life).

In the Risk-TOC decision trade-space, Decision Makers are interested in evaluating the efficacy of mitigation strategies. Each mitigation scenario and milestone decision involve trade-offs and forms the Pareto optimal sets in this Risk-TOC trade-space. Examples of these Risk mitigation approaches appear in Chapter 6 of this dissertation.

Ultimately, the evaluation criteria are used by the Decision Makers to select scenarios that minimize the maximum Risk exposure. This is also known as the MiniMax criteria (see Anderson *et. al.,* 2014 and Savage 1970).

According to Savage (1970)

"the minimax rule recommends the choice of such an act that the greatest loss that can possibly accrue to it shall be as small as possible. A [possible outcome] satisfying the recommendations of the minimax rule will be called a minimax act, and the greatest loss that can accrue to a minimax act will be called the minimax value of the [objectivistic] decision problem. It may well happen that [a solution] contains more than one act that is minimax for the problem, in which case, the minimax rule recommends, not a particular act, but only that the choice be narrowed to a set of minimax acts."

The MiniMax decision utility provides a perspective for the Risk cost-benefit analysis where the least cost, least Risk options available to Decision Maker following the minimax utility approach.

In the Risk-TOC approach, an optimal decision (arguably preference) may be defined as the least TOC at least Risk minimizing both expected $Risk_\alpha$ and expected TOC_α. Similar in concept to Savage's minimax criteria, this is stated as:

$$Min(E(Risk_\alpha)_T, E(TOC_\alpha)_T) \tag{34}$$

These concepts may be used in quantifying the outcomes and optimums for decisions in more complex problems. These and other decision criteria are worthy of further investigation as the scenario number and complexity in Risk scenarios increases.

In summary, SSLCM requires key decisions related to:

- TOC and related costs of $E(TOC_\alpha)_T$
- Availability & Economic Failure (from repairs of progressive serviceability failures)
- Remaining Useful Service Life, End of Service Life. High value at Risk
- Loss of Asset (Availability and EOSL)

Currently, these decisions are made with limited, narrowly focused quantitative approaches, empirically-based evidence, and subjective information. This provides the motivation for a more quantitative approach for making decisions when stochastic processes are involved, and imperfect models are used.

5.6.4 Risk Based Value of Information

Decision Theory defines *VoI* in terms of change in Expected Value or Expected Utility from discrete probabilities (i.e., Decision Trees), are not complete indicators of Risk or value of information, because they do not reflect the range of Risk and uncertainty typically modeled using probability distributions as discussed previously. That is:

$$VoI \text{ in Decision Theory} \Rightarrow \text{Difference in } E(V) \text{ or } E(U) \tag{35}$$

Figure 5.12, developed from Pozzi *et. al.,* (2011) and Hubbard (2014), illustrates the relationship between the value of information derived from uncertainty analysis and information gain as continuous functions. While illustrative in concept, the details of the scenario analysis of alternatives and Pareto Frontier analysis proposed herein and illustrated in Figure 5.10, the *VoI* in Risk Analysis is redefined in Risk and TOC terms.

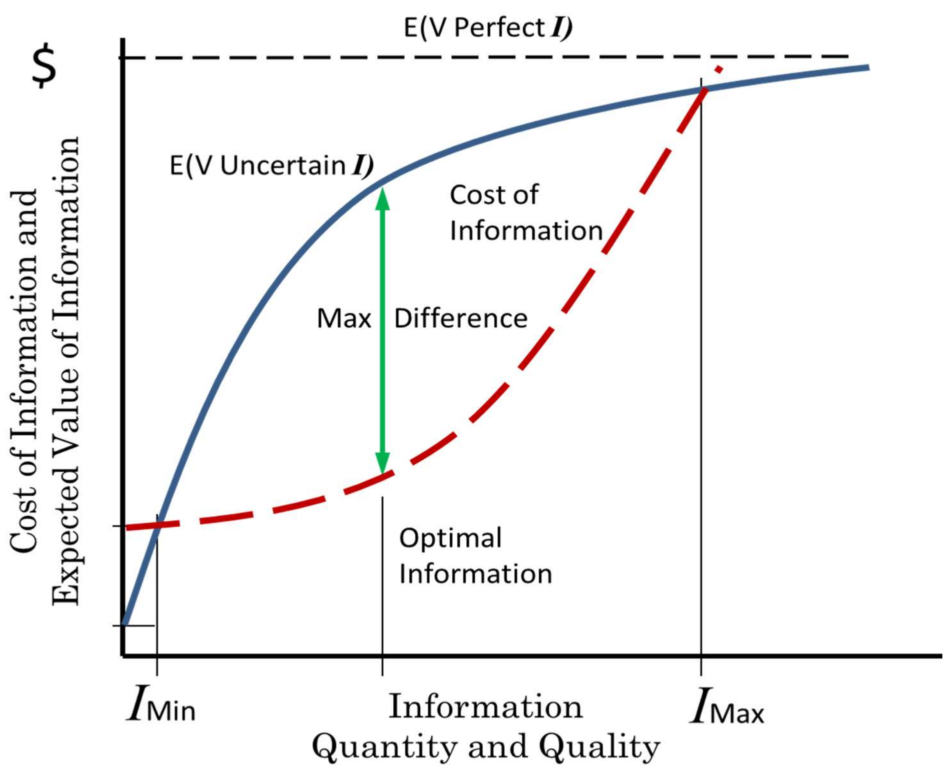

Figure 5.12 – Illustration of value of information defined as a continuous function and one scenario being evaluated (Pozzi *et. al.,* 2011 and Hubbard 2014)

Hubbard (2014) summarizes the *VoI* in Risk Analysis as:

"Understanding how to measure uncertainty is key to measuring Risk. Understanding Risk in a quantitative sense is key to understanding how to compute the value of information. Understanding the value of information tells us what to measure and about how much effort we should put into measuring it. Putting all of this data in context of quantifying uncertainty reduction is central to understanding what measurement is all about."

"All measurements that have decision-value must reduce the uncertainty of some quantity that affects some decision with economic consequences. The bigger the EOSL, the higher the value of a measurement. The difference between the EOSL before a measurement (perhaps based only on initial calibrated estimates) and the EOSL after a measurement is called the "Expected Value of Information (EVI). In other words, the value of information is equal to the value of Risk reduction."

In contract to Decision Theory (discussed previously), the Risk Analysis based definitions of, *VoI* are related to reduction in costs and uncertainty quantified in the following terms:

$$VoI_{RT}= (S_1(E(Risk_\alpha)_T)@(E(TOC_\alpha)_T)) - (S_2(E(Risk_\alpha)_T)@(E(TOC_\alpha)_T)) \quad (36)$$

Where *VoI* in Risk-TOC analysis is the difference in Value at Risk, Conditional Value at Risk, or Shannon Information Entropy for Scenarios 1 and 2.

The proposed decision criterion is reasonable in concept and subject to further development and evaluations by researchers interested in pursuing this topic. Risk Analysis based decision process definitions assume a particular preference of a Decision Maker (i.e., minimax-and related optimization approaches) is left to others to investigate.

5.7 Prognostic Hull Structure Monitoring

The uncertainty (and Risk) reduction is achieved by obtaining information either in knowledge/model (epistemic) or statistical uncertainty reduction by additional data collection (aleatory uncertainty reduction). One approach for reducing both epistemic and aleatory uncertainty is by Hull Structure Monitoring (HSM).

The following Sections present a contrasting comparison with the more commonly proposed Structural Health Monitoring (SHM) approach, Prognostic Hull Structural Monitoring (PHSM), its *VoI*, and related uncertainty reduction for Risk Analysis in general and SSLCM in specific.

5.7.1 SHM vs Prognostic HSM

The monitoring industries definition of Structural Health Monitoring (SHM) is based on a condition-based monitoring and maintenance approach in that structural system degradation is detected prior to system failure for reactive maintenance planning see Pegoretti (2018), Lynch, *et. al.,* (2016), Richards, *et. al.*, (2013) and Roach, (2016). The SHM approach is based on assumptions that the component structural failure will manifest itself in the system response, typically a change in dynamic global vibration characteristics, as the structural failure progresses slowly over time and also has a significant (but safe) detectable influence on the structural response. This is typically applied to redundant or fail-safe structures where system degradation can be repaired prior to system catastrophic failure.

The hypothesis of detecting damage by identifying a change in system response was tested for ships pre and post damage experienced on a US Coast Guard Cutter and reported by Hageman *et. al.,* (2018). The hull girder's first mode of vibration was measured with strain gauges as part of an ongoing hull structural validation effort summarized by Stambaugh *et. al.,* (2014b) and (2019). Their conclusion based on the measurements was the signal noise was higher than any measurable response pre and post significant hull damage. The problematic noise wasn't related to instrumentation; rather, it was produced by environmental and operational variables including ship speed, heading, wave conditions, and water depth. All of these factors change the hydrodynamic added mass and damping and also introduce variability in measurements. Interactions of these variables produce more than strain signal measurement noise. Given this current limitation of not being able to detect the ship hull structure damage until it has become significantly weakened, it is not recommended that such a reactive approach be used for ship structures at this time.

An alternate prognostic approach is proposed for hull structural monitoring where the hull response (strains) are used to infer future damage (i.e., cumulative fatigue or corrosion), budget consumption, and extreme load measurement for proactive maintenance planning. The prognostic approach is intended to reduce uncertainties in the analysis by updating the design profile as BHPs in a BMA approach based on measurements. The resulting forecasted damage reliability and probability of failure are updated as described in Chapter 2.0 and applications on Chapter 6.0 of this dissertation.

5.7.2 Prognostic HSM in Maintenance Planning

Prognostic HSM maintenance planning is a proactive approach where measurements are made to forecast damage, (i.e., in fatigue and corrosion) and plan repairs in a scheduled drydocking availability. This is a less expensive proposition in comparison to the reactive maintenance associated with finding fatigue crack (typically because they leak water in or fuel out) after they occur or excessive corrosion damage. In the worst case of reactive maintenance, the location and severity of damage may require an emergency drydocking, which is significantly more costly than maintenance in a previously scheduled drydocking availability. In proactive maintenance, the regularly scheduled drydocking availability could be part of a mid-life availability or life extension modifications, both of which are more cost-effective if executed proactively. Although SHM is intended to be a proactive planning approach, it is, in reality, a reactive approach to damage detection in the structural applicatoin. Figure 5.13 shows a comparison of activities between proactive and reactive maintenance.

In Figure 5.13, PHSM actions include collecting data, analyzing the data, and forecasting damage, Risk and further proactive actions required to mitigate the Risk. This is in contrast to alternative reactive approaches that collect date to infer damage that has already begun to occur or at least symptoms of the damage. This is accomplished by detecting changes in response, assuming they are detectable at a level where Risk is still acceptably low. It is possible to evaluate both prognostic and reactive approaches within the Risk-TOC trade-space.

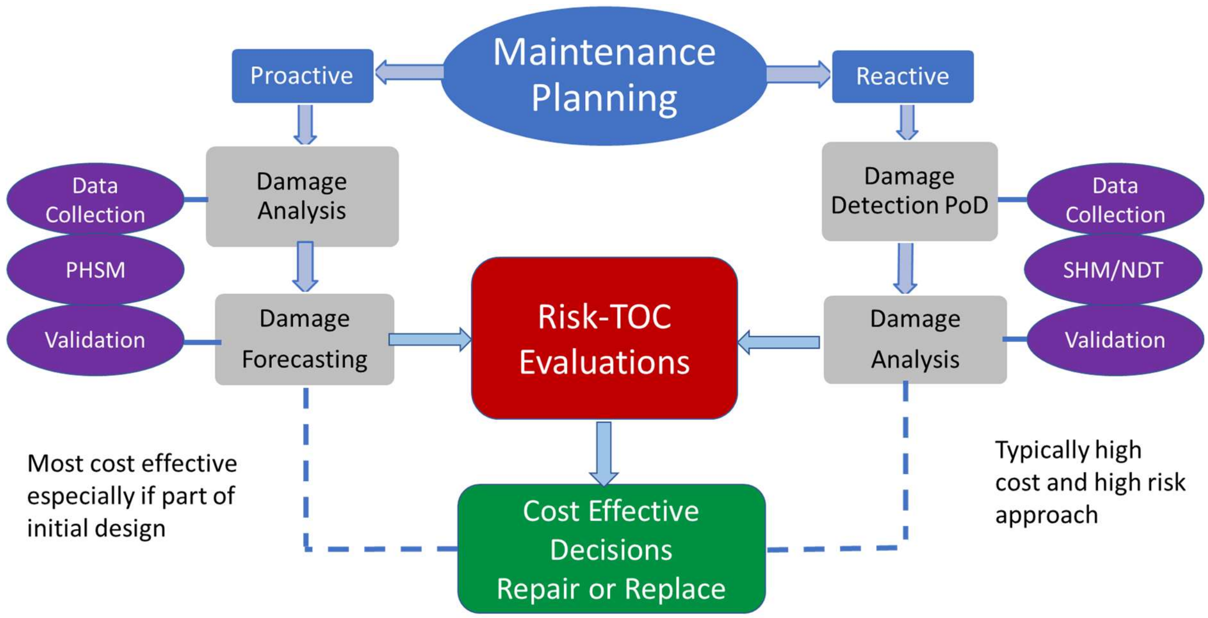

Figure 5.13 - Comparison of reactive and proactive monitoring and maintenance approaches

5.7.3 Prognostic HSM in Uncertainty and Risk Reduction

In the ship structural fatigue analysis process described in Chapter 2.0 of this dissertation, aleatory (random process) and epistemic (model and unknowns) uncertainties are included where data and models are used, and complete knowledge is lacking on the effects of the uncertainties associated with the total process. In the stochastically based design approaches for determining loading history, the ship's predicted operational profile and wave statistics are processed through specialized analysis programs to determine lifetime histograms of hull sectional forces such as vertical bending moments and resulting strain and stress histories known as Spectral Fatigue Analysis (SFA).

For the random processes involved with ship structural loading, ship structural designers use the SFA process and generally consider each 30-minute time frame as independent and statistically stationary. In operating 140 days per year at sea, that equates to over 6000 independent stationary conditions per year. In SFA predictions, the independent speeds, headings, seaways, load conditions are grouped into over 2000 stationary groups for annual and 30-year life estimates of the loading spectrum. The number of variable conditions with random (aleatory and epistemic) uncertainties provides intuitive motivation for measuring

HSM and uncertainty reduction. The initial assumptions the aleatory uncertainties are all based on prior experience, introducing prior information in a Bayesian context to be updated by measurements. The uncertainties and updating process is discussed in more detail in later Chapters of this dissertation.

The conventional approach to HSM includes measurements by strain gauges attached to the hull structure. Recent PHSM on ships presented by Stambaugh *et. al.,* (2014b, 2019) also highlights the benefits of collecting wave data, adding to the value of knowledge and information.

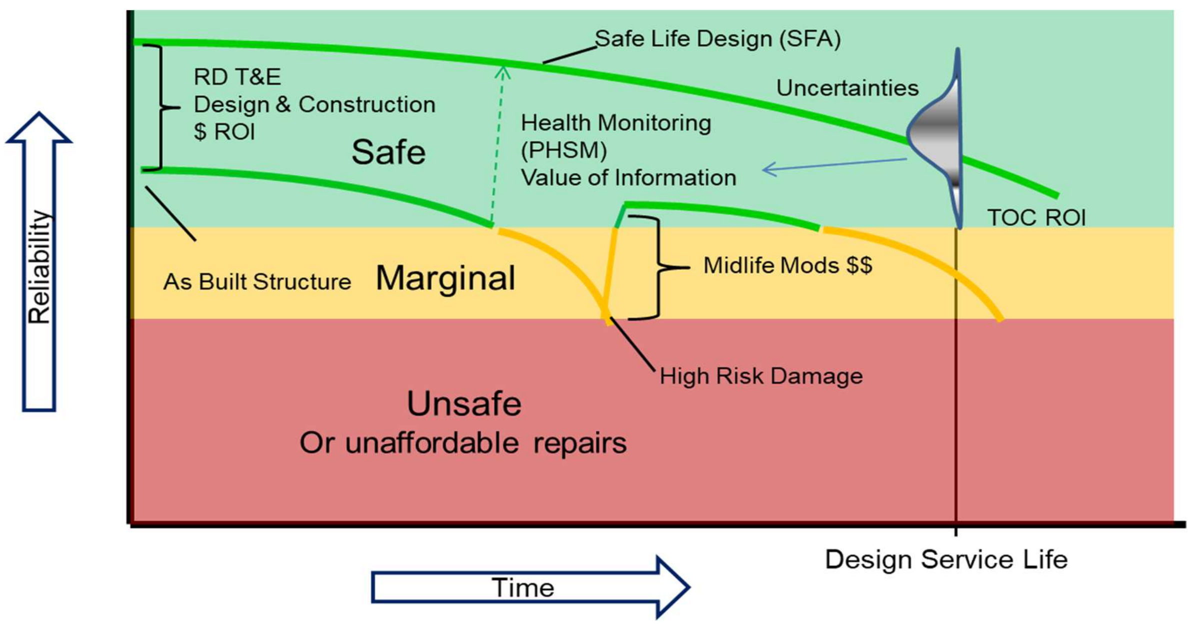

Figure 5.14 - Illustration of structural reliability degradation and decision related to uncertainty reduction

The first principals-based design approaches (primarily in SFA and DLA) provide a single estimate of maximum expected load or fatigue life without regard to the underlying uncertainties and initial assumptions. Structural Reliability Analysis (SRA) offers additional steps in considering how the uncertainties manifest in failures on a systems-level, as described in Chapter 2.0 of this dissertation. A further refinement to this uncertainty forecasting is to consider how these forecasts will change given differences in the initial assumptions, such as significant wave heights encountered, operational profile, days at sea per year, accuracy of analysis tools, and actual quality of construction. Considering a range of uncertainties would provide a range of forecasts if the initial assumptions were weighted according to our state of prior experience, knowledge, and assumptions on the uncertainties involved if there is little or no prior knowledge. This weighted sensitivity forecast is a BMA approach with BHPs as priors in forecasting structural reliability as discussed in Chapters 4.0 and 6.0 of this dissertation. Illustratively, the reliability forecasts and uncertainty resemble a distribution shown at the end of the upper design reliability curve shown in Figure 5.14. Essentially, there will be many forecasts based on an assumed likelihood of each forecast. The next step in this Bayesian thought process is to estimate how the prior weighted BHP probabilities will be updated as time progresses, and information is gained. For example, if hull structure strains and wave heights encountered are measured, the wave heights provide a significant amount of information for updating the accuracy of the analysis tools and for making forecasts. This information gain reduces uncertainties and improves the basis for further forecasts. This process can be updated over time to predict information gain and uncertainty reductions, making it possible to estimate the *RoI*, *VoI*, and what the Decision Makers might be willing to pay for the information if uncertainty is reduced by the measurement process(es). The Risk-TOC trade-space is well suited to make these inferences on *RoI* and *VoI* of monitoring approaches. Further demonstration of this process is presented in Chapter 6.0 of this dissertation.

5.8 Risk-TOC Process Description

With the definitions of Uncertainty and Risk presented (and referring back to Figure 5.14 for decisions in SSLCM), we are now equipped to answer the following questions required to formulate the likely Risks facing the Risk Analysts (RAs) and Decision Makers (DMs).

Fundamental Concepts Framing the Risk Definition include:

1) RAs and DMs have identified a potential or probability for an adverse condition or hazard and cost associated with the hazard. (no hazard or no cost = no Risk)
2) RAs and DMs need to decide whether to mitigate, avoid, or transfer a potentially adverse condition (in this case, structural performance issue).
3) Different versions of the problem include either:
    a. There is some uncertainty, but conditions are ambiguous, or RAs and DMs are uncertain about the probabilities of the conditions.
    b. Adverse consequences occur with probability P, but RAs and DMs are unsure about the value of P.
4) RAs and DMs have some information, but it does not determine the state of nature completely (aleatory), or there is some uncertainty in the application of a prior model of the (epistemic) uncertainty.
5) The assessment of the hazard or its cost has an impact on avoiding or mitigating adverse consequences.
    a. What proactive mitigations are most cost-effective?
    b. What steps can be taken to mitigate the hazard, and at what costs?
    c. What are the costs and consequences of not taking mitigative or avoidance actions?
6) Regarding information about the hazard and its mitigation.
    a. What is the best decision we can make, given the information RAs and DMs have?
    b. How much would more information be worth to reduce the uncertainty

c. Should the DMs expend the time and resources to get that information before choosing to avoid, mitigate, or transfer the hazard or consequences?

The Risk Analysis and Risk Management process relationships proposed to address these questions and implications are illustrated in the flowchart in Figure 5.15

Figure 5.15 shows the Risk-TOC process with monitoring and feedback. This process includes an evaluation of multiple Course of Actions (CoAs) that are considered by those performing the Risk Analysis and making decisions. The following list summarizes the steps in the Risk-TOC process applicable to SSLCM. Implicit in these CoAs is considerations for Risk mitigation, including its reduction, transfer, sharing, contingencies, and acceptance and the need to obtain additional information that is cost-effective in reducing Risk.

One of the unique features of the Risk-TOC process illustration is the flow of information, which is the fundamental ingredient to uncertainty and Risk reduction.

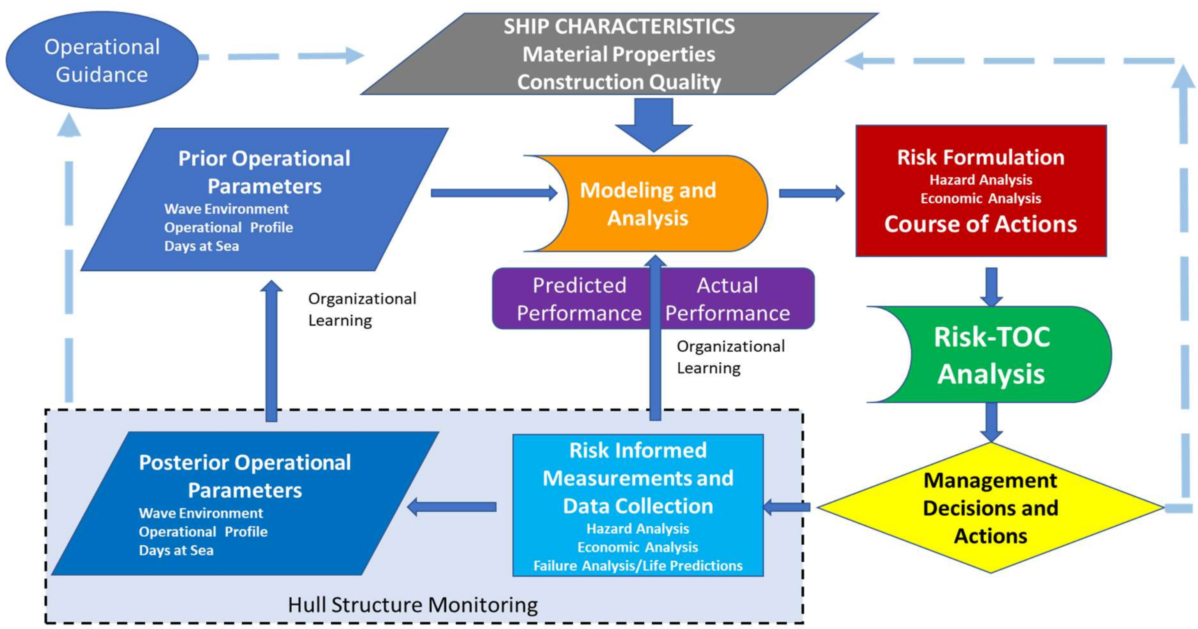

Figure 5.15 - Risk-TOC process with monitoring and information feedback

Risk-TOC Approach for Ship Structure Life Cycle Management Includes:

- Identify serviceability and catastrophic failure modes
- Determine the components failures using reliability analysis (eqs. 7, 8) and expected number (or probability) of system failures as the product of probabilities of failure (*Pf)* and the number of components in correlated groups of components. (eqs. 9, 10)
- Quantify uncertainties and *Pf* associated with failure modes on component and system levels including (but not limited to) fatigue and brittle fracture (*PfBF*) and corrosion and buckling induced progressive failure that have potential to result in ultimate limit state failure of the hull girder
- Identify and quantify consequences *($C)* of failure modes and associated costs in both *LCC* and *$C* associated with ultimate limit state failure
- Quantify Expected $Risk_{Loss}$ = *(Pf)*($C)* of the system (eqs. 20, 21)
- Evaluate Risk measures including conditional $E(Risk_a)$ (Sec 5.6.3) and Shannon Information Entropy (SIE) (eqs. 29)
- Determine Expected *TOC* and conditional *TOC* $(E(TOC_a))$ including costs to reduce or mitigate Risk including cost of serviceability failures (eq. 22)
- Identify alternatives (scenarios and *CoAs*) for Risk reduction and mitigation including prognostic HSM and associated risk reduction by Bayesian Model Averaging (eq. 33) or equivalent uncertainty forecasting and add associated costs to *TOC*
- Determine *NPV* for $E(TOC_a)$ if NPV is important to the application (eq. 26)
- Compare $E(Risk_a)$ and $E(TOC_a)$ scenarios in the *Risk-TOC* space
- Establish Risk tolerance and TOC constraints and compare to non-dominated Risk reduction and mitigation scenarios
- Identify non-dominated alternatives and $Min(E(Risk_a),E(TOC_a))$ (eq. 34)
- Determine *RoI* in Risk mitigative actions both short-term and long-term (eq. 28)
- Communicate Risk, uncertainties, and consequences to Decision Makers
- Make short-term decisions to reduce and mitigate Risk
- Determine *VoI* and system *RoI* for future Risk reduction actions (eq. 35 for *VoI*)
- Make long-term decisions and investments required to manage Risk-TOC
- Take long-term actions including prognostic HSM to reduce uncertainties and Risk
- Repeat process of updating (and reducing) both aleatory and epistemic uncertainties where beneficial according to Risk-TOC.

6.0 RISK-TOC VERIFICATION

Verification of the Risk-TOC approach is conducted by using the data and experience from the decision processes involved with an SSLCM example presented by Stambaugh *et. al.*, (2014b) and (2019) for a US Coast Guard Cutter. The examples are representative of SSLCM process decisions and are used to validate the fundamental approaches to Risk Management proposed and presented in this dissertation. Each example presented builds on the fundamentals of uncertainty quantification, propagation, and reduction described previously. The proposed Risk-TOC approach is demonstrated in assessing Risk reduction alternatives leading to *VoI* and *RoI* type analyses showing the benefits of Risk reduction alternatives.

The following case studies include examples of the Risk-TOC approach verification and include cases involving fracture, corrosion, and hull structure monitoring. Collectively, the examples demonstrate the application of systems failure mode analysis, cost-benefit analysis, and Bayesian Model Averaging in forecasting the structural degradation due to fatigue loading. The SN+FM Total Life approach described in Appendix B is also demonstrated within the fracture failure example. Evaluation of Risk and TOC for various PHSM approaches is also demonstrated. The HSM example is included to show the *VoI* and *RoI* estimates in the context of SSLCM.

6.1 Risk – TOC and Ship Structure Life Cycle Management Decisions

In efforts to manage the uncertainties in the fatigue analysis process, structural reliability approaches have been proposed for ship structure applications Ayyub *et. al*., (2014). Figure 6.1 presents a simplified illustration of degrading reliability in ship structure. The curves shown in Figure 6.1 represent trends in structural reliability defined as one minus the probability of failure (*1-Pf*). This example illustrates conceptual relationships and fundamental considerations of Risk Management derived from examples presented by Hess (2015), Frangopol (2004), and extended to illustrate the cost and safety implications in the life cycle decision process. In these illustrative curves, structural reliability is decreasing with time due to degradations in strength from causes such as fatigue and corrosion. The degradations transitions through acceptable (green) marginal (amber) and unacceptable (red) reliability (set arbitrarily for illustrative purposes). Relating to the reliability illustration in Figure 6.1 from Stambaugh *et. al.,* (2019), key events and decisions influencing structural reliability include:

1) The lowest curve represents the present practice of designing ship structure to prescriptive rules based on experience in empirically derived algorithms.

2) Early decision point to increase strength prior to predicted or observed progressive failures (generally fatigue cracking).

3) Decision point on End of Service Life (EOSL) or high-cost Service Life Extension Program (SLEP). High repair cost in Emergency Drydocking (EDD) as needed or early EOSL without adequate time to plan for replacement. EOSL (typically an economic decision) with adequate plans in place for timely replacement.

4) Repaired strength not equal to original (repair weld quality) based on the original design approach.

5) Low-cost increase in strength in design and construction points 1 tom5.

6) Remaining Useful Life (RUL) decisions supported by Hull Structure Monitoring (HSM) to reduce uncertainty in the EOSL decision.

While simplified for illustrative purposes, these decision points are realistic and involve management of uncertainties and Risk in the life cycle management of the structural system at very high costs (on the order of millions of $US dollars for major ship asset classes). The concepts of structural degradation and degrading structural reliability seem intuitively similar, and they are, dealing with the end results, is less intuitively obvious to the Decision Makers.

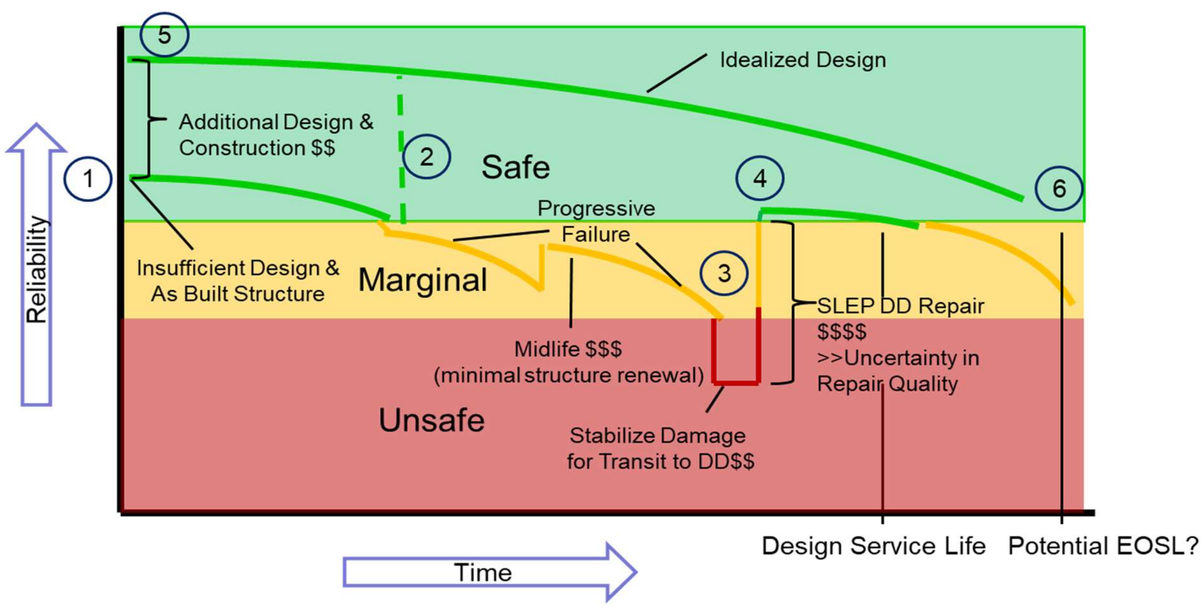

Figure 6.1 - Illustration of major decisions in life cycle management of ship structure.

In the context of structural reliability, the amount of desirable or undesirable reliability is assessed using a reliability index. In structural reliability analysis applications in the civil industry and others, the desirable reliability is defined by a reliability index, β, discussed by Melchers (1999), Ayyub *et. al.,* (2014), and Frangopol (2004). Here, β is related to the probability of failure as follows:

$$\beta = \Phi^{-1}(P_f) \tag{37}$$

The shortcoming of the β index is that the full implications of system Risk (Pf *and* $\$C$) are not explicit, only relative to the prior user's judgment as being acceptable or not. The lack of explicit context of the structural reliability index β is a limiting constraint of the process. Minimal work has been conducted to benchmark β with regards to ship structures applications, let alone reliability-based applications in specific. Furthermore, applications of β are most often limited to Optimal Inspection of individual structural components and extensions to systems analysis has not been made for more complex systems such as ship structures. The Risk-TOC framework presented here is a step in the direction of that calibration.

A Risk-based framework for the life-cycle management of ship structural systems is presented by Stambaugh *et. al.,* (2014a) and Stambaugh *et. al.,* (2017) builds on the structural reliability approaches developed by Ayyub *et. al.,* (2014) and prior efforts by Hess *et. al.,* (2002a, 2002b) and Hess (2003). That is, the probability of failure is used to characterize Risk for decision making vs β indexing based decisions. The Risks (in terms of costs and safety) associated with decisions in ship structural life-cycle management may be quantified as a function of uncertainty and costs for discrete, time intervals, as proposed by Stambaugh *et. al.,* (2014a). This approach may be used to evaluate the decision alternatives in fundamental Risk terms founded in definitions that are more commonly used for Risk communication to those who will be making decisions on large capital-intensive projects. Further work in the application of the systems approach to structural reliability and work on quantifying uncertainty in the fatigue design process and application of hull structural monitoring to help reduce the uncertainty in the life cycle decision process is ongoing in the Valid Joint Industry Project (JIP) (see Stambaugh *et. al.,* 2014b, 2019, Drummen *et. al.,* 2014,2019, and Hageman *et. al.,* 2014, 2019).

6.2 Risk -TOC Estimates

Risk and TOC estimates are presented in this Section as examples to illustrate the Risk-TOC approach. Others interested in using this approach are encouraged to use their own estimates for further investigations and applications of this approach.

6.2.1 Risk Estimate

In current SFA approaches, fatigue failure is defined on a component detail level as a through-thickness crack as observed from component welded structural details. As a practical matter, these cracks often leak as they extend beyond this through-thickness definition and are detected. However, stable fatigue crack growth progresses relatively quickly. The following examples provides insights into the critical nature associated with large cracks and the potential consequences of rapidly growing fractures.

As presented previously, $Risk_{Loss} = Pf{*}C_{Failure}$, estimates for these quantities are provided in the following Sections along with and uncertainty reduction in the *Pf* calculation and the impact on uncertainty reduction of Risk as a result.

6.2.1.1 Probability of Failure Estimate

The examples that follow provide estimates of the probability of failure for loss of the ship due to fatigue, fracture, and corrosion. Estimates are also provided for implications of Risk mitigation options and related decisions for SSLCM, including Risk Mitigations, Remaining Useful Life (RUL), Service Life Extension Program (SLEP), End of Service Life (EOSL), or new construction, etc.

6.2.1.2 Loss Consequences Estimate

The consequences used in the Risk calculation are described in Chapter 5.0 of this dissertation. To summarize, the consequences of ship loss include loss or major repair of the structure if feasible, loss of life of the crew, salvage costs, environmental impacts, political implications (that impact finances), and loss of ship availability for significant periods of time.

The loss of crew members is one of the more difficult losses to frame in financial or economic terms. However, actuaries do provide insights into this critical loss as Value of Statistical Life (VSL) and provide estimated from $12M to $15M. In ship applications, the costs of crew replacement are also a consideration with VSL costs on the range of $20M/crew member.

Because of the nature of a catastrophic event, the entire crew may be lost in one event, a Risk-averse Decision Maker (conservative engineers and naval architects (including the author) may put a higher premium on such loss and political implications. Mission or service loss (Ao) is also very high, depending on the ship type. The estimated value of Ao shown in Table 6.1 results from societal benefits of annual costs benefits in the missions performed by US Coast Guard cutters. Table 6.1 provides an example calculation of a possible range of consequences depending on the Decision Makers' Risk aversion.

Table 6.1 – Consequence of failure estimates

Range of Consequence Loss Estimate ($M)						
	0 Crew	2 Crew	120 Crew	120 Crew	120 Crew	120 Crew
			x1	x10	x100	x1000
Ship Repair/Replace	50	250	1100	1100	1100	1100
Crew	0	240	2400	24000	240000	2400000
Salvage	0	0	1000	1000	1000	1000
Environment	50	100	1000	1000	1000	1000
Political	50	240	2400	24000	240000	2400000
Mission Loss	2000	2000	4000	4000	12000	160000
Total Loss	2,150	2,830	11,900	55,100	495,100	4,963,100

In the following Risk examples, a willingness to pay value is assigned to the consequences. In this case, the owner is willing to invest $15M to mitigate a *Pf* of 10e-6, and the resulting value at Risk is $1.5T($US) per ship. This value represents a consequence adverse value/view of consequences, which falls in the high end of potential consequences of the loss of both ship and crew due to the potentially catastrophic nature of fracture in ship structure. Stochastic models for Risk aversion and avoidance can be developed by Decision Makers in the context of the modes of failure being considered and decisions (i.e., max regret between Risk and TOC as described later in this dissertation discussion) made accordingly. Making the consequence decisions in the Risk Analysis is a more informed approach for making decisions rather than assigning generic Risk utilities.

6.2.2 TOC Estimate

A TOC estimate is provided here to use in subsequent Risk-TOC examples. The TOC estimate, in this case, is simplistic but representative in magnitude, for example purposes. This example includes an estimate for added fuel costs for weight additions that might result from the application of SFA and the implications on operational costs expenditures and the overall TOC. In this example, the added fuel costs are negligible additions to operational costs. Estimates are provided for the increase in costs (i.e., investments) for including SFA in a design. Full implementation of the Risk-TOC process would consider uncertainties in this estimate, which will be left to those with more knowledge of those uncertainties.

Table 6.2 provides an estimate of TOC with and without SFA. In the TOC without SFA, the estimated cost of a new ship is included as if there were a decision that repair costs will exceed available budgets and financial losses are excessive, and a new ship is needed, in this case, the “Do-Nothing” approach includes a zero Remaining Useful Life (RUL) decision has been made.

Table 6.2 – Example Total Ownership Cost estimates used in Risk Analysis

	Operations costs			**Wo/SFA**		**W/SFA**	
				$M		$M	
	Fuel	8$M/yr for 30 yr					
	Fuel Add	240	0.50%	0		1.2	
	Unplanned Maintenance						
	Crack Repair			2		0.25	
	EDD(2)			4		1	
	Availability Loss						
	0.548	$M/day	100	54.8		0.27	
	Total Added O&E			60.8	$M	2.7	$M
	TOC Calculation			**Wo/SFA**		**W/SFA**	
				$M		$M	
	R&D			2		3	
	Acquisition			650		655	
	Operations Cost			2470		2412	
	Midlife			20		15	
	SLEP			0		20	
	New Ship @ 30 Years			750		0	
	Disposal			20		0	
	TOC 30 years			**3912**	$M	**3105**	$M

6.3 Risk -TOC Evaluation of Serviceability and Ultimate Failure

The following example provides insights into the benefits of Risk-TOC analysis for serviceability and ultimate failures in ship structure.

To follow the example follows the reliability analysis shown in Figures 2.4 and 2.5, assumptions on a few basic probabilities and costs include:

- 65% of the cracks will be found and repaired dockside, 33% will be found and repaired in dry dock (DD), and 2% will require an emergency dry docking (EDD) because they leak or otherwise affect operational availability.
- Repair costs are $5K dockside, $10K in planned DD and $500K in EDD
- The ships in this example have expected levels of availability (Ao), and there are costs associated with maintaining the required levels of availability. For the cost of reduced of ship availability for service, a willingness to pay basis equal to the value of the ship is prorated by dividing by the number of days in its expected service life

and apply that to the number of days in drydock, minimum of five days for this example.

Downtime for dockside repairs extended dry-docking (if that is when damage is discovered), and EDDs all have a significant impact on mission availability and Operation and Maintenance costs. Time out of service can be related to the cost of the availability of the asset. For example, a ship valued at $500M and a 30-year target service life results in approximately $50K/day loss if the ship is not able to operate. This cost is incurred in addition to repair costs. Additional costs and associated consequences occur if other assets are not able to fill the Ao gap. Other economic and societal costs may be impacted as well if the ship is not able to fulfill its intended function.

The results in Table 6.3 show a combination of the probability of an Emergency Dry Docking (EDD) and loss of availability for a single ship and twelve ships. In this example, the potential costs incurred between 15 and 20 years becomes prohibitive. In many cases in the commercial shipping industry, the ships are often sold if this amount of fatigue damage is occurring with associated cost and perceived Risk implications, especially if they have provided the owners with a sufficient return on investment. While illustrative, the example clearly shows the EDD costs dominate the overall impact of the LCC if they are required. In Naval ships, Total Ownership Cost (TOC) impacts are much more severe, along with loss of asset availability.

To continue this Risk Analysis example, we will assume that:

- 1% of the cracks will grow to 250mm undetected (i.e., either don't leak or are not in a location to leak)
- The probability of a severe brittle fracture for a 250mm crack is 10e-4 according to Sumpter *et. al.,* (2004)
- The owner is willing to invest $15M to mitigate a *Pf* of 10e-6, and the value at Risk is $1.5T per Cutter (in Table 6.3) as a Risk-averse attitude given the potential consequences of failure.

The results presented in Table 6.4 show the combination of Value at Risk for the probability of severe consequences of brittle fracture and are significant. Few shipowners are willing to self- insure the costs at Risk. This example is illustrative and considers the total Risk from loss of life, and the government-owned asset based on a willingness to pay basis, both are difficult to assign a cost value to and are truly priceless to many Decision Makers as discussed in Section 6.2.1.2.

Table 6.3 – Example Fatigue Failure Risk Analysis

	Years of Service Life					
	5	**10**	**15**	**20**	**25**	**30**
Cracks per Cutter	0.2	7	12	34	81	137
# EDD Repair per Cutter	0.007	0.4	0.6	1.7	4.1	6.9
$ LCC per Cutter	$ 2,744	$ 144,550	$ 247,800	$ 702,100	$ 1,672,650	$ 2,829,050
$Ao per Cutter	$ 10,102	$ 480,392	$ 823,529	$ 2,333,333	$ 5,558,824	$ 9,401,961
$(LCC+Ao)*12 Cutters	**$ 102,768**	**$ 4,999,537**	**$ 8,570,635**	**$ 24,283,467**	**$ 57,851,788**	**$ 97,848,086**
Pcrit 250mm	0.002	0.07	0.12	0.34	0.81	1.37
PfBF	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
$C Loss per Cutter	$ 1,500,000,000,000	$ 1,500,000,000,000	$ 1,500,000,000,000	$ 1,500,000,000,000	$ 1,500,000,000,000	$ 1,500,000,000,000
$@Risk per Cutter	$ 300,000	$ 10,500,000	$ 18,000,000	$ 51,000,000	$ 121,500,000	$ 205,500,000
$@Risk per Cutter*12	**$ 3,600,000**	**$ 126,000,000**	**$ 216,000,000**	**$ 612,000,000**	**$ 1,458,000,000**	**$ 2,466,000,000**

Table 6.4 – Risk of brittle fracture and cost mitigations

	PfBF		$Consequences (Total Loss)	$@Risk	$Mitigation (SFA)	*RoI*
	E(*Pf*BF)	250mm Crack				
No SFA	.000001	.0001	$1.5T	$205M	$2M	~100:1

This example provides valuable insights into the decision process that is often made based on intuitive experiences and perceived Risks. Although the Expected Value *E(V)* is low, there is a significant amount at Risk with a probability of failure by Brittle Fracture (*PfBF*) of 10e-4 for a 250mm fatigue crack. Naval ship operators understand the Risk associated with a major fracture event resulting from fatigue failures in qualitative terms. This fracture example provides quantified justification for mitigating actions such as SFA in the design of the ship structure and hull structure monitoring through service life. Operator guidance should be considered as a Risk-mitigating action depending on the mission or service requirements. Sumpter *et. al.,* (2004) examined the *PfBF* for commercial ships. This following example examines *PfBF* in a Naval ship in more detail.

6.4 Risk-TOC Analysis of Fracture in Ship Structure

Chapter 2.0, Figure 2.5, shows an example where the number of fatigue failures are predicted over the 40-year service life. This is based on a definition of failure of developing a through-thickness crack and Risk associated with this type of failure.

Given the number of fatigue cracks expected to grow to through-thickness cracks shown in Figure 2.5, the questions framing the hazard definition include, how fast will these cracks grow, how many will not be detected and of that subset, what is the probability of brittle or unstable fast fracture? The following Sections provide exploratory work addressing these questions to highlight the hazard posed by fast fracture in quantitative terms. This work is exploratory in nature and should be subject to further investigations needed to quantify the hazards and Risks.

6.4.1 Sub-critical Fatigue Crack Growth Rate

The following example of a fatigue crack growth calculation is presented next to illustrate the impacts of initial flaw size further discussed in the SN+FM Total Life approach presented in Appendix C and the impact of crack growth rates and implications of not finding the cracks by Optimal Inspection as discussed in the formulation of the SSLCM problem.

A crack grown estimate was made using the Linear Elastic Fracture Mechanics (LEFM) approach and the following assumptions and parameters:

- LEFM with C = 4.9e-12, m = 3.1 mean values from DNV (1984)
  - $da/dN = C\,\Delta\,K_i^m$
- Elliptical flaw in plain plate with:
  - $K_i = 1.12\sigma\sqrt{(\pi a/Q)}$
- *Where:*
  - σ = Stress range with a transverse butt weld notch factor is applied from Stambaugh *et. al*., (1994)
  - $Q = 1+1.464(a/c)^{1.65}$
  - $a/c = 2/2.5$ *and* $L=2C$

In this example, annual wave height probabilities are from, Stambaugh *et. al*., (2014b and 2019). Loading predictions are from Sikora *et. al.,* (1983). The stress range for a 30 year lifetime applied as annual loading and length updated in 30 increments. The resulting crack length sensitivity for 0.001mm-1mm initial flaw sizes is shown in Figure 6.2

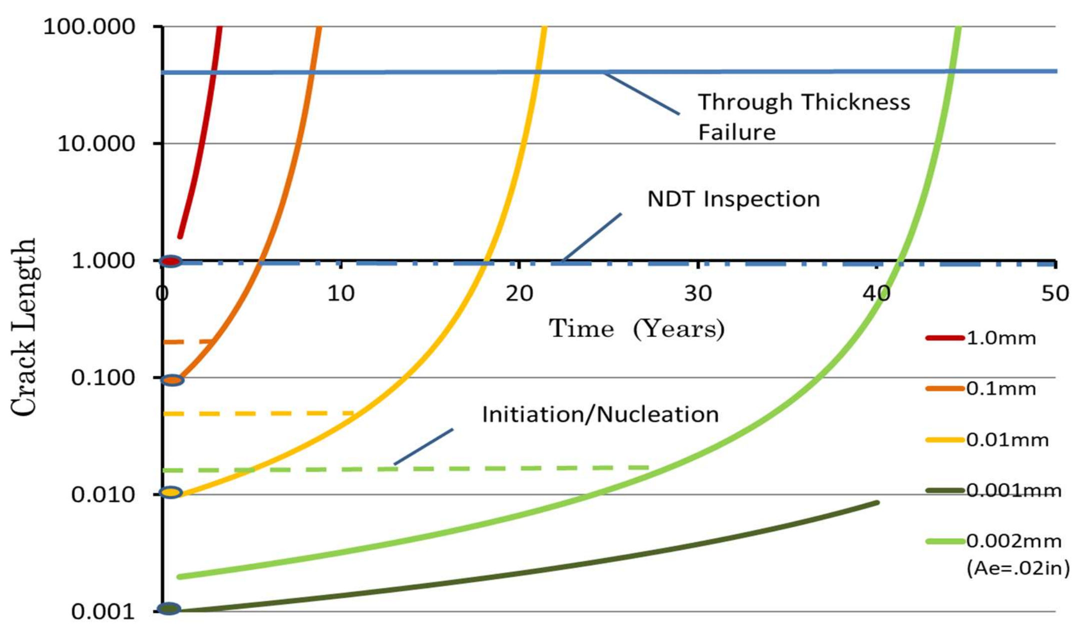

Figure 6.2 – Fatigue crack growth rate sensitivity to initial flaw size

The results of the crack growth prediction are shown in Figure 6.2. An effective initial flaw size of .002mm was back-calculated from S-N curve data for a transverse butt weld and a damage ratio of one, then forward calculated using Fracture Mechanics using the load history estimated for the ship in increments of one year. Initial flaw sizes of 1.0mm, 0.1mm, 0.01mm, and 0.001mm are shown for comparison to the initial effective flaw size of 0.002mm. The length required to produce a through-thickness crack (assuming a 2.5:1 aspect ratio) is shown along with the current acceptance criteria for weld flaws in new construction. The dashed lines in Figure 6.2 represent the effects of time for cracks to initiate as discussed further in Appendix C. Two important observations are apparent from this information.

1) Cracks grow very rapidly after they reach through-thickness and into the 100mm length in less than a year or two, leaving little time for detection before they could reach a critical size.

2) The flaw size inspection acceptance criteria used in construction are very high relative to the initial flaw size. The *PoD* (typically 90% for a 1mm flaw) is relatively high, increasing the probability of their existence given the potential number of them in ship structure. The impact of this crack length is considered in the following example.

6.4.2 Markov Chain and Probability of Detection

The fatigue crack growth rate calculations and rates shown in Figure 6.5 show fatigue cracks grow rapidly within a year and could grow 100mm well within a five-year time-frame. The answer to the probability of fracture question involves estimating how fast these cracks will grow in a five-year time interval, what is the probability they will not be found (*1-PoD*), and what is the probability of fracture if they grow undetected?

The rate of fatigue crack growth and transition in probabilities associated with crack length states implies a Markov process model and probability chain. The transition probability is related to *PoD* and *1-PoD* to calculate the time-varying number of fatigue cracks not detected and reaching each length increment. This can also be performed using fracture mechanics calculations to determine growth rate from initiation; however, the current estimates of fatigue crack growth rates are used to provide a conservative estimate of the number of cracks reaching each incremental length (100mm) in a five year time period given the estimated crack growth rate.

To determine the probability of detecting a crack growing over time, a Markov process approach discussed in Chapter 5 was used to estimate the probability of a crack progressing through ranges of five year periods along with the probability of detection Bayesian prior conditional probabilities.

In the Markov process model, the crack grows through the plate as a random walk phenomenon which respects the mean value and scatter (statistical uncertainty) in time to reach chosen crack depths that are designated damage states. The time statistics to arrive at the various damage states were derived from the fracture mechanics calculations shown in Figure 6.2. The initial state is the through-thickness crack and number of cracks shown in Figure 6.2. The probability the crack will be in each state (five-year period) is assigned as one (certainty) for this example based on inspection of the mean crack growth rates shown in Figure 6.2. As a practical matter, the time spent in each time interval is random based on the actual loading encountered and is not known apriori. Knowledge of the encountered loading is required to fully assess the time spent in each time interval. If this knowledge is obtained through measurements, the need and timing of focused inspections can be determined and proactive maintenance planned.

The probability of non-detection values (*1-PoD*) values calculated from the *PoD* values shown in Figure 6.2. The results of the probability of nondetection are shown in Table 6.6 along with associated high probabilities of cracks growing to 250mm in length because they are difficult to detect visually. NDT inspection to find fatigue cracks in thousands of details is not cost-effective due to the kilometers of welding and thousands of welded structural details in ships. The results of these calculations indicate that *PoD* statistical data is needed to fully characterize the Risks associated with finding cracks as they grow in ship structure, especially the ships that were not designed with SFA.

Table 6.5 – Probability of cracks growing and not detected

Crack Length	Years	5	10	15	20	25	30	40
TTC	Nttc/Pttc	0.2	7	12	34	81	138	183
	PnDetect		0.35	0.35	0.35	0.35	0.35	0.35
	PnRepair		0.05	0.05	0.05	0.05	0.05	0.05
150mm	N150/P150		0.07	2	4	12	30	51
	PnDetect			0.13	0.13	0.13	0.13	0.13
	PnRepair			0.05	0.05	0.05	0.05	0.05
250mm	N250/P250			0.01	0.34	1	2	4
	PnDetect				0.06	0.06	0.06	0.06
	PnRepair				0.05	0.05	0.05	0.05
350mm	N350/P350				0.001	0.021	0.036	0.106
	PnDetect					0.02	0.02	0.02
	PnRepair					0.05	0.05	0.05
450mm	N450/P450					0.00001	0.00045	0.00076

Nttc/Pttc = Number of through thickness cracks or Probability of through thickness cracks
PnDetect = Probability of non-Detection (=1-Probability of Detection)
PnRepair = Probability that a crack will not be properly repaired and initiate a new crack
N150/P150 = Number of 150mm cracks or Probability of a 150mm crack

The full Risk assessment, including the randomness in load, strength, and the probability of detection, is lacking, often leading to inappropriate approaches for mitigation, including Optimal Inspection based approaches.

6.4.3 Probability of Fracture Example

Given the relatively high probabilities and numbers of fatigue cracks for the example described above, what is the probability they will be large enough to cause an unstable fracture, and at what loading conditions? We will now look at the probability of failure associated with the growth of these relatively long fatigue cracks.

According to Sumpter *et. al.,* (2004), fracture mechanics based material toughness provides an index of the severity of loading at a crack tip. The commonly used fracture mechanics parameter is the elastic stress intensity factor.

Critical values of K refer to the condition when a crack extends in a rapid (unstable) manner are given as:

$$KIc = Sc\sqrt{\pi ac} \tag{38}$$

$$Sc = \frac{KIc}{\sqrt{\pi a\boldsymbol{c}}} \tag{39}$$

Here,

$S_{\boldsymbol{c}}$ is the nominal applied stress at crack instability,

and $\boldsymbol{ac}$ is the crack length at instability for a through-thickness crack.

KI_c is the critical stress intensity and related to fracture toughness depending on the material, temperature, strain rate, environment, and thickness. Stress intensity is usually expressed in units of MPa√m.

According to Sumpter *et. al.,* (2004), fracture mechanics based material toughness is measured using a fatigue pre-cracked specimen instrumented to measure load and displacement at failure. The toughness can be expressed in terms of a critical value of the elastic stress intensity factor, K_c; however, in a small specimen where plasticity precedes failure, the toughness is best derived from the J-integral. When expressed in stress intensity units, this toughness is designated KJ_c. The value of KJ_c is dependent on loading rate and temperature, as well as material properties.

Further to Sumpter *et. al.,* (2004), there is typically a considerable amount of scatter in the measured cleavage fracture toughness even from specimens taken out of the same material and tested under the same conditions. This reflects the local variations in cleavage stress within the steel. Failure of a fracture mechanics specimen depends on metallurgical conditions immediately ahead of the fatigue crack tip.

The master critical stress intensity curve approach developed by Sumpter *et. al.,* (2004) uses a mean line to describe the variation in toughness across the brittle to ductile toughness transition, combined with a Weibull distribution to describe the variation in toughness present at each temperature. The mean of the test data with 1% and 0.1% lower bounds were found from the Weibull distribution. *KIc* values are in the 150 MPa√m range for -10 degrees Centigrade.

For comparison to Sumpter *et. al.,* (2004), mean values of *KIc* values 150 MPa√m were obtained from Ramsamooj *et. al.,* (2002) used a CoV varying between 0.09 and 0.12 without specifying a suitable probability distribution for modeling this random variable.

Also, for comparison to Sumpter *et. al.,* (2004), a factor of 0.6 on *Kic* is recommended by Rolfe and Henn (1993) to account for the effects of stiffeners and elastic-plastic effects in the *KIc* and this was used here. This is consistent with *KJc* values provided by Sumpter for a *KJc* of 300 MPa√m/s.

The example calculation of fatigue crack size required to initiate a fast fracture presented here uses the following relationships based on the prior discussion:

$$KJc \sim 2KIc \tag{40}$$

$$Sc = \frac{2KIc}{\sqrt{\pi a c}} \tag{41}$$

The probability fracture was estimated for the example fatigue cracks (shown in Figures 2.4 and 2.5 and further forecast as a Markov process shown in Table 6.6) by using a Load-Strength probability approach. This approach is described by Ayyub *et. al.,* (2014) and Melchers (1999) among others. The probability of extreme loading was estimated using the approach developed by Sikora *et al.* (1983). As described previously, the probabilities associated with the Strength were estimated using fracture mechanics approaches presented by Rolfe *et. al.,* (1993) and Sumpter *et. al.,* (2004). The Stress Intensity *KIc* is for a through-thickness crack as presented by Rolfe *et. al.,* (1993) using LEFM with a 60% factor for ductility. The statistical distribution and scatter of *K1c* were assumed to be normal with a CoV of 15% by inspection of the data provided by Sumpter *et. al.,* (2004). Statistical quantification of the uncertainties of fast and brittle fractures are areas of much-needed work in addition to the visual *PoD* or other *PoD* approaches.

The resulting probability of brittle fracture (*PfBF*) is estimated given the probability distributions of loading stress and response stress using an interference reliability approach for a specific event. If the distributions for both the load (stress) and the strength both follow a Normal probability distribution, then the reliability (R) of a component can be determined by equations 3 and 4 in Chapter 2.0.

A Normal probability function was used for the calculations of material response based on inspection of the work published by Sumpter *et. al.,* (2004) and Rolfe *et. al.,* (1993). The estimate of the probability of brittle fracture is useful for the illustrative purposes herein.

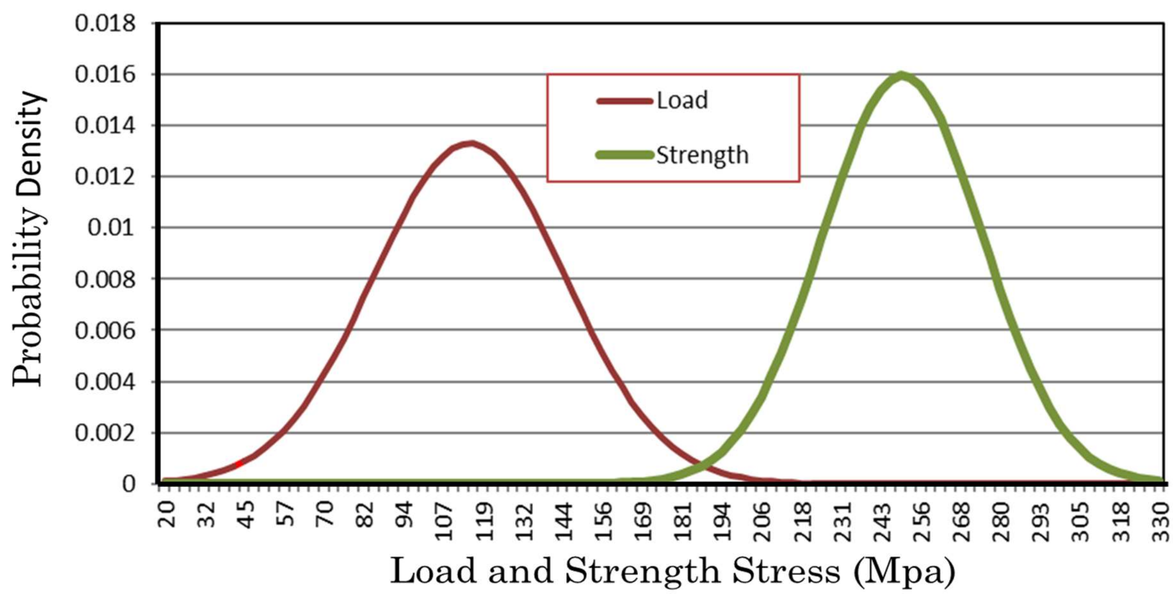

Figure 6.3– Illustration of the Load-Strength interference calculation

The probability of failure *P(Z)* can be determined from a *Z* table or a statistical text (i.e. Walpole *et. al.,* 2014), as shown in Figure 6.3 and results in Table 6.6

The resulting probability of failure calculations are shown in Table 6.6 for maximum annual load and in Figure 6.4 for the design load, maximum annual, maximum operational (SAR), and maximum load in 40-years given the environmental loading histories.

Table 6.6 - Probability of fracture calculation results for annual maximum load

	Crack Length (mm)							
	100	**150**	**200**	**250**	**300**	**350**	**400**	**500**
Direct Calculation	2.10E-07	1.44E-06	6.57E-06	2.29E-05	6.60E-05	1.64E-04	3.63E-04	1.36E-03
Monte Carlo 1e6 Simulations	2.00E-06	2.00E-06	9.00E-06	2.30E-05	5.00E-05	1.60E-04	3.36E-04	1.31E-03

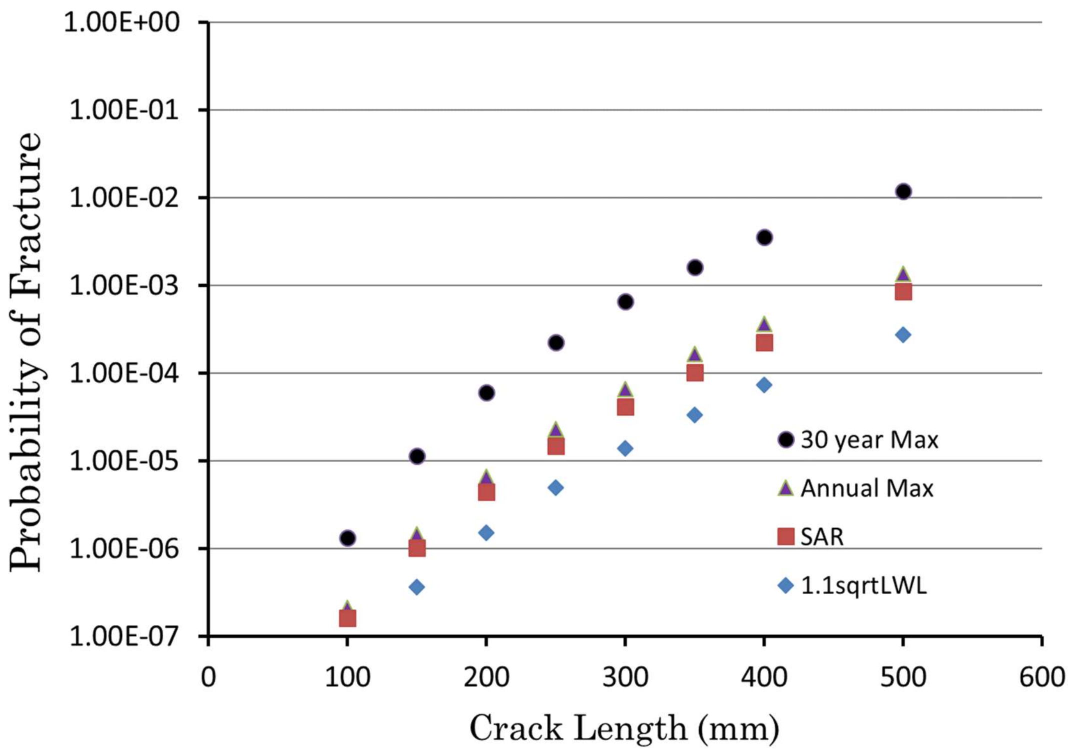

Figure 6.4 – Estimated probability of failure for various loading conditions and crack lengths

In Figure 6.4, loading considered is from the standard design wave, a typical Search and Rescue environment, maximum estimated annual load, and the maximum expected lifetime (30 years) load based on the approach developed by Sikora *et al.* (1983) and the operational environment presented by Stambaugh *et. al.,* (2014b). This example is for a specific crack in a component, but has system implications as discussed in Section 2.2.4

In this example, the *PfBF* shown in Figure 6.4 is consistent with 10^{-4} for a 250mm crack found by Sumpter *et. al.,* (2004). Longer cracks produce higher *PfBF* and unacceptable Risk. However, given the consequences of the failure and potential to lose the ship and crew, the 10^{-4} probability of failure and Risk ($PfBF \cdot \$C$) are very high, indicating a lower level of Risk may be desirable, and methods of finding fatigue cracks before they reach 100mm might be desirable. The Risk mitigation strategies proposed herein and by Stambaugh *et. al., (*2014a) are beneficial in reducing Risk to an acceptable amount through the life cycle.

6.5 Risk – TOC and Evaluating HSM as a Risk Management Approach

Two approaches for HSM, conventional strain gauge, and a more advanced Acoustic Emission (AE) approaches are presented next and evaluated as CoAs in the Risk-TOC approach.

6.5.1 Risk - TOC Analysis of Conventional HSM

This SFA design approach described in Chapter 2.0 is particularly beneficial because fatigue life is proportional to the third power of stress (FL~σ^3) and returns a lifetime benefit for minimal initial investments during design. However, initial design conditions may vary based on operational experience, and Hull Structural Monitoring (HSM) is used to reduce further uncertainties that may be included in the load predictions and actual environments encountered. The following discussion shows how the HSM reduces uncertainty and associated Risk in the following example.

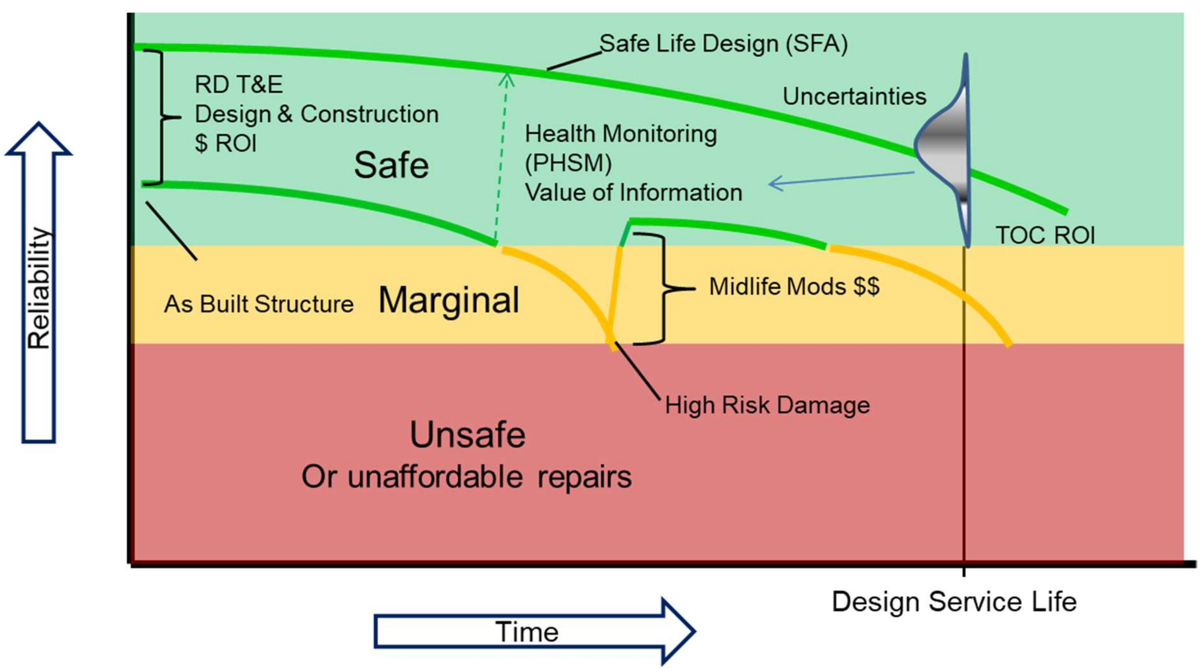

Figure 6.5 - Illustration of structural reliability as a function of time with SFA and HSM

Figure 6.5 expands on the example shown in Figure 6.1 and shows an illustrative comparison of time-dependent reliability for SFA and "Do-Nothing" approach. To summarize this example, the investment of conducting SFA early in design is minimal compared to the Risks of the "Do-Nothing" approach, as it is known in Risk Analysis and decision theory. Furthermore, the practicality of Optimal Inspection as a mitigation strategy is equivalent to the "Do-nothing" approach that is shown to be high Risk in the preceding examples.

The distinct advantages of implementing SFA into a design have been presented. The benefits of Risk Analysis and related decision theory are beneficial in combination with the SFA approach. For example, if we choose to implement an SFA approach, what are the remaining uncertainties in the SFA based service life forecasts, and how do we mitigate these uncertainties? What is at Risk from these uncertainties, and how do they change in the future as information becomes available?

The aleatory uncertainties of the SFA approach included in this example are the wave environment, structural load prediction in the wave environment and the initial quality of the welding discussed in Chapters 5.0 and 6.0 One way to mitigate uncertainties in these quantities is to obtain measurements on the ship in service with an HSM system. However, what should we measure and how much should we invest in the HSM system is related to the Value of Information gain. While the probability of fatigue failure is much reduced with SFA and S-N structural fatigue design, there is sufficient residual uncertainty to consider further analysis and actions to mitigate the Risks of this future uncertainty. The potential for service live extension is considered in this Risk Analysis example. The related question is, how confident are the Decision Makers in the SFA approach based forecast to justify investing in structure upgrades (or not) associated with a Service Life Extension Program (SLEP)? For example, if it will take $15M to upgrade the structure to extend the service life based on initial design assumptions, what part of that is at Risk based on the range of uncertainties in the SFA and mitigation strategies? The BMA and Risk Analysis approaches are proposed for assessment of Life Cycle Cost related decisions as follows.

The structural reliability forecasting with BMA with BHPs include:

- Fatigue Life Reliability Predictions
  - Spectral Fatigue Analysis (Sieve, *et. al.,* 2000)
  - Load Predictions (Sikora *et. al.,* 1983)
  - S-N curves (AASHTO - Sieve, *et. al.,* 2000)
  - Miner's (1945) Cumulative Damage (CoV=0.30)
  - *Pf* from Reliability Calculations (Ayyub *et. al.,* 2014)
- Bayesian Prior probabilities for environment, load prediction, and weld quality
- Latin-Hypercube Sampling described in Section 5.5.1.2
- Calculate expected mean and variance

$$E(V) = \sum_{i,j,k}^{n} f\,(B_{env}\, i,j,k\ B_{load}\, i,j,k\ B_{qlty}\, i,j,k\ Pf_{30}\, i,j,k) \qquad (42)$$

$$E(Vsdv) = \sum_{i,j,k}^{n} f\ ((B_{env}\, i,j,k\ B_{load}\, i,j,k\ B_{qlty}\, i,j,k\ Pf30\, i,j,k) - \text{Ev})^2 \qquad (43)$$

Where B_{env}, B_{load}, *and* B_{qty} are Bayesian priors for wave environment, loading accuracy, and weld quality respectively. The subscripts i,j, and k are specific priors in the Latin-Hypercube sampling. *Pf30* is the probability of failure at 30 years of service life.

For this example, the wave environment, load prediction, and construction quality are considered as dominant aleatory uncertainties in the SFA calculation. While these three dominant uncertainties are not an exhaustive set and do not produce an absolute value of Risk, they do provide valuable insights for the uncertainties we must be able to quantify and resolve in order to mitigate their effects on Risk in question (i.e., to SLEP or not to SLEP).

Typically, marginal probability distributions of significant wave heights encountered in the area of operation form a prior perspective in the SFA process. This prior experience will vary depending on the specifics of the area of operation. While there may be a dominant or preferably conservative (based on Scatter diagrams i.e. Bales-Lee and Classification Society Global Wave Statistics), the significant wave height (*Hs*) used in the design, there may be others that are possible/probable for forecasting applications. Weighting the *Hs* in probabilistic terms is a form of BMA with hyper priors. Initially, the weighting may represent a worst-case, conservative perspective. The BMA weighting may even maximize our state of uncertainty, or in a Bayesian perspective of uniform prior expectations. The marginal probability distribution of significant wave height (*Hs)* priors may be updated as the specific ship progresses through its service life if the information is known or collected either by an onboard system or post-analysis as in a virtual setting using hindcast databases (i.e., WW3 and Copernicus).

For the SFA calculations, a range of three environments are considered including that used in design (BLNP), one from experience of an prior but similar High Endurance Cutter (WHEC) and another from five years of measured data from the Fatigue Life Assessment Program (FLAP) presented by Stambaugh *et. al.,* (2014b). The latter two cases reflect heavy weather avoidance practiced by the operators. The marginal probabilities of the *Hs* examples are shown in Figure 6.6.

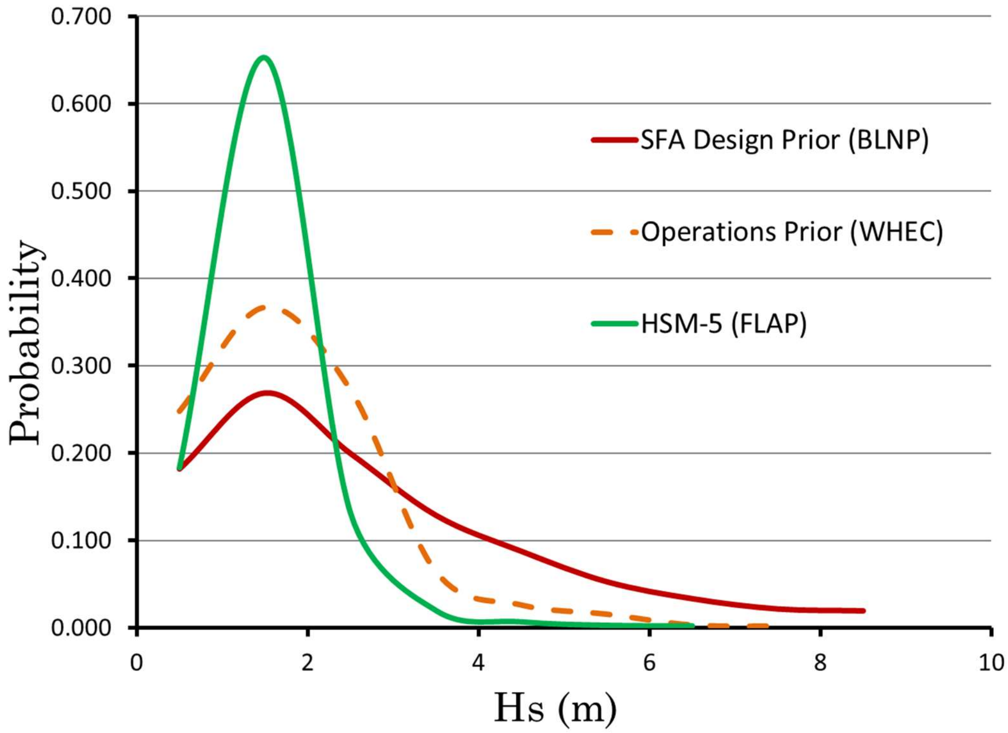

Figure 6.6 – Significant wave height probability density used as hyper-priors

An example sensitivity analysis of Hs is presented based on the results of the reliability analysis and updating of the initial reliability estimates shown in Figures 2.4 and 2.5   In this example, the number of expected fatigue cracks occurring based on varying assumptions/priors are shown in Figures 6.7, 6.8, and 6.9 for the following:

Figure 6.7 - Design Priors for Hs (SFA=0.8, Prior Ops=0.15, HSM5=0.05),

Figure 6.8 - Uniform Priors for Hs (SFA=0.333, Prior Ops=0.333, HSM5=0.333), and

Figure 6.9 – HSM-5 Updated Priors for Hs (SFA=.01, Prior Ops=0.3, HSM5=0.69).

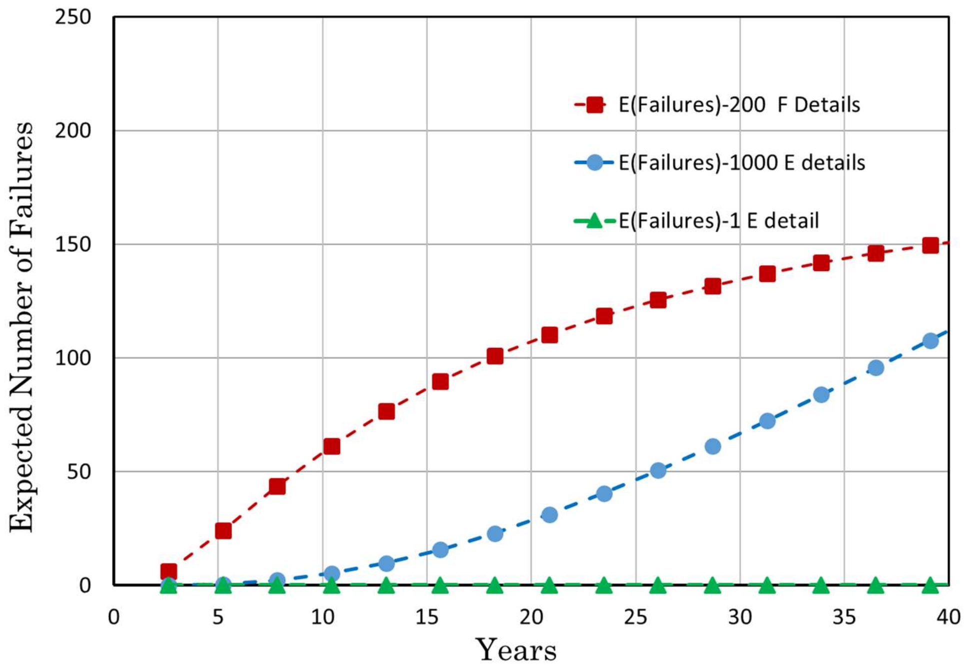

Figure 6.7 - Design priors for Hs (SFA=0.8, Prior Ops=0.15, HSM5=0.05)

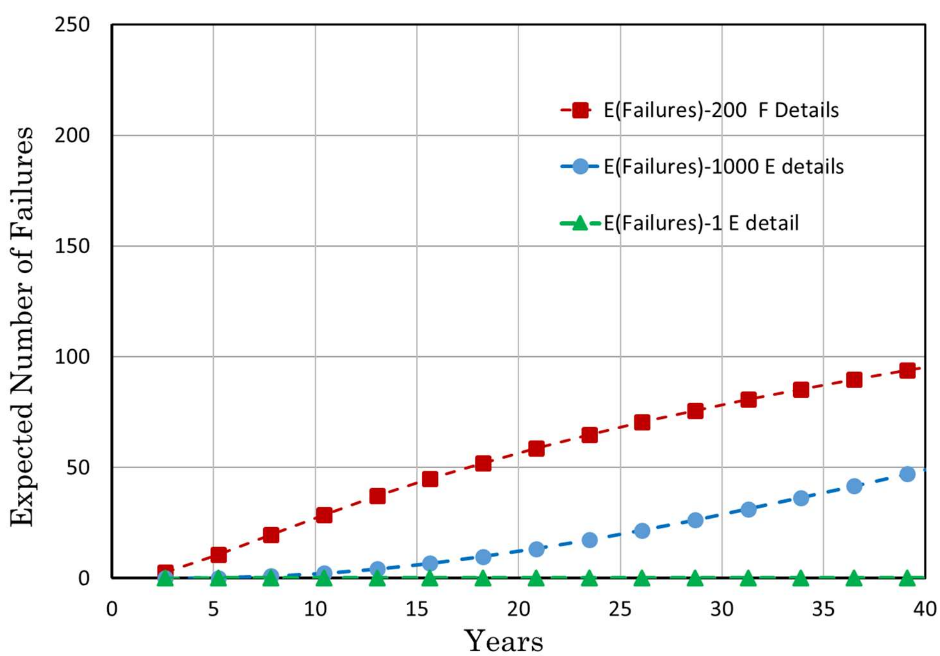

Figure 6.8 - Uniform priors for Hs (SFA=0.333, Ops Prior=0.333, HSM5= 0.333)

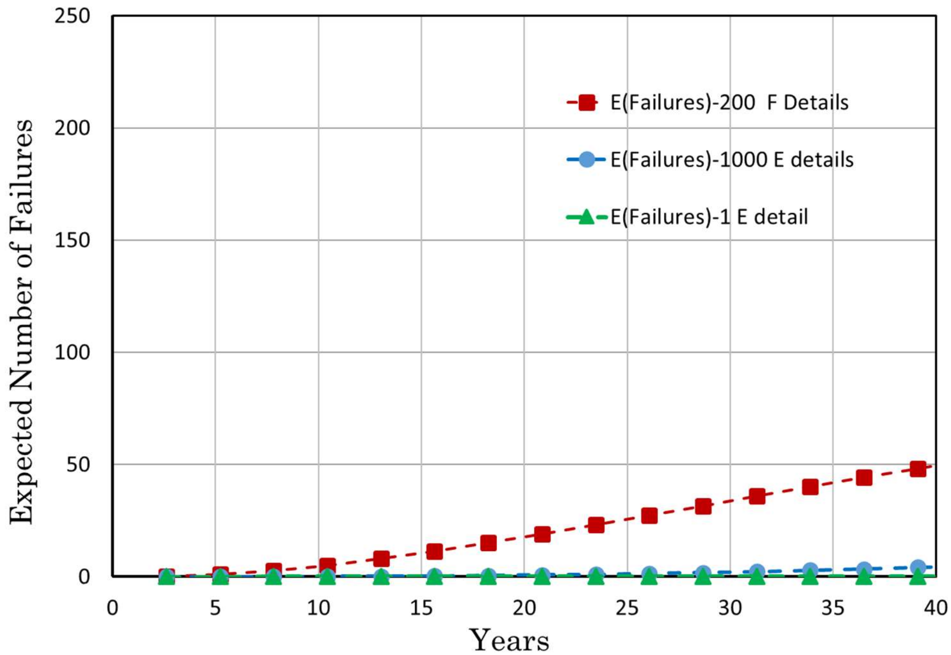

Figure 6.9 - HSM updated priors for Hs (SFA=.01, Ops Prior=0.3, HSM5=0.69)

In this example, the design hyper prior is assumed to be conservative in the initial fatigue design process (SFA), the uniform hyper prior is used to provide insights into a possible scenario where we lack full knowledge of the priors (i.e., uniform prior as Bayes and others have proposed in this case) and as HSM-5 hyper prior when partial information is included but weighted according to our beliefs based on prior experience. A significant observation from inspection of the results in this example is the dominance of the number of details on the number of failures expected, and to a lesser extent, the assumed Hs priors. In other words, the number of structural details (system components) has a significant effect on the number of fatigue failures in the collective systems analysis shown.

Table 6.7 shows the setup of the initial BHPs for the nine combinations in the analysis used in the BHP calculations of structural reliability for additional hyper priors. The structural reliability and resultant probability of failure predictions were made for each of the 27 initial permutations and follow on combinations of the uncertainty parameters. The reliability prediction, according to Ayyub *et. al.*, (2014) and Stambaugh *et. al.,* (2014b and 2019) discussed in Chapter 2.0, was used to determine the time-varying probability of failure. The results of the reliability calculations (*1-Pf*) are shown in Figure 6.10.

The uncertainties in the load prediction were considered as a range of Coefficient of Variation (CoV) for the load prediction approach and included 10%, 20%, and 30%.

The weld qualities of good, bad, and ugly represents a range of initial defects from 0.001mm, 0.01mm, and 0.1mm, respectively (see Figure 6.2 and related discussion). This was represented in the SFA by S-N categories of AASHTO D, E, and F respectively for calculation convenience. A crack growth prediction could be used with a range of flaw sizes shown in Figure 6.2.

Table 6.7 –Bayesian Hyper Prior parameters used in the Bayesian Model Averaging forecast of structural reliability estimates

				Design				
Environment				Loads		Weld Quality		
Bales-Lee	WHEC	FLAP	COV-10%	COV-20%	COV-30%	Good	Bad	Ugly
0.8	0.15	0.05	0.1	0.5	0.4	0.333	0.333	0.333
				HSM-5				
Environment				Loads		Weld Quality		
Bales-Lee	WHEC	FLAP	COV-10%	COV-20%	COV-30%	Good	Bad	Ugly
0.3	0.4	0.3	0.1	0.7	0.2	0.333	0.333	0.333
				HSM-10				
Environment				Loads		Weld Quality		
Bales-Lee	WHEC	FLAP	COV-10%	COV-20%	COV-30%	Good	Bad	Ugly
0.1	0.6	0.3	0.05	0.9	0.05	0.45	0.45	0.1
				HSM-30				
Environment				Loads		Weld Quality		
Bales-Lee	WHEC	FLAP	COV-10%	COV-20%	COV-30%	Good	Bad	Ugly
0.1	0.8	0.1	0.95	0.049	0.001	0.599	0.4	0.001

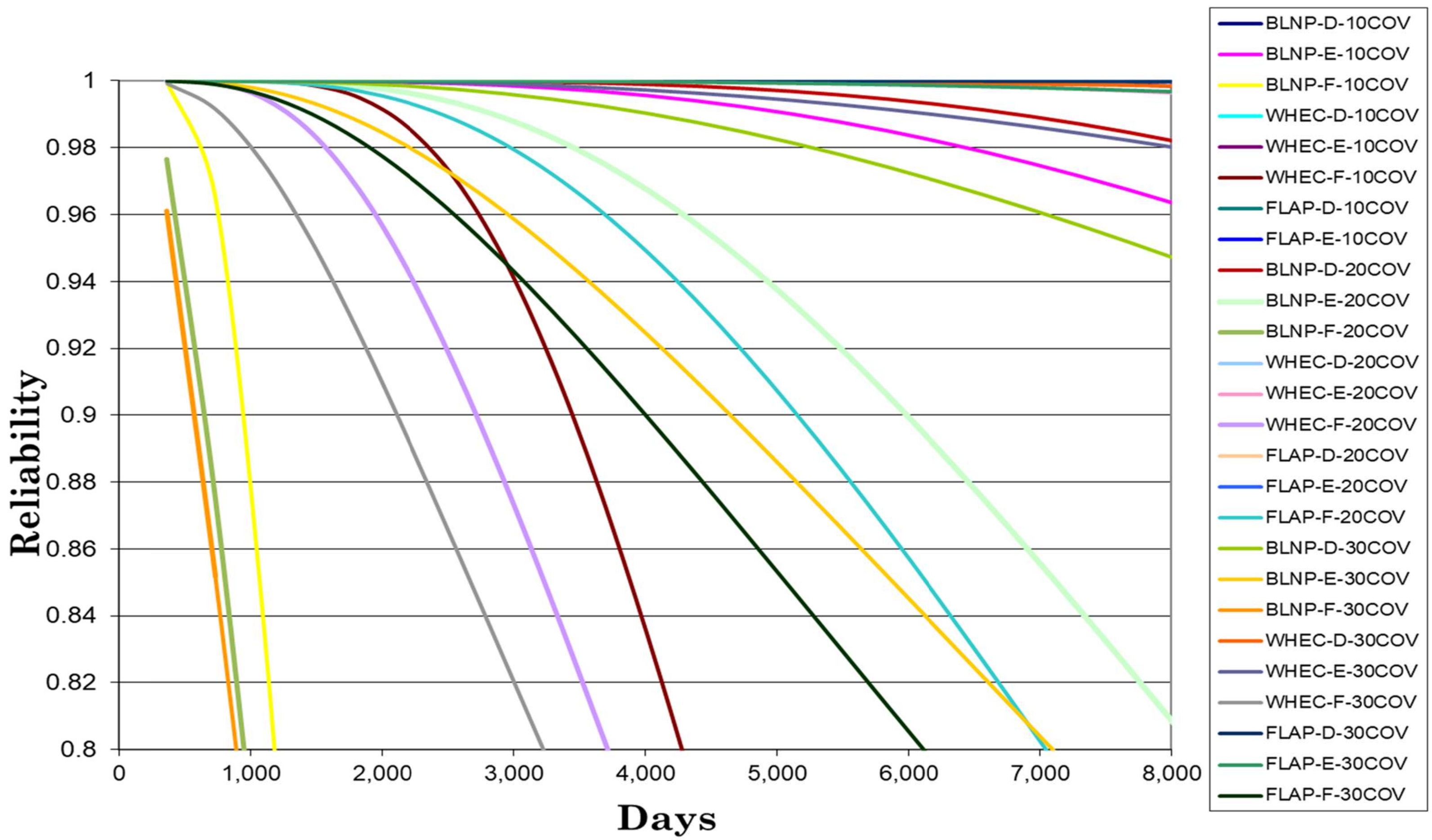

Figure 6.10 – Calculated reliability for the hyper prior parameters

In the Bayesian Model Averaging (BMA) approach, each Bayesian Hyper Parameter (BHP) is multiplied by the probability of failure in 30 years (*Pf30*). The range of the BHPs and Pf30 product histogram provides the statistical distribution of the uncertainties of the parameters considered, as illustrated in Figure 6.10.

Initially, the BHP for weld quality is uniformly distributed, reflecting our lack of knowledge related to weld quality in construction (see Figure 6.2 and related discussion). Over time, more information is gained about the weld quality in service by the presence of fatigue failures early on (i.e., larger flaws will fail early), as shown in Figure 6.2. If no failures are observed early on, either the weld quality was good, or the ship did not experience significant loading relative to its capacity.

Table 6.8 also shows the transition of BHPs with the assumed benefits of an HSM as a mitigation strategy. HSM-5, HSM-15, and HSM-30 represent time frames for the HSM considered in the evaluation of options. As time progresses, additional information is gained, the resulting uncertainties are reduced and calculated the following equations as:

$$E(TOC_{SLEP})_{30} = f((Pf30)\text{x}(\$15\text{M } SLEP)) \tag{44}$$

$$E(VaR_{95})_{30} = f((PfBF\text{x}Pf_{95})_{30})\text{x}(\$1.5\text{T } LOSS)) \tag{45}$$

The results of this BHP Risk calculations are shown in Table 6.8, along with a summary of the Risk of brittle fracture. The Expected Value of $PfBF_{30}$, and Value at Risk ($V@R_{95}$) $PfBF_{30}$ at 95% Confidence Interval CI are shown in Table 6.8 The product of 95% CI and \$1.5T and *PfBF* (0.0001) provides an estimate of the Expected Value at Risk (VaR_{95}) when time is equal to 30 years in this example. The product of 95% CI and \$15M provides an estimate of the SLEP exposure or E(TOC_{SLEP}). The \$HSM is the life-cycle cost of an HSM for the specified timeframe. The *RoI* is the net change in $E(TOC_{SLEP})_{30}$ is divided by the cost of the mitigation action (\$HSM).

The benefits of the HSM are evident in reducing the overall uncertainty and Risk as indicated in Table 6.8. The highest *RoI* from an HSM system represents the maximum *VoI* that a Decision Maker should want to invest in an HSM to mitigate (reduce) the remaining Risk (uncertainty and consequences).

Table 6.8 – Risk and RoI/VoI of Risk Mitigation strategies

	PfBF$_{30}$			**V@Risk$_{95}$ Loss**	**E(TOC) SLEP**	**Mitigation HSM**	***RoI/VoI***	
	E(V)	95% CI	E(SIE)				V@Risk$_{95}$	TOC$_{SLEP}$
SFA Design	.2654	.3783	7.46E-02	$9.6M	$8.7M	$4M	4:1	200:1
HSM 5 years	.0784	.1171	2.60E-02	$3M	$4.7M	$2.50M	3:1	2:1
HSM 15 years	.0359	.05	1.37E-02	$1.3M	$4M	$1M	8:1	5:1
HSM 30 years	.0017	.0023	9.29E-04	$0.06M	$3.5M	$1.75M	6:1	3:1

In Table 6.8, SFA *RoI* is relative to "Do-Nothing". *RoI* for HSM is relative to SFA in design.

The calculation of Expected SIE as *E(SIE)* described in Chapters 4.0 and 5.0 is shown along with *E(V@R$_{95}$)* results in Table 6.8 for a selection of SSLCM scenarios. This example is useful to show there is a reduction in entropy for increased duration of monitoring, which is both verification of the intuitive intent of monitoring and insightful. The most significant reduction in information entropy occurs after thirty years of monitoring, indicating a significant gain in information and a reduction in uncertainty. One of the benefits of calculating *E(SIE)* is that it is independent of formulaic distribution definitions. This feature is beneficial for evaluating the combine probability estimates of Risk with limited data, limited scenarios, and that do not produce detailed information for distribution fitting evaluations. When used in combination with *E(V@R$_{95}$)* estimates, *E(SIE)* provides an alternate means of confirming uncertainty reduction and provides a check that the calculations are reasonable by producing similar relative results.

The relative *E(SIE)* will be very useful as the number of uncertainties, and multi-dimensional uncertainties of Risk and TOC are included. The application of information entropy is an area for future research for more complex evaluations of Risk-TOC involving more CoAs and broader analysis of uncertainties.

The resulting Risk-TOC data is presented in Figures 6.11 and 6.12, reflecting the influence of new ship and SLEP decisions in the Risk-TOC trade-space.

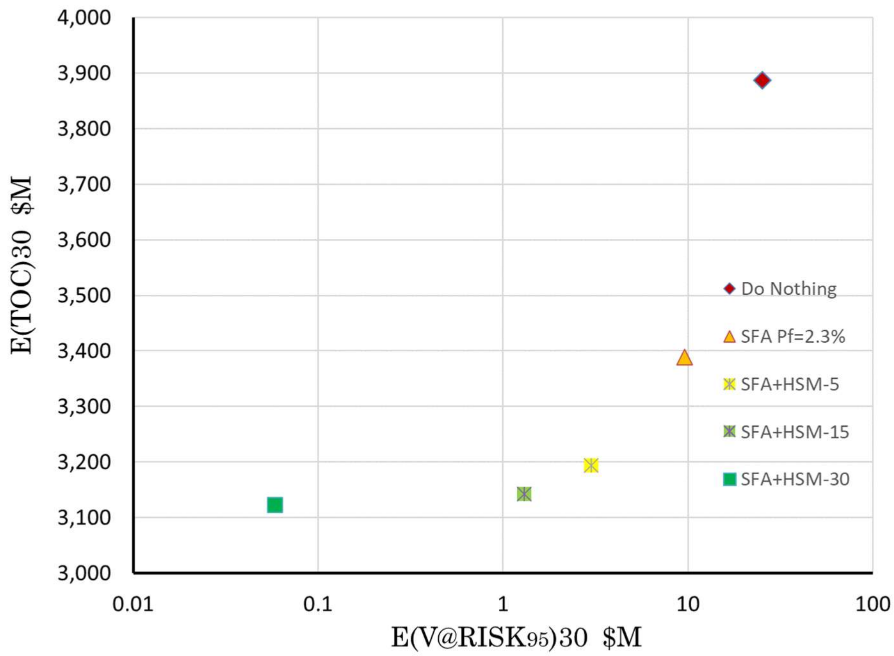

Figure 6.11 – Example of the Risk – TOC trade-space for a new ship decision

The Risk-TOC trade-space examples illustrate the significant reduction of Risk and TOC given the application of SFA in a design. In this case, the information gain includes the uncertainties inherent in SFA (as we know it and variations thereof) and its possible impact on a new construction decision if a zero RUL decision. A later example shows the same estimate with a SLEP assuming a positive RUL decision. In this case, the "Do-Nothing" approach has been removed due to its significant influence on the scale of results. The implications of this scaling magnitude are shown in Table 6.8 for significant *RoI* (~800:1) of SFA relative to the TOC of the "Do-Nothing" approach.

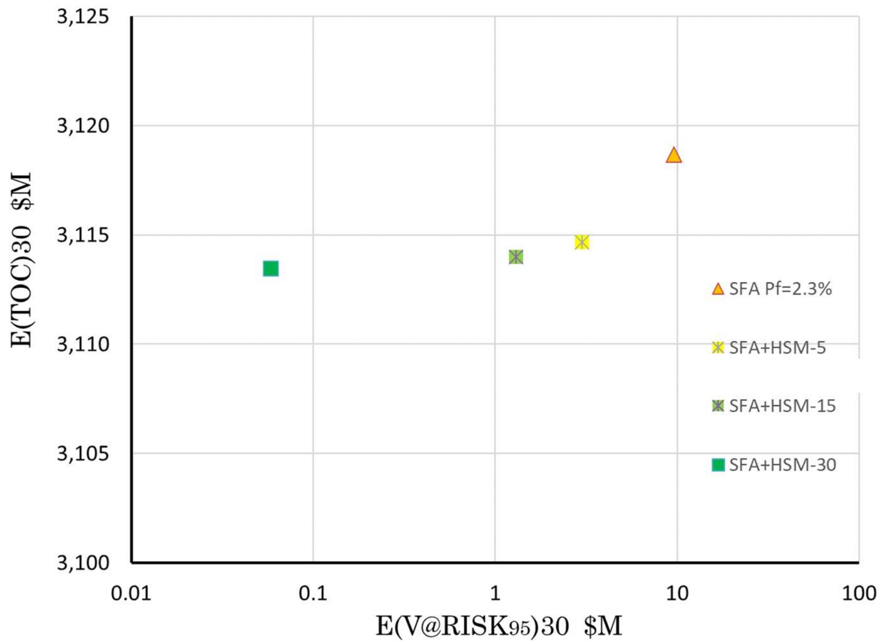

Figure 6.12 – Example of the Risk – TOC trade-space for a SLEP decision

In addition to service life extension costs and Risk shown in Table 6.8, the estimated Risk can be compared to total ownership cost (TOC) increases in a Risk-TOC trade-space. Figures 6.11 and 6.12 show the Risk and TOC the trade-space as described in Chapter 5.0 The increase in Risk and TOC examples obtained from Tables 6.3, 6.4, and 6.8. In this comparison, Risk is calculated for 30 years, as shown in Table 6.4. The $V@R_{95}$ shown in Table 6.8 with a factor for fatigue crack non-detection (very conservatively at 10%). The TOC increase is estimated based on the LCC in Table 6.5, and the cost of Risk mitigation for the specific option shown in Table 6.9 As discussed previously, the HSM and their BHP's options are updated based on the gain of knowledge resulting from measured information and occurrences of failures or not.

Each Risk mitigation scenario shown in Figure 6.12 has its individual trade-space, and local optimization is possible to identify benefits from improvements in the individual options, as illustrated in Figure 5.10. The individual Risk mitigation options may be updated from both new types of measurement approaches and increased knowledge to reduce uncertainties. For example, updated maintenance-related action options could also include improvements in the SFA process and quality and quantity of HSM. Future improvements in the SFA could be obtained from updates based on the measured HSM data and a validation process. Similarly, new approaches for inspection could be developed and considered in this trade-space, and corresponding *RoI* estimated. The "Do-Nothing" approach represents the potential for much higher Risk consequences associated with a potential total loss. Risks associated with this worst-case scenario are less tangible but are significant as shown in the simple examples shown herein. Quantified improvements in inspection approaches will yield quantified improvements in both Risk and TOC, particularly if combined with the SFA and HSM options and targeted inspections based on projected crack growth rates.

6.5.2 Risk - TOC Analysis of Acoustic Emission HSM

As discussed in Chapter 2 and Figure 2.5, an important question to be answered is how long (length and time) cracks grow undetected, and what is there *PoD* or, more precisely, non-detection (*1-PoD*)? A literature search provided example *PoD* data for bridges and offshore structures (see Madsen *et. al.,* 1991 and many more). However, there are few sources for *PoD* data for visual inspection of ship structures. Two sources of visual *PoD* data are by Demsetz (1999) and Takahashi (2007), with results shown in Figure 6.13 along with *PoD* data from Madsen *et. al.,* (1991) for offshore platform and bridge NDT inspection. Similar *PoD* curves ara available from DNVGL (2017) for offshore structures.

Figure 6.13 shows there is a probability that fatigue cracks up to 500mm in length will not be detected by visual inspection. Based on the author's experience (Stambaugh *et. al.,* 1987), cracks in shell and tank plating often leak when reaching the 100mm range; however, this effect on crack detection has not been quantified in terms of *PoD*. More work is needed in the area of *PoD* development for ship structures, and the Risk-TOC framework is proposed for their further evaluation of investments in this regard.

The NDT inspection for all structural welds including welded structural details in the primary structure of ships is cost-prohibitive in addition to significant losses in operational availability Ao. The *PoD* data for ships is very sparse, and any extrapolation is difficult; however, the data is used to illustrate the probability of fracture example.

In addition to the excessive cost of inspecting ships with NDT and limitations of visual inspection *PoD,* Figure 6.13 shows a photograph of the inside of a US Coast Guard Cutter with insulation covering the vast majority of the interior of the primary hull structure. This is a good example where visual inspection and NDT will not be cost-effective. Insulated structure is common in the primary hull girder above the bottom of US Coast Guard Cutters and Naval ships.

In addition to the difficulties and challenges in inspecting ship structure, the *PoD* estimates are shown in Figure 6.13 indicate cracks can easily grow undetected to 250mm in length. The *PfBF* for a fatigue crack 250mm in length is unacceptable levels 10^{-4} as described by Sumpter *et. al.,* (2009) and evaluated in prior sections. This example shows that cost-effective inspection mitigation strategies are desirable to help mitigate the Risks discussed herein.

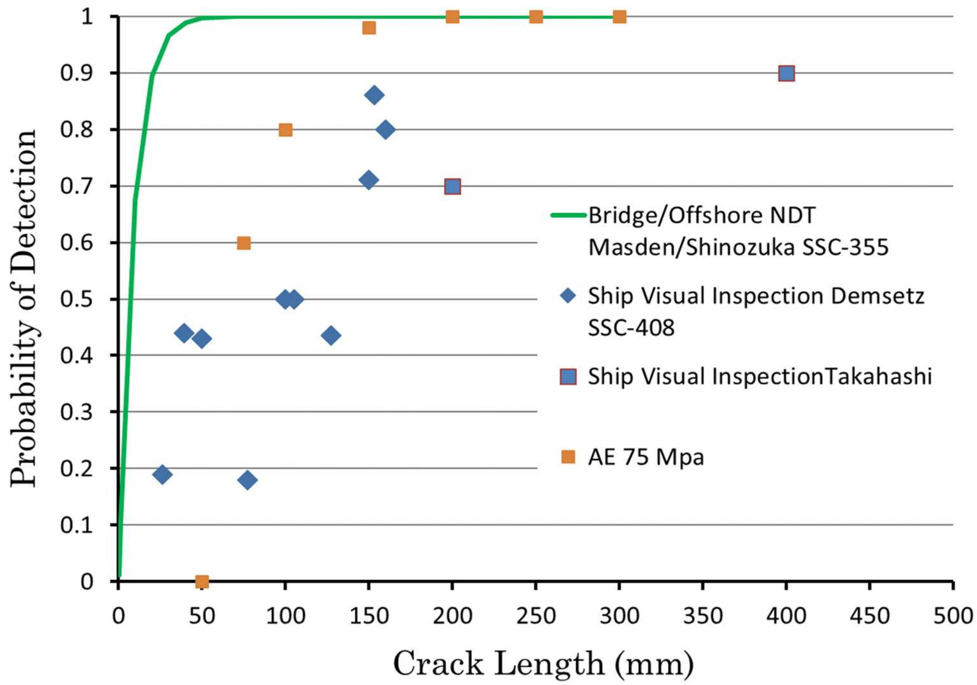

Figure 6.13 – Probability of Detection for fixed structures and ships

PHSM is often used to assess lifecycle conditions. This monitoring is often accomplished by strain gauges (see Stambaugh *et. al.,* 2014b) with other approaches, including AE as an example (Stambaugh 2014c) that are based on finding fatigue cracks in early stages of growth. The Acoustic Emission (AE) crack *PoD* is presented data by Hossain (2013) for comparison. Acoustic Emission data (at AE 75 Mpa) are shown in Figure 6.13 for comparison to other sources of *PoD* data; additional discussed on this topic is presented later in this dissertation.

Figure 6.14 –Inside view of a US Coast Guard Cutter showing insulated primary hull girder structure – relevant to PoD of NDT and difficulties for visual or NDT inspection

Given the cost, difficulties, and limitations of both NDT and visual inspection in ships described above, it is interesting to consider the use of AE fatigue crack growth detection, as discussed by Stambaugh *et. al.,* (2014b) and Drummen *et. al.,* (2019).

The probability of detecting fatigue cracks is related to stress intensity, as presented by Hossain (2013). In the work described here, the stress intensity is translated to crack length for a given nominal stress (range) is by LEFM and presented in Figure 6.13 as AE75Mpa given a stress intensity calculated at 75Mpa stress and stress intensity shown in Figure 6.13 and number of stress cycles exceeding 2000 as recommended by Hossain. This is a nominal stress associated with most probable loads. The *PoD* improves when operating in higher wave heights producing higher hull girder loading and resulting stress intensities.

Results presented in Tables 6.9 and 6.10 show the potential benefit of AE monitoring by lowering the number of cracks growing to longer lengths and lower probabilities they will reach critical crack lengths. For example, the probability of a fatigue crack growing to 250mm is $10e^{-5}$ in 40 years with AE and significantly higher without AE, as shown in Table 6.9. This example is shown in Figure 6.15 Risk-TOC trade-space for illustrative purposes.

There is a need for additional verification of fatigue crack *PoD* for AE technology in ship structure to fully evaluate this approach for ship structural Risk Management; however, this Risk-TOC example provides evidence the investments will likely provide a positive *RoI*.

Table 6.9 – Probability of fatigue cracks growing to various lengths, AE example

Crack Length	Years	30	35	40	45	50	55	60
TTC	Nttc/Pttc	0.2	7	12	34	81	138	183
	PnDetect		0.05	0.05	0.05	0.05	0.05	0.05
	PnRepair		0.05	0.05	0.05	0.05	0.05	0.05
150mm	N150/P150		0.01	0	1	2	4	7
	PnDetect			0.01	0.01	0.01	0.01	0.01
	PnRepair			0.05	0.05	0.05	0.05	0.05
250mm	N250/P250			0.0001	0.0037	0.0063	0.0185	0.0445
	PnDetect				0.001	0.001	0.001	0.001
	PnRepair				0.05	0.05	0.05	0.05
350mm	N350/P350				0	4E-06	7E-06	1.9E-05
	PnDetect					0.001	0.001	0.001
	PnRepair					0.05	0.05	0.05
450mm	N450/P450					0	0	0

Nttc/Pttc = Number of through thickness cracks or Probability of through thickness cracks
PnDetect = Probability of non-Detection (=1-Probability of Detection)
PnRepair = Probability that a crack will not be properly repaired and initiate a new crack
N150/P150 = Number of 150mm cracks or Probability of a 150mm crack

Table 6.10 –Example Fatigue Failure Risk Analysis with Acoustic Emission HSM

	Do Nothing	Design SFA	HSM-5yr	HSM-15yr	HSM-30yr	Acoustic Emissoin
Pf30-95%	2	0.3783	0.1171	0.05	0.0023	0.3783
Pf 250mm Cracks	2	0.7566	0.2342	0.1	0.0046	0.0445
PBf-250mm	2.30E-04	2.30E-04	2.30E-04	2.30E-04	2.30E-04	2.30E-04
PBf30	4.60E-04	1.74E-04	5.39E-05	2.30E-05	1.06E-06	3.87E-06
Value C Low	$ 2,200,000,000	$ 2,200,000,000	$ 2,200,000,000	$ 2,200,000,000	$ 2,200,000,000	$ 2,200,000,000
Mean	$ 55,000,000,000	$ 55,000,000,000	$ 55,000,000,000	$ 55,000,000,000	$ 55,000,000,000	$ 55,000,000,000
Value C High	$1,500,000,000,000	$1,500,000,000,000	$1,500,000,000,000	$1,500,000,000,000	$1,500,000,000,000	$ 1,500,000,000,000
Value at Risk Low	$ 1,012,000	$ 382,840	$ 118,505	$ 50,600	$ 2,328	$ 8,518
Mean	$ 25,300,000	$ 9,570,990	$ 2,962,630	$ 1,265,000	$ 58,190	$ 212,955
Value at Risk High	$ 690,000,000	$ 261,027,000	$ 80,799,000	$ 34,500,000	$ 1,587,000	$ 5,807,851

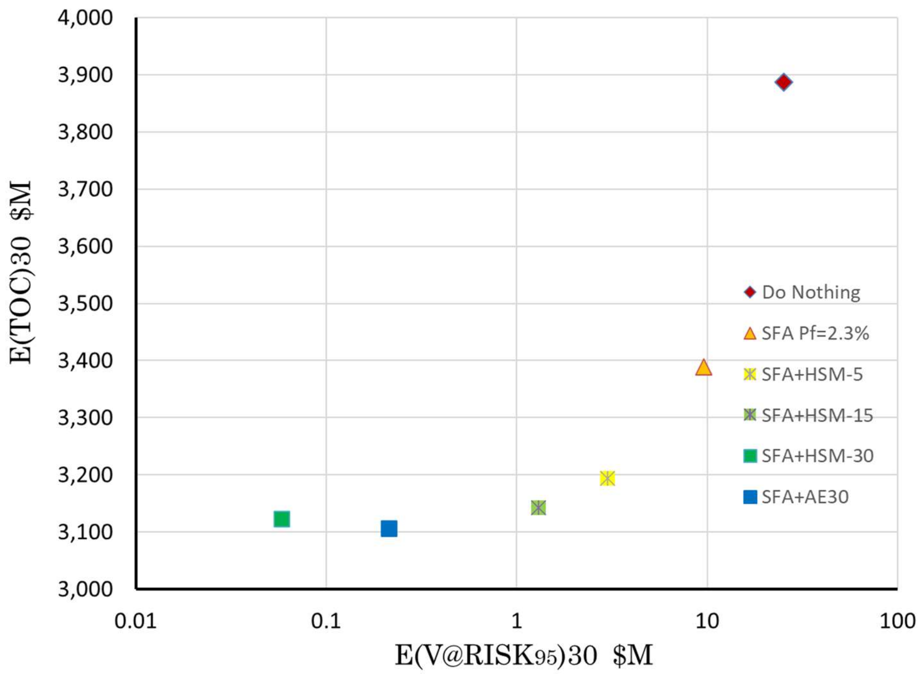

Figure 6.15 – Relative Risk and TOC management approaches Including the AE example with the do-nothing scenario

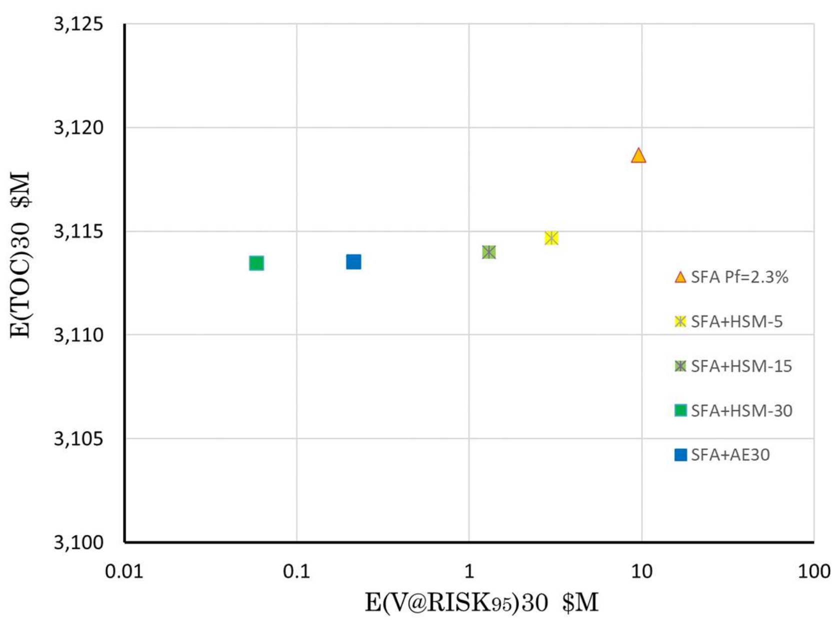

Figure 6.16 – Relative Risk and TOC of management approaches Including the AE example without the do-nothing scenario

Figure 6.16 shows the same scenarios as Figure 6.15, except the "Do-Nothing" scenario is removed for clarity of scale. This difference between Figures 6.15 and 6.16 shows the magnitude of Risk and TOC dominance associated with the "Do-Nothing" approach vs. the mitigation strategies.

6.6 Risk – TOC Analysis of Corrosion in Ship Structure

In the context of a structural system, local panel corrosion could potentially aggregate to weaken the structure globally if not undetected or not repaired if detected as deferred maintenance. The Risk associated with these events are evaluated here in the Risk-TOC approach.

The corrosion and fatigue Risk-TOC estimates are shown in Table 6.11 and trade-space in Figures 6.17 and 6.18 for illustrative purposes. The fatigue management approaches are from Figure 6.16 and include, from top left to bottom right, "Do-Nothing", Fatigue Design (SFA), Hull Structural Validation, and Long-Term Hull Structural Monitoring. The corrosion Risk Management options include:

- Visual Inspection every year,
- Visual Inspection every other year,
- Visual Inspection and spot UT testing every five years,
- Visual and UT inspection mid and end life,
- Visual and UT inspection every (five years) planned Dry Docking, and
- Visual and UT inspection every other (ten years) planned Dry Docking.

The probability of corrosion detection values, maintenance, and the probability of loss are subjective Bayesian prior probabilities based on the author's experience with maximum corrosion rates observed in US Coast Guard Cutters. Additional work is needed in this area to substantiate this information. The estimated LCCM costs, consequences, and associated Risks are presented in Table 6.11, Figure 6.17, and 6.18 as an example range corrosion damage. The trends presented in Table 6.11 and Figures 6.17 and 6.18 appear to be realistic, indicating the Visual Inspection and UT measurements every drydocking provide the most cost-effective approach to managing corrosion in this example. This illustration demonstrates the Risk-TOC trade-space approach applied to corrosion in SSLCM and facilitates LCCM decisions depending on the severity of corrosion.

Table 6.11 –Example Corrosion Failure Risk Analysis

Inspection	Cm1			PoD		Pf		Pf-Tot		Cm2		Cm1+Cm2	Closs
	$K		$K			WT	Buckle	WT	Buckle	$K	$K	$K	$K
	cost/	frequency	total-30	Hull	Internal	Hull	Int	Hull	Int	cost/	total-30	total-30	
Vis-30	2	30	60	0.1	0.01	0.5	0.002	0.45	0.002	10000	4520	4,580,202	1,010,101
Vis-15	2	15	30	0.1	0.01	0.5	0.005	0.45	0.005	10000	4551	4,580,505	2,525,253
Vis-UTspot	50	5	250	0.5	0.8	0.5	0.001	0.25	0.005	10000	2550	2,800,000	2,500,000
Vis-UT Hull-2	150	2	300	0.8	0.5	0.5	0.0005	0.1	0.001	10000	1010	1,310,000	500,000
Vis-UT Hull-5	150	5	750	0.8	0.5	0.1	0.0001	0.02	0.0002	10000	202	952,000	100,000
Vis-UT Hull-10	150	10	1500	0.8	0.5	0.1	0.00001	0.01	0.00002	10000	100	1,600,200	10,000

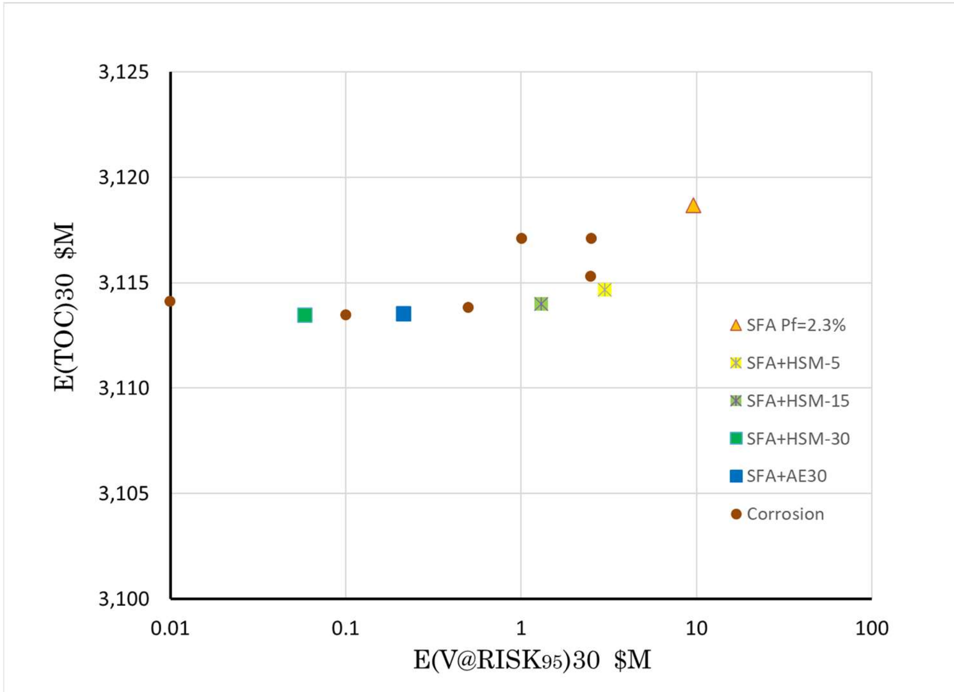

Figure 6.17 – Risk-TOC trade-space with fatigue and corrosion risk control scenario's

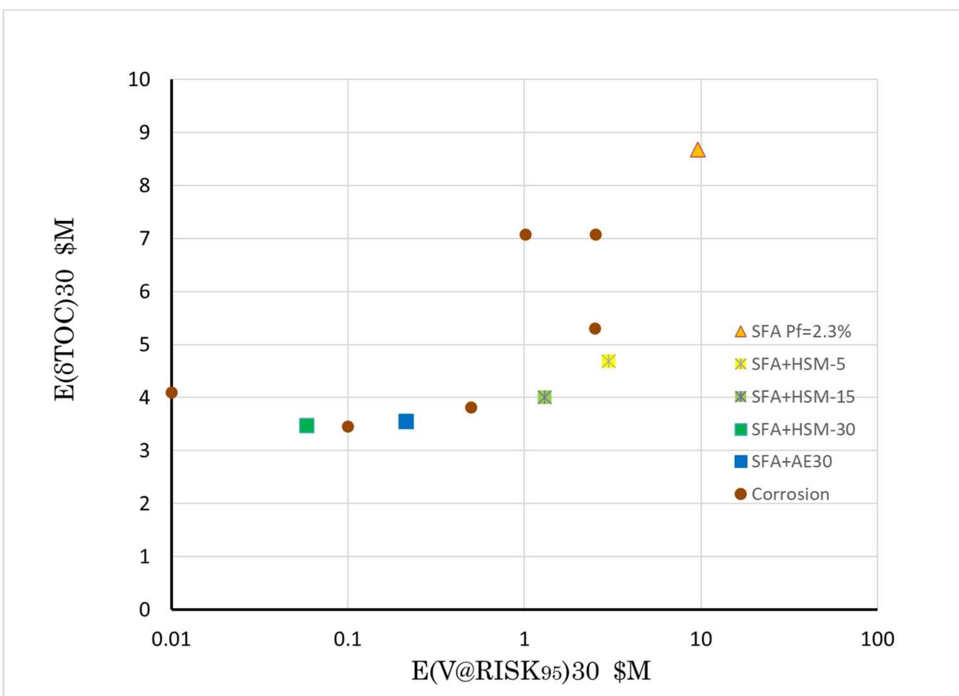

Figure 6.18 - Relative Risk-TOC trade-space with fatigue and corrosion risk control scenario's

Figure 6.18 is the same as Figure 6.17 with corrosion scenarios of Risk-TOC from Table 6.11 added and $E(\delta TOC_{95})30$ shown for clarity of scale and impact of the scenarios.

Figure 6.18 shows an interesting area between $0.5M and $10M for Risk and $1M and $10M for TOC. There are many Risk control options from SFA in design to HSM and corrosion inspection results that could provide acceptable values of Risk based on the preferences and perceived utilities of the Decision Makers. The differences in TOC produce a substantial difference in *RoI* of each option, justifying the investments by Decision Makers. In this example, the Risk-TOC framework is used to evaluate alternatives Risk Management options, technology investments, and the potential *RoI* that isn't as readily evident in any other type of analysis (i.e., Component Reliability, Optimal Inspection, β based).

While less developed in detail than the fatigue reliability examples, the corrosion example is illustrative of the Risk-TOC approach and serves as a starting perspective for further research and development and refinements of the approach relative to corrosion in ship structure.

6.7 Risk - TOC and Evaluation of End of Service Life

Given the definition of Risk and TOC proposed herein, it is possible to quantify the benefits of service life planning efforts for SSLCM. These include establishing an EOSL definition and how to manage minimum TOC at required availability levels during design through service life.

The TOC implications of this time-dependent fatigue reliability degradation from fatigue are significantly different than if fatigue is considered early in the ship's life cycle during design and construction, as shown in Figure 6.1 Additionally, the ability to extend the EOSL of a ship produces significant savings in TOC, not only from a maintenance avoidance standpoint but significant cost savings from not having to acquire a new ship because the structural life is less than planned. In this example, if the cost to sustain required availability levels and safety exceed available budgets, the EOSL is reached. If this economic failure occurs prior to the design service life, the TOC increases by the cost of a new ship required replacing it or other related options required to meet service/mission availability (Ao) obligations. Conversely, extended service life saves the cost of a new ship, prorated in time after expected design service life. There are often other considerations involved in the EOSL decisions, including funding available to buy a new ship or other political considerations. However, the decisions related to EOSL are a matter of TOC and Risk from a technical viewpoint. Therefore, Risk -TOC applied in design proactively will have a significant impact on service life and replacement. There are proactive measures that can be made early RD&TE, design, and construction phases with a significant impact on Risk and TOC. Significant cost savings can be realized by using the Risk-TOC approach early in the design phase, providing adequate buckling and corrosion margins, in addition to addressing corrosion prevention, as proactive measures to minimize both Risk and TOC.

The overall goal is to achieve minimum TOC and Risk at required *Ao,* as shown in Figure 6.19 at the maximum EOSL. See Chapters 7.0 for an additional discussion of EOSL and SLEP decisions.

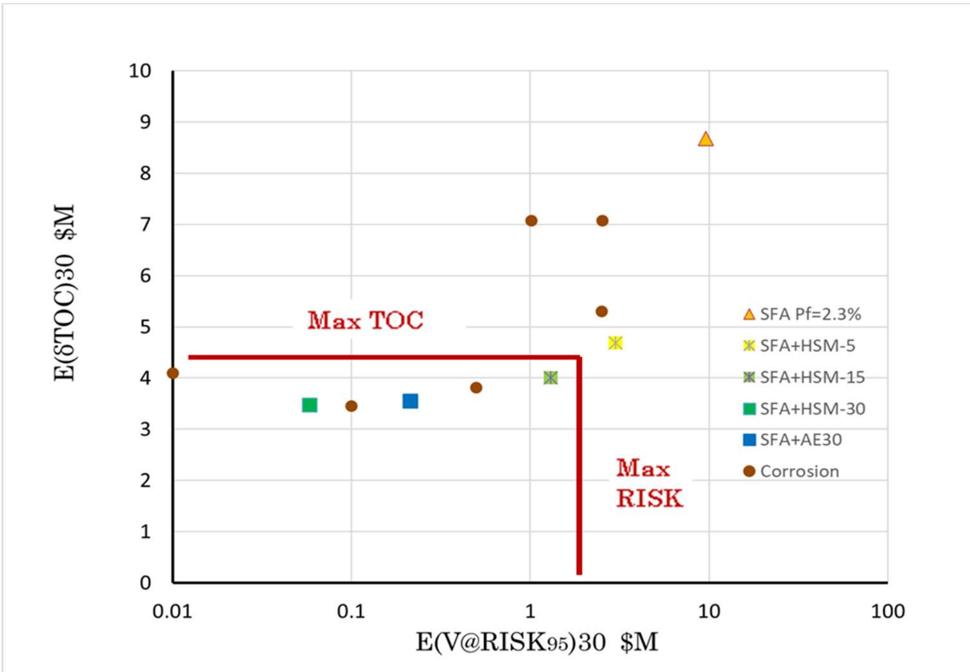

Figure 6.19 – Illustration of RISK - TOC trade-off space for determining EOSL

For the scenarios illustrated in Figure 6.19, both TOC and Risk increase from corrosion, local buckling, and fatigue cracking. In either case, the objective is to minimize their Risk and TOC based on quantified impacts of the actions. In Figure 6.19, fatigue failure related Risks and TOC are shown to exceed the maximum economic TOC. Ships with extensive fatigue cracking become very expensive to repair through their service life; thereby, increasing TOC significantly and implies shorter EOSL. Risk also increases as the cracking becomes more widespread throughout the ship. In any case, if the Risk exposure is deemed too high and the ship is too costly to repair, the useful service life is not adequate as characterized in the Risk-TOC trade-space. Proactive actions early in the ship's life cycle often provide the minimum Risk and TOC, as discussed in prior examples. The objective is to determine the combination of the minimum combination of Risk and TOC for a given design. This process will be applicable throughout the ship's life from RD&TE to disposal.

What becomes clear from this discussion is the definitions of RUL and EOSL are not discrete numbers, and their quantification is possible in the Risk-TOC approach. They are both subject to uncertainties in Risk and TOC that must be considered over an expected lifetime experience. In current SSLCM practice, RUL and EOSL are often decided based on reactive experiences (i.e., repair of fatigue cracks and corrosion become prohibitive especially if the result in EDDs). Proactive Risk-TOC planning is supported by the probabilistic determination of these important SSLCM events.

7.0 DISCUSSION AND IMPLICATIONS

Broader Implications

The prior Chapters of this dissertation present theory and verification of the proposed Risk-TOC approach for management for SSLCM. This Chapter presents the major findings and broader implications of the Risk-TOC approach developed as part of the research presented in this dissertation.

Topics for discussion related to the findings and implications from the research conducted include:

- Risk Definitions
- Systems Analysis in the Risk-TOC Approach
- Risk-TOC trade-space Analysis of Alternatives (AoAs) and Course of Actions (CoAs) for Risk Management
- Return on Investment Considerations
- Total System Performance
- Sustainability
- Hull Structural Monitoring and Risk (Uncertainty) Reduction

7.1 Risk Definitions

Definitions of Risk used in Risk Analysis and SSLCM are presented in this Section to contrast them with definitions used in Decision Theory-based LCM.

7.1.1 Risk and Related Uncertainties

Uncertainly definitions are often "elusive" due to a large number of parameters, variables, and their associated complexities. Therefore, concepts of uncertainty and related definitions are emphasized through-out this dissertation to illustrate the fundamental implications of uncertainty in Risk quantification and its reduction (in terms of both uncertainty reduction and consequence reduction). As described in Chapters 2.0, 3.0, and 4.0, uncertainty concepts and definitions are a fundamental part of understanding, managing, and communicating Risk; therefore, it is essential to understand and quantify uncertainty in order to plan for potential consequences of a failure either minor or catastrophic.

Historically uncertainties are quantified using probabilities, and there are many views on this as discussed in Chapter 2.0 and Appendix B and summarized in Figure 4.1. With Risk, uncertainties are defined by probabilities.

This quantified measure of uncertainty in the hull structural loading and response becomes the characteristic of Risk with significant investments involved in SSLCM decisions and management and how the Decision Maker may quantifiably determine Risk has been reduced.

Given the fundamental definition of Risk as (*Pf*$C*) and a clear definition of *Pf* as representative of uncertainties proposed in this dissertation, it is possible to communicate the Risk to others in more common terms understandable by those making the decisions.

7.1.2 Risk-TOC vs Decision Theory

In the design and engineering of complex structures, there are multiple ways to view and manage and mitigate uncertainty and Risk. This is also true for SSLCM. Key differences between Decision Theory and Risk Analysis and Management are presented in Section 3.1 of this dissertation to highlight these differing viewpoints and their implications on SSLCM.

The quantification of uncertainty with probabilities in Risk Analysis proposed in this dissertation differs in Decision Theory. Proposed approaches to general LCM based on Decision Theory and Optimal Inspection scheduling alternatives presented in Chapter 3.0 are based discrete probabilities, calculated expected value, and often hypothetical personalized expected utility in the decision process related to a single maintenance strategy. In Decision Theory, $E(V)$ and $E(U)$ are calculated as the probability-weighted mean of expected outcomes that are narrowly focused on making the "most probable" successful decision without considering the effects of the range of possible outcomes needed for a fully informed decision on the range of Risk outcomes.

The order of magnitude in Risk-TOC calculations and shown in the Figures in Chapter 6.0 show non-linearity in Risk and the significant magnitudes of TOC involved in the decision processes. This non-linearity is similar to Prospect Theory; however, it is a quantified perspective and not based on personal preferences on Risk. Although the Decision Theory-based approaches reflect the hypothetical preferences of the Decision Maker, the Risk-TOC approach provides quantified information without personal preferences. Therefore, the Risk-TOC approach is most useful for making informed decisions with any preferences being those of the Decision Maker(s). Each entity involved in Risk-based decisions then has an opportunity to apply quantitative utilities based on the application.

The formulations of $E(V)$ and $E(U)$ used in Decision Theory lack focus on the range of outcomes for decision making and is known as the "Flaw of Averages" attributed to Savage (2012). This is in contrast to the approach in Risk Analysis where the range of uncertainties is considered including $E(V)$ and $E(VaR_{\alpha})$ based on a specific Risk tolerance limit of the Decision Maker or overall Risk reduction by information theory-based approaches. Savage (2012) and Hubbard (2009) discuss the transition from Decision

Theory to Risk Analysis by representing decision outcomes by distributions of uncertainty, where appropriate, and Monti Carlo simulations. The results of this analysis are examined at the confidence intervals and other Risk measures in addition to the expected values, as discussed extensively in this dissertation.

Furthermore, in Decision Theory based Optimal Inspection proposals, Risk is defined as a product of a discrete probability of a failed structural component being detected and repair costs being calculated for form an *E(U)* without Risk of total system (or near-total) loss being considered explicitly.

In contract, implementing the Optimal Inspection approach to complex (yet non-redundant) structure results in very high Risk (not finding a crack) TOC (direct and indirect availability - Ao costs) of inspections and repair of serviceability failures.

In the Risk-TOC approach, maintenance costs and serviceability failure repairs are added to TOC and Risk of a major system loss or total loss at worst. In contrast to Decision Theory based Optimal Inspection scheduling approaches, the Risk-TOC approach includes numerous decision options for Risk mitigation that are compared on the basis of cost $E(TOC_a)_T$ the Expected Risk $E(Risk_a)_T$

These fundamental differences in Risk definitions, analysis, and management are particularly important when considering the scale of the system complexity in ship structure. In Optimal Inspection, one or few structural details are included in the optimum inspection schedules. In contrast, the Risk-TOC scales to more complex structures. The scaling process includes the magnitude of the problem in terms of Risk and TOC in as quantified terms as the Risk Analyst has available or data needs to obtain the supporting data (e.g., Prognostic Hull Structure Monitoring).

Ultimately, Decision Theory based Optimal Inspection as failure monitoring, reactive approaches are fundamentally high Risk in complex structures; therefore, there is a need for a proposed Risk-TOC SSCLM approach as presented in Chapter 5.0 and examples in Chapter 6.0

7.2 Systems Analysis in the Risk-TOC Approach

In ship structure, the interactions and correlations between structural load and response are important in system analysis, as has been presented in this dissertation. The analysis of component level correlations is presented in Appendix A, and implications on the systems analysis of fatigue and corrosion failures in ship structures are described in Chapter 2.0. The implications of the system definition lead to a new understanding of systems reliability, failure progression, and related fundamental Risks.

7.2.1 Component Level Correlations

Complex structures in many industries, civil in particular, are purposely constructed of individual members forming independent load paths. In these systems, terms such as series and parallel are used to characterize the system behaviors in failure progression. However, ship structure is continuously welded with no duplicative redundancy in individual members, load paths, and the concepts and terms of series and parallel do not apply to complex ship structural systems. Failure happens to the entire structure as a whole, either progressively or catastrophically. Neither case is desirable and very high Risk, as shown in the examples provided. In ship structures, there must be sufficient reserve strength designed in for the intended service life; however, the current approach for providing reserve strength is empirically based. The Risk-TOC approach proposed in this dissertation provides a means for comparative analysis to develop these concepts for ship structure applications.

7.2.2 Systems Level Implications of Component Correlations

The component-level failures in ship structure are generally uncorrelated independent events initially. In complex structures, component failures become increasingly correlated in complex manners as failure progresses. For example, areas of corrosion are independent locally until they become extensive spatially to weaken the structure until they fail in a collective manner, further weakening to become critical and possibly precipitating the ship's hull girder collapse.

Increasing numbers of progressive serviceability failures increases their correlation while reducing reserve strength, safety. These considerations are addressable within the Risk and uncertainty approach defined in this dissertation in terms of quantified probabilities, consequences, and the combined relative Risk. These quantities also provide insights into reserve strength in relative Risk terms.

7.2.3 Bayesian Network Models

Bayesian Network models are very useful when there are numerous variables in a network that have conditional correlations. Medical diagnosis is one example where Bayesian Networks are used to combine a number of conditional possibilities of diagnosis give evidence of symptoms presented by a patient. Bayesian Networks have been proposed **(**Straub *et. al.,* 2010 and Groden *et. al.*, 2013**)** in very narrowly defined applications with specific types of implementations (*i.e.,* fatigue crack growth estimates), that are defined using statistical process model-centric with random hyper-priors. Kim *et. al.,* (2016) have proposed Bayesian Network models for corrosion rate prediction in a cargo ship using hyper priors.

Bayesian Networks were investigated in the possible application as part of the Risk-TOC and found to be too specific in their development as data analysis tools rather than Risk analysis tools. Ship structural reliability analysis and Risk Analysis applications involve physical modeling of processes that must be reduced to statistical distributions to fit Bayesian Network models. The Bayesian Networks are not able to model time-varying changes and must rely on Markovian processes, as discussed herein. This transformation of physical modeling to stochastic modeling becomes difficult if not formidable considering the large numbers of structural details in ship structures to be analyzed and interconnected with conditional probabilities and correlations. Therefore, the Bayesian Network approach is difficult to use in current SSLCM applications. However, Bayesian Networks may provide insights into overall uncertainties and correlations in the reliability processes for those interested in pursuing this and related to the SSLCM problem. The Bayesian inference will likely be useful as a component of the physics-based approaches, such as embedding the Bayesian Network process within the physical model approach. This approach is a likely way forward to advance this the benefits of the Bayesian Networks in reliability and Risk analysis of complex ship structures. Bayesian Networks may also be used to evaluate the effects of complex correlations and Markovian processes in progressive failure in complex structural systems, many of which are unquantified to date. Bayesian Model Averaging provides insightful forecasting of structural reliability with stochastic variables and hyperparameters, as demonstrated in the examples in Chapter 6.0.

7.3 Risk-TOC and Risk Management

The Risk-TOC approach proposed is scalable to full ship analysis (as demonstrated in the examples in Chapter 4.0 of this dissertation) and well suited to analyze and manage Risk in all phases of SSLCM (including R&D, Design, Acquisition, Construction, Maintenance, Mid and EOSL, and Disposal). The Risk-TOC approach is developed and verified how to quantify Risk and TOC of mitigation options through real applications in this dissertation.

7.3.1 Risk Management Strategies

Risk Management strategies include Risk acceptance (contingencies), avoidance (design), mitigation (HSM, not OI), transfer (insurance), sharing (government institutions). The Risk-TOC trade-space approach is suitable for evaluating these approaches. The relationship of these Risk Management strategies is shown in the diagrammatic format in Figure 5.15

7.3.2 Risk-TOC AoAs and CoAs

The Risk-TOC analysis provides a unique opportunity to compare of Risk Management Strategies in a common framework to facilitate AoAs. The resulting impacts on both Risk and TOC are estimated, and decisions are made in relative terms if not absolute terms given the known information on both Risk and TOC.

In the early development of the Risk-TOC process proposed herein, there are a limited number of scenarios in the Risk Management example provided, largely because they require considerable resources to fully evaluate each variant systematically through the Risk Analysis process. This number of Risk mitigation alternatives will likely increase as the Risk-TOC process is more automated and implemented.

As a practical matter, any number of alternatives and solutions are possible within the Risk-TOC trade-space. Therefore, multi-parameter and Pareto Frontier type optimizations may be developed for each Risk mitigation alternative. In this more involved case, each scenario will be subject to a Pareto analysis as a subsystem and then compare using the overall scenario analysis comparison of alternatives in the Risk-TOC trade-space. Multi-parameter optimization is also possible. Further, development is required, when multi-parameter analysis of Risk-TOC alternatives, especially if the range of uncertainty is to be considered. In this case, information entropy will likely be useful to quantify the full range of uncertainties. Discrete CoAs are presented in the Risk-TOC examples for verification purposes. It is likely that future applications will include more CoAs as the applications and data are more fully developed.

The proposed Risk-TOC decision criteria $Min[E(Risk_{\alpha})],[E(TOC_{\alpha})]$ is relatively basic but fundamentally correct and useful to build on. Increasing the number of CoAs will also require more data to obtained/develop the stochastic characteristics (i.e., distributions and parameters) in both Risk and TOC. This increase in required data will also be necessary for automated Pareto Frontier type analysis. This will ultimately occur in the future based on big data analysis. Joint entropy or similar criteria will suit the complexity in the joint distributions of Risk and TOC as the number of CoAs and Pareto Frontier are developed within the Risk and TOC trade-space.

Given the concept of subsystems of Pareto Frontiers illustrated in Figures 5.9 and 5.10, and developed in Chapter 6.0, the Decision Maker will assess the scenario that meet their decision perspectives and requirements. The Decision Maker's considerations may be either based on stakeholder consensus, budget constraints, or institutional guidance on acceptable Risk. The Decision Makers will also like to consider the "optimum" trade-off between Risk and TOC. This investigator hypothesizes a Decision Maker will choose the minimum of both Risk and TOC. The hypothesis is proposed because, within the Risk-TOC approach, the Decision Makers primary objective is to minimize the Risk exposure within the available budget and their associated constraints. If the optimum Risk exposure is too expensive, or the minimum Risk is still not institutionally acceptable, the Decision Makers will likely consider other investments to reduce both Risk and TOC. This may require gathering additional information to reduce uncertainties (i.e., by HSM). The *RoI* and *VoI*, are then calculated as improvements in Risk-TOC. If a satisfactory combination of Risk and TOC are not found, the Decision Makers will investigate implementing a new scenario or collecting more information in quantifiable terms. Each Pareto frontier of CoAs individually and collectively may reflect the state of the art in practice; however, new investments in technologies may be evaluated to lower both Risk and TOC, thereby lowering the state of the art floor to the Pareto Frontiers.

Given the fundamentals of Risk Analysis (and uncertainty reduction) approaches discussed, it is relatively straight forward to obtain important findings regarding the immense magnitudes of costs involved in SSLCM.

7.4 Return on Investment Considerations

The Risk-TOC approach provides a means of comparing ship structural management approaches and guiding related decisions based on their relative TOC and Risk. The relative return on investment is determined by the change in TOC for the options of Risk management being considered.

An inherent natural *RoI* is created by the structural fatigue process where fatigue failure is proportional to the third power or fifth power of stress range (i.e., σ^3 or σ^5). In the context of the SSLCM applications described herein, *RoI* is determined by the total monetary benefits divided by the initial investment. This conclusion applies to both success (survival) and failure producing a large range between success and failure of the structure and a significant natural *RoI*. One of the most difficult aspects of ship structural designers relying solely on class rules and SFA is that it is impossible to achieve the exact fatigue life due to the numerous uncertainties in the fatigue analysis process (see Colette 2018). In semi-probabilistic approaches (i.e., Sieve *et. al.,* 2000, ABS 2017) are intended to be on the conservative side as an engineering approach, and the conservatism is beneficial; however, these approaches do not account for many uncertainties in the process or the systems level failure. In fact, designing to minimum criteria in the fatigue design space of wave height probabilities, loads prediction, fatigue response, and construction tolerances will ultimately lead to the "Flaw of Averages." (Savage 2012) or worse leading to the inadequate design of these complex systems.

The good news related to this natural *RoI* is that the effort required to be slightly conservative (i.e., added structural analysis and structural details with minimum stress concentration factors and minimum welding) is very cost-effective because small investments produce very large returns on fatigue life with confidence bounds in a reliability process setting. This natural *RoI* provides significant incentives for conducting reliability and Risk Analysis. The investments for conducting a reliability analysis and quantified Risk Management should be viewed as insurance against high costs and contingency costs analysis. The proportional relationships between fatigue life and uncertainties include the following:

$$FL \sim (STRESS_{range})^{3*}$$

$$Risk \sim (STRESS_{range} + uncertainties)^3$$

$$Reward \sim (STRESS_{range} + uncertainties)^3$$

$$RoI \sim (STRESS_{range} + uncertainties)^3$$

$$VoI \sim (STRESS_{range} + uncertainties)^3$$

* Exponent is 3 at midcycle fatigue, 5 at low cycle fatigue, and ∞ (infinite) at stress ranges less than the fatigue limit

One example of a high return on small investment results from fatigue life being proportional to $STRESS_{range}$ to the third power. This can be seen from fatigue response being plotted on a log scale Risk-TOC plots in Chapter 6.0. In this example, small changes in stress (via design or HSM operator guidance) produce very large increases in fatigue life. In this example the *RoI* from HSM is so large that *NPV* (given the current difference between inflation and discount rate) is almost irrelevant given the relative magnitude of Risk and TOC alternatives; however, *NPV* is easy to include for more detailed AoAs with many uncertainties, similar cost alternatives or efficient frontier based solutions. For example, refinement of options (i.e., number of sensors in an HSM) are considered, then *NPV* will become more important and still within the Risk-TOC approach for overall evaluation and AoA and provides a framework SSLCM Furthermore, commercial investment opportunities and expected rates of return might be used instead of the discount rate. In any case, any financial analysis relevant to the user's problem can be easily incorporated into the Risk-TOC approach

Given the current state of SSLCM and the possibilities of significant savings, the Risk-TOC approach is a powerful approach in assessing SSLCM approaches and related management decisions. The following benefits may be evaluated using the Risk-TOC approach.

- Defining and quantifying investment opportunities in what if mitigation strategies. This is illustrated in the applications and Risk-TOC analysis in Chapter 4.0
- Framework for assessing/estimating *RoI* of approaches to improve SSLCM decisions including RUL, SLEP, $E(TOC+)$, $E(TOC_{\alpha})T$
- System TOC and implications for AoA decisions including+ weight+ fuel (minor) – repair costs in terms of raw materials, resources, and energy involved in terms of environmental impacts can be quantified in uncertainty and terms if data is available of course.

- The lack of long-term planning results in the least favorable *RoI* defining the proverbial "penny wise and pound foolish" in quantified terms. This is especially true for fatigue and corrosion in ship structures.

7.5 Total System Performance

The Risk-TOC approach is applicable to short-term, long-term, and total ship systems design and assessments. The discussion that follows provides a unique perspective for every timeframe applicable to SSLCM and total ship system design.

7.5.1 Short-Term Approaches for SSLCM

The following Section presents a discussion on the short-term implications of SSLCM approaches (i.e., profit-focused objectives) based on the Risk-TOC approach.

7.5.1.1 Short Term Design Objectives

There is a common perception that an increase in safety necessarily influences performance and TOC. This perception is not founded in Risk-TOC type analysis and is considered an "urban myth" based on the convenience of the often-stated simplistic minimum weight objective. For the considerations of fixed design (i.e., all else being equal) SSLCM, the Risk-TOC objectives provide dominant objectives as a trade-space for decision making.

For example, the minimum structural weight design objective is not cost-effective in the long-term and has significant effects on Risk and TOC, especially fatigue cracking and potential losses in LCM, as shown in the application Sections of this dissertation. Saving weight in construction is a very short-term *RoI* perspective. Saving LCC is longer-term *RoI* and long-term profitability and sustainability. The primary reasons ships are sold early in their service lives are typically economical obsolescence due to changes in trade routes, the cost of fuel, or other factors that occur prior to significant structural failures. However, this approach is NOT economical, nor is it environmentally sustainable. More discussion on sustainability is presented in a later Section on the long-term implications of the Risk-TOC approach.

It is entirely possible to achieve a minimum weight design objective that is safe and cost-effective with the Risk-TOC trade-space. By definition, the minimum weight objective must be met within the Risk-TOC minimum objectives to provide the best trade-off in system safety and cost-effectiveness while meeting performance objectives. In other words, the performance objective can dominate the cost objective, if that is the Decision Maker's preference; however, it should not dominate safety objectives or sustainability objectives if they are also important objectives to the Decision Maker(s). In either case, the trade-off is still in the Risk-TOC trade-space.

From a perspective of the alternate hypothesis (to the minimum weight urban myth theory), it is possible to add a performance objective dimension if the Decision Maker believes that it will be significantly affected by Risk-TOC based decisions for SSLCM.

7.5.1.2 Short Term Profit Implications

In a commercial ship industry application of the Risk-TOC approach, short-term profit could be considered as a third dimension in Risk-TOC trade-space. However, in the Risk-TOC context, profit as a relatively short-term goal/constraint and as an independent variable dominates the decisions based on the sole purpose of short-term gains. This is at total odds with long term sustainment objectives quantifiable in the long-term based Risk-TOC approach. Additionally, the owners and operators are focused on short term profit. They are not responsible for long-term Risk because they have transferred it to insurance companies based on certification by classification societies. In commercial ship applications, there is no long-term incentive to reduce Risk or TOC. In the long-term, minimum Risk and TOC provides maximum profit (by definition). However, commercial ship profit objectives focus on recovering the owner's initial investment over a five to ten-year period. Thereafter, the ships are sold to other owners less concerned with decisions on structural LCM and service life are further driven by short term goals.

The short-term profit approach to SSLCM is not sustainable for institutions (i.e., governments and public funding) that are self-insured, operate assets for the long-term, and must take both financial; therefore, technical Risks assumption. Additionally, because short-term profits are not required, and Risks are assumed, the institutions are more likely to consider the longer-term TOC. From a sustainability perspective, the goals of reduced Risk and TOC maximizes long-term sustainability.

7.5.2 Long Term Implications of RUL and EOSL

The TOC calculations and CoA examples shown in Chapter 6.0 of this dissertation include both expected costs incurred from maintenance, either as a cost increase or deduction depending on the specifics of the application. These maintenance costs incurred or saved are largely resulting from the costs avoided by preventative maintenance or, conversely, the costs incurred from inadequate design, manufacturing, deferred maintenance. The added maintenance costs from inadequate design, manufacturing, and deferred maintenance typically include unplanned maintenance activities and potentially an emergency drydocking. The emergency drydocking produces high costs in the tens of millions of dollars, depending on how long the ship is in service.

One of the most common arguments for adding structural weight is that it will increase fuel cost to transport the additional weight over the lifetime of the ship. This objection for increased structure must be evaluated on a case by case basis; however, for military ships, the added fuel cost is negligible in comparison to cost saved over the life of the ship, from both fatigue and corrosion. Risk-TOC focused structural design, and proactive maintenance can be optimized for longevity minimizing weight impact at all. Furthermore, there is substantial *RoI* in any case of increased accuracy and fidelity of design tools and approaches. In practice, failures affecting serviceability must be repaired to achieve expected levels of operational safety and will result in increased TOC. In addition to the practical failure limits defining serviceability, the economic considerations often define service life or the EOSL. However, the failure limits frame the definition of service life in the context of TOC.

Given the range of uncertainties involved in Risk and TOC, it should be no surprise that RUL and EOSL are not discrete numbers as preferred by many Decision Makers. Rather RUL and EOSL are processes that transition over time, reaching either a threshold in TOC or Risk or both. The benefits of evaluating both Risk and TOC in the framework proposed that planned replacements can be made with a quantified basis. One of the primary benefits of PHSM includes supporting information to reduce uncertainties (i.e., in fatigue life) associated with EOSL decisions. This also applies to RUL considerations.

The Risk-TOC approach provides the Decision Maker with a means to quantify the full scope of uncertainties involved in SSLCM and evaluate the benefits, cost, and Risks associated with SLEP and EOSL decisions.

7.5.3 Risk-TOC and Total Ship Life Cycle Performance

Although the Risk-TOC approach proposed in this dissertation addresses the primary hull structure, is may also be considered for a holistic approach to the entire ship design process and total ship TOC. In this holistic design approach, TOC and Risk could extend beyond the hull structure to include key performance metrics, reliability, and availability. In this application, the uncertainty is a monetized component of Risk. Dorrey *et. al.,* (2015) addresses monetizing Risk in a Decision Theory approach. The Risk-TOC approach monetizes uncertainty in broader terms of Risk and discussed extensively in this dissertation. This holistic approach to Risk-TOC could form a basis for future research and development efforts.

Performance requirements are important in initial requirements analysis and development where performance trade-offs are made in trade-space trade-offs. In this case, the major considerations may include the number of crew and their performance, high-speed, and seakeeping as examples. As the design matures, the decisions within the Risk-TOC trade-space become more restrictive, and the Risk-TOC trade-space considerations dominate the SSLCM decision process.

7.6 Sustainability of Ship Structure

The current commercial approach to Risk Management is for operators/owners to transfer Risk to class and insurance companies. This reduces the incentive to favor short term profits and not long-term Risk Management strategies to increase long term profits and long- term sustainability. Ship Classification Societies have limited incentives to reduce long- term Risk, TOC, or sustainability without outside societal influences and initiatives.

This is in contrast to government institutions that do not transfer Risk and have far different goals to Risk Management, including Risk avoidance, both minimizing TOC at maximum service life and thus maximize sustainability.

It is proposed here that sustainability be defined in terms of resource allocation and consumptions include the economics associated with the sustainability of energy and entropy with minimum TOC as a good starting point for future work in this area. Risk-TOC provides the fundamental basis for long-term decisions. This illustration (and hypothesis) is further developed by testing data in the context of sustainability.

Given budget-constrained economic conditions and aging legacy fleets, there appears to be an outdated perception that the added cost of preventative measures (i.e., additional structure) will lead to increased structural weight, resulting in higher fuel costs and no payoff in LCC savings. This antiquated design philosophy is based on the time-honored approach of estimating shipbuilding costs by the pound of steel used in construction. However, with the current capabilities available to predict loads, structural response, probabilistic reliability, HSM, and cost implications, this may no longer be the case. In commercial applications, Gratos and Zachariadis (2005) found by using LCC analysis, the statement "carry cargo, not steel" does not stand up to scrutiny in any foreseeable economic environment. Gratos *et al.* (2009) states,

"ships built with corrosion allowances, which are truly adequate for the ship's design life, when all factors have been taken into account, have a lower Life Cycle cost per annum (AAC) for the maintenance of the integrity of their structure. This, despite the fact that they would carry a slightly smaller quantity of cargo and, therefore, their income over time would be marginally less. This appears to be a general truth regardless of the inflation environment. Furthermore, these ships are more reliable performers having a lower average annual downtime. A side benefit of such construction would be greater safety since it is accepted that steel renewals do not always restore the effectiveness of the ship's structure. In addition, the increased scantlings serve as a much-needed safety margin for hull strength and fatigue."

Preventative measures and their TOC implications warrant a closer look in all phases of a ship's life cycle. Keane *et. al.* (2017) discuss the importance of TOC reduction in military ships.

Minimizing Risk-TOC will be a valuable decisional approach for optimum long-term profitability and maximum sustainability. Risk-TOC with profit and sustainability considerations requires trade-offs in societal values that are voluntary based on perceived value or societal emphasis required to achieve sustainable industries. Risk-TOC provides a reasonable approach to inform long term decisions. The Risk-TOC framework presented in this dissertation is well suited for evaluating the effectiveness of long term sustainability management strategies; however, details of their inclusion is recommended for future research.

7.7 Prognostic Hull Structural Monitoring

Hull structural health monitoring has multifaceted benefits in providing feedback on design assumptions, operator guidance, and provide valuable information on the ability to extend the hull's service life. It is possible to assess the *RoI* of implementing an HSM system using the Risk-TOC approach.

7.7.1 SHM vs. HSM

In many industries, the long-term structural monitoring is termed Structural Health Monitoring (SHM). Although the name Structural Health Monitoring seems generic on the surface, a closer look at the literature (Pegoretti 2018, Lynch, *et. al.,* 2016, Richards, *et. al.*, 2013 and Roach, 2016) reveals that SHM applies to an approach for detecting structural failure in a specific structural member consisting of multiple independent load paths. Often, the failure is detected by a reduction in load carry capacity, and failure of that member is inferred. Detecting a change in vibratory response has been proposed for detecting a change in structural response due to partial or complete failure. Given these approaches have been applied successfully to redundant structures, modern ships do not have any structural redundancy in the sense of multiple independent load paths that are able to carry the load if one member fails. Modern ships are welded monocoque structures. Although there is often an unquantified measure of reserve strength in ships, there is no structural redundancy. This is very critical when there is a potential for fast fracture to occur. In regard to monitoring approaches for ships, the author is proposing an alternate prognostic approach for SSLCM as contrasted to the monitoring of redundant structures.

In the context of the work presented in this dissertation, PHSM forms a proactive approach for measuring structural response and forecasting the probability of failure in the future. The prognostic HSM approach is in direct contrast to SHM that is used to measure and detect a failure in progress. As a reactive approach, SHM results in much higher Risks in ship structural applications for reasons similar to Optimal Inspection described previously.

As described previously, long-term monitoring is required to track independent hyper-parameters and to quantify the uncertainties in prognostic forecasts. Long-term fatigue damage assessments are a cost-effective approach for life cycle management as presented by Stambaugh *et. al.,* (2014b and 2019).

The differences between HSM and SHM, as defined here, are analogous to the medical profession and differences between proactive preventative care and reactive care to diagnosed illness and disease. PHSM is a proactive approach, and SHM is a reactive approach.

7.7.2 HSM VoI in Prognostic Applications

The basics of an HSM are well defined by Kaminski *et. al.,* (2010) and Collette *et. al.,* (2013), including the structural sensing devices, recording equipment, and data storage. The traditional sensing equipment typically includes strain gauges that record the response of the structure and fatigue damage is calculated as given by Drummen *et. al.,* (2014 and 2019). The number of sensors can be minimized with calibrations from Finite Element Models (FEM). The data reduction can be accomplished onboard or ashore.

Hull Structural Monitoring, when initiated early in the ship's life, will provide significant reductions in both TOC and Risk. Uncertainty propagation and reduction, as illustrated in the examples presented in Chapter 6.0, reflect the importance placed in this dissertation on the definition of uncertainty and how it is quantified, in order to show the benefits of reducing uncertainty by gathering additional information.

For example, an HSM system provides measured information on the fatigue load history such that proactive measures can be made to extend the ship's service life by proactive maintenance limiting damage rather than reactive maintenance after the fact. The cost of unplanned maintenance from an emergency dry-docking often exceeds available maintenance budgets and losses from reduced Operational Availability (Ao) are incurred. The value of HSM can also be gauged by having quantified information on the remaining fatigue life (if any) as the ship approached its EOSL. If the measured fatigue damage is low and a SLEP is possible, the TOC savings are on the order of the cost of a new ship minus the cost of the SLEP, or prorated fraction there-of. The TOC savings associated with HSM are in the millions of dollars for a single ship and in the billions of dollars for a class of ships based on the quantified ability to extend the service life, replacement cost of the asset, cost of the SLEP, and the number of years associated with the service life extension. These examples highlight the enormous benefits from minimal proactive HSM investments, given the major TOC investments involved in ship assets. These TOC savings form a basis for estimating cost savings associated with HSM, value of information, and *RoI* calculations.

7.7.3 Long-Term Prognostic HSM and Implications

In ship structural design, the SFA, and extreme loads estimates, annual wave probabilities are used to infer load histories. In reality, the wave loading profile is not a stationary process; it is built up of a probabilistic summation of individual independent stationary load probabilities given a specific set of assumed operational and wave environmental profiles. The SFA approach is a good approximation to the lifetime loading for initial design; however, it does not reflect the actual occurrences of influential loading from the random occurrences of the loading. In other words, load magnitude, frequency, and sequence all matter within the lifetime experience of the ship's structure and has a significant effect on crack growth. All of these factors have a significant influence on fatigue and extreme loading as compared to the annual wave expectations. The effects of heavy weather on crack growth has also been reported by Hodapp *et. al.,* (2013).

The structural loading history and independent hyperparameters (e.g. environmental and ship operator influence (or not) by avoiding heavy weather) are important considerations in fatigue crack growth. The exact loading and magnitude sequencing cannot be known a-priori because the loading is a non-stationary process over the long-term; therefore, the time that a crack will grow in the storms cannot be known a-priori. Furthermore, crack growth rates are very high in conditions with high wave heights and producing high stresses in the hull structure. Crack growth is proportional to the square of stress intensity and is intern directly proportional to wave heights encountered. The fact that cracks grow fastest in heavy weather and storms also plays an important role in assessing Risk of fracture, given a crack exists, as shown in the example Risk-TOC application. This implies the ship structure should be monitored and inspected after a heavy weather event because those conditions drive crack growth. In the context of LCM planning, the load histories are circumstantially related to heavy weather events and a lesser extent, the degree of heavy weather avoidance being practiced by the ship operators. This weather focused inspections can be supported effectively by HSM results to further focus inspections in critical areas as determined by the systems analysis. This weather-related inspection is in contrast to proposed LCM approaches based solely on Optimal Inspection scheduling at fixed intervals. The fixed interval sampling of the highly random non-stationary process is, in fact, a randomized sampling process, not as assumed by Optimal Inspection for sole LCM processes proposed at all.

Irrespective of the limited quantified benefits of inspection approaches, they appear to have provided limited qualitative benefits when cracks have reached lengths where they either leak or are very large and visually obvious (and high Risk as shown in Chapter 6.0). In practice, ships are inspected for both corrosion wastage and fatigue cracks. There appears to be a correlation and symbiotic benefit between corrosion inspections and finding large fatigue cracks that form part of the qualitative, prescriptive approach for designing and maintaining ship structures. This approach benefits from modern steels with enough toughness to limit the most catastrophic fractures and leak-before-break approach suggested by Moan (2018). More research and development will likely be beneficial in providing cost-effective with quantifiable benefits of inspection approaches for ship structure. The Risk-TOC approach does provide a means for assessing new or emerging technologies as to their effectiveness and *RoI*.

7.7.4 Evaluating Long Term Monitoring Alternatives

The examples presented in Chapter 6.0 of this dissertation show the cost benefits of HSM in lowering both Risk and TOC. The *RoI* is derived based on the initial cost and uncertainty and Risk reduction for the examples shown. The Risk-TOC approach applies to the evaluation of other HSM approaches as well, including Virtual Hull Monitoring, relying on determining wave height post-deployment/voyage from a database (i.e., NOAA Wave Watch III (2019) and Copernicus Marine Environment Monitoring Service (2019). Combinations of approaches may be evaluated, as well. Table 7.1 from Stambaugh *et. al.,* (2019) provides a qualitative comparison based on the author's experience. In Table 7.1:

- FDS is a passive Fatigue Damage Sensor that is spot welded near structural details (see Kaminski *et. al.,* 2010).

- Strain Gauge (Ad Hoc Wave) refers to hull structural strain measurements with conventional strain gauges and obtaining wave height data on an as-available basis via dedicated trials with wave buoy, local wave buoys, or similar approaches.

- Strain Gauge (SAWB/Radar) refers to the measurement of hull structural strains and either inferring or measuring local wave height continuously with real-time or post data analysis.

- Strain Gauge (Satellite Wave) refers to the measurement of hull structural strains and either inferring local wave height continuously from a database with post data analysis.

- Vship (Satellite Wave) refers to the measurement of hull structural strains and either inferring local wave height continuously from a database with post data analysis.

Each HSM option has a trade-off between cost and accuracy. Quantitation of the cost-benefit (i.e., accuracy) of these approaches awaits specific applications of the Risk-TOC approach.

Monitoring a complex structural system involves Vship via analytics, including FEA models, because it is not cost-effective or even possible to monitor 100% of the structure. The number of monitoring sensors becomes a trade-off between accuracy and Risk (i.e., uncertainty) reduction. This trade-off is best made in the context of Risk and TOC.

For the AE and Vship examples, subsystem optimization is conducted in the context of the Risk-TOC trade-space. The subsystem optimization (illustrated in Figure 5.9) provides a means for evaluating the effectiveness of resource investments

Table 7.1 shows an accuracy category for Operator Guidance. This option has not been discussed herein as a Risk mitigation strategy; however, it is certainly possible to assess the implications of this approach in the context of Risk and TOC. Assessing the Operator Guidance CoA is complicated by the uncertainties of both policy of setting the operational limits or Risks and the human in the loop (operators at least for the short term) interpretations of the prescribed limits or guidance. In other words, implementing operator guidance has potential for misinterpretations; however, it is a worthy goal to pursue with benefits in reducing TOC and Risk.

Table 7.1 Example Considerations in evaluating HSM alternatives

		Fatigue Damage Sensor (FDS)	Strain Gauge (Ad Hoc Wave)	Strain Gauge (SAWB/Radar)	Strain Gauge (Satellite Wave)	VShip (Satellite Wave)
Accuracy	Real Time Guidance	N/A	High	High	High	Moderate/Low
	Validation	Low	Low/Moderate	Moderate	High	Low
	Life Cycle Maintenance	Low	High	High	High	Moderate
	Remaining Useful Life	Low	High	High	High	Moderate
Cost	Planning	Low	High	High	High	High
	Hardware	Low	Moderate	Moderate	Moderate	Low
	Installation	Low	High	High	High	Low
	Maintenance	Low	Moderate	Moderate	Moderate	Low
	Data Collection	Moderate	Moderate	Moderate	Moderate	Moderate
	Data Analysis	Low	Low	Moderate	High	Moderate/High
Other	Cyber Security	Low	High	High	High	Low
	Ship Location	Low	Low	Low	High	High

7.7.5 Fleet Perspectives

A systems structural reliability approach has been proposed herein for a single system, and there is no reason to believe it cannot be extended to fleet applications. This also implies that the Risk-TOC approach can be extended to fleet applications also. Fleet systems analysis will provide valuable insights into life extension strategies associated with homeport rotations or trade routes as necessary to level the fatigue load among the fleet. However, the details of this effort are left for other researchers to consider.

7.8 Human Error and Risk

The aspects of human error have not been considered explicitly in this Risk quantification approach but do exist in all aspects of design, analysis, construction, and operation. Any one of these options are possible to consider within the Risk-TOC approach as deemed necessary by the Risk Analysts and Decision Makers. This is particularly important when considering prescriptive and direct analysis approaches that are not fully validated for all types of ships. Furthermore, analysis tools are not currently able to adequately predict slamming impact-related fatigue loading in higher speed ships and boats, and underprediction of loading is common.

One all too common example of human error in the structural design engineering, in general, is discussed by McRobie (2004) as:

"Loosely speaking, structural engineering involves "loads versus strength". It is a failure of our system of educating structural engineers that the strength side of this dichotomy is usually given so much pre-eminence. It would be a caricature to suggest that designers expect to look up loads in a code of practice, and then invest many man-hours in detailed finite element analysis of the structural behaviour under those loads. Sometimes, though, this caricature does not seem to be so far from the truth. Structural behaviour is often calculated to assumed accuracies of a few percent. Although codes may dictate specific figures for what a structure "should" be designed for, the reality of what a structure may subsequently experience is far more intangible. Ultimately, structural design is a question of the management of uncertainty, and the greatest uncertainties are usually in the loads. If structural engineers wish to be involved in the design process as decision-makers rather than as mere service-providers, then they need to engage with this process of assessing the possibilities that may occur to their structure. There is a three-stage hierarchy: 1) How does a structure behave, given a load environment, 2) What is the nature and physics of that load environment, and 3) What is the chance that such a load environment will occur? Improved modelling only addresses the first two stages: fully coupled fluid-structure interaction CFD simulations of long-span bridge aeroelasticity; explicit finite-element simulations of aircraft impact events; computational models of crowd behaviour; - none of these address the question "which storm/ aeroplane/ crowd/flood/ earthquake/ terrorist/ incident/ accident/ tsunami/ volcanic event etc. ***Again, to caricature the process, someone will pick a scenario, and the structural engineer will then try to design a structure that just satisfies that criterion, usually to a remarkably inappropriate degree of [presumed]accuracy." [Emphasis added by author]***

"Until such time as the Bayesian perspective is the norm, designs will be built which await not-to-be-quite so- unexpected surprises; engineers will have the easy excuse at the ready; clear thinking and coherent debate will be absent, and the rationale behind engineering decisions will be obscured by the myth of objectivity and the frequentist language inherited from historical scientists who had very different aims. Frequentist methodologies are the wrong approach to the decisions that engineers need to make, decisions that involve assessments of abstract future possibilities based on incomplete and abstract information."

This quoted statement is fully applicable to the current state of ship structural analysis.

The human error aspects in design, construction, and operation are important in any engineering analysis in general, Risk Analysis in specific, and further research is recommended in this area.

7.9 Risk-TOC Reserve Strength Robustness and Resilience

When Risk Analysts and Decision Makers plan for the known unknowns (i.e., uncertainties), they will be positioned to evaluate and respond to rare(r) events (unknown-unknowns). This planning reduces vulnerability (increasing resilience) even if the hazard is uncertain. This is implied by Krugman (2006):

According to Paul Krugman, NY Times, 3/3/06

"If good luck happens when preparation meets opportunity, bad luck is what happens when lack of preparation meets a challenge".

In general, luck is more likely when you plan, prepare, and position for success and opportunity (Also Known As upside Risk or Opportunity Management)

Resilience and robustness are also important aspects of Risk Management, and further efforts in this area in the shipping industry will benefit from the fundamental Risk-TOC approach presented herein.

There are many definitions of resilience in the literature, and many relate to reserve capacity in terms of robustness (Yodo *et. al.,* (2016) and Wolinski (2013)). A new definition is proposed based on the reliability and failure limit states discussed in Section 2.1.4, as a transition from serviceability failure to progressive failure and ultimate collapse failure. This definition of reserve strength can be characterized by total changes in system Risk. For example, the author's proposed Risk based definition of robustness is:

$$R_R = \sum_{i}^{N} \frac{R_{ui}}{R_{si}} \tag{46}$$

Where R_R is the total Risk based Robustness, and R_{ui} is the Risk of ultimate failure, i, and R_{si} is the Risk of serviceability failure i.

In this example, the transition of risk also involves the transition of reserve strength as calculated from structural reliability approaches. The transition of reserve strength and its implications on resilience depend on the severity of the hazard and extent of recovery actions required to restore capability over a period of time as the transition of the reserve strength, amount of robustness, and mitigative actions. In this process, the hazard definition and amount of robustness provided are key ingredients in the amount of failure that occurs and the amount that has to be restored over a period of time. In short, planning and preparation in all aspects of the hazard estimation, reserve strength, robustness, and recovery actions are all topics to be considered in the Risk-TOC approach.

In theory, when Risk planning, mitigation planning has taken place, and contingencies have been considered. This planning also has implications in resilience in "avoiding" or minimizing unexpected occurrences, or infamous Black Swans (Hajikazemi, *et. al.,* 2015). The examples of *RoI* included here also provide a perspective on upside Risk or opportunity costs savings. A corollary to Risk planning is upside Risk is what happens when planning meets opportunity. Both implications of Risk planning and upside Risk are areas to develop in further research.

8.0 CONCLUSIONS

In the design and engineering of complex structures, there are numerous ways to view and solve problems, and this is also true for Ship Structure Life Cycle Management (SSLCM). The Risk-TOC framework is general enough to allow further development and integration of existing approaches and new technologies as they become available. The Risk-TOC approach presented in this dissertation is developed to provide designers and engineers with an overarching framework to evaluate SSLCM objectively, quantitively addressing uncertainties for Risk Analysis and Risk Management, and to stimulate further discussion and development of Analysis of Alternatives (AoAs) and Course of Actions (CoAs). The Risk-TOC framework provides an approach for evaluating SSLCM alternatives from feasibility development to disposal. The Risk-TOC general framework also provides a quantitative means for comparing the effects of different failure modes (i.e., corrosion and fatigue cracking) on the structural system. This approach also provides information for the Decision Makers to quantify uncertainties required to make cost-effective decisions to the extent possible with available information.

8.1 New Research Perspectives

The research presented in this dissertation began with the goal of understanding how to make quantified Risk-based decisions for complex SSLCM system. In reviewing prior Decision Theory-based approaches for SSLCM, many fundamental issues were identified along with their underlying assumptions in the approaches that did not match the realities of the decision making processes or the full range of Risks. It became clear there was a need to review the fundamental assumptions and start over with basic definitions of uncertainty and Risk in the context of the ship's structural system (Chapter 2.0 and Appendix A) as compared to other structures. In reviewing the decision processes for SSLCM, it also became clear there is a trade-off between Risk (safety) and Cost when in making decisions. Therefore, the new perspectives resulted in further investigation into the fundamental definition of systems failure and its implication for Risk Analysis and Risk Management. This investigation resulted in the Risk-TOC approach for SSLCM. The extension of this process is the incorporation of Prognostic Hull Structural Monitoring and its role in SSLCM.

The Risk-TOC approach is intended to be a foundational approach for further development. The Risk-TOC approach, as described, will be useful in this context of tailoring approaches in technology transfer from other industries as well.

Key topics of this research presented in this dissertation include:

- Analyzed measured hull strain data and found correlations and independencies required to perform a systems correlation analysis for thousands of structural details (typical of ship structures), not just one or few structural details as proposed by others.

- Introduced a new concept for systems-based analysis of complex ship structure applicable to transitions in serviceability failure, progressive failure, to the ultimate strength of the primary hull girder and subsequent failure modes of fatigue, fracture, buckling, yielding, and watertight integrity.

- Developed and demonstrated an approach on how to compare individual alternative Risk Management approaches in a Risk-TOC trade-space.

- Proposed and demonstrated an approach on how to propagate independent uncertainties with BHP and evaluate uncertainty related to Risk. Benefits of PHSM are shown as an effective Risk Management approach in reducing uncertainty and Risk by the BHP approach.

- Developed and demonstrated an approach for making optimal decisions in the proposed Risk-TOC context. The proposed best decision approach is the minimum combination of both Risk and TOC within the constraints of the Decision Makers budget and safety expectations, typically intuitionally based when decisions are being made in public settings. $Min(E(Risk_{\alpha})_{T}],(E(TOC_{\alpha})_{T})$

- Developed and demonstrated an approach how resulting systems reliability, Probability of Detection *(PoD*) and Optimal Inspection (IO) leads to high Risk approach for managing SSLCM and an improved approach to schedule inspection (i.e., after encountering a heavy weather storm)

- Discussed insights from the results of example applications of the Risk-TOC approach and recommendations to extend the Risk-TOC approach for SSLCM, including decisions that affect environmental sustainability.

- Proposed a new hybrid SN+FM Total Life approach as a simplified approach (vs initial flaw-based Fracture Mechanics) for estimating the time for fatigue cracks to reach a critical size and related Risk. This approach is intended to be useful in preliminary assessments of total failure estimates in Risk-TOC analysis and to be useful as a starting point or point of comparison for further research on this topic.

The following conclusions are drawn from these new research perspectives.

8.2 Research Conclusions

The Decision Theory and Optimal Inspection based Risk Management approaches proposed for ship structures are based on those developed for civil and offshore structures with numerous assumptions that are not applicable to ship structures. The misapplied assumptions include complete disregard for the number of welded structural details, kilometers of weld, probability of detecting fatigue cracks, and the total lack of redundancy in ship structures. Those misapplying Decision Theory and Optimal Inspection based Risk

Management approach often state the benefits of redundancy in ship structure. This is a complete misunderstanding of the structural characteristics of ship structural failure from unstable fast fracture along with numerous other assumptions that are not applicable to ship structures. Although ships are constructed using many structural members; 1) there are no independent load paths between them, 2) there is little reserve strength when fast, unstable, brittle fracture occurs, and 3) Decision Theory and Optimal Inspection based Risk Management approaches do not explicitly consider the Risk of catastrophic failures in ship structural system.

Furthermore, Decision Theory and Optimal Inspection based Risk Management approaches are:

1) Based on discrete probabilities and not based on the realities of the continuous probabilities,
2) Based on expected value or expected utility and,
3) Lack clarity in the full range of uncertainty required for a full Risk assessment and related decisions.

The Decision Theory and Optimal Inspection based Risk Management approach definitions of uncertainty use discrete probabilities that are rarely discrete in complex structural systems because the natural probabilities occurring over time are typically continuous and not discrete events as modeled by classical Decision Theory.

The Decision Theory and Optimal Inspection based Risk Management approach proposed for ship structure produces Risky conditions when considered in the context of the realities of random non-stationary hull structural loading, probability of failure, probability of not detecting failure, and cost of the approach and consequences if failure does occur.

The Risk-TOC based SSLCM proposed considers the likelihood of brittle fracture when fatigue failures are probable based on an analysis of the stochastic nature of SSLCM over the service life.

This dissertation builds on the fundamentals of systems reliability and Risk Analysis that are unique to ship structural components and system, including a correlation analysis of the system loading, serviceability definition, failure progression processes, redundancy, and definitions for *RoI* and *VoI* within the Risk-TOC framework.

The Risk-TOC approach provides tangible and relatable benefits of understanding uncertainty in Risk terms. The Risk-TOC approach provides a more informed perspective than Reliability and relative Beta (β) parameters proposed in many civil industries that do not quantify the uncertainty in the processes associated with SSLCM. Reliability Beta (ß) based approaches have no quantified way of comparing the financial impact of uncertainty or its propagation. The Risk-TOC approach is a quantified basis for comparison given the magnitude of sums of money at Risk (i.e., significant Risk exposure). The Risk and TOC framework quantifies and monetized uncertainties and facilitates Risk Analysis of alternatives in uncertainty and Risk reduction in terms of *RoI* and *VoI*. Monetizing uncertainty provides an objective base for decisionmakers to apply their utilities and make informed decisions.

The Risk-TOC approach provides a framework for making informed decisions for SSLCM. Further conclusions that are drawn from the demonstration and verification of the Risk-TOC approach include:

- Assessing fatigue failure and its life cycle management alternatives using Risk Analysis provide a basis for making decisions involving estimates of statistical uncertainty, the costs to mitigate the uncertainties, and assess related consequences.

- Management of ship structural reliability by visually detecting fatigue cracks and repairing them is potentially high Risk for a ship with thousands of structural details**.** Application of SFA is a safe life approach for SSLCM, and PHSM is useful in quantifying RUL and EOSL for major SSLCM decisions.

- The Bayesian Model Averaging (BMA) based approach with Bayesian Hyper Parameter (BHP) perspectives provide valuable insights into stochastically quantified uncertainties, their reduction, and the VoI evaluations of perspective Risk mitigation strategies.

- Redundant Structures benefit from Structural Health Monitoring (SHM), while non-redundant structures benefit from Hull Structure Monitoring (HSM). SHM is a reactive approach, and HSM is more proactive in forecasting maintenance needs.

- Reliability-based analysis and PHSM reduces uncertainties in failure forecasts needed to quantify Risks associated with SLEP and EOSL decisions that involve significant capital expenditures and result in high Return on Investments that also result from Fatigue Life being proportional to the third power of stress (FL ~Stress^3).

- A discussion Chapter presents a full range of implications from short-term profit motivations to long-term environmental and industrial sustainability.

Ship structural design has evolved based on structural engineering principles with a prescriptive rule-based elements derived from empirical factors. This approach has produced a damage tolerant structure with empirical safety factors that have not been fully characterized in Risk terms. Currently, analytical approaches based on physics-based hydrodynamic predictions of the hull loads and high- fidelity Finite Element Analysis have been applied without the benefits of the empirical elements and have resulted in failure when uncertainties have not been fully quantified, as discussed in this dissertation. There is a significant need to correlate the new analytically based approaches with measured information (HSM) to reduce the uncertainties and Risks that have been empirically included in the prescriptive rules. The Risk-TOC approach provides a framework to evaluate the new approaches and their related uncertainties.

9.0 RECOMMENDATIONS

In the process of developing the fundamentals of systems reliability, uncertainty propagation, and Risk-TOC trade-space, it became apparent there are numerous areas for further data collection and refinement. The research presented is based on fundamental considerations and is subject to verification, further development of the Risk-TOC approach, and additional applications. Additional research is recommended to improve the Risk-TOC processes including:

- The decision criteria based on Expected Value *E(V)* used in Decision Theory are subjective discrete values and do not reflect the continuous processes associated with SSLCM. There is a need to consider a wide range of uncertainties associated with Risk in complex systems. It is recommended that other researchers and engineers revisit the decision philosophies (i.e., Savage 1970, MiniMax) and the proposed $Min(E(Risk_a)),(E(TOC_a))$ based on the Risk application where loss aversion is in play vs loss with potential gain as in the financial and economic applications.

- The Bayesian Model Averaging (BMA) and Bayesian Hyper Parameters (BHP) approach proposed for reliability forecasting is based on limited amounts of data on the hyper-parameters and full characterization of them. Additional research is recommended to further develop the BHP approach with statistical parameters and probability functions. The BHP and alternate approaches for reliability forecasting will be useful in the further development of uncertainty forecasting in the SSLCM context.

- Risk associated with human error (accidental or unintended based on ignorance) in structure failure, *PoD* of fatigue cracks, and fracture failure requires further consideration in Risk Analysis of SSLCM.

- In the context of Risk-TOC, *VoI*, and design of experiments are key areas that will benefit from additional research and decision-making processes for instrumentation selection and SSLCM related implications.

Additional research was identified in the process of developing the Risk-TOC approach in general and include:

- The structural reliability approach presented by Ayyub *et. al.,* (2014) was used to develop a probability of failure estimates that include the dominant uncertainties in loads and responses. Most of this work was based on prior efforts in structural reliability by Hess *et al.,* (2003), Hess *et al.,* (2002a), Hess *et al.,* (2002b) and at the Office of Naval Research (ONR) for the structural reliability response and

Stambaugh *et. al.,* (2014b and 2019) and Hageman *et. al.,* (2014 and 2019) for the structural reliability loading. There is continuing research in this area sponsored by ONR and highly recommended based on the potential economic implications of Risk-TOC. Further research in identifying and quantifying uncertainties is recommended along the lines recommended herein and by Collette (2018) and Moan (2018). The systems reliability, updating, and Risk-TOC framework are intended to be useful guidance in these future efforts.

- Acquire and quantify the Probability of Detection (*PoD*) data for ship inspections during construction and in-service that is compatible with fatigue, design approaches. This effort should consider related benefits of hull structural monitoring. *PoD*, for random field modification and additions, should be investigated along with quality tracking in construction. The in-service inspections should include consideration for the relationship between ship inspections scheduling and encountered heavy weather.

- Investigate and quantify the uncertainties related to catastrophe theory or outlier events will be beneficial as an extension to the total system Risk-TOC process for analysis and decisions.

- Quantify the systems approach to progressive failure of both corrosion, local deformations, and buckling that correlate spatially and temporally, as was shown in this dissertation for fatigue cracking. It is envisioned that the correlation will resemble the Markov processes shown for fatigue cracking to fracture transition.

- Quantify the uncertainties in fracture failure prediction and related aspects required for a full Risk Analysis of ship structure. Fracture in the hull structure remains the elephant in the room and source of ignorance on the full Risk assessment of ship structures. Related to this, Bayesian updating of structural reliability of extreme events using measured and censored data will be useful. Additional refinements are recommended for the SN+FM Total Life approach for practical estimates of the implications of fatigue crack growth and its relationship to fracture predictions in Risk Analysis

- A systems structural reliability approach has been proposed for a single system, and there is a reason to believe it can be extended to fleet applications. This finding also implies that the Risk-TOC approach can be extended to fleet applications also. Fleet systems analysis will provide valuable insights into life extension strategies associated with homeport rotations or trade routes as necessary to level the fatigue load among the fleet. However, the details of this effort are left for others to consider and progress.

Many processes in ship design in general and ship structural design in specific are based on empirical formulations, including calm water and quasi-static approaches where results are treated as deterministic. However, the majority of ships and boats operate in a random seaway, the structural material responses are random, and the models are imperfect (i.e., linear assumptions for simplicity). This reality leads to many instances where failure is treated with an amount of surprise and Root Cause Analyses (RCA) are lacking. As a result of this situation, there is a need for a text or similar reference works on statistics for Naval Architects in general and ship structural designers in specific. Related recommendations include:

- Statistics course(s) and texts to provide a fuller understanding of statistic history and philosophy with required reading to include: "Flaw of Averages" by Savage (2012), "Willful Ignorance," by Wiesberg (2014), and "Signal and the Noise" by Silver (2015)

- Statistics course(s) and texts on Bayesian updating that reflects the original philosophy of Reverend Bayes and not specific to conditional probabilities and examples borrowed from the medical fields as examples. The majority of SFA analysis relies on prior information (e.g., sea conditions, speeds, headings, and loading) that are subject to updating throughout the ship's life with PHSM for useful forecasts of structural condition, RUL and EOSL determinations, and decisions

Additional research and development are recommended for the integration of the Risk-TOC approach Risk and TOC for ship design process applications to the monetization of uncertainties in the processes.   This holistic approach will be highly beneficial to apply quantitative Risk Analysis and Risk Management through the entire SSLCM. The basics of the Risk-TOC could form a foundation for further work in this emerging area. The application of this holistic Risk-TOC approach should include industrial and environmental sustainment investigations with implications and benefits for the role and evolution of ship classification and regulatory requirements.

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Appendix A

Statistical Correlation of Structural Component Loading

A.1 Introduction

Estimating the fatigue reliability of large complex systems of numerous fatigue sensitive structural details requires knowledge of how the probability of failure or each detail relates to the other on a systems level. This system reliability estimation depends on the amount of statistical correlation between the critical structural details in the system on both the load and resistance part of the reliability calculations. Assuming the levels of correlation associated with structural detail construction are covered in the assignment of fatigue classification, the resulting levels of structure correlation is dominated by the encountered loading. In the loading predictions, if the details are correlated, they experience similar load histories, and the probability of failure is calculated as independent events as described by Walpole (2012) and Ayyub (2003). In the case of failure being defined as an independent event, the system probability of failure is determined by the minimum probability of failure calculated. The objective of this investigation is to determine the statistical correlation of measured strains occurring in a naval frigate type hull girder structure and local details in response to wave induced hull girder bending.

A.2 Approach

According to Walpole (2012), Pearson's correlation coefficient (r) is the covariance of the two variables divided by the product of their standard deviations written in simplified form as:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]\,[n\sum y^2 - (\sum y)^2]}} \qquad \text{(A-1)}$$

Here x and y are time-ordered pairs in the time history, and n is the number of samples.

Pearson's correlation coefficient ($\boldsymbol{r}$) is a measure of the linear association of two variables. The values of the correlation coefficient vary from +1 to –1. Positive correlation coefficients indicate the paired variables are increasing or decreasing together. Negative correlation coefficients indicate the paired values are varying in opposing magnitudes. The positive correlation typically indicated variables in-phase and negative correlation as out of phase. Values of correlation coefficient close to zero indicate a low association between variables, and those close to –1 or +1 indicate a strong linear association between two variables.

A correlation analysis also benefits from a graphical representation of the relation of data pairs using a scatter diagram where the time-ordered pairs are plotted together on opposing axes. The resulting graphic provides additional information on linearity and graphic representation of the amount of scatter about a mean line. The less scatter, the higher the correlation of the two variables, both positive and negative, often depending on their phase relationships in time histories and noted in the following example of measured strain data in a ship structure in a seaway.

The measured strain time history data from the FLAP/Valid Program, as presented by Stambaugh *et. al.,* (2014) and Drummen *et. al.,* (2014), were used to determine the level of statistical correlation between various structural details on from different locations over two transverse sections of the ship. Three sets of test data were analyzed from head (Test 90) and bow quartering (Test 89) seas of 2.7-meter significant wave height and head seas (High Latitude) in 4.6-meter significant wave height. Ship speed is approximately 10 knots in all cases. Strains were sampled at 200hz, and the sample sizes are nominally 30 minutes in length. The "S" strain gauges were conventional resistance gauges bonded to the steel structure. The "L" strain gauges are long base strain gauges with Linear Variable Displacement Transducer (LVDT) sensors approximately one meter in length welded to the deck at each end,

The strain data sensor names and locations included in this investigation are:

F47S1 – Frame 47 – Axial strain - 02 Level Starboard at stress concentration

F47S2 – Frame 47 – Axial strain - 02 Level Port at stress concentration

F47S3 – Frame 47 - Axial strain -02 Deck - Starboard

F47S4 – Frame 47 - Axial strain - 02 Deck - Port

F47S5 – Frame 47 - Axial strain - Bottom - Starboard

F47S6 – Frame 47 - Axial strain - Bottom - Port

The 47S1-6 gauges provide a good representation of hull girder axial strains and relatively highly loaded local details for this section near midship.

F47L1 – Frame 47 – Axial strain – First Platform – Port

F47L4 – Frame 47 – Axial strain - 01 Deck – Starboard

The F47L gauges are long base strain gauges located on opposite corners of the hull girder section at Frame 58 just aft of midship.

F58S13X – Frame 58 – Axial strain – 01 Deck – Starboard

F58S14Y – Frame 58 – Transverse strain – 01 Deck – Starboard

The F58S13X and F58S14Y gauges are conventional resistance strain gauges with X-axis being oriented in the longitudinal axis relative to the ship and Y being oriented orthogonal to the longitudinal X-axis as part of a rosette.

Figure A.1a Shows an illustration of the cutter's inboard profile with locations of frames and decks for reference.

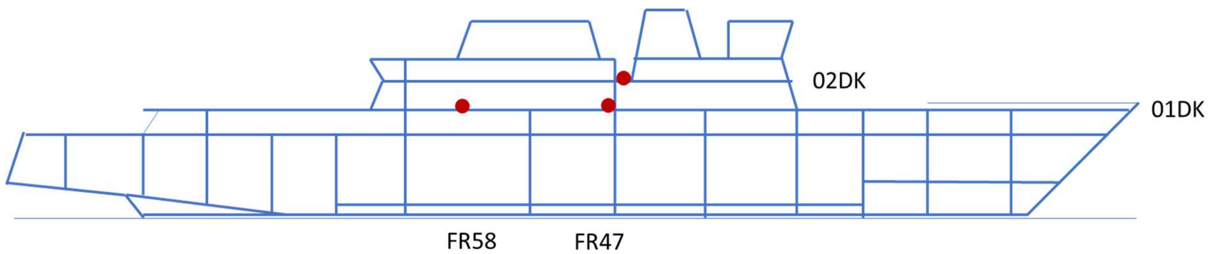

Figure A.1 Illustration of the cutter's Inboard Profile with frame and deck locations.

The statistical correlation tests included preparation of XY plots and Cross-Correlation calculations and plotted results of time series data are from the Time Series Tools in MatLab software (2012).

The correlation calculations for two time series indicate the amount of linear correlation coefficient with 1 being highly correlated and 0, not correlated at all, as described by Walpole (2012). Negative cross-correlation indicates out of phase correlation. The XY plots provide a visual perspective on the amount of cross-correlation between the data sets. The time lags are in the sample point scale.

A.3 Results

The first set of test results are shown in Figures A.2 and A.3 for XY and cross-correlation tests of the two local detail gauges both port F 47S2 and starboard F47S1 axial strain gauges. The structure isn't symmetrical; therefore, there is a small degree of offset between the gauge response; however, the level of statistical cross-correlation is very high, above 0.95

The second set of test results are shown in Figures A.4 and A.5 for the 02 deck F47S4 and bottom F47S6 axial strain gauges. In this test, the level of statistical correlation is high, above -0.94 for the hull girder strains at this transverse section. Negative cross-correlation reflects the opposite hull girder loading with the F474 gauge being in tension when the F47S6 gauge on the bottom is in compression and reversed when the load is reversed and 180 degrees out of phase.

The third set of test results are shown in Figures A.6 and A.7 for the local detail 47S1 and bottom strain gauge 47S6. The level of statistical correlation is high, above -0.98 for the hull girder strains at the far extremes of this transverse section. As with the previous comparison, a negative correlation value reflects the opposite hull girder loading with the F47S1 gauge being in tension when the F47S6 gauge on the bottom is in compression, and the strains are reversed when the load is reversed.

The fourth data set compares strain measurements from the 47Ll and 47L4 long base strain gauges shown in Figures A.8 and A.9 for Test 90 conditions. The 47Ll and 47L4 gauges are on opposite top and bottom of the hull girder, where the loading is experiencing reverse directions of compression and tension for each wave encounter cycle. The cross-correlation is on the order of -0.9

The fifth data set is for the same strain gauges as the previous set; however, in higher wave heights. Comparisons are shown in Figures A.10 and A.11 The level of cross-correlation in this condition is over -0.95 indicating a slightly higher level of correlation than the lower sea condition of Test 90.

The sixth data set compares to adjacent orthogonal strain gauges that are part of a rosette configuration with 58S13X measuring longitudinal bending strain and 58S14Y measuring strains in the transverse orthogonal direction. Additional cross-correlations are shown in Figures A.12 and A.13 for the High Latitude conditions. In the comparison, the level of correlation is on the order of -1, indicating a very strong negative correlation with the orthogonal strains being out of phase in the principal strain plane. The bow quartering sea condition produces high biaxial strain in the structural detail. The high degree of bi-directionality shown in the XY plot is striking, indicating a very consistent dominant direction of principal strain variation. Additionally, the level of principal strain is higher than the axial strain level indicating fatigue damage calculations based on axial stress will be non-conservative.

A.4 Conclusions

The results of these data set comparisons do indicate a very strong statistical correlation for measured strains in the hull girder and local details. Therefore, it can be concluded the level of statistical correlation is high and well within the accuracy of structural reliability calculations.

Local structure response from slamming or hull side wave impacts are subject to further investigation to determine their level of correlation for ships where this type of loading is common but are not directly relevant to longitudinal hull girder strength and can be handled as a special evaluation in addition to longitudinal strength on a systems level.

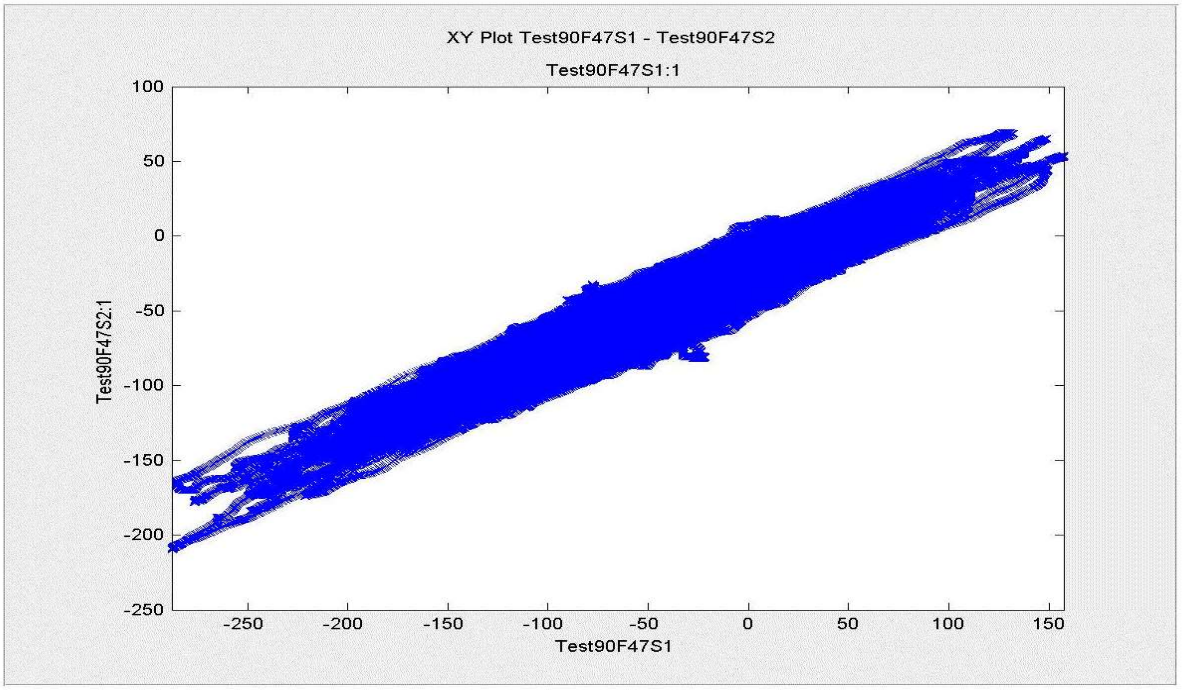

Figure A.2 - Test 90 XY plot of F47S1 and F47S2 strain measurements

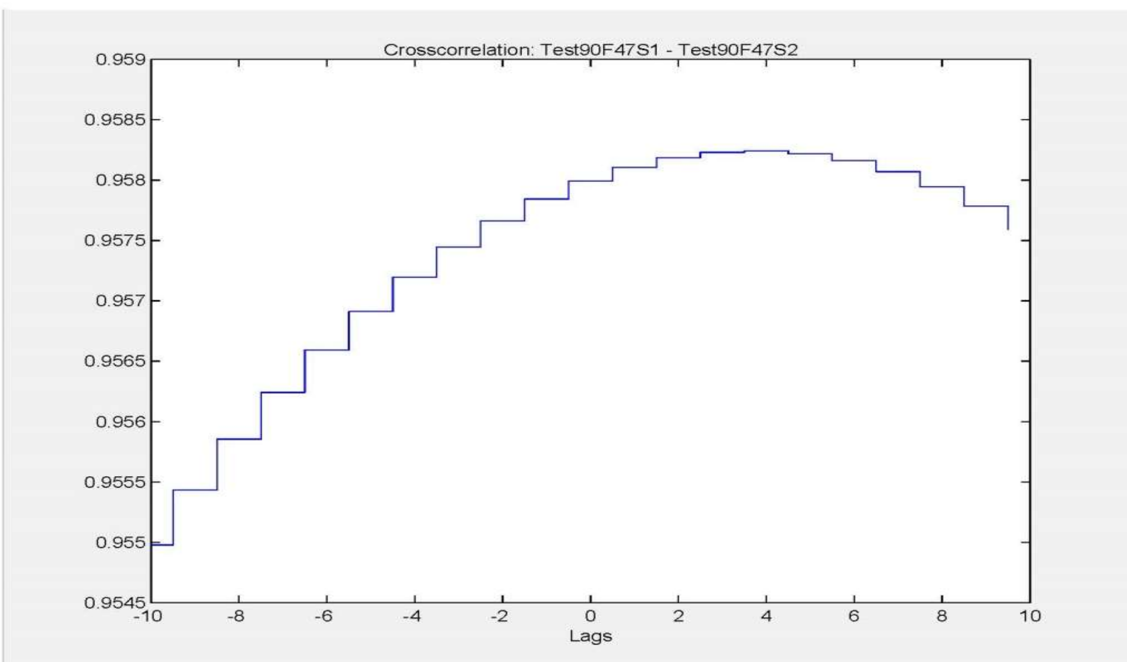

Figure A.3 – Test 90 Cross-Correlation plot of F47S1 and F47S2 strain measurements

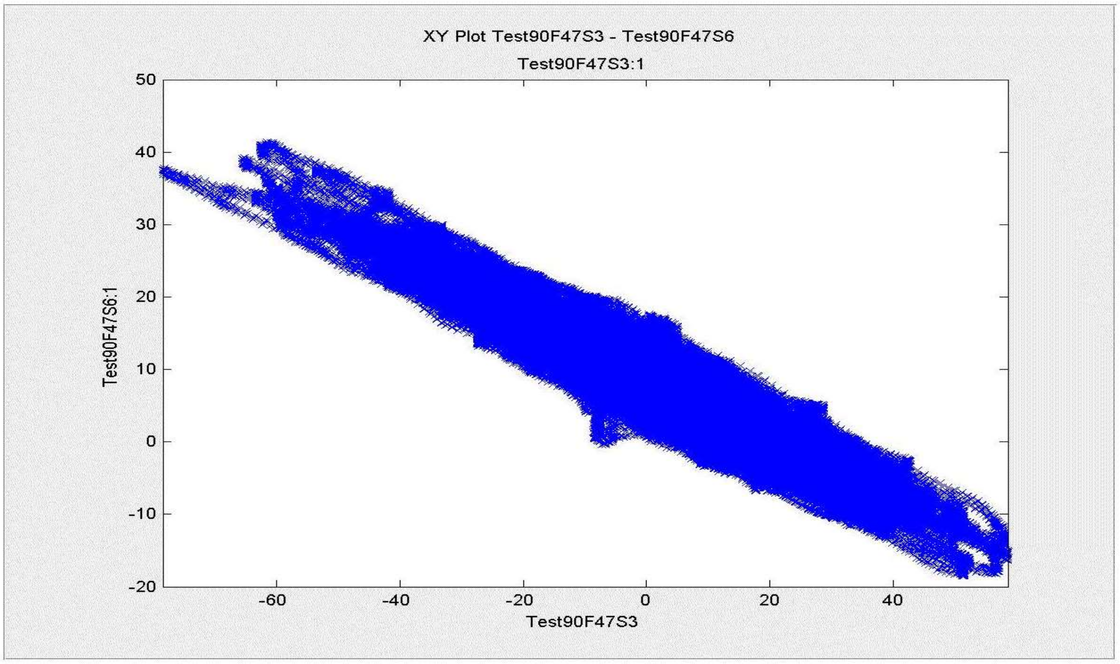

Figure A.4 - Test 90 XY plot of F47S3 and F47S6 strain measurements

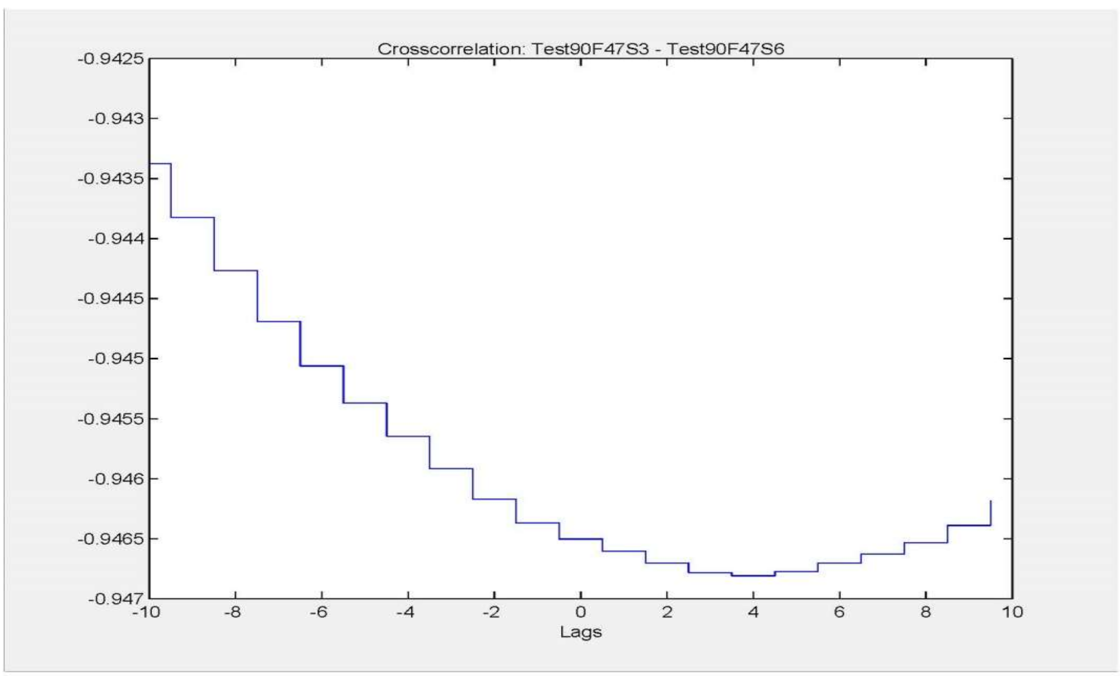

Figure A.5 – Test 90 Cross-Correlation plot of F47S3 and F47S6 strain measurements

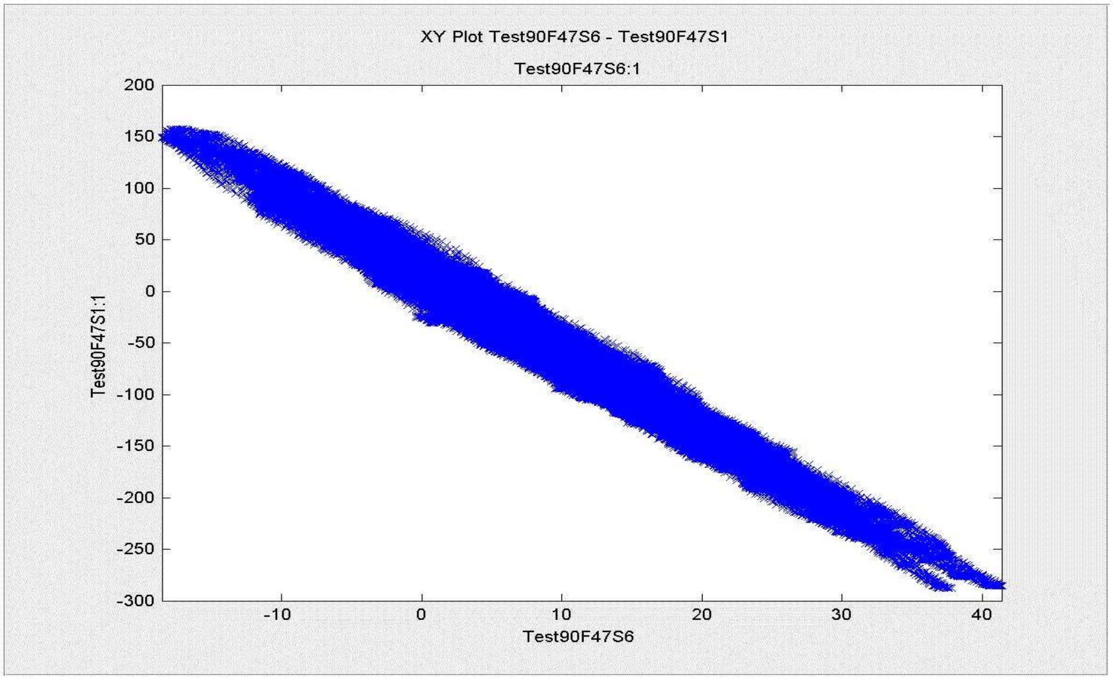

Figure A.6 - Test 90 XY plot of F47S1 and F47S6 strain measurements

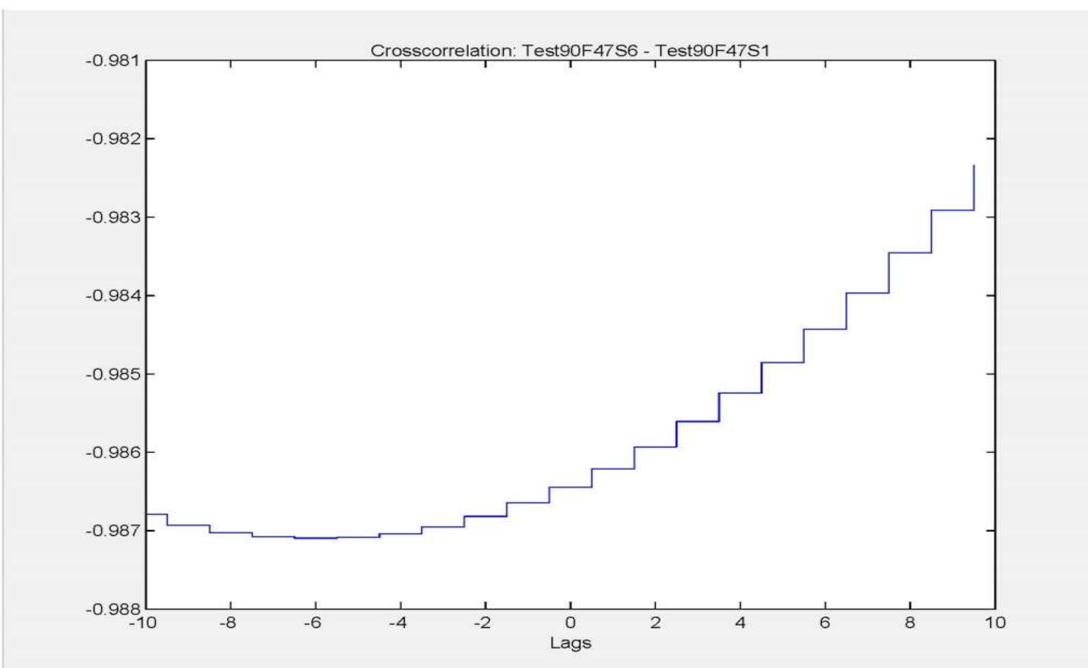

Figure A.7 – Test 90 Cross-Correlation plot of F47S1 and F47S6 strain measurements

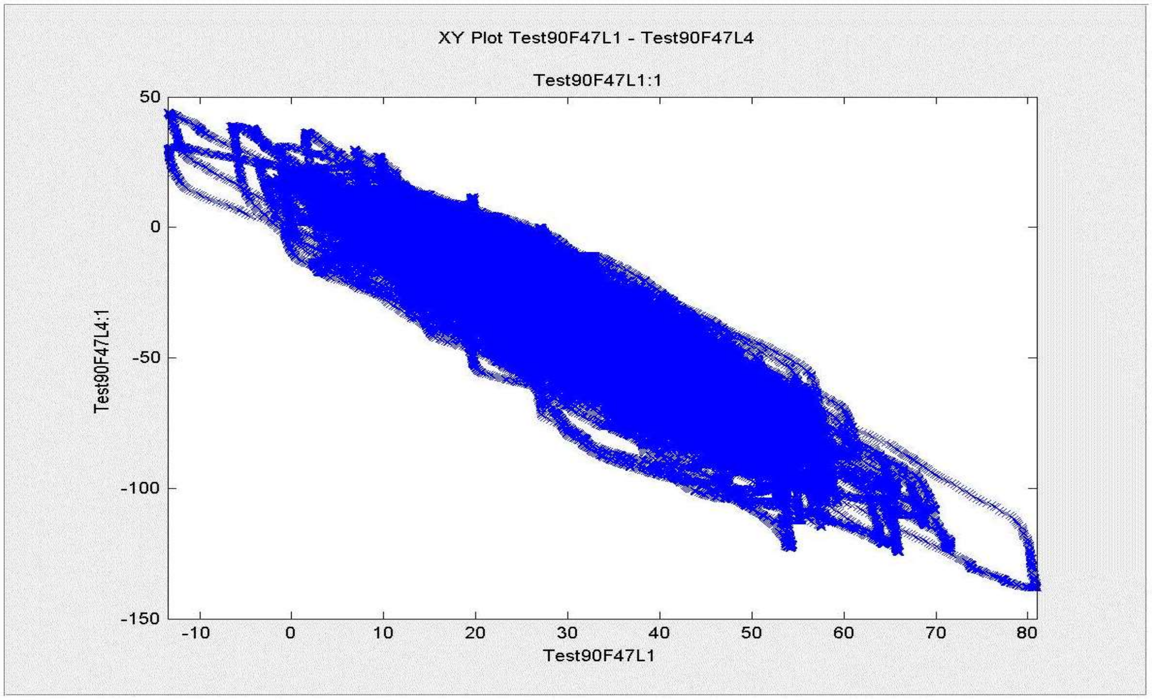

Figure A.8 – Test 90 XY plot of F47L1 and F47L4 strain measurements

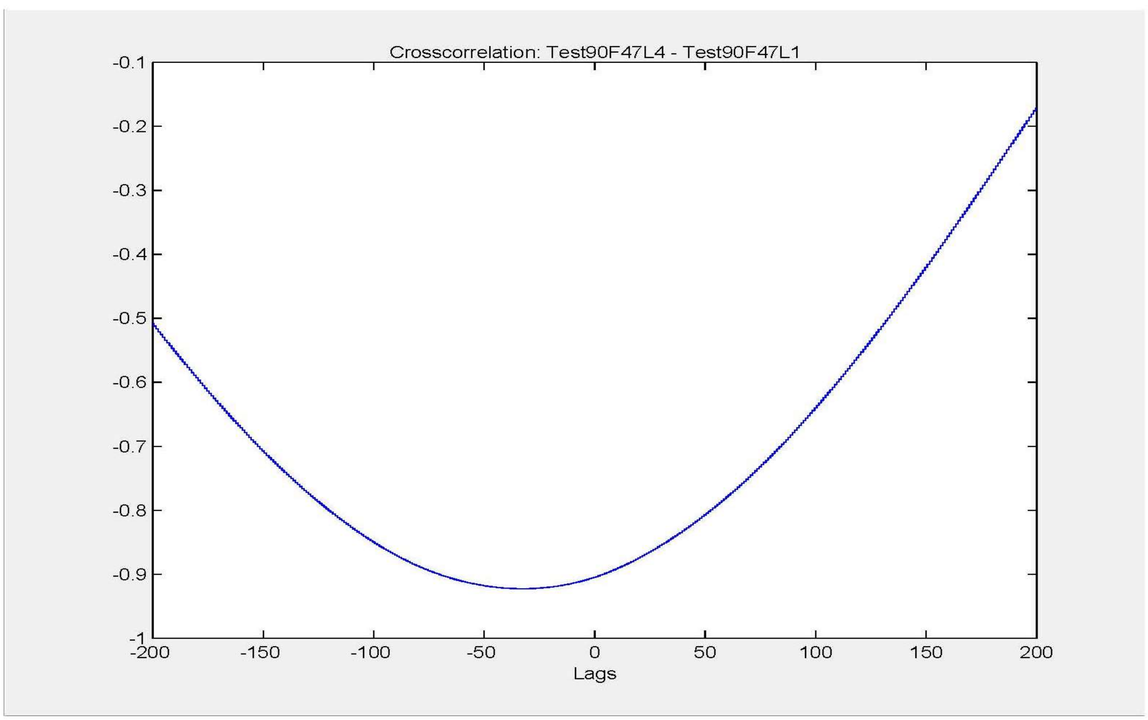

Figure A.9 – Test 90 Cross-Correlation plot of F47L1 and F47L4 strain measurements

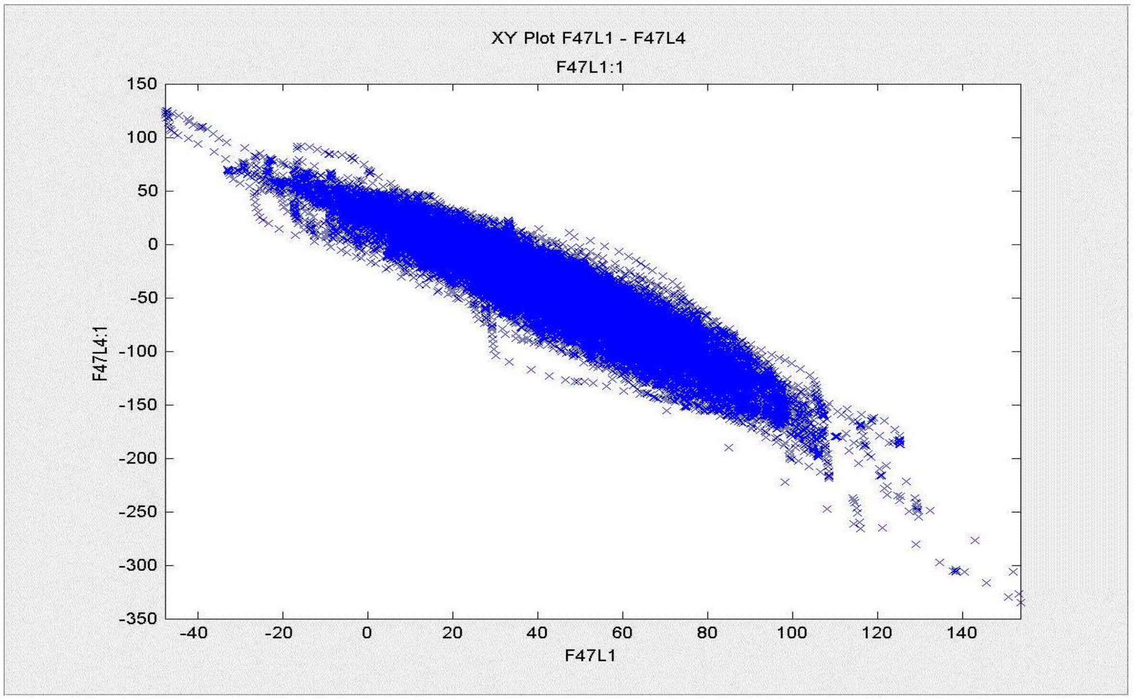

Figure A.10 – High Latitude Deployment XY plot of F47L1 and F47L4 strain measurements

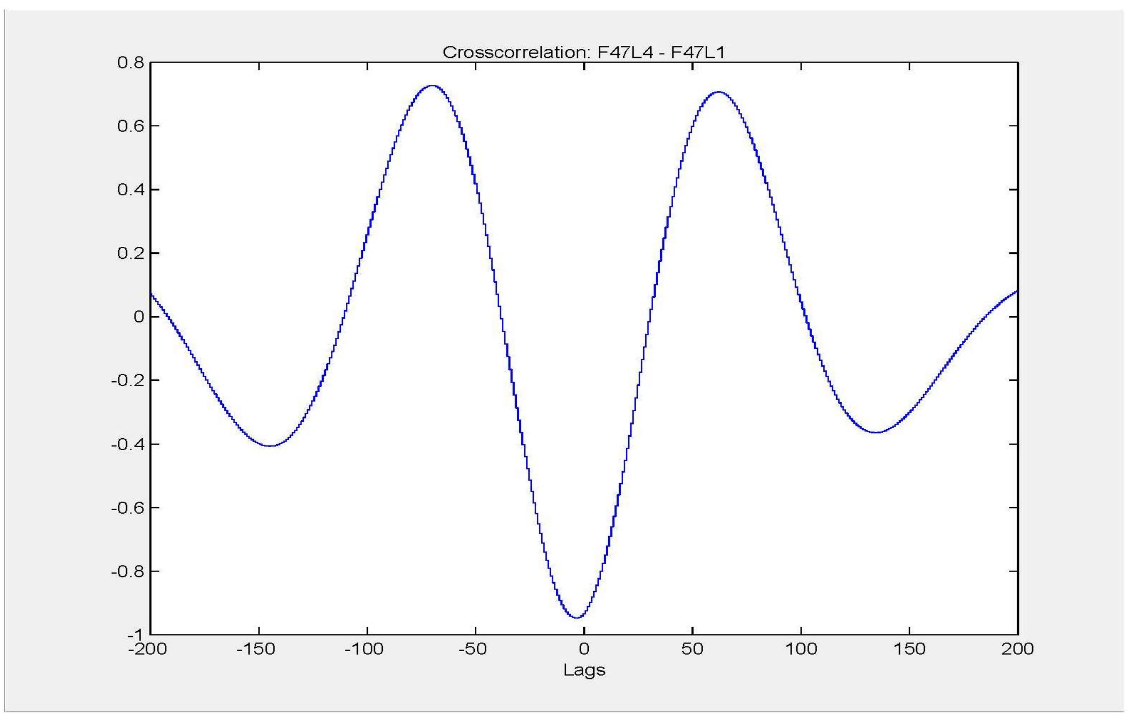

Figure A.11 – High Latitude Deployment Cross-Correlation plot of F47L1 and F47L4 strain measurements

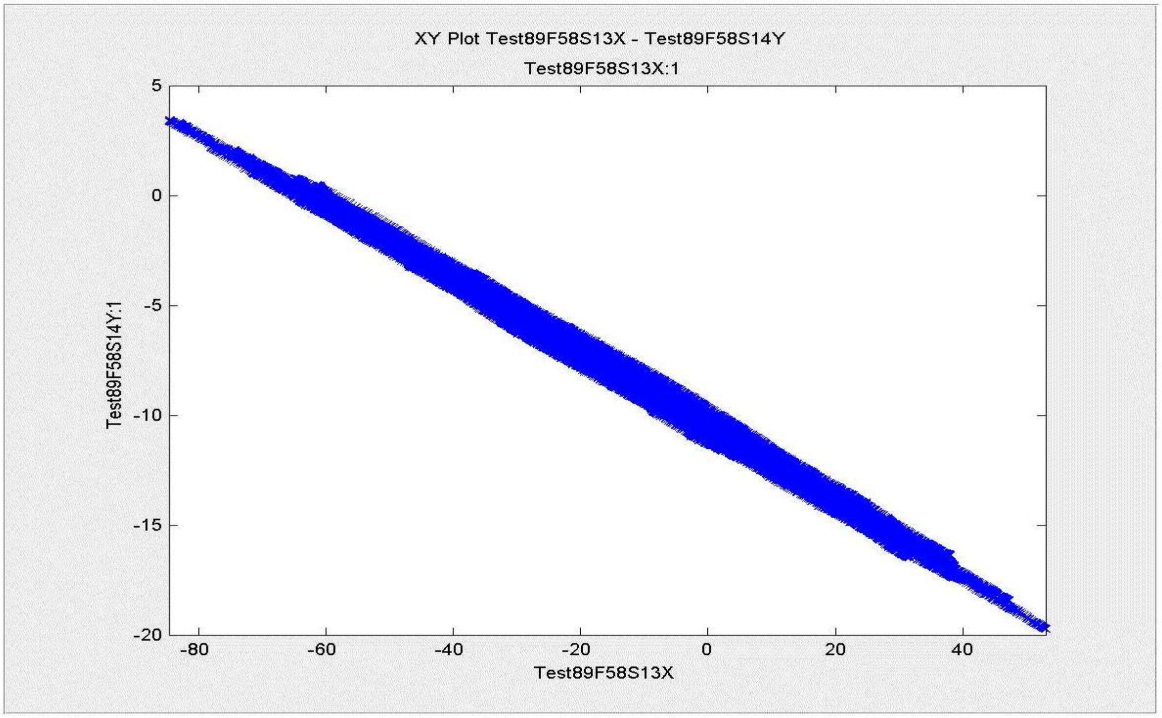

Figure A.12 – Test 89 XY plot of F58S13X and F58S14Y strain measurements

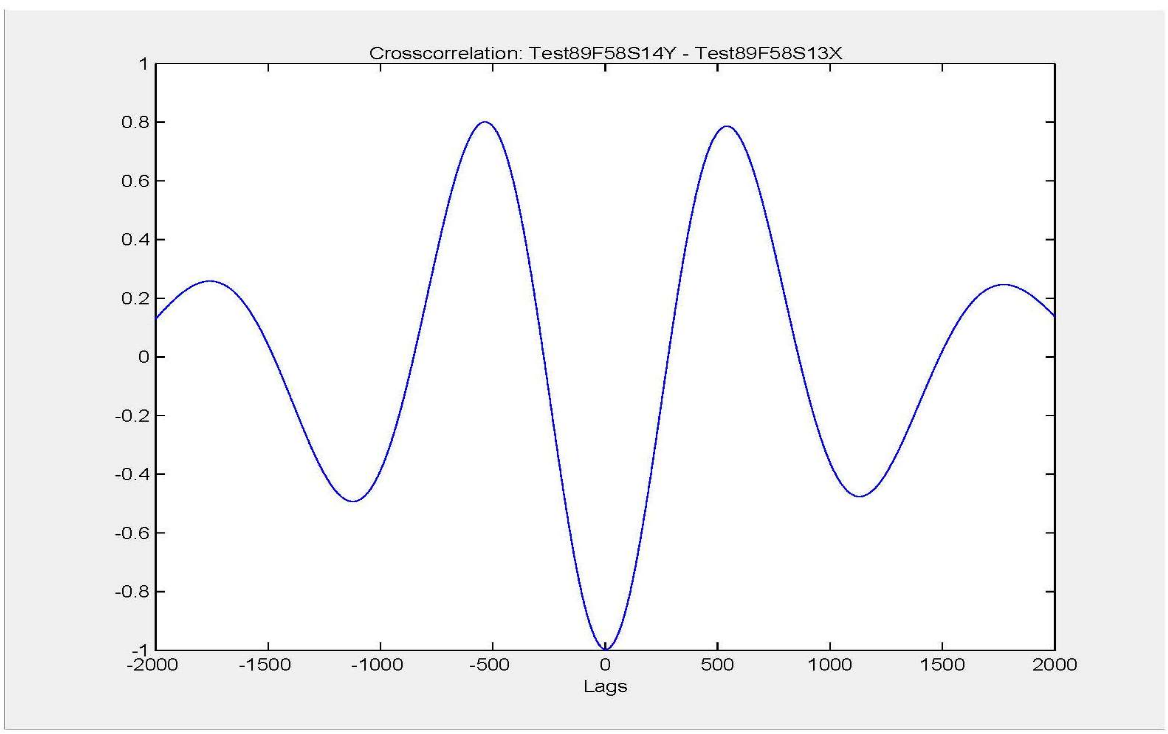

Figure A.13 – Test 89 Cross-Correlation plot of F58S13X and F58S14Y strain measurements

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Appendix B

A Search for Bayesian Updating

Bayes Theorem has a long and interesting history that transcends the simple equation and applications currently attributed to it. The fundamental philosophies proposed by Reverend Bayes lead to a deeper understanding of the uncertainties surrounding relative frequency and prior probabilities used in the analysis of complex systems. A literature review on the history of Bayes Theorem is presented here to summarize and highlight the important aspects of Bayes philosophy as it relates to the treatment of uncertainties characterized by probabilities used in Risk Analysis. Very few modern introductory-level texts on statistics discuss this fully. The objective of this summary is to inspire other researchers and engineers to investigate the applications of Bayesian perspectives in characterizing and forecasting uncertainty using probabilities and statistics in Risk Analysis and the marine field.

As described by Weisberg (2014), games of chance were common through history back to ancient times. The games of chance of that time were based on dice type features with a countable reference set of outcomes. In the time of Bayes, with advances in physics and mathematics developing rapidly, these games of chance and derived odds ratios were being understood as a means of quantifying uncertainties in the observable world. New terminology (i.e., probability) was developing along with a shift in thinking of how the uncertainty is characterized. The new approaches used to characterize uncertainty with the mathematics involved observations and counting frequencies in terms of the odds ratios as new thinking about probabilities developed. Even the definition of probability in earlier times was purely qualitative, similar to our use of the term uncertainties, but with qualitative weighting, in thought only, i.e., "that an event will probably happen" without any quantified reference. The shift in thinking about uncertainty left out a very important aspect of the former counted odds ratios, namely the reference set definition. In the observational characterization of uncertainty outside of games of chance and countable odds ratios, a reference set is most often an infinite number of random values. Later, concepts of probability distributions developed without regard to the definitions associated with a fixed or countable reference set. This transition to probabilities without a reference set began a philosophical debate initiated by Bayes that continues today.

B.1 Bayes and Updating Prior Beliefs

Reverend Thomas Bayes was an eighteenth-century British mathematician, and Presbyterian minister whose most famous contribution to statistics would not be published until after he died. Bayes (according to Reverend Price, a close friend of Bayes, who published Bayes writings posthumously 1740s) understood the lack of underpinning of the reference set and how to deal with this shift became a thesis in his now-famous works and a basis for statistical inference.

According to Hubbard (2014):

*"Most Students of probability and statistics do not realize that Reverend Bayes derived [*his thesis sic.*] not for statistics, but in order to solve a particular philosophical problem of great importance. Here is how he stated this problem:"*

"Given the number of times in which an unknown event has happened and failed: Required the chance that the probability of its happening in a single trial lies somewhere between any two degrees of probability that can be named."

"Bayes was after big game, nothing less than a general solution to the problem of induction – how can we generalize based on past experience."

"We quantify this initial uncertainty and the change in uncertainty from observations by using probabilities. This means that we are using the term "probability" to refer to the personal state of uncertainty of an observer or what some have called a "degree of belief."

Bayes' theorem, describes how new information can update prior probabilities. "Prior" could refer to a state of uncertainty informed mostly by previously recorded data, but it can also refer to a point before any objective and recorded observations. At least for the latter case, the prior probabilities are [referred to as] subjective." Although priors may be subjective by name, they may also be quantitative probabilities.

According to Price's published account, Bayes' had four prominent points in his work, namely;

1) Random characterization of uncertainty in terms of probabilities is relative to the observer,
2) The observer may or may not have prior knowledge of uncertain events,
3) If no prior knowledge is available, equal likelihoods are possible/probable,
4) The observer may update their prior knowledge as new observations are obtained.

At that time, the equation of conditional probabilities currently used today had not been part of the thought process presented by Bayes and Price.

According to Morris (2017), Bayes proposed a new paradigm on concepts of inductive reasoning that can be summed up as follows:

$$\text{An Initial Belief} + \text{New Evidence} = \text{A New, Updated Belief.}$$

Bayes became consumed with figuring out the approximate probability of a future event he knew nothing about except its past, that is, the number of times it had occurred or failed to occur.

According to Hubbard (2014):

"What seems clear is that Bayes's mathematical development required that prior and inverse probabilities be considered in some senses comparable. As a result, it became permissible to think about the probabilities of a probability!

*Particularly controversial has been the assumption of a uniform prior probability distribution for the probability of interest, **p**. The idea that we can represent complete ignorance about **p** by assuming all possible values to be equally likely is something called Bayes's Postulate, but more often principle of insufficient reason or (following Keyenes) the Principle of indifference. Bayes himself expressed reservations about this seductively simple solution. It had the huge advantage of allowing a composition of inverse probabilities. However, it seemed too facile. How can pure ignorance do so much? This question continues to haunt statistical theory to the present day."*

In the years that followed Bayes' death and the publication of his work by Reverend Price, Pierre-Simon Laplace recreated Bayes' inference and developed the equation more commonly known today. Where the Bayesian paradigm transformed to :

posterior information = prior information + data information

More formally to:

$$p(\theta \mid y) \propto p(\theta)p(y \mid \theta), \qquad \text{(B-1)}$$

where $\propto$ is a symbol for proportionality, θ is an unknown parameter, y is data, and $p(\theta)$, $p(\theta \mid y)$ and $p(y \mid \theta)$ are the density functions of the prior, posterior and sampling distributions, respectively.

Laplace used the equation to infer the mass of Saturn based on orbital physics and uncertainty from observational measurement error.

According to Weisberg (2014), concepts of prior knowledge and probability updating based on new observations were proposed because of this key understanding of the importance of the perspectives of the observed probabilities. These basic concepts were later reformulated into a basic equation by Laplace; however, his equation does not relay the original thinking about the uncertainty that Bayes was struggling with and proposed in his draft thesis manuscript later presented by Price.

As early science developed after the postulation of Newton's Laws, scientists began to think that all measurable phenomena would be based on similar mathematical laws, and this included the application of statistics. The new sciences set up conflicts of interpretation of statistics as systems became more complex and ambiguous.

According to Weisberg (2014), Ronald Fisher, the statistician who developed and promoted the concepts of statistical significance testing, *"was aware that mathematical probability depends on what I have called willful ignorance. Like Laplace, he perceived that probability has an "as-if" character that is relative to our limited knowledge (of complex random events). However, methods based on this useful expedite (of statistical significance) soon took on a life of their own. Statistical methodology transcended from helpful technology to aid scientific reasoning into a central aspect of scientific practice. Statistical significance in particular came to play a dominant role."*

"*For example, suppose that a material scientist is studying the response of a new metal alloy to various kinds of stress. He is performing an experiment in which measurements are obtained using sophisticated instruments. Under each specified set of conditions, multiple measurements are made. The outcomes of the measurements can vary slightly because of subtle unknown factors. However, this variability is essentially random; the individual observations are like indistinguishable draws from a metaphorical lottery."* (However, without a reference set definition). (Additions by the author)

The example of a controlled experiment involves more complex uncertainties when applied in the real world with random inputs and other uncontrolled or unknown/unquantified random factors. Levels of correlations and prior knowledge are important in contextual applications. Further to Weisberg (2014),

"*When efficacy is highly context-dependent, an overall probability in a general population of patients is not meaningful. There is simply too much ambiguity about the context. Only if ambiguity can be resolved satisfactorily for our purposes can we move into the realm of doubt. Then we may be able to conceive of a metaphorical lottery in which some fraction of "chances" favor the events of interest. With respect to a particular reference class, the degree of evidence for occurrence of an event could be represented on a scale between zero (impossible) and one (certain)."*

The statistical inference aspects of Bayes theorem as proposed by Bayes were further lost and were accused of being an error by Fisher (1935) who believed that large numbers of samples could overcome the fundamental difficulty/problem of no fixed reference set (and associated attempts at definitions of statistical significance), and became known as a frequentist perspective. The lack of fixed reference and loose interpretations of "statistical significance" and related measures that were found difficult to define by others Weisberg (2014)

Savage (1954 and 1971), Jaynes (1957), and Weisberg (2014) further exposed the fallacy of the frequentists perspective and propose the personal perspective of uncertainty in probabilities and mathematical statistics and the importance of reference set(s) and not having one for maximum uncertainty characterization. The works of Savage (1971) and Jaynes (1957) provided a foundation of more informative works and broader perspectives of uncertainty and maximum ignorance associated with the prior (i.e., maximum entropy) that Bayes had struggled with (i.e., uniform prior) many centuries ago.

Jaynes (1957) built on the concept of entropy and proposed a method for assigning probabilities based on partial information. Jaynes called it maximum entropy principle and is stated from his original paper as follows:

"In making inferences on the basis of partial information, we must use that probability distribution which has maximum entropy subject to whatever is known. This is the only unbiased assignment we can make; to use any other would amount to arbitrary assumption of information, which by hypothesis we do not have."

B.2 Bayes Theorem as We Know it Today

The current form of Bayes Equation is written as:

$P(A)=P(A|B)P(B)+P(A|\sim B)P(\sim B)$ Weighted sum conditional probabilities

Flip the conditional probability $P(B|A)$ to $P(A|B)$

General form of Bayes Theorem is:

$$\boldsymbol{P(A|B) = \frac{P(A)P(B|A)}{P(B)}} \tag{B-2}$$

This simple equation has interpretations that include $P(B|A)$ is a conditional statement, and $P(B)$ is a marginal distribution. Others define likelihoods, priors, and posteriors, all in specific applications associated with conditional probabilities.

In contrast to Bayes ideas on updating based on experience, Bayes equation (as presented by Laplace) is often interpreted in terms of discrete probabilities in simple examples of conditional probabilities and Ven diagrams for concepts of uncertainty ranges, and then again characterized, by discrete probabilities; however, real uncertainties are most often characterized by observed probability and inferred or assumed formulaic distributions of various types from different processes that must be predicted and then combined to form a forecast of uncertainty over time. This forecasting process that combines uncertainty must recognize the limited nature of the uncertainties in lack of reference set, and prior knowledge may be used as a perspective with updating based on new information being gained. This approach to forecasting is in the true Bayesian perspective as originally intended.

Moving forward with analyses that are based on limited information on the behavior of complex systems, the application of Bayesian philosophies, especially limited experience and limited resources, becomes essential for dealing with the uncertainties associated with the complex systems. For example, the application of fatigue failure of a class of structural details subject to constant amplitude loading to ship structural details subjected to a highly random environment. These examples imply a Bayesian inference, whether intended or not.

B.3 Discussion

The various perspectives of Bayes theorems are equally important in characterizing uncertainty in Risk assessments in ship structures because of the vast amount of uncertainties involved, including random loads from a random seaway (aleatory uncertainty) and their modeling (epistemic uncertainty) to the similar randomness of the structural material response and modeling. We have limited data in any real application, and design is all based on prior knowledge. This prior knowledge can and should be updated based on new observations and measurements. However, the approaches for doing this updating are not clearly defined by the equation attributed to Bayes currently in fashion.

In collecting data to support a reliability analysis for ship structures, we find that the data is rarely of sufficient quantity that would support a frequentist's requirements for sufficient data quantity as is typical for aircraft, spacecraft, nuclear power plant, or even production run of light bulbs in the extreme. In reliability and Risk Analysis of ship structure, we most often use prior data of similar structures (S-N curves) or smaller data samples (Stambaugh *et. al.,* 2014) that we can use to support analysis and major decisions using best information available and collect more data in efforts to reduce uncertainty and assessment of Risk in a *VoI* context (see Hubbard 2014). With this approach, what-if scenarios in a future predicted state, reflects a Bayesian perspective to use prior and current knowledge and update our beliefs as we collect more data, analyze the value of this information/data a-prori in the design of experiments in *VoI* context, and post data collection for updating our beliefs in formal or informal Bayesian context. The prior probabilities may be updated in a pre-posterior manner from what-if scenarios, then re-evaluating the change in uncertainty and Risk to quantify the value of information of the uncertainty reduction. It follows that the return on investment may also be quantified based on the updating.

B.4 References

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Appendix C

SN+FM Total Life Approach for Forecasting Critical Crack Life in Ship Structures

The Risk-TOC approach proposed in this dissertation reflects the realities and Risks associated with the brittle fracture (Stambaugh *et. al.,* 1987, Ship Structures Committee Website), given a crack is present and that the crack will grow undetected. There are a number of approaches developed to estimate and predict fatigue crack initiation and crack growth given a loading spectrum (Beghin 2006 and Sieve *et. al.,* 2000). Two fundamental underlying approaches include: 1) the cumulative damage based on Stress-Number (S-N) of cycles to failure (generally through-thickness crack) from fatigue test data on welded specimens and 2) linear elastic Fracture Mechanics (F-M) based on fatigue test data of the growth of stable fatigue cracks, given a crack or notch exists in a structure. In order to predict the crack growth from initiation to fracture, a hybrid approach is presented, building on the strengths of two generally accepted approaches for predicting crack initiation and propagation. The following Sections provide a brief overview of the S-N and F-M approaches and how they are used together to predict the probability a crack will grow to a size needed for a brittle fracture to occur and how to assess them in the context of a reliability based approach presented in Chapter 2.0 of this dissertation. Other variations of the S-N and F-M approaches may be used; the basic versions are discussed for illustrative purposes and how they are used in the context of the Risk-TOC approach presented in Chapter 6.0 applications of this dissertation.

C.1 Cumulative Damage Summation Approach

The S-N cumulative damage estimate for fatigue life (Miner 1945) is, in effect, a point calculation for fatigue life based on experimental test data for welded structural details. The test specimens are typically welded joints of various configurations representing a set of structural details that are assumed to be of good (but unquantified) weld quality and good weld profile geometry. The predicted or measured fatigue loading and number of cycles are compared to the loading and number of cycles to failure of a number of test specimens, as illustrated in Figure C.1. In the S-N approach, the fatigue failure is determined to have occurred when a visible fatigue crack appears on the surface of the test specimen and in the as-built structure. In most cases, the crack is visible on the surface when it becomes a through-thickness crack. In the context of fatigue life and number of loading cycles, the difference between visible crack and through-thickness crack is relatively small.

The methods relating the stress level and number of load cycles, S-N curves, are used to predict the number of cycles to failure at a single stress level. The S-N curves conveniently display basic fatigue data on a plot of cyclic stress level versus the number of cycles to failure. Analytical representation of S-N curves [Beghin 2006] are given in the form:

$$N_i = Ak_s^b S_i^b \tag{C-1}$$

where b and k are material parameters estimated from test data obtained using standardized test specimens that are intended to be representative of those used in service structures and:

A = intercept of the S-N curve

B = slope of the log-log S-N curve

S = stress range

S_i = stress range of the *ith* stress range block of a stress range histogram

K_s = fatigue stress concentration or uncertainty factor

N_i = fatigue life, or number of loading cycles expected during the life of a detail due to S_i

The S-N approach uses the Miner's cumulative damage approach (1945) for fatigue life estimates and is used to predict the cycles to failure under constant and variable amplitude loading. The Miner approach is based on the premise that the damage fraction Δ_i at any stress level S_i is linearly proportional to the ratio of n_i, the number of cycles of operation under this stress amplitude to Ni, the total number of cycles that would produce a failure at that stress range level. The accumulated damage fraction is computed as:

$$\Delta_i = \frac{n_i}{N_i} \tag{C-2}$$

Where $n_i > N$ is typically associated with an acceptable level of failure depending on the reference number of cycles to failure. The reference failure limit of two standard deviations is typically used in the design of structural details (Beghin 2006) and the mean and coefficient of variation in structural reliability analysis, as discussed in Chapter 2.0 of this dissertation. If the stress range is changed, a new partial damage is calculated for this new amplitude level, where the appropriate Ni is found form the S-N curve. The total accumulated damage D is then given by Miner (1945).

$$D_t = \sum_{i}^{t} \frac{n_i}{N_i} \tag{C-3}$$

and failure is estimated to occur when D_t >1. The main deficiencies with linear damage rule used are its load level independence, load sequence independence, and lack of load interaction accountability, especially important in fatigue life forecasts. However, the S-N approach is generally accepted for modeling the initiation phase, and uncertainties may be addressed in the context of reliability analysis.

C.2 Fracture Mechanics Approach

One of the most often used fatigue crack propagation models is based on the Paris equation (Paris and Erdogan 1960). This equation is an empirical formulation that relates the cyclic crack growth rate to stress intensity factor range, as follows:

$$\frac{da}{dN} = C(\Delta K)^m \tag{C-4}$$

where a [mm] is crack depth, N is the number of load cycles at a specific ΔK [MPa$\sqrt{m}$] stress intensity factor range, i.e., Kmax - Kmin, whereas C and m are material and environment specific constants. The exponent m is dimensionless, whereas the dimension of the parameter C is such that its product with $(\Delta K)^m$ is the length (i.e., mm). The Paris equation assumes that the crack growth depends only on the stress intensity factor range. It also assumes that the stress range is constant and that it is small enough so that the linear elastic properties of the material are applicable and that the crack growth rate is independent of the previous load history. The Paris equation describes crack growth only at intermediate values of fatigue crack growth curve, see Region II in Figure C.2. Region II represents the intermediate crack propagation zone where the length of the plastic zone ahead of the crack tip is long compared with the mean grain size, but much smaller than the crack length, whereas Region I is where the stress intensity factor range threshold is below which fatigue cracks do not propagate consistently in the same manner as Region II and Region III is characterized by rapid and often unstable crack growth just prior to final failure. Failure occurs when the stress intensity factor exceeds the critical fracture toughness of Kcr at a_{cr} and Tcr illustrated in Figure C.2.

In the F-M approach to fatigue life estimates, the initial flaw or crack is assumed to exist in every weld and grows according to the Paris Law illustrated in Figure C.2. However, the weld flaw size has many uncertainties associated with it, including shape, size, orientation relative to the applied loading, to name a few. All of these characteristics of the initial defect affect the time for the crack nucleation to be established and growth process to begin initially, before it grows at a rate associated with the Paris Law (*da/dN and dKf*) as illustrated in Figure C.2 Therefore, in F-M approaches, the fatigue notch and crack are manufactured into a test specimen, and the crack growth is observed for a range of loading and number of cycles.

For fatigue life estimates where initial conditions must be considered, crack initiation in Region I is not fully quantified in physical or statistical terms for early life crack growth analysis (see Annis 2003). Most flaws require some time for an actual crack to develop, and this time is highly variable and random in nature (aleatory uncertainty).

The time in the initiation phase of fatigue life can be substantial and result in overly conservative fatigue life predictions by the F-M approach is all cracks are generally assumed to begin growing at time equals zero (t = 0). Or a delay period is developed based on empirical data as proposed by Straub and Sorenson (2005). For example, there is an initial nucleation time for fatigue cracks to grow from a flaw that depends on loading magnitude and loading sequence.

For crack initiation, the F-M approach must characterize the uncertainties of weld geometry and quality by statistical approaches that are inherent in "representative" welded details of the S-N approach. This is a major effort in accurately predicting fatigue life from the F-M approach of welded details. In the end, similar uncertainties exist to predict fatigue life from both the S-N and F-M approaches to the through-thickness crack that determines fatigue life for most practical applications of fatigue life estimates.

The problem in using a crack growth model is that the initial crack size is not known. This problem was addressed by the introduction of an Equivalent Initial Flaw Size (EIFS) in the aircraft and civil structure industries (Iyyer *et. al.,* 2008, Cahuao 2006, and Sankararaman *et. al.,* 2005). The concept of EIFS was introduced to by-pass small crack growth analysis and to substitute an initial crack size in long crack growth. However, the EIFS determined in this manner have a time lag based on the time it takes for crack nucleation. The EIFS are back-calculated from S-N data but do not match up with actual measured initial flaws due to the approach not predicting the initiation phase, as discussed above.

According to Lassen (1997), the crack depth limit where F-M is applicable to the description of crack growth behavior is ao = 100mu-m. Also, typical grain sizes in welded steel are in the order of 10-100mu-m. Because the application of F-M is not reasonable at crack sizes less than the size of a typical grain, the initial crack size should be larger than 0.1mm. This seems to indicate that 0.1mm is a reasonable lower bound of the range where F-M is applicable.

Building on the strength of the F-M approach is best suited for fatigue crack growth given an actual crack has grown to through-thickness, vs from initiation as developed by Paris. The S-N approach is still the accepted practical standard for estimating fatigue life from crack initiation to through-thickness crack (*TTc*) considering the initial variables of the initial flaw, weld quality, and weld profile geometry. Given the primary strengths of each approach, a combined approach is proposed using the S-N to predict the loading and time to occurrence of a through-thickness crack and transitioning to the F-M approach given a through-thickness crack has occurred and using the F-M approach is then used to predict the remaining life to critical crack size is proposed.

C.3 SN+FM Total Life Approach

In the context of predicting large crack growth for Risk Analysis of fracture failure, the uncertainties of using the F-M approach for the initiation phase of crack growth are replaced with the S-N approach, and the F-M approach is utilized given a crack has initiated and is growing to a length appropriate for the F-M based approach. In this approach, the time it takes to develop a through-thickness crack (TT_c) is predicted using the S-N approach and the time it takes to reach critical size (T_{cr}) is then predicted using the F-M approach give the probabilities (in Chapter 2.0 of this dissertation) have been predicted based on the empirical S-N curve approach.

The S-N approach includes the uncertainties of crack nucleation from a flaw empirically, and not all small flaws produce growing cracks from first cycle experience as assumed by linear elastic fracture mechanics based approaches. F-M approaches require extensive amounts of testing to determine the statistical nature of the physical parameters influencing crack initiation from a flaw using the F-M approach. The strength of the F-M approach is predicting fatigue crack response given the existence of a growing crack. This growing crack is the fundamental premise of the Paris Law (Paris and Erdogan 1960).

Figure C.3 illustrates the relationship between the SN+FM Total Life approaches for fatigue crack length as a function of time. In Figure C.3, the crack depth a is shown with initial crack length a_o, through-thickness crack, a_{tt}, the crack's length increases rapidly to a length where the cracks typically leak in ship structures, a_l, and if they do not leak and are not otherwise detected, they will increase in length until they reach a critical length a_{cr}. An important feature of the illustration is the time for initiation, as captured by the S-N approach. Also, the relatively short time between through-thickness crack, leaking crack length, and critical crack length is an important feature in predicting the time it takes for a crack to grow from through-thickness to critical size. The hybrid SN+FM Total Life approach captures all of these aspects, using the proven benefits of each approach. The S-N part of the SN+FM Total Life approach may be calculated with a structural reliability approach (Chapter 2.0 of this dissertation) to determine the associated probability of occurrence of a through-thickness crack (*TT_c*). In turn, the probability of through-thickness crack occurrence (*TT_c*) is multiplied by the probability of non-detection (*1-PoD*) to determine the overall probability the crack will grow to a through-thickness length and not be detected in a given inspection period. Given a non-detected growing fatigue crack, the probability of critical crack size is determined by a reliability approach and shown in the application example in Chapter 4.0 on Risk of brittle fracture in the Risk-TOC approach.

In the resulting proposed combined, S-N and F-M approaches are approximately equal at the time the crack reaches through-thickness (a_{tt}, T_{tt}), as illustrated in Figure C.3. This approximate common point is a very useful interface between the S-N and F-M approaches and enables a hybrid approach between them in predicting fatigue crack growth from (a_{tt}, T_{tt}) well within the applicable range of applicability of the F-M approach. The definition of starting point for F-M estimates differs from prior approaches proposed by Straub (2003) and De Souza *et. al.,* (2000), where the starting point is a back-calculated initial flaw, similar to the EIF approaches described previously.

Reliability based approaches then can be used to estimate both the time to a_{tt} of one (1) and the probability that a_{cr} will be reached. The rapid growth of a_{tt} to a_{cr} is the Risk most threatening to the structural integrity of the ship structure system, given a_{tt} has occurred. Controlling time to a_{tt} is within the structure designer's scope to address if SSLCM and safety are important goals to the ship owners and SSLCM managers.

From a_{tt}, T_{tt}, the estimated time to a_{cr}, T_{cr} is relatively straight forward for performing Risk assessments involving brittle fracture as in the example Chapter 6.0 of this dissertation.

C.4 Discussion on SN+FM Total Life Approach

Although brittle fractures are rare in ship structures because of the successful evolutionary development of ship structural design processes, requirements, and material properties, most of which are ultimately empirically based, they have not been eliminated from occurring (Stambaugh *et. al.,* 1987, SSC website, Sumpter and Kent 2004). Furthermore, the Risk of critical crack length being reached in operation is not explicitly determined or even explicitly considered in any of the Optimal Inspection based approaches used in other industries, civil and offshore, in particular, and proposed for ship structures, as noted in Chapter 2.0 of this dissertation. Probability of Detection (*PoD*) values are assumed in Optimal Inspection approaches high enough to detect all cracks less than an arbitrary threshold (i.e., 100mm). This is not practical for ships, as described previously in Chapter 3.0 of this dissertation.

The fatigue life management approaches based on optimal inspection schedules proposed by others and summarized in Chapter 3.0 do not include a provision for cracks to grow to a critical length required to initiate a fast-growing brittle type fracture. Optimal Inspection based approaches assume the probability of detecting a fatigue crack is high enough that all cracks are found and repaired before they reach the critical length necessary for fracture to occur. This does not reflect the realities of ship inspection approaches, *PoD*, their costs to implement, nor the ability to inspect the structure given availability schedules and accessibility to the structure.

Although the SN+FM Total Life approach is not being proposed for design applications, it does provide a valuable perspective for Risk and Life Cycle Management (LCM) based decisions based on quantified analysis and Risk of catastrophic failure that is possible even likely given a brittle fracture has occurred.   The common definition of failure *TTc* for design is 2.3% and is still sound based on historical experience (Stambaugh *et. al.,* 1987). The SN+FM Total Life approach presented in this Chapter is extremely useful in assessing Risks and decisions to mitigate significant Risks.

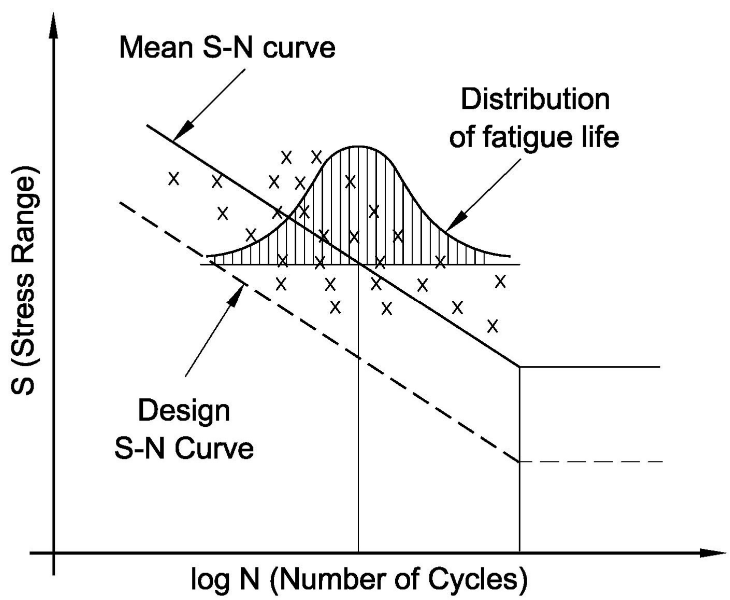

Figure C.1 - S-N data used for fatigue crack initiation to through-thickness crack based on stress cycles to failure (Redrawn from Hughes 2010).

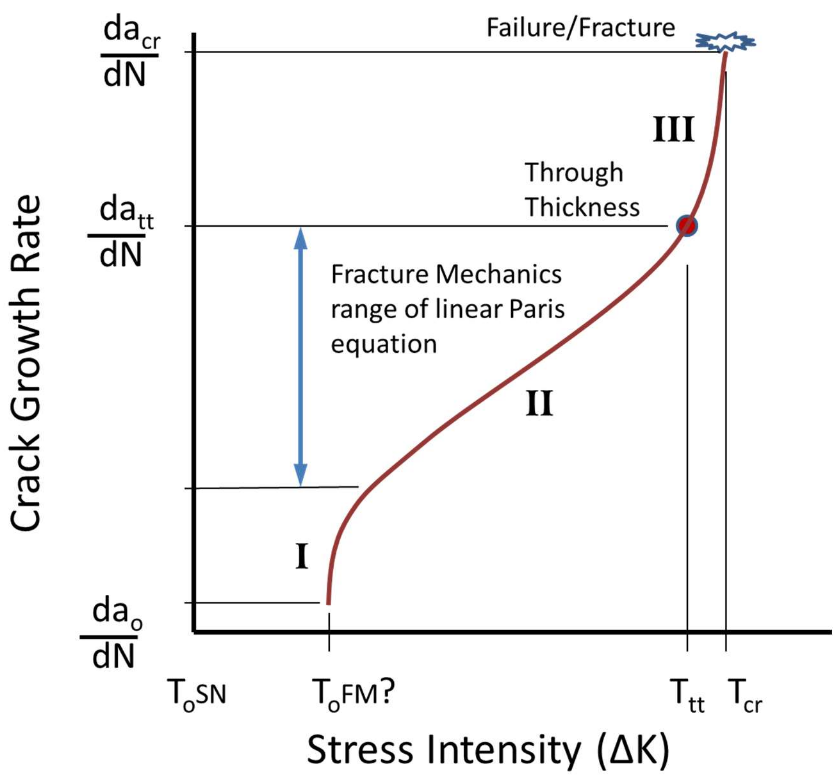

Figure C.2 – Illustration of the relationship between the F-M approaches for fatigue crack length over time.

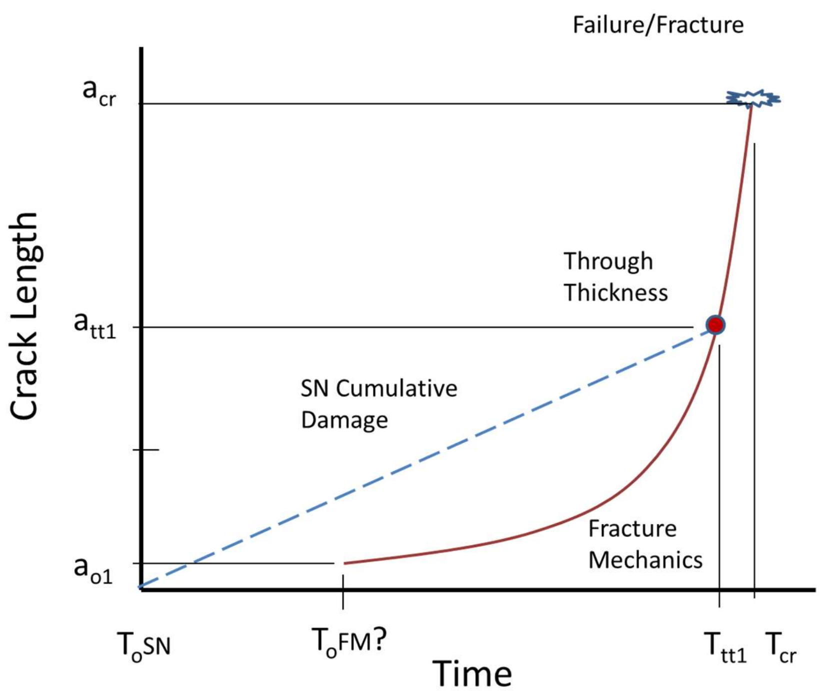

Figure C.3 - Relationship between the S-N+F-M Total Life approaches for fatigue crack length as a function of time.

C.5 References

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Nomenclature

Abbreviations

Ao	Operational Availability
ABS	American Bureau of Shipping
AASHTO	American Association of State Highway and Transportation Officials
AE	Acoustic Emission
AoAs	Analysis of Alternatives
BHP	Bayesian Hyper Parameters
BLNP	Case study fatigue design environments
BMA	Bayesian Model Averaging
CoAs	Course of Actions
CoV	Coefficient of Variation
DOD	US Department of Defense
DD	Drydocking
DMs	Decision Makers
EDD	Emergency Dry Docking
EIFS	Equivalent Initial Flaw Size
EOSL	End of Service Life
FDS	Fatigue Damage Sensor
FLAP	US Coast Guard Fatigue Life Assessment Program
F-M	Fracture Mechanics
FPSOs	Floating Production Storage Offshore
GAO	US Government Auditing Office
Hs	Significant Wave Height
HSM	Hull Structural Monitoring

JIP	Joint Industry Project
LEFM	Linear Elastic Fracture Mechanics
LCC	Life Cycle Cost
LCM	Life Cycle Maintenance
MTBF	Mean Time Between Failure
NDT	Non-Destructive Testing
NL-FEA	Non-Linear Finite Element Analysis
NSWCCD	US Naval Surface Warfare Center Carderock Division
IO	Optimal Inspection
OM	Operation and Maintenance
PfBF	Probability of Brittle Fracture
PHSM	Prognostic Hull Structure Monitoring
PoD	Probability of Detection
RAs	Risk Analysts
R&D	Research and Development
RoI	Return on Investment
RBI	Risk Based Inspection
Risk-TOC	Risk-TOC trade-space approach for Risk related decisions
RUL	Remaining Useful Life
SAR	Search and Rescue mission
SAWB	Ship as Wave Buoy
SCF	Stress Concentration Factor
SHM	Structural Health Monitoring
SLEP	Service Life Extension Program
SFA	Spectral Fatigue Analysis
SIE	Shannon Information Entropy

SLS	Service Limit State
S-N	Stress-Number of Cycles
SRA	Structural Reliability Analysis
SSLCM	Ship Structure Lifecycle Management
TOC	Total Ownership Cost
U	Uncertainty
ULS	Ultimate Limit State
UT	Ultrasonic Thickness
Valid	Joint Industry Project organized around validating the fatigue design approach used for the US Coast Guard National Security Cutters
VoI	Value of Information
WHEC	US Coast Guard High Endurance Cutter

Equation Symbols

a	Crack length
a_1	Corrosion strength reduction factor
a_2	Non-linear corrosion strength reduction factor operating on a_1
a_{cr}	Crack length at instability for a through-thickness crack.
ac	Crack length
A	Intercept of the S-N curve
B	Slope of the log-log S-N curve
C	Consequence
$\$C$	Consequence in currency (dollars)
Ci	Individual Consequence i

C_{LCC}	Life Cycle Costs
Cm	Cost of maintenance
Cmp	Cost of preventative maintenance
Cna	Cost of non-availability
C_o	Initial investment
C_t	Total of cash flows
CI	Confidence Interval
$CVaR$	Conditional Value-at-Risk
d	Discount Rate
$E(V)$	Expected Value
$E(U)$	Expected Utility
$E(Risk_{\alpha})_T$	Expected Value of Risk at Confidence Interval α and Time T
$E(SIE)$	Expected Shannon Information Entropy
$E[TOC]$	Expected Value of TOC
$E[TOC]_{NPV}$	Net Present Value of Expected Value of TOC
$E(TOC)_{So}$	Expected Total Ownership Cost for Risk mitigation scenario (o) at time T
$E(TOC)_{Si}$	Expected Total Ownership Cost for Risk mitigation scenario (i) at time T
$E(TOC_{\alpha})_T$	Expected Value of TOC at Confidence Interval α and Time T
F	Final forecast in Bayesian Model Averaging
$g(t)$	Limit state performance function including ship specific loading
H(X)	Information entropy
i	Integration limit equals 1 to n and n is equal to the total number in the system being considered unless otherwise noted
I	Inflation Rate

L_{sw}	Still-water loading random variable
$L(t)$	Load at time t
L_w	Wave loading random variable
KI_c	Critical stress intensity
KI	Stress intensity used in Fracture Mechanics
KJ_c	Stress intensity toughness derived from the J-integral
Kcr	Critical stress intensity factor
ΔK	Stress intensity factor range
N	Number of load or stress cycles
N_c	Number of component structural details in the correlated group
N_d	Number of structural component details
N_{df}	Expected Number of details that have failed (through thickness crack)
N_{dt}	Total number of structural details or components considered in the system
N_{du}	Number of updated details or components
Ni	Number of loading cycles
NPV	Net Present Value
$PfBF$	Probability of Brittle Fracture
Pf_c	Probability of failure for a specific component
Pfs	Systems Probability of failure
Pf_{SU}	Updated systems probability of failure
R_c	Component reliability
R_R	Risk Robustness
R_S	System reliability

R_{Su}	Updated systems reliability
R_{si}	Risk of serviceability failure i.
$R(t)$	Reliability at time t
$Risk_{DT}$	Risk definition used in Decision Theory
$Risk_{Loss}$	Risk of system loss
$Risk_{T}$	Risk at a specific time in planning horizon T
R_{ui}	Risk of ultimate failure i
S_{R}	Stress Range
S_{Ri}	Stress range of the ith stress range block
S_{c}	Nominal applied stress at crack instability
Su	Ultimate strength
s'	Standard deviation of a statistical distribution
T	Service planning horizon Time
Tcr	Critical Crack Thickness
TOC	Total Ownership Cost
TOC_{T}	TOC at a specific time in planning horizon T
$TOC+$	TOC extended to include SLEP and Ao
tt_{c}	Through thickness crack component failure
TTc	Through thickness crack at system failure
U	Uncertainty
VaR	Value at Risk (V@R)
VoI_{RT}	Value of Information defined by Risk-TOC analysis
Z	Reliability performance function of a component or system
α	Confidence interval value

β	Structural reliability index with Φ^{-1} function
μ	Mean value of a statistical distribution
ξ	Effective discount rate

Curriculum Vitae

Karl Allen Stambaugh

Education

1973-1978 BSE degree in Naval Architecture and Marine Engineering, College of Engineering, University of Michigan, Ann Arbor, Michigan.

Employment Record

1978 – 1989 Giannotti and Associates, Annapolis Maryland, Naval Architect

1989 – 1991 Columbia Research Corporation, Annapolis Maryland, Naval Architect

1991 – 2003 Chesapeake Marine Design, Severna Park MD, Owner Naval Architect

2003 – Present Department of Homeland Security, United States Coast Guard, Sr Naval Architect

Specialty Areas

Ship and boat seakeeping, hydrodynamic loads prediction, structural analysis, structural fatigue, and hull structure monitoring

Professional Memberships

Society of Naval Architects and Marine Engineers, American Society of Naval Engineers

Related Publications

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