Smart design choices to reduce the vulnerability of naval vessels

by

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Submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

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Declarations

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Located in chapter 3.

The candidate was the sole author on this paper.

Paper 2, A framework to improve the naval survivability design process based on the vulnerability of a platform's systems (DOI: 10.1016/j.oceaneng.2018.12.074)

Located in chapter 4.

The candidate was the primary author and with author 1 contributed to the conception and design of the research project. Author 1 and 2 contributed to the writing and finalisation process. The candidate contributed approximately 85% to the planning and execution of the work.

Paper 3, Inclusion of system reliability in a survivability assessment framework (Under review)

Located in chapter 5.

The candidate was the sole author on this paper.

We the undersigned agree with the above stated "proportion of work undertaken" for each of the above published (or submitted) peer-reviewed manuscripts contributing to this thesis:

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Acknowledgments

In the first place, I would like to thank my family for their never-ending support from the day I started this journey. Without their help, I would have never attempted or even completed this big task. Vielen Dank liebe Mutti, Lieber Vati und meine Lieblingsschwester Maxi. Thanks a lot for the patience from my dear fiancé Trini.

I would also like to thank my friends and peers from the University of Tasmania for their support during the years it took me to complete the thesis work. Their encouragements and advise made it possible to complete this work.

I’m also grateful for the cooperation with DST Group, particular in the feedback and support from Warren Roberts, Grant Gamble, Brigitta, Tom Whitehouse and Anthony Travers. Special thanks also to my industry partner TnE Solutions, Derek Skahen, Dan Foos and Zackery Stull, whose support and collaboration was very fruitful and creative time during my PhD candidature.

Finally, I also wish to acknowledge the support of the Australian Research Council Research Training Centre of Naval Design and Manufacturing (RTCNDM). The RTCNDM is a University-Industry partnership established under the ARC Industry Transformation grant scheme (ARC IC140100003). Many thanks to my supervisors Dr. Jonathan Binns, Dr. Abbassi and Dr. Vikram Garaniya for their guidance throughout the duration of this course.

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Abstract

Survivability is the ability of a naval vessel to survive a combat incident by avoiding (susceptibility), withstanding (vulnerability) or recovering (recoverability). Vulnerability assessment is often divided into the structural and system vulnerability assessment.

System vulnerability assessments are traditionally performed using manually built fault and success trees that model a simplified version of the functional failure relationships. This traditional approach has been very limiting, but more accurate and realistic methods were too computationally expensive to use.

Furthermore, traditional vulnerability assessments also assume that the onboard systems are perfectly reliable and fully functional, which is a further simplification that may have significant consequences on vulnerability assessments. System reliability has never been included in traditional vulnerability assessment methods mainly due to the limitation in available computational power. However, with increasing readily available computing power, such enhancements are now realisable.

For an accurate vulnerability assessment of a naval vessel, it is important to know the functional failure relationships between the systems of that vessel is not prone and subject to human erroneous input. Furthermore, to include system reliability into the vulnerability assessment helps to understand the actual vulnerability performance of a vessel better and to support naval architects to make design decisions with regards of longevity vulnerability enhancement at minimal cost.

The objective of this research is to demonstrate and to develop a framework that can automatically generate, via machine learning, the functional failure relationships from an actual design of a naval vessel and that then identifies critical and sensitive components that negatively contribute to the vulnerability performance of the vessel. Once these failure relationships are derived, they are then used to model the system reliability with the help of Bayesian Network operations.

In order to derive the machine learned failure relationships of an actual naval vessel and to determine the reliability effect of the naval vessel's equipment, the research is divided into

three major methodological chapters. The first part investigates contemporary and state of the art vulnerability assessment techniques and uses a selected tool to perform an actual survivability assessment of a chosen system. This study also served as a basis to become familiar with the nature of the research domain. The second part extends the model of the naval vessel and performs a vulnerability assessment with further naval systems modelled to complete a holistic and comprehensive naval model. The results of this model are then analysed with a Bayesian machine learning algorithm and built into various Bayesian Network models. These Bayesian Network models are then used for a sensitivity analysis to identify critical systems and single point of failures. The third part uses the derived Bayesian Network from the previous part and utilizes the learned failure relationships of an actual vessel to include the reliability effect of the naval vessel's equipment into the survivability assessment.

The results of this methodology are of diverse nature. The first study performing a state-of-the-art vulnerability assessment for various firemain layouts with different automation levels resulted in an overview comparing different firemain systems across various levels of automation and their according vulnerability performance. The second part of this study resulted in the development of a complete naval vessel and a framework that has the ability to analyse output results from a vulnerability assessment of that vessel. The framework automatically derives probabilistic failure relationships between the naval vessel's systems and to identify critical systems and single point of failures of that design. The third part of the methodology resulted in a study that demonstrates the proof of concept to include the naval vessel's systems reliability and to predict the naval vessel's vulnerability performance with respect to service time, resulting in a demonstration of the significance of system reliability in vulnerability assessments.

The research has demonstrated the feasibility to use Bayesian Networks as a tool to analyse naval vessels and to improve their vulnerability performance. The developed framework uses Bayesian Networks to identify single point of failures, which when eliminated from the design, lead to an improved design. As the inputs from the survivability assessment are readily available, these inputs just have to be entered into the vulnerability analysing framework and their analysis is automated. This framework enables shipbuilders to quickly analyse and assess naval ships, which can then be done in less time and with fewer resources.

Furthermore, the developed framework produces probabilistic functional failure relationships that, when supplied with the information about the naval vessel’s system reliability, can estimate the degraded vulnerability performance of the naval vessel after a certain amount of service years. Thus, the results and outcome of this research can benefit the vulnerability assessment process as it allows for the quick identification of single points of failure and the ability to model the naval vessel’s future service behaviour.

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Chapter 1

Thesis Introduction

1.1. Prologue – A brief overview of naval survivability

The concept of naval survivability, defined by different national naval standards as the capability to survive combat and maintain mission capability, reaches back to antiquity when the first true warships were built by the Egyptians, Greeks and Persians (Kok 2012). Some of the more well-known recent examples that demonstrate the various aspects and design choices are briefly introduced in this section. Survivability has historically mainly been a naval vessel's ability to withstand combat, which is primarily the aspect of vulnerability.

To achieve a high performance in vulnerability it is not as simple as comparing each vessel's features to its counterparts, but rather to understand that certain vessel features like high firepower can be rendered ineffective by another countering features that allows the target to avoid being hit be staying out of range, for example.

One of most famous examples of this idea are the battles between the Spanish Armada and the English Navy in the Anglo-English war in 1588 (illustrated in Figure 1). The Spanish had built an armada of large and bulky ships with high superstructures and heavy firepower that were outmatched by the English fleet made up of seemingly inferior ships. The English ship's better manoeuvrability enabled the English fleet to avoid unfavourable combat situations and enabled them to attack at moments where the Spanish Armada were left to bad manoeuvrability due to their lack of mobility of their bulky galleons.

Figure 1: Ships of the Spanish Armada attacked by English demolition ships which led to its demise (Loutherbourg 1796)

As technological advances like explosive shells were introduced in the early 19th century, wooden sailing ship designs suddenly became very vulnerable to enemy gunfire. This led to changes in ship design like reinforced steel plating and integration of steam engine propulsion, which resulted in the first ironclad designs.

The first encounter between traditional wooden ships and newly developed steel reinforced ships took place in the Battle of Hampton Roads in 1862 during the American Civil War, which is shown in Figure 2. The CSS Virginia destroyed a number of wooden naval ships on the first day, but after the USS Monitor had joined the battle on the 2nd day, it quickly became apparent that both ships armour was impervious to each other's armaments and thus both resorted to ramming tactics (Quarstein 1886). The fast pace of the development and change of naval designs concluded in newly built ships already being obsolete by the time they were completed (Ireland 1996).

Figure 2: The first encounter between two ironclads took place in 1862 between the CSS Virginia and the USS Monitor in the Battle of Hampton Roads (Quarstein 1886)

From the mid-19th century to the mid-20th century, naval ships were equipped and designed with stronger and heavier armament. This resulted in a naval design philosophy that lead to larger ships with larger displacement. Greater enemy firepower was countered with more armour and vice versa, but as history shows naval warships were never perfectly safe and thus always have remained vulnerable to some extent.

One of the most famous examples of that era is the German battleship Bismarck (shown in Figure 3), which was one of the largest and most powerful ships of the 2nd World War. The ship was rendered unmaneuverability by a torpedo dropped from a plane and eventually led to its sinking in the following days (Ireland 1996). The heavy armour and armament could not save the battleship as even though the ship with exception of its rudder was undamaged, it had lost its ability to steer and leave the combat scene.

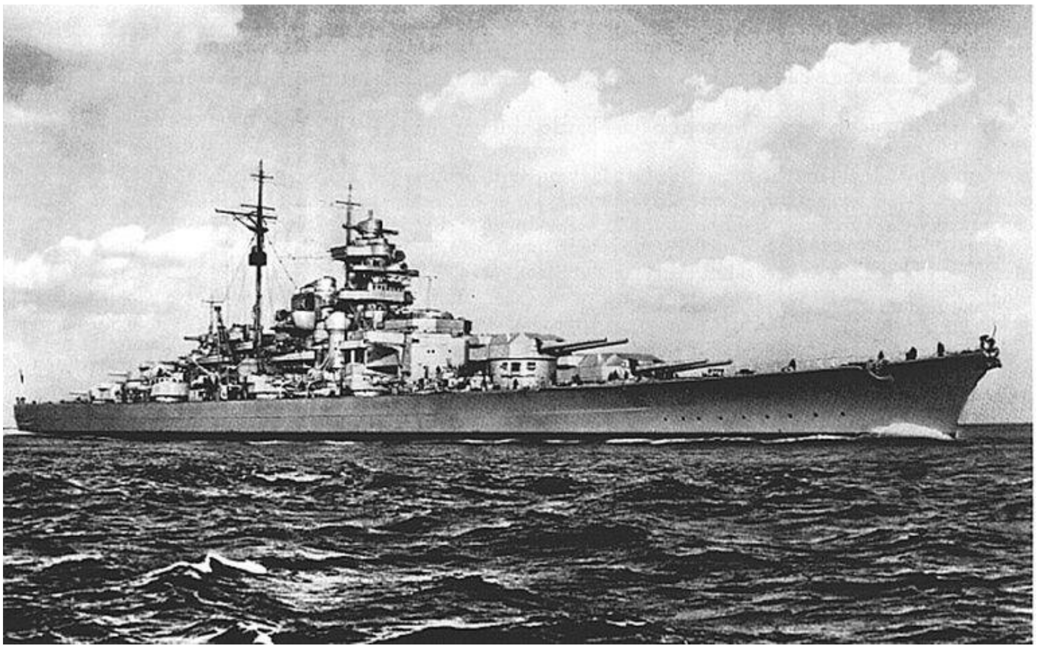

Figure 3: German Battleship Bismarck with its clearly visible weapon turrets (Garzke, Dulin et al. 2019)

The navies during the 2nd World War learned that bigger and stronger ships weren't always better and that a loss to one of these huge ships was a massive loss for the whole fleet. Thus, since the 1940s navies have decreased the size of their ships and the developed ship's roles became more specific and sophisticated.

It became clear that regardless of the size and armament, ships are always prone to fail in combat and there was no such thing as an invincible design. The post-war designs of naval vessels, such as the USS Zumwalt in Figure 4, became smaller and started to use novel technologies such as stealth as a measure to stay undetected and not get targeted or hit. It can be seen from the past couple of decades that the technological advances contributing to the survivability of the vessel are designed to keep the ships at a small size while expanding their operational roles and capabilities.

Figure 4: Characteristic for the USS Zumwalt is its lineal shape that helps to reduce the ship's signature and grants the ship its stealth capability.

1.2. Previous and related work

Naval Survivability is one of the oldest shipbuilding disciplines and many attempts were undertaken to build better and more survivable ships. Through precise modelling and simulation, a vessel's performance can be predicted from the early design stage. The nature of the simulation and modelling has changed over time, from rather simplistic calculations by hand through experimental simulation through to highly sophisticated computer-aided simulations. Particularly in the 20th century, major achievements were accomplished in developing new performance estimation methods. The new methods managed to more accurately simulate and quantify naval survivability performance and combat outcome due to the development of the personal computer. Many of the various aspects that can be simulated and predicted remain individual aspects that have not been linked up to present days.

Among these research projects, there has been primarily interests to simulate individual mechanisms that drive the survivability performance of vessel such as fire-spread, blast and fragmentation, various types of signatures estimations and many more (Goodfriend 2015, Stark 2016). Each of these individual mechanisms are very important and have a strong effect on survivability, however survivability must be seen as a multi-disciplinary concept as it is defined as “the ability of the vessel to perform its mission after impacted by a threat” (U.S.Navy 2012).

The first report that laid the foundation and treated naval survivability as a multi-disciplinary research area (Ball and Calvano 1994) dates back to E. Ball, who transferred the concept of survivability from aircraft design onto naval design. In that work naval survivability was divided into three aspects, which are susceptibility, vulnerability and recoverability for the first time. This framework was adopted by many countries and has remained almost unchanged (Lloyd's_Register 2006, Royal_Australian_Navy 2010, U.S.Navy 2012).

There have been diverse attempts to understand the nature and underpinning principal relationships within Survivability. One of the major research areas examines the use of regression analysis of modular auto-generated ship models followed by a parametric analysis to extract principles and relationships between design choices and their effect onto survivability (Brown and Mierzwicki 2004). However, as Brown’s approach to derive principal survivability relationships between design measures and the survivability performance is possible, but albeit adding more detail to the modelling of the simulation, this approach remains limited in realism due to the lack of computational power required to perform the vast amount of necessary exhaustive design permutation (Brown and Salcedo 2003, Brown and Mierzwicki 2004).

Another approach in the field of survivability research is attempting to link various survivability mechanisms resulting in the development of different models and tools that combine disparate survivability factors and effects from within susceptibility, vulnerability and recoverability (Konovessis, Cai et al. 2013, Liwång 2015).

A wide range of vulnerability assessment tools that focus on the reduction of vulnerability through separation have been developed dealing with structural hardening, general layout modification and fire suppression (Kok 2012, Stark 2016). The change of a vessel’s layout and the hardening of the structure or components are usually major design changes that are difficult to achieve as they drastically affect the vessel’s design. The developed tools allow vulnerability assessments at a very basic design stage as these tools require very little design detail. They often simulate weapon effects on a ship and then assess the failure of vulnerability capabilities through fault trees and deactivation diagrams to then identify critical areas of the vessel's architecture (Stark 2016).

Fault trees and deactivation diagrams are typically modelled through Boolean Logic as they are easy to build and comprehend. However, in offshore process engineering and other risk-based engineering areas have successfully demonstrated the implementation of Bayesian Networks (BN) as a superior tool over Fault Trees (Khakzad 2011, Khakzad, Khan et al. 2013, Konovessis, Cai et al. 2013).

Fault Trees can also model joint effects of system failures and events, when clear functional relationships are known, but as cause and effect relationships in naval vulnerability are very complex, the manual modelling of Fault Trees is predisposed to erroneous human input. Recent research on the deployment of Bayesian Networks applied on vulnerability, highlighted the lack of objective detailed vessel models and thus utilised subjective human modelling of the Bayesian Network (Liwång 2015).

Manual modelling of BNs was shown to be capable of solving problems with a high amount of uncertainty and to identify root-cause effects (Lee and Misra 2005). Additionally, through the BN's ability to support decision making, simple events and scenarios could be solved (Lee and Misra 2005). However, as these BN models are still developed by human experts, they're prone to erroneous and subjective due to human input. Even though detailed vulnerability assessment tools are available at this point, various regression techniques and Bayesian machine learning algorithms remain still largely unexplored (Konovessis, Cai et al. 2013, Liwång 2015).

Bayesian machine learning algorithms have the capability to derive unbiased functional failure relationships and can present the relationships of graphical Bayesian Network models. Bayesian Networks don't require any additional modelling of naval vulnerability models, because advanced naval vulnerability simulation models and their results can be entered readily as input into the learning algorithm of Bayesian Networks. Thus, Bayesian machine learning algorithms can bridge the gap to build complex Bayesian Networks and display functional failure relationships from any vulnerability simulation data without any human interference (Koller and Friedman 2009, Friebe, Skahen et al. 2018).

Bayesian Networks also have a particular strength in determining the cause of a failure and thus are very helpful to identify critical areas of a naval design of naval system's architecture as the Bayesian Networks can be used to perform sensitivity analyses and update its probabilities (Konovessis, Cai et al. 2013, Liwång, Ringsberg et al. 2013). Furthermore, Bayesian Networks are particularly helpful when additional historic information is available, which then can be linked with each other through manual Bayesian Network expansion.

All vulnerability assessment tools are built on the assumption of perfectly reliable systems and thus neglect conventional equipment failure situations that can be caused by fatigue and lessen the reliability of the system. Recent research argues that conventional equipment failures have an affect onto the performance of the vulnerability of a naval vessel as most systems have usually a reliability of between 85-95% (Malakhoff, Klinkhamer et al. 1998). However, no study of how conventional equipment failures, such as the reliability of the equipment, affect ship Vulnerability has been performed up to today (Guzie 2004, Liwång 2015).

1.3. Problem Description

Current research to enable vulnerability design assessments, though promising in their continued development, presently employ statistical models which prohibit identification of unknown design inter-relations between naval vessel's systems and operational capability (Goodfriend 2015). Currently, cause-failure relationships as part of naval vulnerability assessments are modelled manually and are thus prone to human error as they're built subjectively by human experts. The error of a human expert can be accredited to different reasons, which can be categorized into 1) erroneous subjective human thinking and 2) lack of knowledge. Whereas, an automated tool is objective and does not makes mistakes like a human expert.

Thus, it is necessary to develop a naval engineering vulnerability estimation framework to support industry in the design evaluation and assessment of vulnerability enhancements applicable in identifying true objective causes of vulnerability performance failures of vessel designs when confronted with complex naval models at a detailed design stage.

Though current tools allow the modelling and simulation of the interconnection between systems and equipment as part of the vulnerability assessment, the process to identify causes for the failure of the naval vessel's operational requirement is very tedious and often underlying causes may stay undetected. Also, vulnerability assessments are always performed under the major assumption of perfectly reliable systems, which can lead to overly optimistic designs as the systems are in fact not perfectly reliable. Naval vessels are modelled for a high performance under the assumption of perfectly reliable systems, which cannot be achieved if the naval system reliability is taken into account.

1.4. Purpose

The purpose of this research is to derive probabilistic failure relationships that describe the vulnerability performance of a naval vessel's systems and operational capability. For this purpose, a framework is developed to support industry in design evaluation and assessment of vulnerability enhancements within the already existing arrangement and complex model of a vessel. The aim is to improve the vulnerability performance through better understanding the underlying failure relationships and thus the resulting ability to perform smart design modifications that do not lead to additional space or weight of the vessel.

The same novel framework can also be deployed on civil vessels to identify underlying failure relationships; however, the concept of vulnerability is only applied to naval vessels. The limitation to naval vessels is primarily due to the fact that vulnerability is defined as a vessel's capability to withstand an attack – which is not a feature that civil vessels are currently designed for.

The developed vulnerability estimation framework is applicable in assessing single point failure of a naval vessel's vulnerability design while considering overly complex naval models that have a considerable amount of information and level of detail. The amount of detail is mainly due to the necessity to consider naval capabilities such as offensive capability, defensive capability, safe return to port and personnel protection. The framework will also be capable of deriving probabilistic failure relationships and help to obtain a better understanding of the modelled vessel's behaviour.

The derived probabilistic failure relationships are then used to include reliability into the vulnerability assessment of a naval vessel. This will help to understand the aging effect of naval equipment onto the vulnerability performance of naval vessels and thus then support the naval architect to make design choices that affect the lifecycle of the naval vessel.

The research focuses on the equipment analysis and excludes structural blast and fragmentation assessments. Furthermore, the developed framework enables identification of system-to-system, layout-to-system, and system-to-crew, inter-relations in order to identify single point of failures. Furthermore, this research attempts to include common system reliability factors into the vulnerability assessment, which enables the modelling of a more realistic ship's vulnerability performance and enable the prediction of its future degradation effect to then feed the information back into the design process.

1.5. Research Objective

The first objective of this research is to perform a literature survey and identify a research area within vulnerability domain that allows the utilization of affordable tools and unclassified models. Thus, the opening research question for this research becomes:

What is the state of the art in vulnerability assessment and how does one conduct a contemporary vulnerability assessment with the available tools?

The primary objective of this research is to demonstrate whether and subsequently how Bayesian Networks (BN) are capable of identifying probabilistic failure relationships from models in vulnerability assessing software in order improve design and evaluation of vulnerability enhancements. Furthermore, the performance assessment of Bayesian machine learning algorithms and their ability to build BNs from output of vulnerability assessing software is of central essence and is studied.

Thus, the second research question for this project becomes:

Can the Bayesian machine learning algorithm be used to automatically investigate the vulnerability performance of a vessel during the detail design stage?

The vulnerability assessment and chosen Bayesian machine learning algorithm are used in the development of framework that enables, through the identification of probabilistic failure relationships, the inclusion of system reliability into an otherwise assumed perfectly reliable system.

Therefore, the third research question of this project is:

Can the developed framework and Bayesian Network be extended with system reliability values to model the aging effect of the vulnerability performance of the naval vessel?

All three research questions and the previous research objectives were investigated and are outlined in chapter three, four and five.

1.6. Hypothesis

Bayesian machine learning algorithms and Bayesian Networks (BNs) allow building inference models by linking data of different sources such as historical data, simulation results and expert judgement. Machine learning algorithms have the ability to objectively identify correlations in complex systems that then can be modelled through Bayesian Networks, which then can be extended through expert manipulation to capture inference relationships not only within a single source of data but also between and across.

Equipment vulnerability assessments are often overly complex and have a high amount of information that make them almost incomprehensible to manually identify cause failure relationships. It is evident that an automated algorithm to identify objective cause failure relationships is necessary and very likely beneficial to the assessment process. The identified cause failure relationships of the vulnerability assessment are of probabilistic nature and allow the inclusion of additional equipment information such as system reliability, which will help to overcome the major assumption of perfectly reliable systems in vulnerability assessments.

Equipment vulnerability assessments for naval vessels are still predominantly performed through Fault Trees and that full model simulations are overly complex and exclude uncertain information this research demonstrates an approach to include uncertain information into vulnerability assessments through the application machine learning algorithms and provide a more realistic few into the nature of naval vulnerability.

1.7. Methodology

As described in section 1.3, the difficulties in current vulnerability assessment research can be briefly summed up as the difficulty to identify failure relationships between systems and operational requirements, which is often caused by the detail and complexity of naval models, but also the usage of deterministic vulnerability assessments, which tends to ignore a lot of uncertain but likely effects such as system reliability. The approach chosen to answer the research questions and solve the research objectives from section 1.5 is outlined and described in the following section Figure 5.

As shown in Figure 5, the research was structured in three main parts and publications. The first part starts off with a modelling and research exercise on a contemporary vulnerability assessment tool Integrated Recoverability Module (IRM). This study models a basic firemain system in different configurations and layouts to demonstrate the capability of the tool and obtain a better understanding of the latest vulnerability assessment techniques.

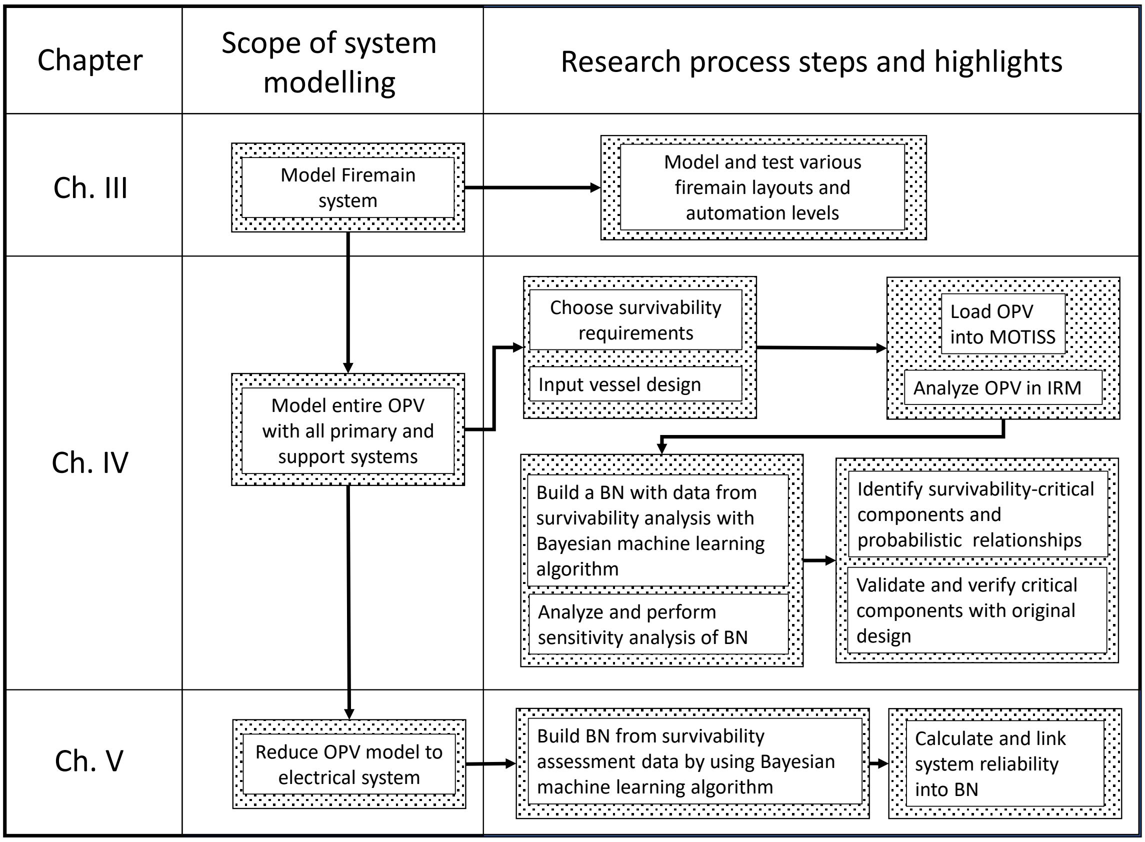

Figure 5 Top level methodology breakdown of the research project

As can be seen in Figure 5, the research continues from chapter three to four by expanding the case study model from a single firemain system to a detailed design of a naval vessel, which is done in cooperation with the joint-industry 'Test and Evaluation Solutions', a US contractor for survivability assessments. The case study vessel is an Offshore Patrol Vessel (OPV), with a length of about 55m. Vulnerability goal and threshold requirements for ship survivability analysis in multiple areas such as the ship's primary mission systems, propulsion, auxiliaries (electrical power), crew loss, DC/FF, and self-defence are created for the OPV to complete the model from chapter three. Next, the model of the vessel is loaded first into Measure of Total Integrated System Survivability (MOTISS) tool to assess the blast and fragmentation of a hostile attack and then the results are loaded back into the IRM and a dynamic demand and supply analysis is run to evaluate the post impact performance of the vessel. Thereby, flooding, fire and smoke are taken into account as well.

The output from the vulnerability analysis then is parsed into a Bayesian machine learning algorithm, which tests the input data for correlation and sensitivity and builds many varying

BN and chooses automatically the best fit. Once the BN is built, it then becomes possible to perform sensitivity and criticality assessments on the model to identify critical components and single points of failure. The sensitivity analysis in the Bayesian Network is done through assessing the cross-entropy of the Bayesian Network and identifying components that have a high contribution rate to the failure of other systems and subsequently the performance of the vessel. The validation and verification are achieved by cross-checking the results of the Bayesian Network sensitivity study and the model of the vessel in the IRM. Also, the developed framework is tested for variability to estimate the performance of finding design issues depending on the Bayesian Network size.

In the third part in Chapter 5 , the developed naval model is reduced to the electric system and the concept of including system reliability is included. As can be seen from Figure 5, this is achieved by deploying again the machine learning algorithm to construct a Bayesian Network through the validated approach from Chapter 4 . The Bayesian Network then is then manually extended through the inclusion of pre-calculated system reliability data, which affects each system and cascades its effect to the operational requirements of the naval vessel. Through altering states and in the Bayesian Network it then it becomes possible to predict the vessel's degraded performance in a certain amount of service time.

1.8. Novelty of Methodology

The presented methodology is a holistic vulnerability assessment implementing BN and featuring concurrent assessment of vulnerability and recoverability design features. While reference to implementation of BN within naval design has been found within the current survey of literature (Friis-Hansen 2000, Lee and Misra 2005, Liwång 2015), the effective implementation of BN has been limited to individual system or feature relationships with a combined whole ship assessment of vulnerability and recoverability yet to be accomplished due to the inability to establish sufficient detailed information to effectively populate inclusive and non-subjective probabilities into a BN.

Furthermore, present survivability assessing software (IRM), albeit capable of realistically simulating the effect of design choices onto the naval ship's survivability performance, lacks the ability to effectively analyse the cause failure relationships between survivability performance to design choice.

The present methodology overcomes this failure by eliminating the causal traditional FT methods and uses Bayesian machine learning algorithms to evaluate the input and output of the survivability assessment. The machine learning algorithm is applied onto the data of an actual ship design to build a BN and populate according conditional probability tables automatically without any human input.

In chapter 4, the developed framework creates a BN that is then used to detect single point of failures of naval vessel's systems through testing the BN's nodes, which represent systems and operational capabilities, for sensitivity with respect to other systems and operational capabilities. Through sensitivity tests and the according detection of single point of failures and following design modification, the design and the performance of the vessel can then be improved. Key benefit of this method is that no further information must be entered other than the available information from the classical vulnerability assessment process.

Additionally, the developed framework to derive BNs representing the system and performance relationships assumes perfectly reliable systems. The systems as part of the vulnerability assessment are assumed to be perfectly reliable systems, which is an overly optimistic assumption, but the impact of this assumption has not been researched yet. Thus, the developed framework to derive a BN from vulnerability assessment is extended by introducing and including the reliability factors of each system into the developed BN. The BN from chapter 4 is taken and manually expanded by the inclusion of reliability factors through basic BN operations. The benefit of this approach is to include the systems reliability into the vulnerability assessment to obtain a more realistic performance prediction of the vessel and to model and predict the vessel's future performance.

1.9. Thesis structure

To achieve the outcomes of the study, the research questions from section 1.5 are addressed through following four main components that have been partially published and others are still under review:

Chapter 2 :

- The first publication is the main literature review and hypothesized the methodology of this research, that then had been refined and reused in (Friebe, Skahen et al. 2018).
- A literature review on survivability has been performed to identify research gaps and available software. Limitation of previous research and current survivability assessment methods are addressed as well as benefits of the novel methodology are undertaken (Friebe and Waltham-Sajdak 2017)

Chapter 3 :

- Development of a basic naval model and familiarization with the provided software tool along with a comparison study. The study performs a comparison of different layouts of a firemain system modelled with different levels of automation implement in a generic design of a patrol boat. This study is performed on a rudimentary basic model that is extended in chapter 4 to a holistic model.

Chapter 4 :

- Development and refinement of the framework from (Friebe and Waltham-Sajdak 2017) to assess the vulnerability performance of a vessel and to derive the probabilistic failure relationships of a naval vessel. The rudimentary case study model from Chapter 3 is extended to fully and holistically model a naval vessel with all its equipment, systems, crew and operational capabilities. This phase demonstrates the development of a novel framework to derive the probabilistic failure relationships of a naval vessel through a Bayesian machine learning algorithm (Friebe, Skahen et al. 2018).

Chapter 5 :

- This chapter reuses the model from Chapter 4 and reduces the data to only the electrical system. Then the developed framework is used to build a Bayesian Network, which then is used to include the system reliability into the derived Bayesian Network (Friebe 2019 under review)

Chapter 2 **Literature Review**

As indicated in chapter 1.1, the naval design philosophy during the period of the 2nd world was a one-dimensional trend depending the size of guns of the vessels. That lead to bigger naval ships as the operational philosophy was simply to overwhelm the enemy. By the late 40s, governments already realised that the oversized battleships, heavily armoured cruisers and very large frigates were un-economical and consequently the trend shifted towards smaller and more versatile designs (Smith 2013).

This trend had been accelerated by the events of the Six-Day War in 1967, where the INS EILAT was the first destroyer sunk by a small missile boat and demonstrated the capacity of surface to surface radar guided launches in naval conflicts. This event marks a major milestone in naval surface warfare and aroused worldwide interest in the development of small missile boats (Stark 2016).

Thus, since post 1968 the more survivable vessel was the one that could avoid being hit and as a consequence, the concept of naval warfare had changed to a more defensive strategy to disable the incoming threat by reducing the susceptibility, and thereby enabling an offensive return (Waltham-Sajdak 2012).

During the Arab-Isreali War in 1973, it proved the advanced survivability of the new and modern defensive naval warfare doctrine at the Battle of Latakia. Almost 40 Styx missiles were fired, but the vessels which employed reduced susceptibility suffered no hits. Thereby, the Battle of Latakia confirmed there the potential of small, fast missile boats equipped with advanced Electronic Counter Measure (ECM) packages (Foos and Skahen 2008, Waltham-Sajdak 2010).

As ECM and susceptibility reduction measures improved the potential threats also improved, which resulted in the sinking of the HMS SHEFFIELD in 1982 during the Falklands War and the USS STARK in 1987 during the Iran-Iraq War (Navy 1988).

In response to improved threats, the late 1980’s and early 1990’s produced the first ships designed fully for survivability, with the Arleigh Burke Class 1989 and the Sa’ar 5 Class in 1993 were the first major stealth effort designs of naval vessels.

Albeit designed for stealth, the new century has proven that solely reducing susceptibility does not ensure survivability. This resulted in the modern concept of Naval Survivability (Waltham-Sajdak 2010) of the 21st century, which can be briefly described as:

- Lower the Probability of Being Hit (but recognize that there always exists a probability of being be hit)
- Increase the ability to sustain damage and continue fighting (but recognize that it's possible to protect against all damage events)
- Increase the ability to rapidly regain damaged mission critical systems (increase recoverability)

Ship Survivability is the ship's capability to prevent the loss of mission capabilities under a given threat environment. The process by which Ship Survivability is assessed provides a useful and generalized framework for rationally setting requirements and making design decisions.

However, it can be summarized that modern navies are no longer dominated by capital ships as they were during the 40s of the 20th century, but a number of medium to small ships, much of the time with different roles like, mine hunting, anti-submarine, air, surface and many more. The dogma of 'the bigger, the better' has shifted towards a design philosophy of having smaller ships with multiple purposes and to combine their abilities in combat when necessary.

Since the 1950's, the size of class of vessels being constructed has decreased as shown in Figure 6 (Smith 2013). During the same time, the numbers of more powerful systems installed onboard naval ship have increased in conjunction with reduced manning (Smith 2013). Figure 6 shows that ships having grown in inverse relation to their number. As the size of ships decreases and the number of their installed systems grow, every ship becomes a more important and valuable asset. To protect these assets, ships have be able to survive combat and thus, one of the most important feature modern design features for a military vessel is that of Survivability (Said 1995). Survivability refers to the integrated capability of a ship and its systems to maintain mission performance when subjected to a hostile environment.

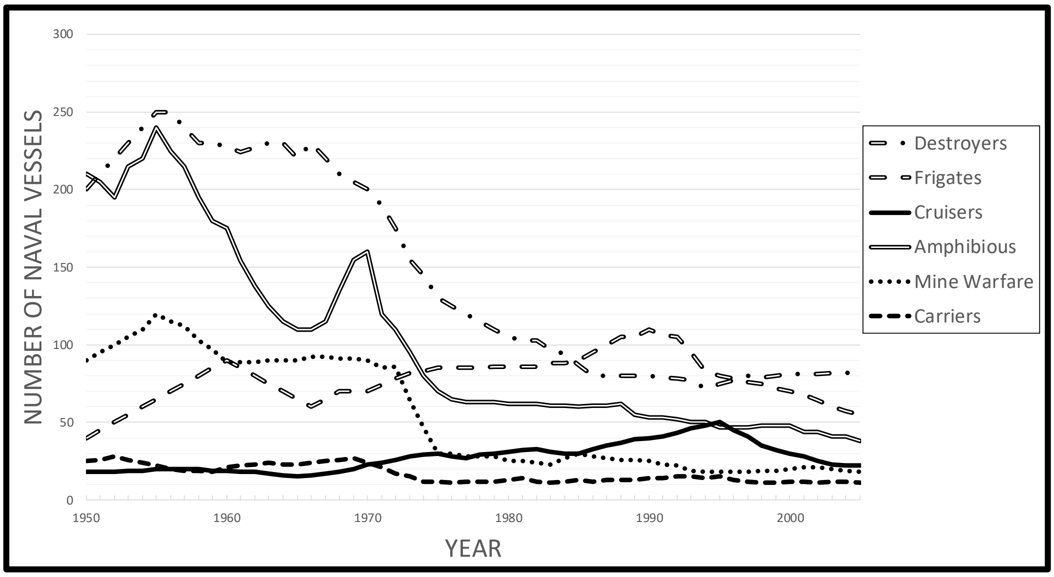

Figure 6: Number of USN Ships by Class by Decade

As ships become smaller and change their roles from single-purpose to multi-purpose ships, the system density on-board of such ships grows and they become more difficult to build. This complexity makes it more difficult to understand the combat-related characteristics of a naval ship as the interaction between its active and defensive design features depends on a number of variables.

The majority of survivability-related issues are addressed in detailed design stage, where models are overly complex and adaptations are heavily constrained by choices made in the earlier design stages (Piperakis 2013). The deficiency corrections can be prohibitively expensive as is illustrated in Figure 7. The cost to extract defects is shown to increase by a factor of 3 to 6 at the end of concept design, by a factor of 20 to 100 within detail design development and by a factor of 500 to 1000 within production (Doe 2006). Therefore, changes in the early stages of design are significantly less expensive than making the changes later design stages, if they are even possible at the later stages.

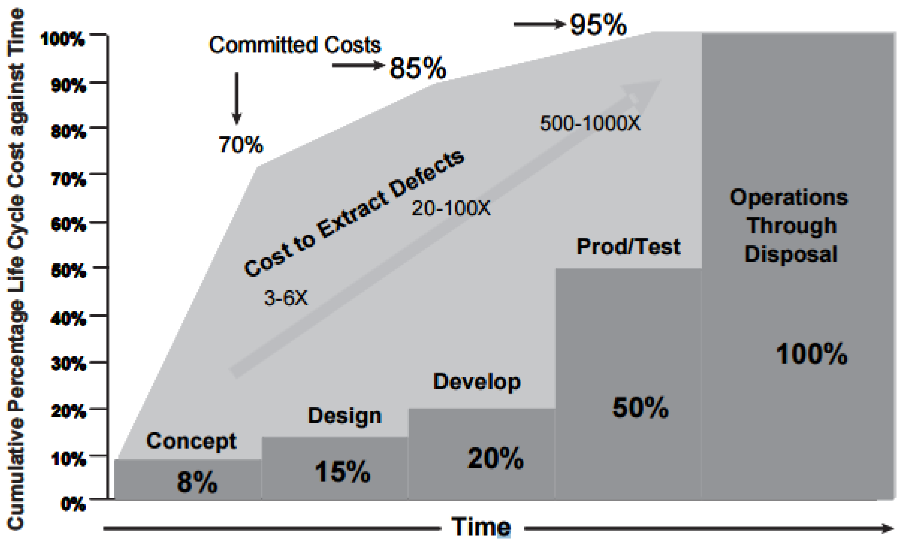

Figure 7: Committed Life Cycle Cost against Time (Doe 2006)

Naval survivability is often discussed in context of the kill chain model (Figure 8) which represents a sequence events to be completed successfully by an aggressor in order to achieve target neutralization can be represented as the Probability of Kill (P_{kill})- *i.e.*, denying the ship the capability to complete its intended mission. Each event of the diagram of Figure 8 is represented by a link whose name is derived from the aggressor's state of progress against the target ship. Historically and for the scope of this thesis, this kill chain model is considered for conventional attacks that include explosives only. Attacks that are within the definition scope of Chemical, Biological, Radiological and Nuclear scenarios (CBRN) (Hernandez, Kotzian et al. 2012) are not considered, since the focus of this thesis is on the design modifications of naval ships, whereas CRB-attacks are mainly targeted towards the crew and that requires specialized equipment. Nuclear attacks however are not considered as the effort and potential gain to design against such an overpowered and very unlikely attack is disproportionally large (Hernandez, Kotzian et al. 2012, Waltham-Sajdak 2012).

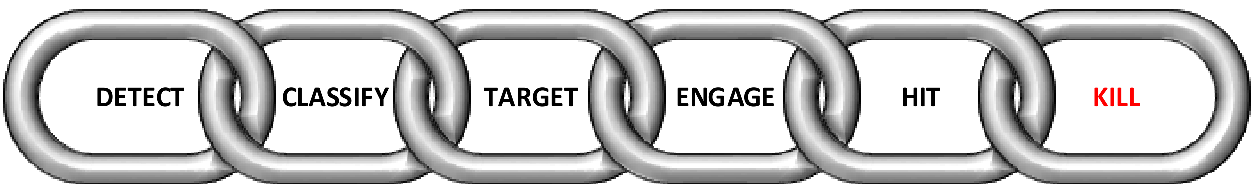

Figure 8: Kill Chain Model - The Aggressor Perspective

Within Figure 8, the state at the end of each link is defined as:

1. Detect – the target ship has been detected by the aggressor's sensors.
2. Classify – The detected target ship has been classified by the aggressor as a friend, foe, or unidentified, as well as the type and class of the target.
3. Target – The target ship has been designated as non-friendly, and is tracked (position, velocity, and direction are established).
4. Engage – The aggressor's fire control system has computed a firing solution (choice of weapon to be used, and intercept of the target ship's position, velocity, and direction determined) and a weapon has been launched.
5. Hit – The propagator has acquired the target ship, homed in, and hit it. Within this model, the launching of a propagator may initiate an additional and separate kill chain, such as in the case of "fire and forget" weapons.
6. Kill – The target ship has been neutralized as a consequence of its inability to withstand and recover from the weapon's effects.

For a given set of conditions leading into the kill chain, there is a probability associated with the survival of a ship (P_{survive}), which is a complementary event to the probability of being killed (P_{kill}) which is stated as follows:

$$P_{\text{survive}} = 1 - P_{\text{kill}} \quad . \tag{1}$$

As the kill chain may be dissected into two successively occurring events: the susceptibility chain, which is concerned with the events leading to a hit (i.e. detect, classify, target, engage and hit), and the vulnerability and recoverability link, which is concerned with the consequences of the ship being hit. Therefore, the probability that the ship will be killed (P_{kill}) is the product of the probability that the ship will be hit (P_{hit}) and the conditional probability that the ship will be killed given that it is hit ($P_{\text{kill|hit}}$). Consequently, the probability of being killed is given by,

$$P_{\text{kill}} = P_{\text{hit}} \cdot P_{\text{kill|hit}} \quad . \tag{2}$$

Wherein Equation 2 the conditional probability that the ship will be killed given that it is hit, is understood to encompass the likelihood that given that the ship's capability is degraded beyond the level that the ship's mission cannot be accomplished. The remaining available capabilities, and that the damage is such that the ship cannot recover lost capabilities to complete the mission within the intended timeline. Therefore, the probability of being killed is dependent on the conditional probability given by,

$$P_{\text{kill|hit}} = P_{\text{CD|hit}} \cdot P_{\text{NRec|CD}} \quad . \tag{3}$$

where,

$P_{\text{CD|hit}}$ - Probability of capability degradation to the point of mission failure if hit

$P_{\text{NRec|CD}}$ - Probability of failing to recover lost capability following damage

And where substitution of Equation 2 and Equation 3 within Equation 1 yields the traditional formula for the probability of survivability,

$$P_{\text{survive}} = 1 - P_{\text{hit}} \cdot P_{\text{CD|hit}} \cdot P_{\text{NRec|CD}} \quad . \tag{4}$$

Thus, the assessment of the survivability of a naval vessel is often divided into separate assessments (U.S.Navy 2012, Liwång 2015, Crawley 2016) of susceptibility, vulnerability and recoverability where, by formal definition:

- **Susceptibility** is the measure used to define the capability of a vessel to avoid or defeat an attack (generally taken as P_{hit} and most often concentrates on signatures that determine the detectability of the vessel such as Radar Cross Section, Infra-Red and Acoustics),
- **Vulnerability** is the measure of the ability of a vessel's and critical systems to withstand initial damage effects of an attack. Generally represented as $P_{\text{CD|hit}}$ and most often concentrates on internal and external blast and fragmentation damage as well as underwater shock and whipping damage yielding a binary state of equipment failure (functional or non-functional) used assess mission capability via some form of roll-up such as a fault tree, a deactivation diagram or a network diagrams - all of which are fundamentally based on reliability block diagrams (RBDs),

- And **Recoverability** is the measure of the capability of a ship to control secondary damage and to regain mission performance. Generally represented as $1\text{-}P_{NRec|CD.}$and most often concentrates on the progression of fire and flooding as well as the capability of the crew to mitigate cascading damage by means of man-in-the-loop (MITL) operations).

Within each of the three areas of survivability, various methods and software tools have been used to assess a wide range of a vessel's features, with some of the more common features shown in Table 1. The individual metrics in Table 1 are leading to the determination of a vessel's susceptibility, vulnerability or recoverability.

Survivability Area	Feature	Assessment Method(s) / Tool(s)
Susceptibility	Radar Cross Section	(Ross 1966, Knott 2012)
	Infra-red Signature	(Thompson and Vaitekunas)
	Magnetic Signature	(Poteete 2010, Naus 2013)
	Acoustic Signature (Noise)	(A. Kinnas, Lee et al. 2007, Berg 2015)
	Probability of Raid Annihilation	(Blake, Little et al. 2006)
	Active Countermeasures (Decoy)	(Kok 2012)
Vulnerability	Air Explosions (Internal and External)	(Bharatram, Schimmels et al. , Baker 1974, D. Pritchard, Freeman et al. 1996, Kathryn Ackland, Michael Buckland et al. 2010, Stark 2016)

Survivability Area	Feature	Assessment Method(s) / Tool(s)
	Underwater Explosions (Shock and / or Whipping)	(Geers and Hunter 2001, D. Sulfredge, R. H. Morris et al. 2008)
	Fragmentation (and ballistics)	(Karpp and Predebon 1975, Justice 1985, Wadley 2007, Choi Y.S. 2015)
	Shaped Charges (Jetting and Explosively Formed Penetrators)	(Plooster 1982, Kwang and Jang 2012)
	Cascading Damage (System Degradation)	(Kathryn Ackland, Michael Buckland et al. 2010)
Recoverability	Fire and / or Smoke Progression	(Pitts 1994, Bailey 1995, LeBlanc 1998, Vegara 2000, Floyd 2004, Floyd and Hunt 2005, Lee and Misra 2005, Henley 2008, Paik, Czujko et al. 2011)
	Flooding and stability	(Andrewartha, Thomas et al. 2008)
	Cascading Damage (System Isolation and Reconfiguration)	(Doerry and Fireman 2006, Foos and Skahen 2008)

Table 1 Tabulated survivability features with according assessment methods and tools

The disparate methods and tools (Table 1) have enabled naval engineers to assemble a collage of analytical techniques to ascertain a form of quantitative risk assessment (QRA) of the traditional formula for the probability of survivability (Equation 4). Within QRAs, fault and event tree techniques are utilized to analyse the hazards that arise from combinations and sequences of adverse circumstances by assuming each branch represents an independent outcome. These fault tree (FT) and event tree (ET) methods use a collection of statistical logic nodes or gates to roll-up the mission capability of the ship and provide the probabilistic result ($P_{survive}$) via a Monte-Carlo method employing multiple hit scenarios (Rausand 2013, Kim, Hwang et al. 2014) – i.e. P_{hit} assumed equal to one ($P_{hit} = 1$).

Unfortunately, the assumption that each branch represents an independent outcome dictates that mutual dependencies must be pre-defined and known, or neglected (as done with the $P_{hit} = 1$ assumption). This assumption of event independence limits the assessments effectiveness in identifying previously unknown inter-relations as well as mandates that the tree be expanded exponentially as new events are defined. Quantitatively therefore, as the trees increase in size and detail, eventually new data will be required which does not have any historical evidence. This consequently leads to a dependence on subjective sources where by the nature of the tree being a binary state evaluation, uncertainty, cannot be quantified (Konovessis, Cai et al. 2013).

The disparate methods and tools (Table 1) have enabled naval engineers to assemble a collage of analytical techniques to ascertain a quantitative risk assessment (QRA). However, limited by the assumption of event independence, the primary complaint of both industry and naval customers has been the cost associated with needing multiple simulation models to achieve a single vessels survivability rating. More-over, as a result of this cost, the selection of assessed features eventually compiling $P_{survive}$ within a QRA is artificially constrained prior to determination of importance by assessment. For example, when customers select methods to assess events to determine a features effectiveness prior to ascertaining the relative importance of the event or feature to the design.

Consequently, integrated approaches to assess survivability have recently been developed and implemented. Therein the assessments attempt to utilize a “one model one tool” approach where the concepts of vulnerability and recoverability have been merged. This development addresses the total ship functionality (or capability) post impact (Foos and Skahen 2008) and at the point of impact or damage occurrence - referred to as zero-time[1].

Though more refined than traditional QRA, these conglomerate tools (such as MOTISS, SURMA, ASAP, PREVENT, SURVIVE, CETENA, RESIST)[2] still utilize Event Tree and Fault Tree constructs and as such retain the limitations of event independence, namely:

1. Cannot identify previously unknown system-to-system and system-to-operability and,
2. neglect factors of uncertainty such as system reliability

It is because of these two constraints within present day survivability assessments that identifying and including system uncertainty survivability-related issues is conducted only under major limiting assumptions by industry – which leads to a skewed perception of the vessel's real behaviour.

An attempt to overcome the limitations of the Fault Tree modelling lead to the development of the Integrated Recoverability Model (IRM). This process was driven primarily due to the events of the late 20th century as discussed earlier and the efforts of the US Government to adapt the needs of a more holistic survivability design process (Floyd, Hunt et al. 2005, Foos and Skahen 2008). The tool, which is also used throughout this research, is the only available survivability software which operates independent of Fault Tree deactivation logic and simultaneously manages to holistically integrate onboard systems, ship structures and to evaluate the vulnerability performance in a dynamic and bi-

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[1] Pre zero-time (0^-) susceptibility assessments are strictly applied to enhance survivability as much as possible within given cost constraints and after zero-time (0^+) functionality assessments (vulnerability and recoverability) are strictly applied to enhance survivability as much as possible within given cost constraints.

[2] The author notes that most of these tools serve their intended purposes quite well and assess the survivability features they were developed for, but they do not serve to address the intended purpose of this research which is to assess relative values of a vessels' survivability design

directionally (Friebe, Skahen et al. 2018). The IRM is a software tool that is used to model and assess the performance of different naval vessel systems and that allows the engineer through a unique approach of automatic system connectivity to track complex cross-connection of systems, crew and progressive damage such as fire and flooding to evaluate the vulnerability of naval vessels (Foos and Skahen 2008).

The automatic system connectivity allows the evaluation of the effect of different system layouts and system specifications to evaluate their impact on the vulnerability and recoverability of the naval vessel (Foos and Skahen 2008, R. Gregg Fresa, Zackary R. Stull et al. 2017, Friebe, Skahen et al. 2018).

However, to address the limiting necessity of a vessel's failure relationships between the systems and operational ability, also Brown (2003) established a novel approach to estimate the effect of survivability within an overall measure of design effectiveness at concept design.

In the first stage of Browns work, a framework calculating an Overall Measure of Effectiveness (*OMOE*) was built utilizing Analytical Hierarchy Process (*AHP)* (Keeney and Raiffa 1993) and Multi-Attribute Utility Theory *(MAUT)* (Saaty 1996) blended into a single method called Multi-Attribute Value Theory (*MAVT*) (Belton 1986). Using MAVT a hierarchy of critical ship attributes that follows a logical breakdown is generated with the top level being the OMOE comprised of subordinate Measure Of Effectiveness and Measures of Performances *(MOPs)* in a hierarchy as exampled in Figure 9.

Within Browns MAVT approach a multiple-objective genetic design optimization using mission effectiveness, risk and acquisition cost, as objective attributes, was developed to search the design space. The optimization algorithm performs design trade-offs considering various combinations of hull form, hull materials, propulsion systems, combat systems and manning. A ship synthesis model balances these parameters within a total ship design to assure feasibility and to calculate cost, risk and effectiveness. The final feasible design combinations are then ranked by cost, risk and effectiveness, and presented as a series of non-dominated frontiers, representing ship designs in the design space that have the highest effectiveness for a given cost and risk compared to other designs in the design space.

Browns MAVT approach utilizes multiple-objective genetic optimization (MOGO) algorithms for their ability to explore design spaces that are very non-linear, discontinuous, and bounded by a variety of constraints and thresholds, which prevent application gradient-based optimization techniques such as Lagrange multipliers, steepest ascent methods, linear programming, non-linear programming and dynamic programming. Within Browns initial MAVT approach (Brown and Salcedo 2003, Brown and Mierzwicki 2004, Demko 2005) the value and relationship of the MOPs to the OMOE was established using purely expert opinion and pair-wise comparison (via AHP) to establish relative weightings (w's) and values of performance (VOPs) as depicted by Equation 5.

$$OMOE = \Sigma w_i VOP_i(MOP_i) \quad . \tag{5}$$

Where a particular VOP is assigned a value of zero corresponding to the AHP MOP threshold, and a value of 1.0 corresponding to the AHP MOP goal as dictated by MAUT. Browns recent works (Goodfriend 2015) replaced expert opinion and pair-wise comparison methods for establishing the value and relationship of the MOPs to the OMOE (i.e. disbanding the need for VOPs by direct calculation of vulnerability based MOPs) with low-order physics based zonal damage methodologies (Brown and Salcedo 2003, Brown and Mierzwicki 2004) combined with simplified FT assessment methods (Waltham-Sajdak 2011).

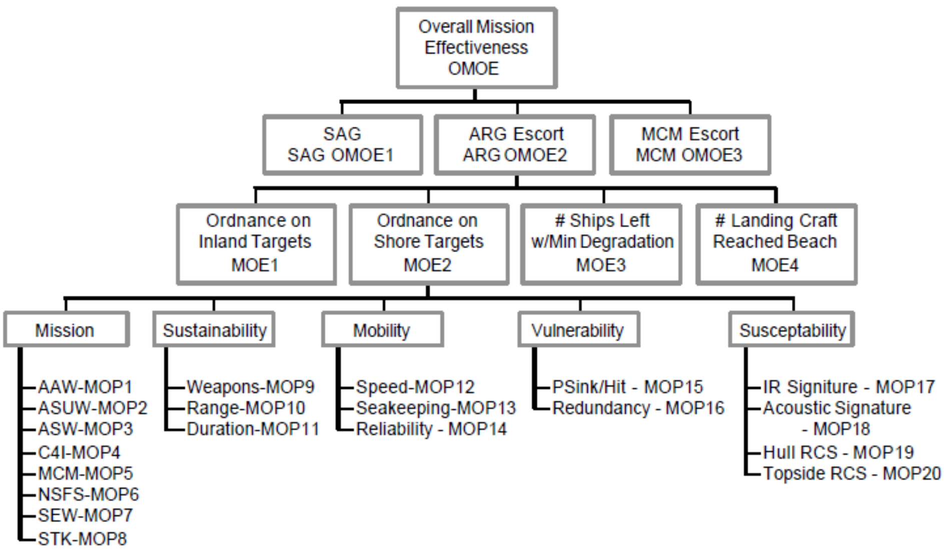


Figure 9. OMOE Hierarchy (Brown and Salcedo 2003)

These recent efforts have proved sufficiently effective in concept to understand a vessel's survivability for the sacrifice of modelling detail. However, the use of FT assessment within the MAVT approach continues to promulgate the inability of survivability assessments to identify previously unknown system-to-system, or system-to-crew inter-relation limitation as previously identified within the QRA and conglomerate tools. Also, this work has not been able to include factors of uncertainty within approach due to the deterministic nature of this work. Furthermore, Brown's approach is limited by the amount of required computational power to automatically design and assess detailed ships.

Methods and tools from Table 1 share another deficiency, which is their inability to link different types of survivability assessment and information into a single tool. This fact has been highlighted (Friis-Hansen 2000, Liwång, Ringsberg et al. 2013) and is an essential step of achieving a realistic and holistic view into the performance of a ship in a combat situation. Previous research (Liwång 2015) highlighted the applicability of Bayesian Networks (BNs) for maritime platform survivability assessments and its capability to evaluate design choices and perform risk assessments effectively. BNs are particularly useful as they allow historical information to be included into the uncertainty treatment of risk assessments. However so far there is no probabilistic causal relationship model that is not subject to erroneous human input (Liwång 2015).

The probabilistic causal relationships in the resultant BN model are then assessed using Bayes' Theorem and Influence Diagrams to study cause and effect relationships on the design of a vessel. BNs and Influence Diagrams are especially useful when there is no empirical data and there is a need to identify the underlying causal relationships (IMO 2013). These causal failure relationships are then used to predict the expected cause of failures of systems or operational capabilities. Additionally, the strength of a BN is its capability to present probabilistic relationships and causal dependencies graphically and to facilitate the study of those dependencies (Liwång, Ringsberg et al. 2013, Musharraf, Khan et al. 2013). These probabilistic relationships can be either derived from simulation or historical data (Konovessis, Cai et al. 2013, Liwång, Ringsberg et al. 2013).

To derive the probabilistic failure relationships from a simulation it requires a precise and detailed model of a naval vessel in a combat scenario. As the current literature shows, no machine learning algorithm has been applied onto a naval vessel on an attempt derive the probabilistic failure relationships. Whereas, the aforementioned IRM software and its unique approach to track the demand and supply of various onboard systems can estimate the system and vessel's behavioural performance in a combat scenario, the tool is limited in the identification of design choices that drive the vessel's performance evaluation during the design. The current approach to identify causing system failure to a behavioural performance of a model is a manual data filtering that searches for the failed system a combat scenario. The methodological attempt to overcome this shortcoming is described in section 1.7.

Chapter 3 **Valve Automation and Firemain Layout Study**

The literature review highlighted that all vulnerability assessments are operating on the assumption of perfectly reliable systems. The naval onboard systems are assumed to be perfectly reliable, always available and will never fail before or during a combat situation. To include and test the effect of system reliability on a naval vessel, a software license was required in order to perform a state-of-the-art vulnerability assessment.

Throughout the beginning of the project it was challenging to find and obtain a license for a software package with the ability to perform vulnerability assessments as a lot of defence work is classified and not accessible to the public. Through fortunate circumstances, a cooperation with Test & Evaluation (TnE) Solutions, an American vulnerability assessment company, was set up. TnE Solutions provided the opportunity for a 10-month internship in order to investigate the most recent vulnerability assessment techniques and tools. Through joint effort, a rudimentary model of a naval vessel was developed. This model was used to study the most recent vulnerability assessment techniques and to investigate advantages and disadvantages of various firemain designs in a vulnerability context, which is explained further below in this chapter.

The developed model served as a base model in the later research phases to include and test the inclusion of system reliability on a naval vessel. For that purpose, the base model of the naval vessel had to be enhanced to include additional systems and functionalities, which is demonstrated and discussed in Chapter 4 and Chapter 5

Title: The Effect of System Layout and Valve Automation on firemain survivability in a Naval Vessel

3.1. Abstract

Recent advances in automation technology and the need for naval vessels to respond quickly and with high performance require naval architects to make well-informed design decisions. This study assesses the effect of automation of various firemain layouts on the vulnerability performance of naval vessels through a case study. This study will assist design decisions that decrease the firemain response time while also increasing its capability following a damage incident.

3.2. Introduction

Survivability is defined as a naval vessel's capability to maintain mission capability in a high threat environment (U.S.Navy 2012, Brett, Gamble et al. 2017). Survivability can be broken down into susceptibility – the platform's ability to avoid detection, classification and successful targeting by an adversary; vulnerability – the ability to withstand damage effects; and recoverability – the ability to recover mission capability following damage effects, as shown conceptually in Figure 10.

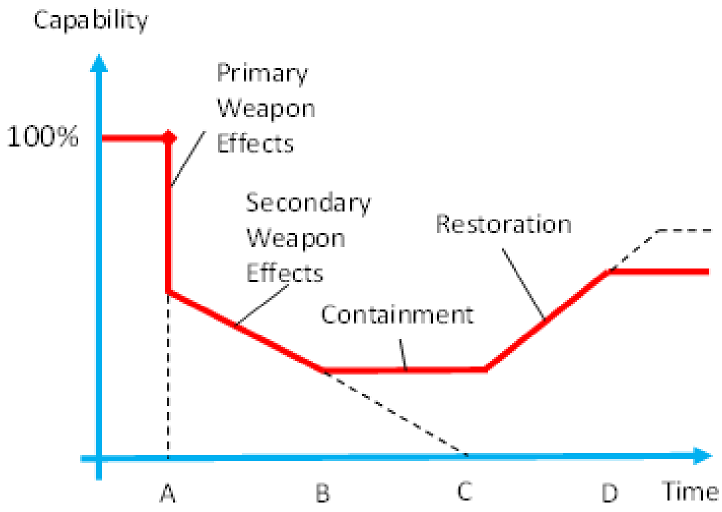


Figure 10 Survivability Performance Curve

This study focuses on the time frame after the naval vessel has suffered damage, that is, the vulnerability and recoverability of a vessel or, in other words, the ability to withstand the inflicted damage and the ability to recover mission capability. The inflicted damage affects the structure and systems and is the cause of the flooding and the fire. The goals of damage control actions, regarding firefighting on board a naval vessel, consist of containing and mitigating fires. These goals are achieved using firefighting agents (i.e. water, AFFF, Halon, etc.) that are usually applied by personnel or an installed automatic firefighting system. Much like in buildings, the firemain in a naval vessel is the backbone pipe network that supplies and enables these damage control capabilities. It supplies equipment used for fire extinction and suppression purposes. These include sprinklers, fireplugs and fire hoses, all of which are referred to as "end users" for simplicity in this study.

The firemain system aboard a naval vessel has been designed in many different layouts by naval engineers through the years. These layouts are implemented to achieve specific requirements, and each has their benefits and limitations. In this study three of these layouts, shown in Figure 11, are assessed based on their survivability performance (Lestina, Runnerstrom et al. 1999, 2018, Friebe, Skahen et al. 2018) and are as follows:

- Single Main: Usually located on the centreline of the naval vessel and extends from fore to aft. It is often located in the central passageway and placed under the deck for ease of accessibility.
- Horizontal Loop: Consists of two parallel longitudinal piping runs that are transversely cross-connected. The horizontal loop is located on one deck and supplies end users on other decks with risers.
- Vertical Offset Loop: Consists of two longitudinal piping runs that are transversely cross-connected, but unlike the horizontal layout both longitudinal piping runs are on different decks and are separated vertically and transversely as far as possible.

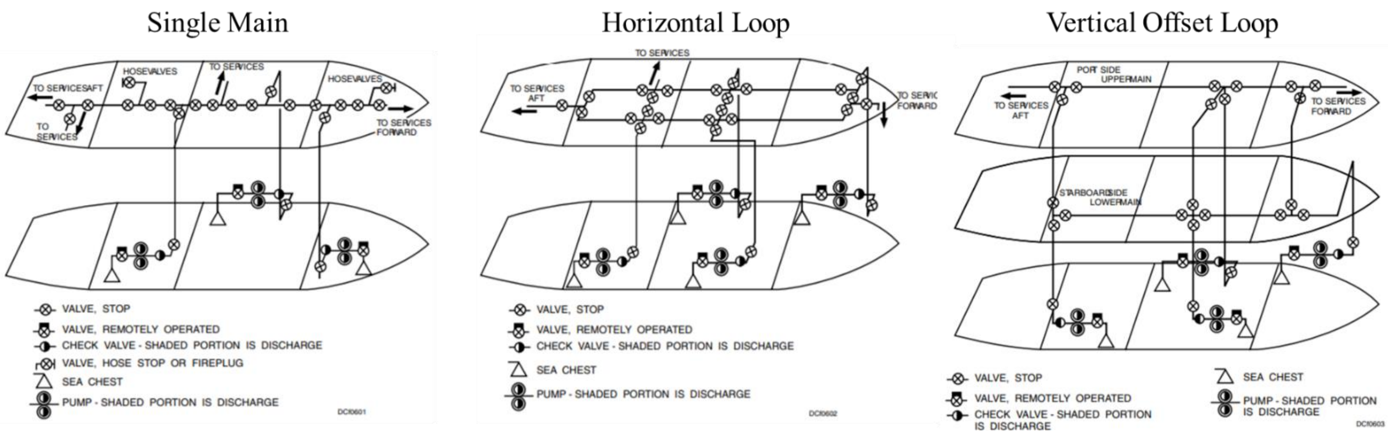


Figure 11 Firemain Layouts

Naval vessels are at risk of suffering damage while in hostile environments. Damage tolerance and system restoration are important for a vessel to maintain and recover mission capability. For a firemain this includes piping and supply pump redundancy as well as appropriate valves to isolate damaged sections. Due to recent advances in automation across all engineering disciplines, system response times have decreased. However, system automation improvements often come at a high cost and are difficult to justify if not quantitatively compared to alternative solutions. Even though the automation technology has arrived in the commercial shipbuilding and other engineering industries, the naval defence industry relies on high crew numbers. As the current crew numbers of naval vessels are relatively high, the effect of automating a manual system on a naval vessel is commonly believed to be rather small. Thus, it is important to be able to measure and quantify the performance of different system variants with various automation levels to enable effective comparison. Two possible comparison parameters for naval vulnerability requirements that can be taken from Figure 10 are the percent of capability recovered and the time it takes for a system to recover.

Historically, naval vessels have operated their firemains manually due to the lack of automated design solutions. The high purchase price and maintenance costs of automated solutions slow the adoption of these systems. Additionally, the effect of automated solutions on a naval vessel's vulnerability performance has not yet been measured so there is minimal evidence available for system designers to justify a system upgrade from manual to autonomous. However, cases such as the 2002 HNoMS Orkla incident (Navy 1988) show that it is critical to maintain the firemain's operational capability in the event of damage to the vessel.

In the early hours of November 19th in 2002 the HNoMS Orkla suffered shaft failure that resulted in a machinery room fire. The crew responded quickly and within 2 minutes of the fire alarm had connected five fire hoses to the firemain. Unfortunately, pressure was lost within 30 seconds interrupting the crew's firefighting efforts. It was not until later that the crew could resume firefighting, but by that time the fire had grown and spread to other compartments. Because the fire could not be mitigated quickly it continued to spread across much of the vessel and eventually resulted in the crew abandoning ship. This event showed that time delays in maintaining or recovering the damage control capabilities such as the firemain are essential to a naval vessel that is in imminent danger of complete loss. It is therefore crucial that after a naval vessel suffers damage that it can recover a high level of performance in a short period of time (Friebe, Skahen et al. 2018). This is especially true if the naval vessel is in a hostile environment and needs to maintain mission capability.

One automation technology that can potentially improve damage control response times and has attracted a lot of interest by navies internationally is "smart" valves. "Smart" valves use integrated sensors and control logic to detect when they need to open or close and can operate independently of crew interaction (Lestina, Bradley et al. 2001, McCullagh, Fraser et al. 2013). This means that "smart" valves can isolate damage in a system within seconds of detecting a rupture in the piping and can restore pressure to the system. There have been studies that show system implementation of "smart" valves can isolate damage faster than in systems with only manual valves (Durkin, Williams et al. 2000). This study assesses three levels of automation related to "smart" valve implementation as follows:

1. Fully Manual: All valves in the firemain layout are manual valves that require crew to activate locally or via a remote handwheel.
2. Fully Autonomous: All valves in the firemain layout are "smart" valves and can operate either independently of the crew or with local crew activation.
3. Partially Autonomous: "smart" valves are placed at key locations on the firemain (watertight bulkheads, branches, etc.) with manual valves implemented throughout the rest of the layout.

By taking into account the automation level as well as the firemain system layout this study attempts to assess the vulnerability performance of various firemain designs. A direct comparison between the designs is possible with the three layouts and automation levels described.

3.3. Methodology and Software

Using a case study, the authors explore the performance of the various firemain designs in this study as implemented on a generic naval vessel. Each firemain design is a combination of the three firemain layouts and three automation levels discussed previously. In order to appropriately compare the designs' performance a standard damage pattern must be assigned. In this study the authors applied two damage patterns: compartmental and zonal. The framework of this comparison process is shown in Figure 12.

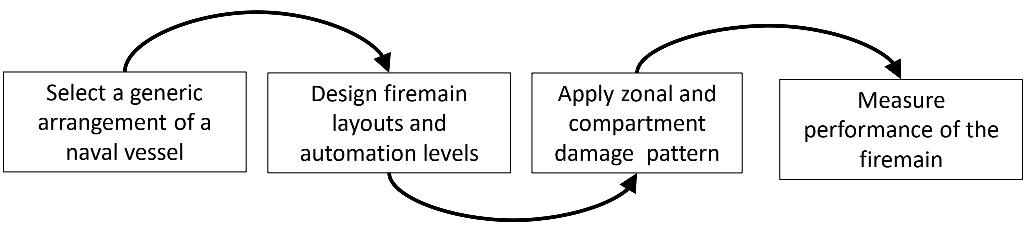


Figure 12 Flowchart of Comparison Study

First, a generic arrangement of a naval vessel is chosen that can appropriately facilitate the three firemain layouts.

Second, the interface for the various firemain systems is modelled to ensure consistency for each firemain layout and automation level. The interface is defined by the number and location of available seachests, firemain pumps and end users to supply. Then the three firemain layouts are modelled and matched to the ship-interface. Once the firemain layouts are in place the three levels of automation are implemented.

Third, the standard damage patterns are applied to the designs. These patterns consist of a compartmental pattern in which damage is limited to a single compartment and a zonal pattern in which damage is limited to a single zone, where a zone is a designated group of compartments.

Fourth and last, the performance of the designs is measured based on how quickly they recover and how much capability is restored.

3.4. The Integrated Recoverability Model

The only market available survivability software which is operable independent of Fault Tree deactivation logic is Test and Evaluation Solutions (T&E Solutions) Integrated Recoverability Model (IRM). The IRM is a software tool that is used to model and assess the performance of different naval vessel systems. The IRM tool enables the engineer through the unique approach of automatic system connectivity to track the complex interaction of systems, crew and progressive damage such as fire and flooding to evaluate the vulnerability of naval vessels (Foos and Skahen 2008).

The automatic system connectivity allows the study of the effect of different system layouts and system specifications to evaluate their impact on the vulnerability and recoverability of the naval vessel. Another important feature of the IRM is its capability to model the crew as an integral part of the system interactions and assess the significant role different crew actions and alignments have on the result of a damage scenario (Foos and Skahen 2008, R. Gregg Fresa, Zackary R. Stull et al. 2017, Friebe, Skahen et al. 2018). This enables the authors to assess the effect of crew actions and automation on the required firemain performance and consequently the vulnerability of the naval vessel. The information used to populate the structural and equipment IRM model is derived from key system drawings.

The IRM includes graphical database editing tools, Simulator, Fire Module, Flooding Module, Agent Module, Output Visualization, and Statistical Analysis tools and was initially developed to provide the naval ship programs a means to evaluate shipboard vulnerability over time, considering the effects of secondary damage (fire, smoke, and flooding), system interaction, and damage control and recovery efforts. The development of IRM was influenced by lessons learned from the DDG 51 Class Total Ship Survivability Trial (TSST), development of Automated Common Diagrams (ACD), and Ship Survivability Design Improvement (SSDI) studies.

Since designing naval ship systems for survivability requires an understanding of the dynamic behaviour of threat hazard events (such as fire spread) and the dynamic interdependencies of critical systems (such as the shutdown of electronics equipment after cooling is lost), integrated recoverability assessments have become critical in understanding how to minimize the primary, or immediate, damage from a threat hazard, how to prevent cascading secondary damage and how to recover functions of surviving portions of systems. The IRM allows batch processing of thousands of scenarios using damage specifications and ship system initial conditions. Design studies can be conducted using compartment or design zone damage patterns or weapon specific battle damage predictions imported from various weapon effects models (e.g. ASAP, SURMA, MOTISS and CVAM) or finite element shock and whipping analysis tools (e.g. DYSMAS and LSDYNA). Initial conditions can be developed to include different crew manning assumptions, various configurations of on-line components and alignments of valves and breakers. Once a scenario is initialized, the IRM emulates the system response to piping ruptures, severed cables, damaged components, and injured personnel. Fire and flooding modules (such as the Fire and Smoke simulator – FSSIM, and the flooding model and advanced stability assessment - FLMASA) use a common database with the IRM to coordinate the state of the ship and location of secondary damage at every time step such that modelled components can become damaged when they are exposed to appropriate thresholds of heat or flood water. The FSSIM module is an algorithm that is based on a one-dimensional network representation of the real world. The FSSIM model consists of nodes and edges that present spaces and connections respectively, where the nodes contain physical variables that allow the computation of the fire development and the edges the transfer in between spaces (Floyd, Hunt et al. 2005). The modelling with the IRM and FSSIM relied on the default values that are provided by the software packages i.e. temperature in a compartment, average amount of combustible material in a compartment, average amount and supply of oxygen in a compartment etc.

Damage control efforts, including manual fire-fighting and dewatering, interact with the fire and flooding modules to determine the ability of the ship and crew to contain damage. The status of all components, resources, compartments, and crew over the course of each scenario coalesce into a single output log which can be played back for individual scenario analysis or mined for statistical results over many hundreds to thousands of runs.

The unique 'hive' approach of the IRM's network behaviour algorithm eliminates the need for traditional FTs and allows the impact of different system alignments to be analysed to determine their impact on the ships survivability. Within IRM, a hive is a set of components (called nodes) in the same system which are all connected to each other through pipes or cables (called edges). If a system is split into separate starboard and port loops, then the starboard and port loops would constitute separate hives. Similarly, if both the port and starboard sides of a system are connected (through a node representing an open valve) then they would form a single hive. Within the IRM, every pipe, cable, conduit, or wireless data stream (i.e. every edge) is a member of exactly one hive. Some forming a hive unto themselves, while others becoming part of huge hives with thousands of members. Equipment however, can be connected to as many hives as it has connections (i.e. input and output ports).

From one time-step to the next, two hives might coalesce (because the nodes representing valves that separated them opened) or a single hive might split into two (because the nodes representing valves closed – thus 'isolating' the hives). Thus, hives do not necessarily persist from one time-step to the next and must be recomputed at each time-step – a capability not available within traditional FT assessments. Conceptually, a hive can be thought of as a pressure vessel to which all nodes of the system are directly connected. In this context, pumps whose output is connected to the hive provide flow into the hive and users connected to the hive consume this flow (see Figure 13). The flow into, through, and out of a hive is the balancing equation which is recomputed each time-step and which can be used to determine where, within each hive construct, isolation is most advantageous in order to ensure maximum utilization of services (such as power, chilled water, fire water, compressed air, foam solution) to the surviving portions of the mission systems.

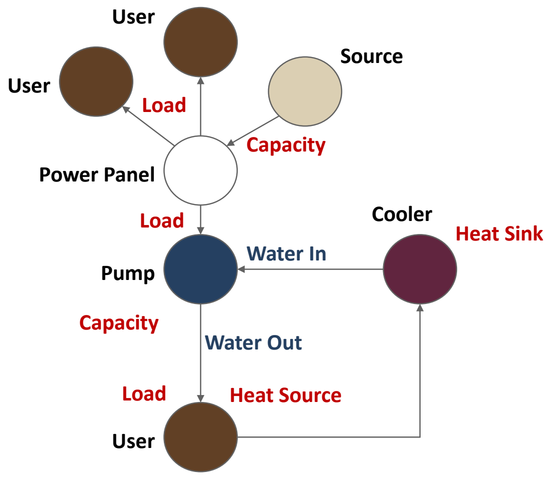


Figure 13. IRM basic concept

Thus, using IRM to conduct late stage survivability assessments an inference model of dependent probabilities can be developed to feed a Bayesian Network which can then be used on future vessel concept designs thereby overcoming the limitation of needing detailed early stage design models, while concurrently eliminating the shortcoming prior solution constraints as are present in the methods applying FT’s.

3.5. Case Study

The chosen naval vessel for this case study is a 68 m long patrol vessel. The vessel has a beam of 13 m and a draft of 4.6 m with a full displacement of 2300t. Driven by diesel-electric propulsion it reaches approximately 40 knots. The vessel has multiple decks and watertight bulkheads that extend across decks as shown in Figure 14. This vessel’s arrangement was chosen as it can facilitate all three firemain layouts. There is a centreline passageway for the single firemain layout, port and starboard separation for the loop layouts, and multiple decks for the vertical offset loop. Additionally, there are enough compartments and separation to place end users that allow for long piping runs increasing the vulnerable area of the firemain.

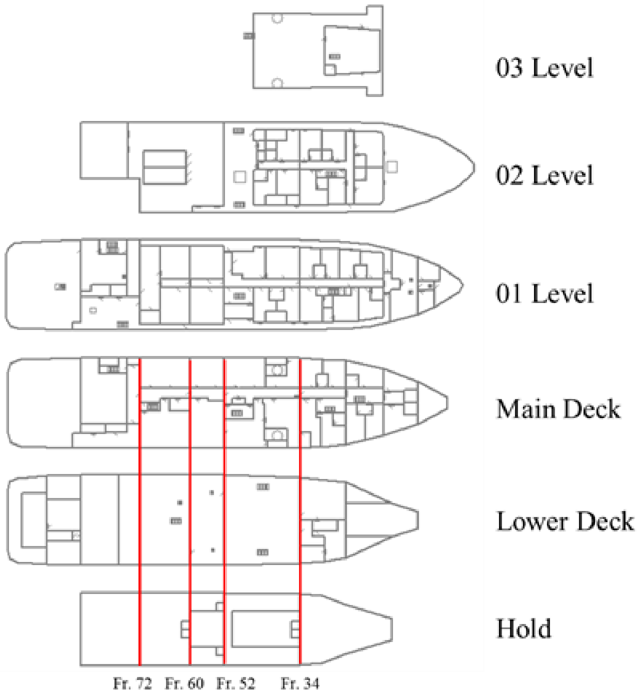


Figure 14 IRM layout of model

The naval vessel was modelled in IRM based on information derived from key system drawings. The IRM model consists of a structural as well as an equipment model of the vessel. The arrangement of the IRM structural model is shown in Figure 14. The naval vessel's structure consists of six decks with compartments and passageways. Doors and hatches are modelled that allow for crew accessibility of the entire vessel. The red lines in Figure 14 highlight important watertight bulkheads that separate major sections of the firemain designs.

The IRM equipment model is composed only of the firemain system which is categorized into three equipment groups: a) the water supply from the seachests b) the firemain piping c) the branch piping to the end users. In this study the water supply from the seachests and the branch piping to the end users remains constant while the firemain layout and automation level is varied.

The water supply is modelled with four seachests located in the hold of the vessel that are connected to four fire pumps. Valves on either side of the fire pumps are modelled as manual valves that can be operated either locally or from the main deck via handwheels. The four fire pumps supply the firemain. The most forward and most aft fire pumps are designed to have large pumping capacities whereas the two amidships are smaller pumps with relatively low pumping capacities. The two small fire pumps are initially off and are only turned on by the crew when the firemain does not have enough supply. An end user is modelled in every compartment on the ship. Each branch and riser from the firemain have valves to enable damage isolation.

The three firemain layouts are modelled in IRM as shown in Figure 16. The single firemain is located on the main deck in the centre longitudinal passageway. The horizontal loop is on the main deck as well with longitudinal piping along both the port and starboard sides of the naval vessel. The offset loop consists of longitudinal piping starboard on the main deck and port on the 01 level. Additionally, for each firemain layout the valves on either side of the bulkhead at frame 52 are initially closed. This segregates the firemain into forward and aft sections which limits the effect of damage on the firemain across the naval vessel.

Furthermore, each firemain layout is modelled given three different levels of automation: fully manual, fully autonomous and semi-autonomous. This is achieved by using "smart" valves with an activation time of 3 seconds in the design of the firemain. The activation time was chosen to demonstrate the rapid response of “smart” valves and is greater than the IRM time step of one second to enable analysis of firemain system response following “smart” valve actions. The fully autonomous design uses only "smart" valves except for the valves on either side of the fire pumps. The semi-autonomous design uses mostly manually operated valves except at key locations on the main where "smart" valves are used. These key locations are immediately off the firemain on branches and risers as well as the initially closed valves at frame 52 that segregate the firemain. The fully manual design uses only manually operated valves. There are a total of 3 crew members that form a single damage control team that is assumed to perform damage control activities during combat situation. Naval vessels can have multiple damage control teams, but it is assumed that this vessel operates only with one team to perform damage control actions. This includes actions such as the operation of valves and fire pumps. The crew have an assumed 600 second delay before action to account for investigation and organisation of damage control activities.

To model the water demand draining from the firemain, each compartment has end user equipment that is attached to the firemain. If damage occurs in a compartment the equipment and piping rupture, requiring the nearest valves to be closed and isolate the damage. In turn, if there is no rupture in the piping the valves are required to re-open.

3.5.1. Damage Patterns

The damage is applied using two methods. The first is a compartmental damage pattern that damages all the equipment and piping within a single compartment resulting in 80 compartmental damage scenarios. The second is a zonal damage pattern that damages all the equipment and piping within a defined zonal area resulting in 22 zonal damage scenarios. Zones represent contiguous areas of the ship through which progressive damage such as fire could spread rather quickly. For the simplicity of the study, zones were assumed not to span multiple decks except where multi-level compartments are located. Figure 15 shows the zones that were used for the analysis. Compartments without colour did not have equipment or piping and were therefore not included. The compartmental and zonal damage patterns are intended to represent the damage from a small and large threat, respectively. The water load of ruptured pipe is modelled to exceed the capacity of the firemain pumps and thus requiring damage isolation to nearest valves.

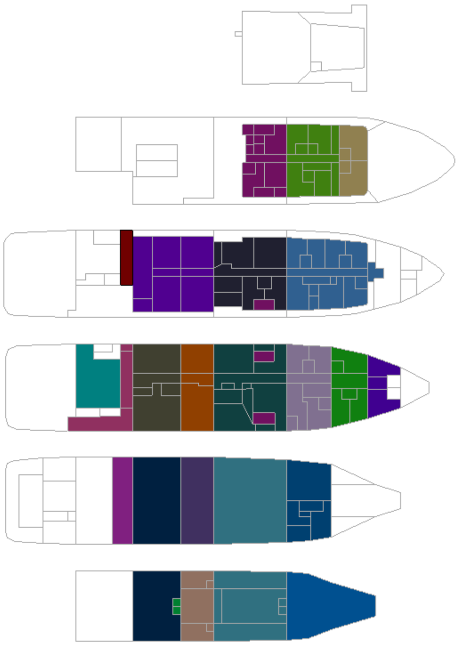


Figure 15 Damage Zones in the IRM Model

3.5.2. Performance Metric

To measure the vulnerability of the firemain after damage, pressure sensors are placed along each longitudinal run of the firemain in each zone as shown in Figure 16. The pressure sensors record a positive state when the supply to the firemain equals or exceeds the demand from end users and does not experience an unisolated rupture. The performance criteria is that a firemain recovers from the inflicted damage. The firemain is considered recovered when all but one of the sensors register a positive state. This design of the performance criteria ensures that the measurement is not skewed by the pressure sensor being isolated from rest of the firemain when its compartment is included in the damage zone. The performance level of each firemain design is then the number of damage scenarios that pass the performance criteria.

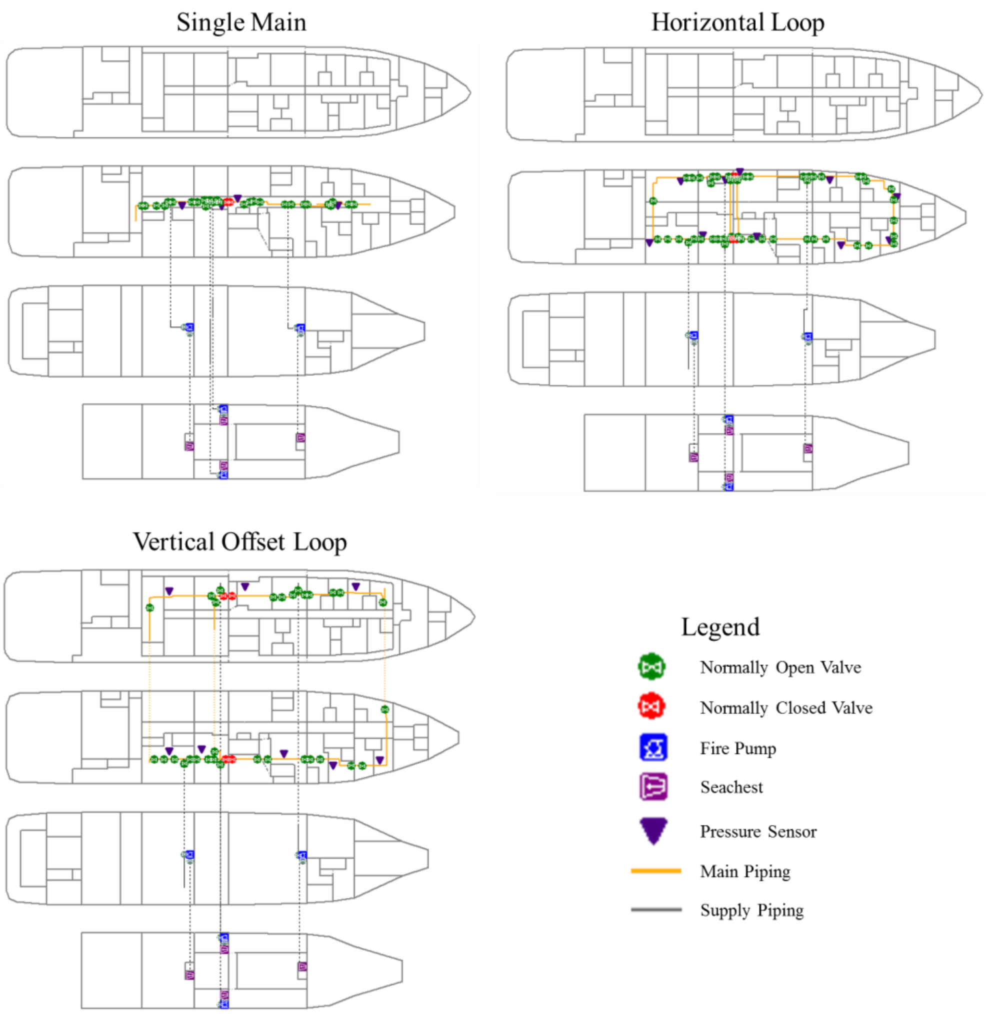


Figure 16 Firemain Layouts in IRM

3.6. Assessment Results

As described earlier the naval vessel was analysed with both compartmental and zonal damage patterns. The results of these analyses are presented in the following subsections. The compartment analysis consists of 80 damage scenarios, whereas the zonal damage analysis consists of 22 damage scenarios. The performance of each firemain design in the following figures is measured as the accumulated successful recovery of the firemain after the damage occurrence.

3.6.1. Compartmental Analysis – Small Threat

The performance curves in Figure 17 show that the maximum performance level (total recovered damage scenarios) of each firemain layout is independent of the automation level and achieves the same maximum performance level over time for each automation level. The single firemain has the lowest recoverable performance, whereas the horizontal and offset loops both achieve very similar maximum performance level.

The performance curves also show how quickly each layout recovers. In all three layouts there is a significant performance difference between the different levels of automation. In the first 600 seconds when the crew is investigating and organizing damage control actions the autonomous systems outperform the other two. The higher level of automation allows the firemain system to quickly adapt by isolating the damaged area and opening up supply from other sections of the firemain.

The fully autonomous systems recover most scenarios within the first 10 seconds while the semi-autonomous systems recover a little over half as many in the same timeframe. The fully manual systems remain inoperable until the crew begins closing valves to isolate damage after 600 seconds. The recovery seen in the single firemain and horizontal loop layouts after 1000 seconds is from fire pumps turning on and adding supply to the firemain. This additional recovery is not necessary for the offset loop since the layout prevents damage that takes out supply from both large fire pumps.

A difference between the loop layouts and the single firemain design is that the loops manual recovery at approximately 700 seconds takes longer. This is due to the larger number of valves in the design and thus a longer time is needed for the crew to fully isolate the system. Additionally, the horizontal and offset loops have different rates of recoverability. This is attributed to the distance the crew must move to reach access and operate the valves in the system. For all layouts, the crew is initially located on the 01 level and is thereby closer to the firemain in the offset loop since it spans the 01 level and main decks. This allows the crew to execute its damage control actions faster than in the case of the horizontal loop which is located entirely on the Main Deck.

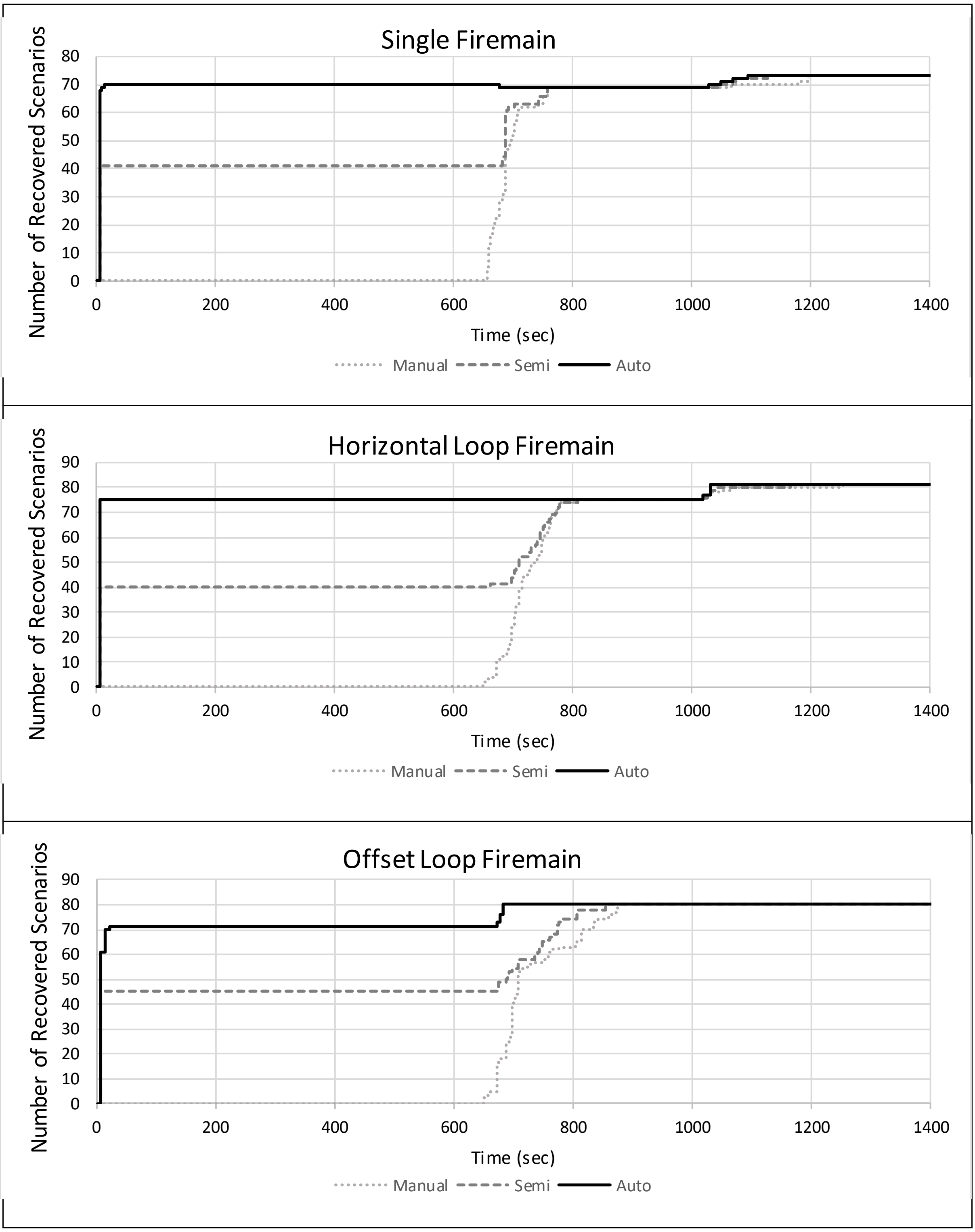


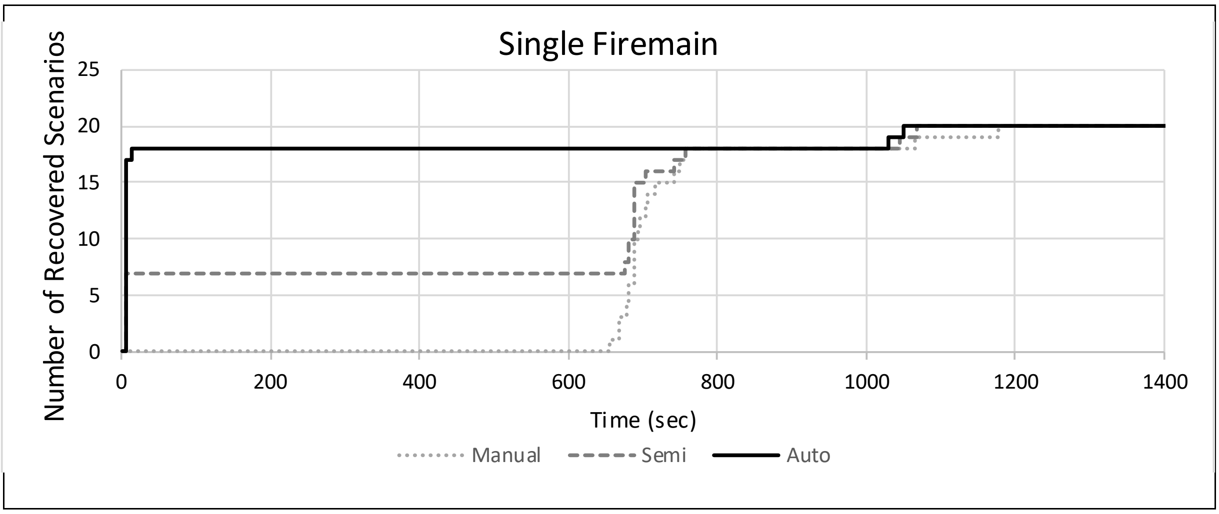
Figure 17: Performance measurement as accumulated successful recovery of firemain for compartment analysis for manual, semi-manual and automated valves

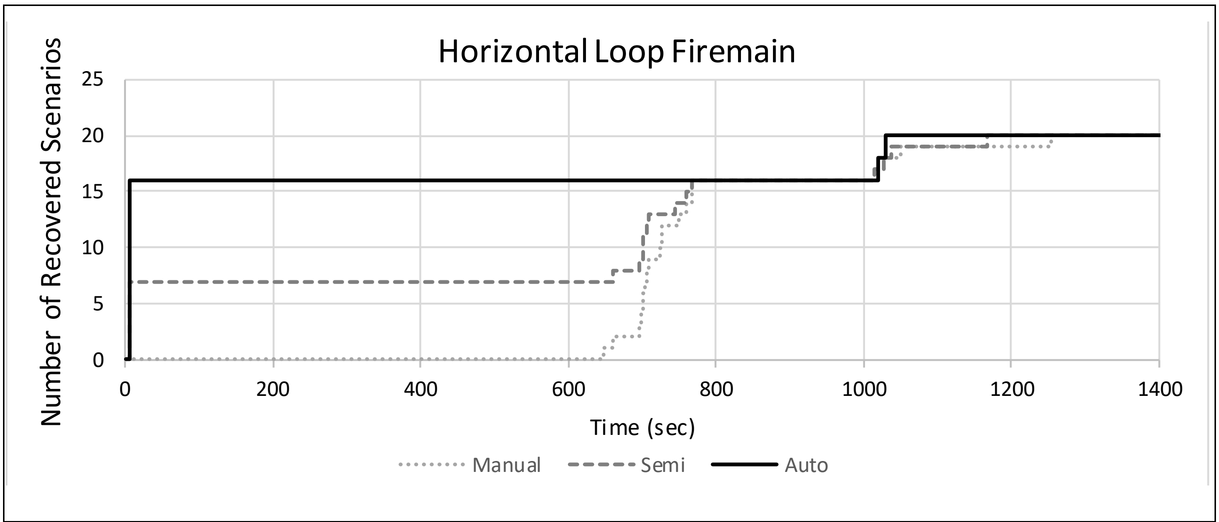
3.6.2. Zonal analysis – Large Threat

The results of the zonal analysis are very similar to those of the compartment analysis. The performance curves in Figure 18 show that the maximum performance level (total recovered damage scenarios) of each firemain layout is independent of the automation level. However, the single firemain and horizontal loop layout achieve the same maximum recoverable performance level in the zonal analysis.

As in the compartment analysis, the fully autonomous designs outperform the semi-autonomous and manual designs in the first 600 seconds while the crew response delay is in effect. The manual designs have no firemain capability during this time and do not begin to recover until after the crew begins turning the valves. The time delays before recovery of the different automation levels are similar to what is seen in the compartment analysis.

The results also show that manual recovery at approximately 700 seconds of the single firemain is faster than the manual recovery of the two loop designs, which is attributed to the lesser complexity of the single firemain. Interestingly, the horizontal loop performs very similarly to the single firemain during the first 600 seconds. This is because large portions of the loop are cut in a similar manner to how the single firemain when one longitudinal section is damaged. Hence the horizontal firemain mimics the results of the single firemain. This problem is avoided by the offset loop since it spans two decks and retains connectivity throughout its loop despite the larger damage zone.





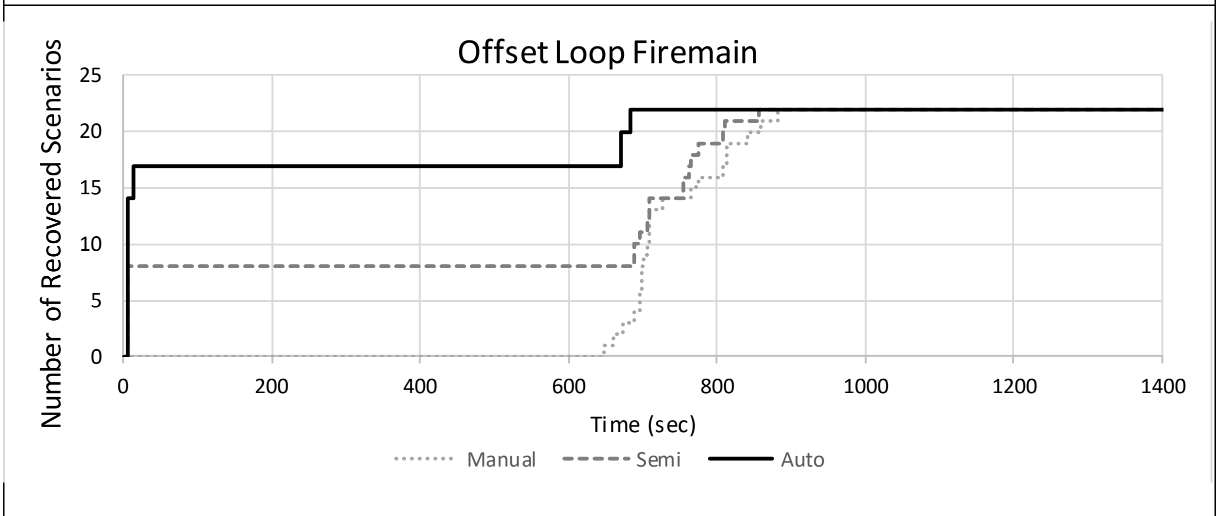


Figure 18. Performance measurement as accumulated successful recovery of firemain for zonal analysis for manual, semi-manual and automated valves

3.7. Discussion

A piecewise comparison of the different simulation results is necessary to differentiate between the various benefits and limitations of varying layouts and automation levels.

A comparison of the compartmental and zonal damage assessment showed interesting findings. For the zonal damage assessment, the single and horizontal loop firemain layouts perform similarly and achieve the same percentage of recovered performance. The longitudinal piping of both of these firemain types are cut off by the zonal damage, removing the advantage the horizontal loop has over the single firemain. Without its loop intact, the horizontal loop layout behaves like a single firemain. This result is interpreted by the authors to indicate that for large damage the horizontal loop is not an ideal choice as it would be costlier to implement than a single firemain. For better vulnerability at a similar cost to the horizontal loop it is best to use the offset loop design for the vessel studied.

Likewise, for small damage scenarios there was no increased performance found between the offset and horizontal loops, whereas both have an increased performance over the single firemain. This implies that either layout provides sufficient vulnerability and the potentially more complex offset design provides little extra benefit.

While the offset loop was found to have the greatest level of vulnerability across both damage patterns, it does have a downside. Manual recovery of the offset loop takes longer than the other designs because crew members must traverse two decks to reorient the firemain. However, the authors consider the added benefit of deck separation of the firemain to outweigh the effect of longer manual recovery. Furthermore, ship procedures may be able to adjust crew positioning for DC operations

At this stage it is not realistic to build a fully autonomous firemain as the price for this would be staggeringly high. Semi-autonomous systems, however, have a lower price point and have only been partially implemented. Their immediate recovery capability is a significant factor allowing a naval vessel to quickly recover partial mission capability after damage is incurred. The "smart" valves instantly sense the pressure loss in the system and close to isolate the rupture and thus provide the rest of the system with sufficient water pressure.

Due to the static nature of the damage, the maximum achievable recoverability performance for all three layouts is only determined by the layout of the system and not by the crew response time. In the event of progressive damage such as a fire, the performance of a manual system would be much lower than a semi-autonomous system since the additional damage would impede the damage control actions required by the crew to secure pressure to the firemain.

The vulnerability performance of each firemain layout and automation level are sensitive to the naval vessel's size and can vary for smaller and larger vessel designs. Also, it is important to note that an industrially performed vulnerability assessment will consider the most likely damage patterns and do not rely on equally distributed damage scenarios only.

3.8. Conclusion

This case study intended to quantify and compare the recovery of different firemain layouts with various levels of automation for a generic naval vessel. This quantification and comparison were conducted on a dynamic simulation study under the application of all possible static damage patterns for three firemain layouts. The recovery time and recoverable performance for the different firemain layouts were then recorded and assessed. For firemains with only manually operated valves, the case study showed almost no firefighting capability for at least the first 10 minutes post damage impact under the assumption of crew decision making of about 10 minutes. It was found that partial automation at crucial points in the firemain has a significant positive effect on the availability of the firemain capability in the immediately post damage.

It was also found that for larger threats (zonal damage) the intended redundancy of a horizontal firemain over a single firemain is rendered obsolete. For a relatively small threat (compartment damage) the effect of the offset loop over the horizontal loop is minimal as the damage enveloped is not sufficient to affect the redundancy of the horizontal main. Future work will have to address non-uniform damage patterns on single, but also multiple-decks. Additionally, physics induced primary and secondary damage would emphasise even more the importance of high automation and quick response actions.

Chapter 4

A framework to improve naval designs

This chapter has been published in the Journal of Engineering. The citation for the research article is: *Friebe, M., Skahen, D., & Aksu, S. (2018). A framework to improve the naval survivability design process based on the vulnerability of a platform's systems. Journal of Ocean Engineering, pp. 677-686. doi:10.1016/j.oceaneng.2018.12.074*

In Chapter 3 the most recent vulnerability techniques were tested on a rudimentary model of a naval vessel. A base model was developed that possessed only a firemain system and a simplistic crew model. This chapter utilizes the developed base model and systems to further elaborate on this naval design and develop a complete naval design that then can be assessed.

The objective of this chapter, as stated in Section 1.5, is to test the ability of Bayesian machine learning algorithms to improve the vulnerability performance of naval vessels. Therefore, a model containing all major and auxiliary systems and their interaction is required. Thus, in this chapter a more sophisticated naval model is developed that can serve as input into the Bayesian machine learning algorithm with realistic data of a naval vessel.

The base model of the naval vessel was described in Chapter 3 . It contains the main dimensions of the naval vessel, the crew and their behaviour and a firemain system. In Chapter 4 , the model of the naval vessel was enhanced to include all major systems such as combat, communication, navigation and propulsion as well as its auxiliary systems such as cooling, power and the lube oil system. The enhanced model of the naval vessel was then evaluated in a vulnerability assessment and analysed by means of the framework developed in Chapter 4 .

This novel framework utilizes the Bayesian machine learning algorithm to support naval architects in improving their naval design models. The Bayesian machine learning algorithm builds probabilistic failure relationships between system-system and system-crew interactions. Through the ability of Bayesian Networks to perform sensitivity checks, single point of failures can be found, which are then validated and verified by naval vulnerability experts.

Title: A framework to improve the naval survivability design process based on the vulnerability of a platform's systems

4.1. Abstract

Offshore Patrol Vessels (OPVs) are a relatively small type of vessel designed for quick naval defence response in littoral zone. OPVs also have a complex system layout, because they are constructed to include both commercial and naval aspects with functionality to facilitate its operational defence duties and capability. Furthermore, this complex system layout may not be optimised for survivability. This study presents a novel framework to examine survivability related system and functional dependencies of an actual OPV, combining different modelling techniques. The OPV is modelled and analysed using a physics-based vulnerability assessment model and integrated into a dynamic system supply and demand model. The output is then analysed through a machine learning algorithm to identify functional relationships between systems and the vessel's operational capabilities to then build a Bayesian Network for further analysis. The Bayesian Network model is used to identify single point failures and analyse the OPV's equipment/on-board systems for sensitivity to the survivability of the platform. The results demonstrate the ability of the machine learning algorithm to build a Bayesian Network that can effectively improve the naval design process and subsequently contribute to enhancing the survivability of OPVs.

4.2. Introduction

Offshore Patrol Vessels are relatively small compared to other naval combat vessels, but requirements to their capabilities are growing as more systems and technologies become commercially available. A major challenge in integrating new systems and functionalities lies within identifying single point of failures that make a system vulnerable. Survivability in the context of defence is defined as the capability of a vessel to survive a damaging event such as an engine fire or a weapon threat and maintain its mission capability. It is usually divided into three categories (Ball and Calvano 1994, U.S.Navy 2012) which are:

- Susceptibility - the ability to defeat an attack;
- Vulnerability - the ability to withstand an attack structurally and operationally, and
- Recoverability - the ability to recover mission capability.

Though susceptibility, vulnerability and recoverability are interdependent, this paper focuses upon the vulnerability aspects of survivability only.

Currently, vulnerability assessments of naval combat vessels are performed at the detailed design stage, when comprehensive information of the systems and associated equipment first become available. Often, design changes at this late design stage are costly and design errors are hard to resolve (Doe 2006, Haskins, Forsberg et al. 2006). It would thus be beneficial to know the critical relationships between a vessel's systems and their contribution to a vessel's operational capabilities at the early design stage (Waltham-Sajdak 2012). These relationships can vary depending of the role and function of the vessel, but generally are similar with vessels of similar size (Brown and Salcedo 2003).

Current vulnerability assessment tools for early stage design work with existing designs and are predisposed to erroneous results due to the assumptive nature of the design work (Ball and Calvano 1994, Goodfriend 2015, Friebe and Waltham-Sajdak 2017). Thus, it would be beneficial to know statistically significant dependencies between naval systems, events onboard the vessel and their effect onto the vessel's operational capabilities. Furthermore, this research is based on a previously discussed methodology (Friebe and Waltham-Sajdak 2017) using Bayesian Networks (BNs) to represent the failure relationships between systems and their effect onto the operational capability to assess the effect of parameters of uncertainty to the survivability performance. The parameters of uncertainty describe the scenarios of the naval vessel in combat and can vary from environmental effects, crew states and mission states, and can be extracted from historical databases (Friis-Hansen 2000, Khakzad, Khan et al. 2013, Liwång 2015). Previous research (Liwång, Ringsberg et al. 2013, Li, Chen et al. 2016) relied on subjective human BN modelling with limited naval vessel information, whereas this research attempts to model and learn BNs through a machine learning algorithm from a far more holistic and accurate model of a naval vessel.

This study provides a framework to identify complex failure relationships from an early design between platform systems, sub-systems and components to then link the various parameters of uncertainty through a machine learnt BN that is not prone to subjective human input. It also demonstrates how that framework can be utilized to improve the vulnerability performance of an existing vessel through possible design modifications. As part of this research a case study has been performed, which demonstrates that the survivability performance through the application of the developed process has improved as shown in Section 4.6. Furthermore, this research will enable naval architects to use the learnt critical relationships describing the functional state between the systems to study the change in the uncertainty of parameter values and evaluate their effect on vulnerability performance holistically.

4.3. Theory and Methodology

4.3.1. Background

At the early design stage of a vessel, where little information is available, the uncertainty of the critical relationships between onboard systems may be large (Giachetti 2016). This uncertainty with the associated simplifications and assumptions made in the vessel and system models consequently decreases the confidence level of overall risk or survivability assessments (Abrahamsson 2002).

Previous research (Liwång 2015) highlighted the applicability of Bayesian Networks (BNs) for maritime platform survivability assessments and its capability to evaluate design choices and perform risk assessments effectively. BNs are particularly useful as they allow historical information to be included into the uncertainty treatment of risk assessments, however so far there is no probabilistic causal relationship model that is not subject to erroneous human input (Liwång 2015). This paper demonstrates that the use of BN theory can mitigate model uncertainty in survivability predictions by deriving probabilistic causal relationships between a vessel's functional systems from simulation results.

The probabilistic causal relationships in the resultant BN model are then assessed using Bayes' Theorem and Influence Diagrams to study cause and effect relationships on the design of a vessel. BNs and Influence Diagrams are especially useful when there is no empirical data and there is a need to identify the underlying causal relationships (IMO 2013). These causal relationships are then used to predict the expected cause of failures of systems or operational capabilities. Additionally, the strength of a BN is its capability to present probabilistic relationships and causal dependencies graphically and to facilitate the study of those dependencies (Liwång, Ringsberg et al. 2013, Musharraf, Khan et al. 2013). These probabilistic relationships can be either derived from simulation or historical data (Konovessis, Cai et al. 2013, Liwång, Ringsberg et al. 2013), but are learned through Bayesian machine learning algorithm in this study.

4.3.2. Bayesian Network

A BN is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG) (Khakzad, Khan et al. 2013). For example, a BN could represent the probabilistic relationship between damage imparted to a vessel by a weapon and the vessel's survivability. For a specific vessel's system configuration a BN can be used to predict the probability of the functional state of each modelled capability when subjected to a weapon threat (Liwång 2015). BNs are helpful in assessing the probability of each on-board system's functional state and consequently, analyzing functional inter-system relationships where: 1. uncertainty of input is high (for example, a weapon strike location); 2. historical data is too limited to enable effective regression; 3. and/or where physical dependencies such as overly complex detailed engineering systems design (Liwång 2015).

The BN was chosen due to its reverse reasoning capability, enabling the identification of those systems and design parameters that are critical to the survivability performance of the vessel, and also its ability to create the BN structure which builds conditional probabilistic relationships between them. It is then possible to assess the performance of multiple systems for a single threat size simulation with varying hit locations, and also to assess the effect of variables such as type of threat or crew. Also, BNs are graphical models and thus capable of clearly displaying causal relationships.

4.3.2.1. Bayes' rule and inference

A generic BN model comprises a set of variables representing nodes in the network. For example, in Figure 19 the nodes are 'Rain', 'Grass Wet' and 'Sprinkler'. Links between the nodes represent the probabilistic relationships between them also shown in Figure 19. Nodes that are not connected represent variables that are causally unrelated, whereas arrows that proceed from one node to another represent a causal parent - child relationship. For example, in Figure 19 the relationships between 'Rain' and 'Grass Wet', 'Sprinkler' and 'Grass Wet', and 'Rain' and 'Sprinkler' are shown in the computational probability tables (CPTs) next to their respective nodes with 'T' representing true and 'F' false as logical states of that node. The BN algorithm then performs backwards reasoning to identify the causes that led to the logical state of the node. For example, if 'Grass Wet' is showing wet, then the probability that 'Rain' is true can be determined, but it will be updated with the observation from the node 'Sprinkler'.

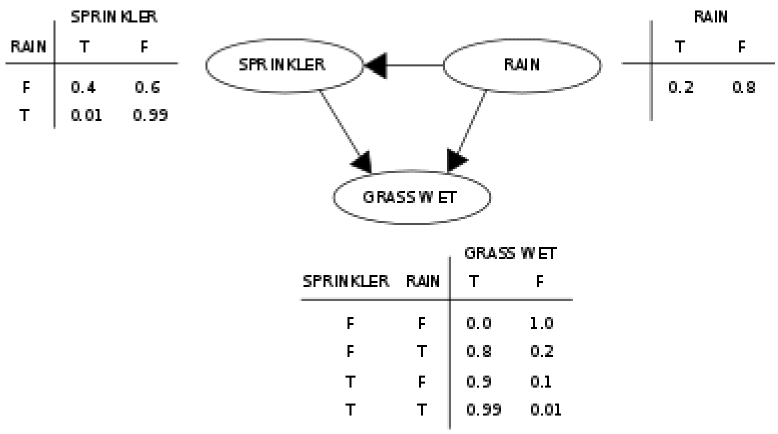


Figure 19 Exemplary BN with associated CPTs

The key feature of a BN is its capability to form a risk-knowledge model enabling reasoning about the uncertainty of each variable. Each node is associated with a probability function that uses as input a particular set of values and returns the probability of the variable represented by the node. Furthermore, BNs represent the joint probability distribution *P(U)* of each variable in the network (Friis-Hansen 2000) as shown in Equation 1.

$$P(U) = \prod_{i=1}^{n} P(A_i \mid Pa(A_i)) \tag{1}$$

where $Pa(A_i)$ are the parents of A_i. BN's are also used as inference engines in accident analysis (Friis-Hansen 2000, Khakzad, Khan et al. 2013) for updating the prior occurrence probability of events given new information, called evidence E as shown in Equation 2. For any two events, *U* and *E*, where '*P(E)*' reads as "the probability of *E*" and '*P(U|E)*' as "the probability of *U* given that *B* has been observed", the joint probability distribution *P(U|E)* can then be computed as in equation 2.

$$P(U \mid E) = \frac{P(E \mid U) \cdot P(U)}{P(E)} = \frac{P(U,E)}{\sum P(U,E)} \tag{2}$$

4.3.2.2. Structure learning algorithm

GeNIe, a software tool developed for BN applications, is used to create and analyse the structure of the BN because it contains a suite of analysis algorithms to choose from. One of these algorithms is the Bayesian Search structure algorithm which is commonly used (Cooper and Herskovits 1992).

To find relationships between the variables and visualize them, the Bayesian Search algorithm learns the BN structure using set of a training data and a hill climbing procedure with random starts (Lestina, Runnerstrom et al. 1999). The Bayesian Search algorithm also requires, a scoring function and a set of possible structures to determine a BN having a maximized scoring function (Koller and Friedman 2009). The algorithm creates the BN by testing different network operations such as edge additions, edge removals and edge reversals to maximize the scoring function. A shortcoming of this algorithm is that it will find local maxima rather than a global maximum. Thus, the learning algorithm must be restarted using different seeds to find numerous BN's, which are then evaluated by a scoring function to find the best fitting BN.

4.3.2.3. Cross-Entropy

One measure that is commonly used to evaluate BNs is the cross-entropy. This is a method used to quantify the difference between two probability distributions. These are the actual probability distribution *q(x)* and the one that is created by the learning algorithm, *p(x)*. The cross-entropy *H(p,q)* measures the summed difference between both as shown in Equation 3. The cross-entropy in this study is used to evaluate the relative significance of parent nodes to their child nodes (Lestina, Runnerstrom et al. 1999, Koller and Friedman 2009). This is done through individual selective choice of observation nodes and estimation of the change in entropy of the questioned node in the BN.

$$H(p,q) = -\sum_{x} p(x) \log q(x) \tag{3}$$

4.3.2.4. GeNIe

GeNIe is graphical user-interface that allows the manual, but also machine-learned modelling of Bayesian Networks (BN). Where a Bayesian Network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG) (Khakzad 2011). For example, a Bayesian network could represent the probabilistic relationship between damage imparted to a ship by a threat weapon (Liwång 2015) and the ships vulnerability when differing vulnerability features are applied. Given a vessels vulnerability configuration; the network can be used to compute the probabilities of the functional state of the ships systems (i.e. the vulnerability) when subjected to a threat weapon. Bayesian Networks (BN) are helpful in assessing probabilities and analysing relationships where uncertainty of input (e.g. a weapon strike location) is high, where historical data is too limited to enable effective regression, and / or where physical dependencies (such as detailed engineering systems design) are overly complex [31].

A generic BN model comprises a set of nodes (typically representing design state variables), with links between the nodes representing the probabilistic relationships. Nodes that are not linked represent conditionally independent variables while nodes that are linked represent dependent variables. Therefore, in order to develop a useful BN model, it is necessary to establish both the state variable nodes as well as the probability links between the dependant nodes – i.e. an inference library. Since BNs are applicable where historical data is too limited to enable effective regression, it is possible to construct an inference library based on a reduced set of detailed vulnerability assessments as would be conducted at late stage design and to use these assessments to construct the necessary inference library for the early stage BN model (Friis-Hansen 2000, Lee and Misra 2005, Konovessis, Cai et al. 2013).

In order to avoid populating the BN with inferences which are tainted by the limitations of FT methods, including that the full system behaviour must be known in order to construct the FT deactivation logic (which on naval vessels is often too complex to capture precisely and accurately), the detailed vulnerability assessments used to construct the BN inference library must not employ FTs.

4.4. Framework

As discussed in section 4.2, a novel framework of assessing and improving a survivability of a vessel has been developed and is shown in Figure 20. This framework uses a novel combination of well-established tools for vessel structure and equipment modelling, threat simulation and system behaviour assessment and a machine learning algorithm to derive a BN. The equipment modelling combined with the threat simulation allows the simulation of realistic damage scenarios as they occur during real life combat scenarios. However, the major challenge lies in identifying which equipment is the most sensitive equipment with respect to failure of a specific operational capability. As the number of systems is so large and complex and often not the immediately adjacent system is the cause, but eventually a system that is indirectly linked that drives the failure of a system. Therefore, Bayesian Networks are used as it allows the learning and the assessment of the direct and indirect critical system relationships of the vessel. Furthermore, this process can be applied to a notional initial design which complies with the minimal survivability requirements (Goodfriend 2015) from traditional analyses (Foos and Skahen 2008). Simulation outputs from this process are then used to derive the critical causal system relationships within the vessel.

The machine Bayesian Learning algorithm is used to derive the critical causal system relationships between the systems and the operational requirements. This BN is then used as a basis for Bayesian sensitivity testing to identify sections of the BN that possess a relatively strong contribution to the survivability performance of the vessel and might be a single point of failure. If the survivability performance of the vessel does not meet its requirements, the supposedly single point failures are investigated, and the design is adjusted if deemed necessary. The process is then reiterated until the vessel's design passes the survivability requirement.

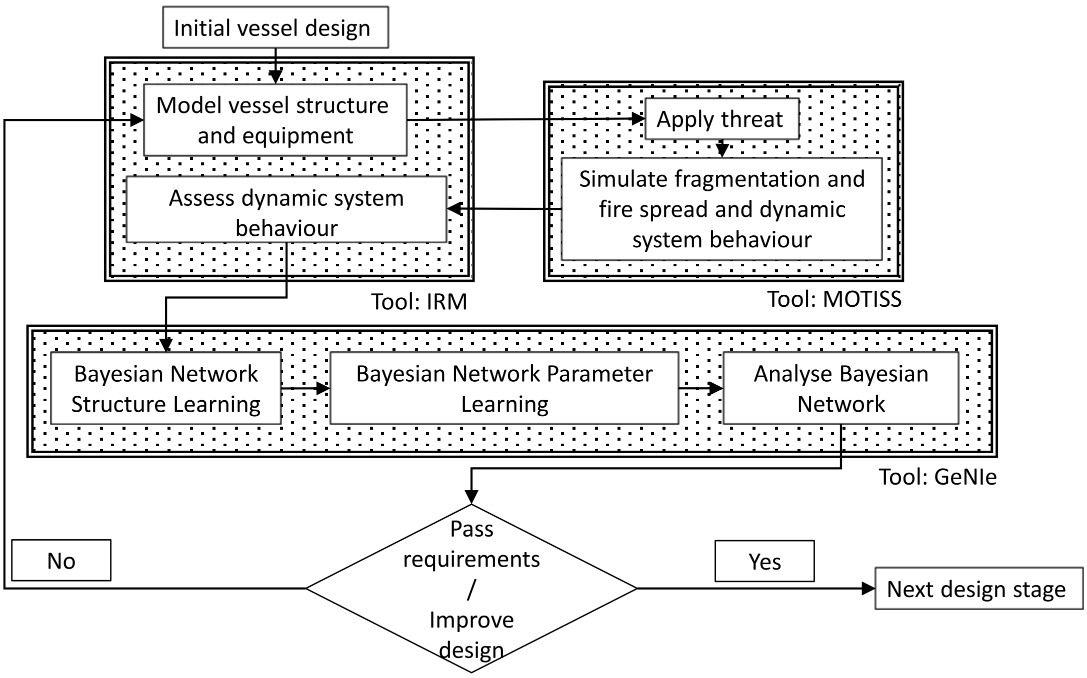


Figure 20 Framework flowchart depicting the process of improving a vessel's survivability design

4.4.1. Equipment modelling

The framework begins with an initial vessel design at the basic design stage, when key system information first becomes available. The structure is modelled in the Integrated Recoverability Model (IRM) tool (Foos and Skahen 2008), and then populated with the equipment and its onboard location, and behavioural characteristics. Furthermore, the operational requirements are expressed through Fault Trees (FTs) as availability monitors of necessary equipment. The structure and equipment data are then transferred into the

Measure of Total Integrated System Survivability (MOTISS) tool (Stark 2016). Both software packages, IRM and MOTISS, are tested and validated by the US Navy and are frequently utilised for survivability assessments of ships of the US Navy.

4.4.2. Apply threat and simulate blast and fragmentation

Within the MOTISS tool a realistic threat scenario is applied to the vessel. This threat is assumed to be a weapon hit from a missile which will be matched to an appropriate warhead size such that the vessel could remain afloat. Then MOTISS simulates the blast and fragmentation damage resulting from the threat. MOTISS then evaluates the probability of a fire ignition and provides the damage results in the form of damage specifications.

MOTISS integrates fragment and blast effects into a single vessel and equipment assessment. It uses Axis Aligned Bounding Blocks to model a vessel, which decreases the runtime to perform damage assessments. Using basic physics principles coupled with empirical data, MOTISS provides a rapid damage prediction to an event using Monte Carlo simulation, by varying each test threat parameter such as fragment size and flight direction (Waltham-Sajdak, 2011). Damage simulations are repeated hundreds of times with each simulation having different combinations of charge and detonation parameters such as fragment sizes, speeds and trajectories. This provides a set of results that captures the chaotic nature of the of the damage event. MOTISS stores the model information and performs damage assessments, to evaluate the survivability. This process creates a damage specification sheets that contains information relating to hull breaches and damaged equipment. Currently, MOTISS is capable of simulating and assessing blast, fragmentation, collision, grounding, flooding and fire (Stark, 2016) damage.

4.4.3. Assess dynamic system behaviour

The MOTISS damage specifications are then transferred back into the IRM tool, which then continuously interacts with the Fire and Smoke Spread (FSSIM) tool (Floyd 2004). This network fire model dynamically computes the fire spread throughout the vessel's compartments and takes into account the firefighting measures from the vessel modelled within the IRM. IRM then records the equipment's state and survivability requirement performance, and then processes them into binary values as shown in the example in Table 2. These binary values represent the availability of operational capabilities and are recorded as ‘1’ if the requirement is met and ‘0’ if the requirement fails. Appendix A contains a detailed description of IRM.

	Equipment 1	Equipment 2	Equipment n	Performance 1	Performance 2	Performance n
Hit Location 1	1	0	1	0	1	0
Hit Location 2	1	0	0	0	1	1
Hit Location 3	0	1	1	0	1	0
Hit Location n	0	1	0	0	1	1

Table 2 Exemplary binary representation of equipment survivability requirement performance

4.4.4. Bayesian Network structure and parameter learning

The binary data in each column in Table 2 are then compared with every other column by GeNIe. Initially, a null hypothesis between all columns assumes that the columns are unrelated to each other. To determine the existence of a probabilistic relationship between the individual columns, the statistical significance of the null hypothesis rejections are tested (Lestina, Runnerstrom et al. 1999). Each column of data becomes an individual BN node in the BN structure and whenever a null hypothesis is rejected by a statistically significant test result, a link is formed between the two nodes tested, otherwise there is no link.

Next, GeNIe is used to determine the BNs probabilistic values of the relationship between each node, i.e. each column in Table 1, and all others, using causal dependencies and correlations. These probabilistic values form the basis of the CPTs for each node, (see Section 4.3.2). To fill the CPT tables the nodes that have a probabilistic relationship are compared row by row to determine the parameters of conditional distributions between the nodes. The distributions within each CPT are then automatically optimized with a Maximum Likelihood Estimation (MLE) algorithm to fit the data holistically for the whole BN (Lestina, Runnerstrom et al. 1999).

4.4.5. Analyse Bayesian Networks

Analysis of the BN's sensitivity to critical systems and components enables single point of failures and design issues to be identified. If they are identified as significant, the design could be modified, and the improvement process repeated until the performance of the systems or the overall survivability performance of the vessel's single points of failure are removed.

4.5. Case study

The goal of this case study is to demonstrate the viability of the proposed novel framework combining the capabilities of three well-established software tools. A BN model describing the association between mission outcomes (i.e. functional survivability) and vulnerability of on-board systems/components of a typical vessel is derived. This BN is tested on its cross-entropy, which makes it possible to identify critical equipment that has a significant contribution to the mission capability of the vessel. The outcome of this case study is considered successful if the vessel's survivability can be improved by the process outlined in the framework.

4.5.1. Vessel design and systems specifications and configuration

The framework was applied to a notional design of a high-speed OPV equipped with rockets for fast counter-attacks. The vessel has an overall length of 50m and has a combined structure of steel hull and aluminum superstructure. The vessel is fitted with a propulsion system that is comprised of two waterjet propulsion systems, and a combat system with a forward and aft gun. The power is generated by two generator sets and supplied to the corresponding switchboards to distribute the power throughout the vessel. Necessary support systems for power generation, distribution and combat functions and the crew-system interactions were modelled at the basic design stage level. This vessel has both internal and external communication systems. The internal communication system consists of three individually operating communication sub-systems which are: 1 Main Circuit (1MC), Wireless Calling System (WICS) and Sound Powered Telephone (SPT). The external communication system is a radio system. In this case study, damage control is composed of a fire main and fire plugs.

4.5.2. Vulnerability performance measures

In this case study, it was assumed that for a minimal level of survivability of the vessel, the performance depends on the survivability of at least seven operational capabilities: power; propulsion; internal communications; external communications; damage control; combat; and the crew. Survivability requirements of each operational capability and crew were also assumed based on common knowledge and expert opinions (Skahen and Foos 2017). Expert opinions were gathered through interviews with seven survivability engineers from Test & Evaluation Solutions over a period of nine months, who then also verified the accurate representation of the system and the operational capabilities. The assumptions and scenario parameters for the performance requirements of the operational capabilities and the crew include:

1. Power performance: This requires at least 50% of the generator systems and corresponding support systems to be functional.

2. Propulsion performance: This requires 50% of the propulsion generating systems (steering and propulsion equipment) to be functional.

3. Internal communications: This requires either Wireless Calling System (WICS) or Sound Powered Telephone (SPT) or 1 Main Circuit (1MC) to be functional. A WICS system is assumed operational if 50% of the WICS antennas are functional. The SPT is assumed to be working if it is possible to communicate at least between two out of the three SPTs.

4. External Communications: This requires either the Radio equipment rack or the Radio operator console to be functional. This system has two components that can be used to perform emergency calls: a Radio equipment rack and a Radio operator console.

5. Damage Control: This requires a minimum of 50% availability of the fire pumps and 50% availability of the fire plugs in both forward and aft of the vessel.

6. Combat: The vessel has a 71mm forward Gun and an aft Rocket Launcher and requires both of them to be a 100% functional for combat missions. These system’s inputs such as cooling, power and operator input is recorded temporally. To be operationally functional also requires the Combat Information Centre control console, which needs to be manned and supplied with power, and the sensory inputs from the Gyro, wind gauge and radar.

7. Crew fatality limit: Fatalities are grouped into instant fatalities and from secondary weapon damage effects such as fire and smoke. The total number of fatalities should not exceed 80%, which are 18 out of the 22 crew members for this type of vessel (OPV).

4.5.3. Modelling in IRM

The model constructed in IRM is comprised of the vessel's structure, and the main systems, those that are considered essential for vessel survivability, and the support systems that enable the main systems to function. The conceptual layout of the power system and the seawater system are shown in detail in Figure 21 and Figure 22 to demonstrate the depth of modelling. However, the remaining systems were modelled in similar detail.

The system shown in Figure 21 is a power system that consists of two generators (GEN I and GEN II), providing power to the switchboards (SWBD I and SWBD II). From the switchboards, the power is distributed to either an ABT (Automatic Bus Tie breaker) or MBT (Manual Bus Tie breaker). These bus tie breakers operate as switches, and switch between a normal power source and an alternate power source when the former is not available. Furthermore, IRM allows the user to assign crew to specific systems if that system needs a trained crew member to operate the system (i.e. change state between 'off' and 'on'). In total 22 crew members were modelled with specific skills such as the capabilities of a mechanic, electrician or a damage control personal and also incorporates how long it takes for the crew to perform recovery actions on the system. From the bus tie breakers, power is further distributed to the power panels (Power Panel I and Power Panel II), which are usually situated throughout the vessel to provide electrical supply to closely located equipment.

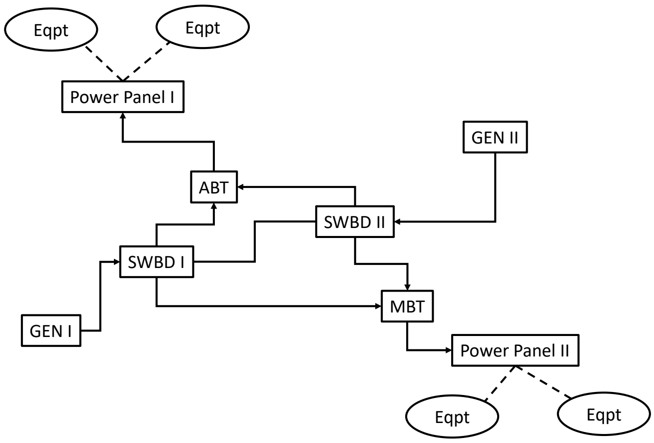


Figure 21 Conceptual layout of the power system

The seawater system shown in Figure 22 is modelled in such that it always has a source, a pump and a sink. In this model there are six Sea Chests, each providing access to sea water. There are 2 Fire Main Pumps that provide flow from the sea chests then merge on a major Fire Main system through valves. This Fire Main can branch out into a sea water cooling system, providing cooling to various equipment. This is shown as the branch at Fitting III. This equipment is modelled to also have other necessary fluids set up to operate. For example, lubricate oil or fuel, which are operated similarly to the sea water system. At Fitting IV the Fire Main system also branches off into an installed firefighting system, (not shown in Figure 22). This firefighting system is comprised of sprinklers that are modelled with heat sensors and a water discharge rate. If the sensor detects a rise in temperature, it will release water and attempt to extinguish or suppress the fire.

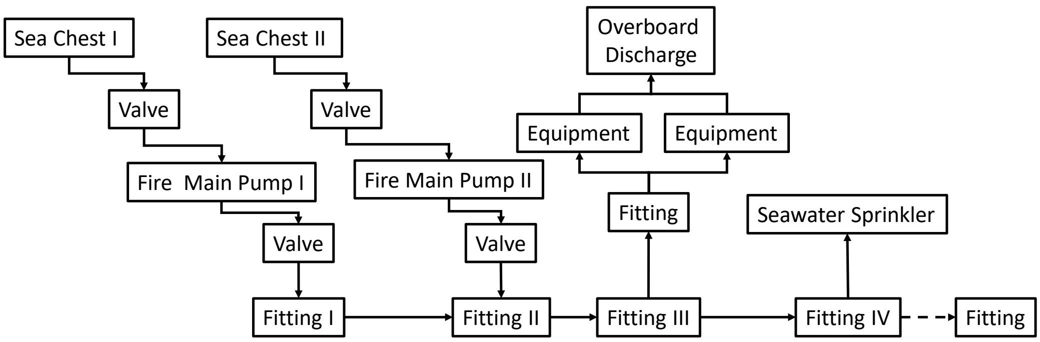


Figure 22 Conceptual layout of the seawater system

The IRM enables modelling of survivability requirements of the vessel by utilizing a Fault Tree approach (Foos and Skahen 2008). The FT structure shows the required availability of equipment necessary for successful operation. The Top-Level FT structure for the survivability of the OPV vessel is shown in Figure 23.

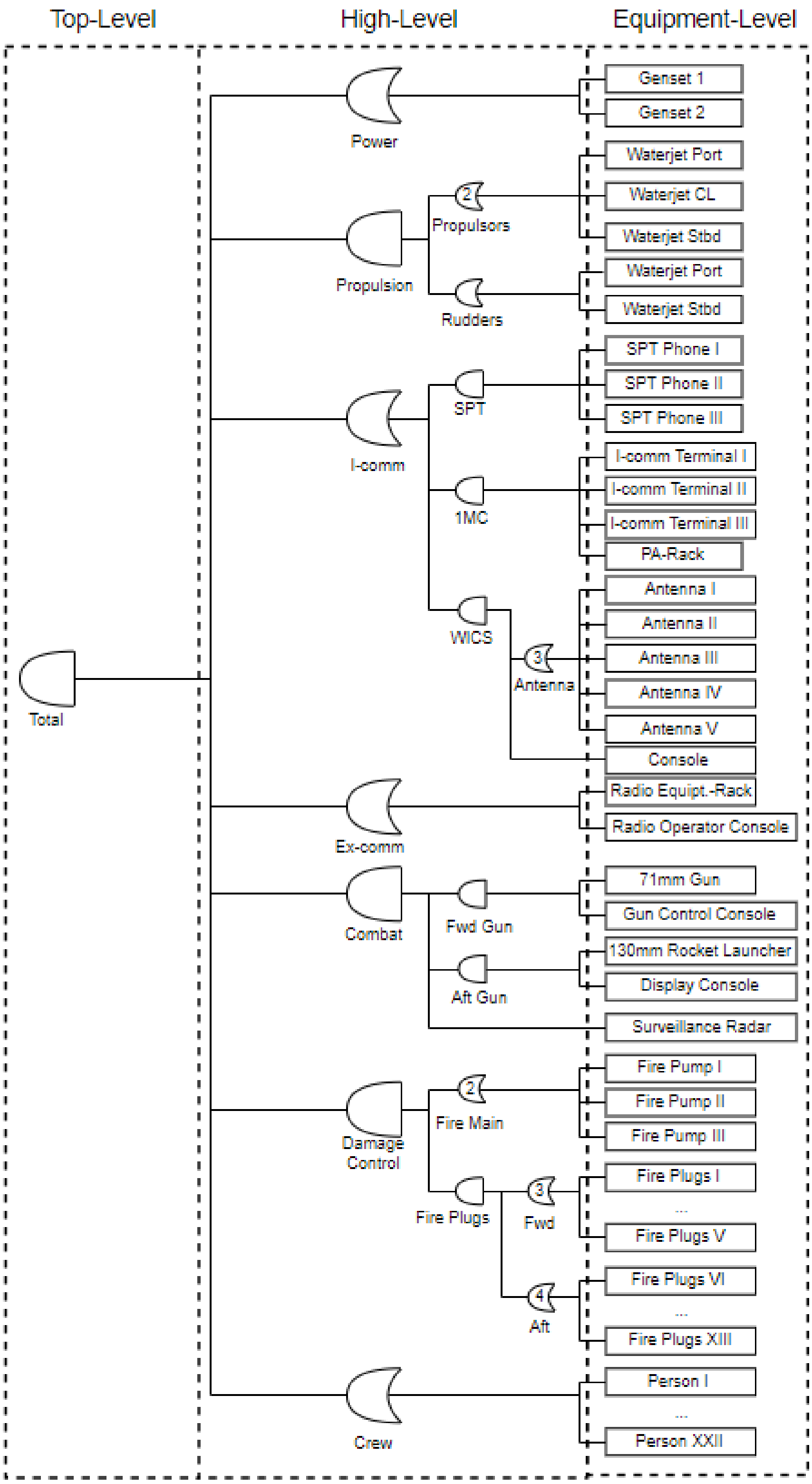


Figure 23 Top level performance measurement is defined by 7 high level requirements which are based on the availability of essential equipment

4.5.4. MOTISS model imported from IRM

To simulate weapon attacks and damage scenarios, the probabilistic vulnerability assessment tool called 'MOTISS' was utilised because model data can be transferred directly from IRM. This data includes vessel structure and corresponding system's dimensions and locations. For weapon attack simulations, the MOTISS requires the size of the threat to be defined.

In this case study a threat was selected such that it could cause structural damage, and also be small enough to allow the vessel to float and be stable. Survivability of a vessel from a weapon attack is defined as a function of warhead charge weight combined with the floodable length of the vessel as illustrated in Figure 24 (Waltham-Sajdak 2012). The correlation between the charge weight floodable length related to the warhead damage can be described through the empirical formula

$$WD = 0.0135 \times (FL\_allowable)^3 \qquad (4)$$

Where, WD is the TNT equivalent warhead charge weight in kg and FL_allowable is the floodable allowable length which is assumed to be 12.5% of the length between the aft and forward perpendicular of the vessel (Waltham-Sajdak 2012). The vessel's length is about 50m and thus the threat size for this vessel was selected with a warhead size of 3.1kg TNT.

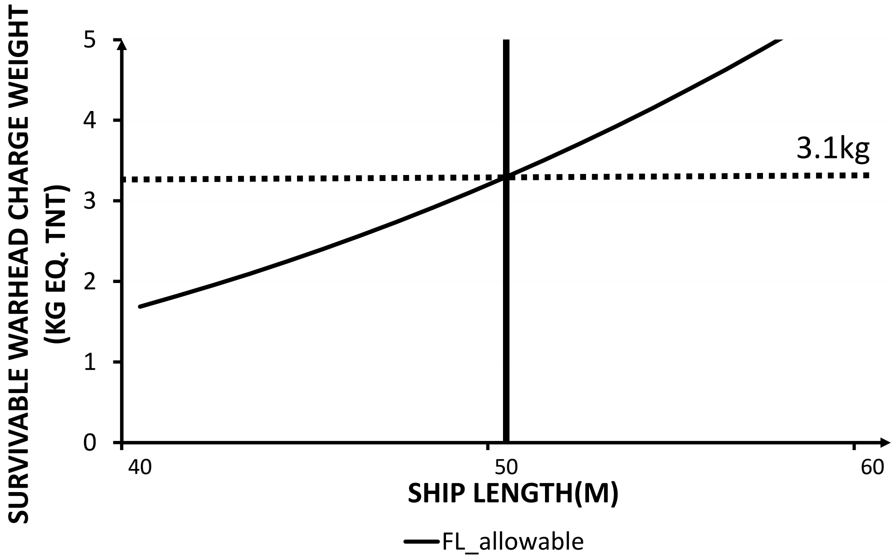


Figure 24 Selected threat size for a 50m long patrol vessel calculated based on equation 4

The MOTISS tool also requires the user to input a weapon hit grid. These are uniformly and evenly distributed across the vessel as shown in Figure 25. The hit grid in this study consists of 11 locations in the longitudinal direction, 4 locations in the vertical and 5 locations in the transverse direction, that is, 220 locations. Most port and starboard locations were chosen to be in very close proximity to the hull, not further away than 30cm. Each of the 220 hit locations is simulated and an output file is created, that contains the damage information for each damaged piece of equipment and the location of potential fires.

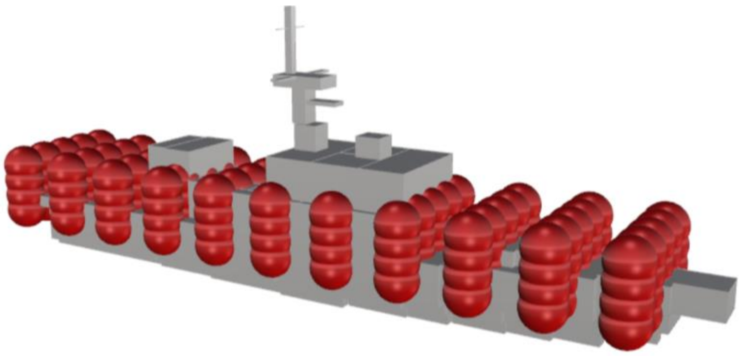


Figure 25 Uniformly distributed hit point locations marked as red spheres

4.5.5. Re-importing into IRM and measurement states

On completion of the assessment of the effect of threats on the vessel's systems using MOTISS, the damage files are re-entered into IRM. This enables IRM to model the systems performance for each hit simulation. The systems and their functioning performance are modelled from the moment of impact and for 30 minutes onward. Experts (Skahen and Foos 2017) advised that simulating the vessel for 30 minutes after the weapon hit is reasonable, anything longer would be irrelevant as the combat scenario is not expected to last that long.

A total of 220 hits were simulated once, with each simulation measuring the on / off state of 750 single pieces of equipment. Additionally, 7 top performance levels and 12 sub-performance requirements from Figure 23 were tracked, which totaled 769 columns of data with each them having 220 rows of binary data for each weapon hit. This data can now be imported into GeNIe.

4.5.6. Bayesian Network settings

GeNIe contains learning algorithms that consist of two analytical methods. The first is a heuristic search and scoring function and the second is an independence test. The Bayesian search algorithm was used in this study (Lestina, Runnerstrom et al. 1999). This algorithm uses a hill climbing scoring procedure with random restarts. As the required data storage for the probability table increases with the number of variables and states, it was found to be useful to limit the maximum number of parent nodes to five. The decision to limit the parent nodes does not have a significant negative impact, because the relative difference between the parent nodes to the child node diminishes as parent nodes are increased (Koller and Friedman 2009). The link probability was reduced to 10^{-6} in order to eliminate the accidental probabilistic relationships and build a lean BN, which in turn helped to keep the number of parent relationships low.

4.6. Results

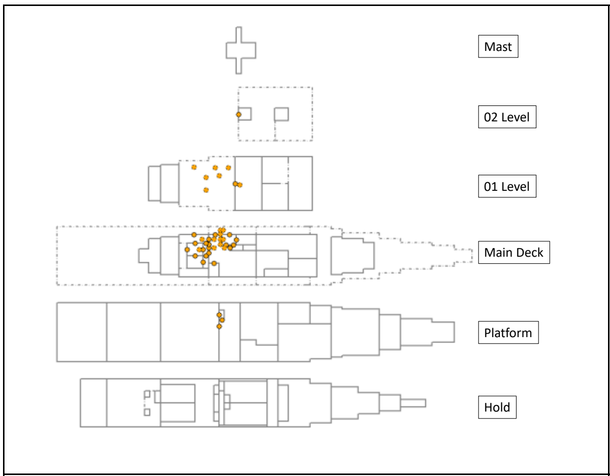
The results are twofold. Firstly, the IRM simulation results show a detailed crew and system interaction for the first 30 minutes after the weapon hit. Secondly a BN is derived from the crew and system states at the 30-minute time interval. The results are separated into Initial Results (4.6.1) and into Model Iteration results (4.6.2) as the design was modified in between.

4.6.1. Initial results

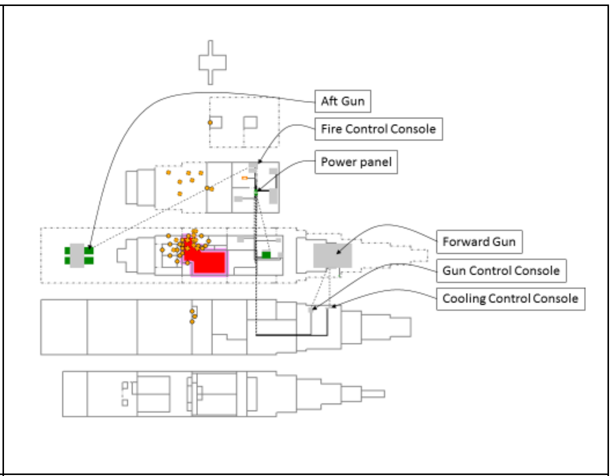
First the results of the stability analysis are discussed. It should be noted that any hit under the waterline that damages two sections at once leads to an ingress of seawater and a loss of floatability and consequently the loss of the vessel. Out of 220 hit locations, 55 are under the waterline. The damage two watertight compartments the hit needs to be in close proximity to the watertight bulkheads, which is the case in 23 out of 55 hit locations. Further details on the vessel's damage stability and righting moment curve can not be obtained as each compartment is modelled box shaped and the vessel's centre of buoyancy therefore is not realistic enough.

Second, one of the major findings of this analysis is shown in Figure 26. The screenshot in Figure 26a. shows decks of the vessel from the hold up to the mast. The orange circles in the aft area on the decks: Platform, Main Deck and 01 Level indicate damage to the structure due to a hit aft on the deckhouse. The screenshot in Figure 26b shows that in this scenario the aft and forward guns are disabled 1 second after the weapon hit. A fire has also been caused by the weapon hit and is indicated by the red colour. Both guns are connected to the same power panel on the 01 Level and are lacking power because the power supply to the power panel has been interrupted. At 25 seconds, the power panel regains power after a crew member has operated the MBT on the 01 Level. At 75 seconds, the forward gun becomes non-functional again, due to overheating, because the cooling circuit is non-functioning and without coolant the gun will not function.

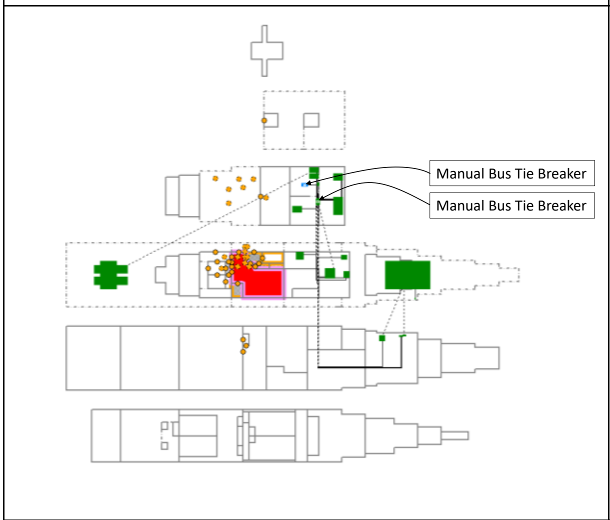
Both guns are dependent on the same power panel, which is a single point of failure. Existence of a single point of failure in a design is a critical design weakness that should be resolved. A viable solution to the problem could be to power each gun from a separate power panel.



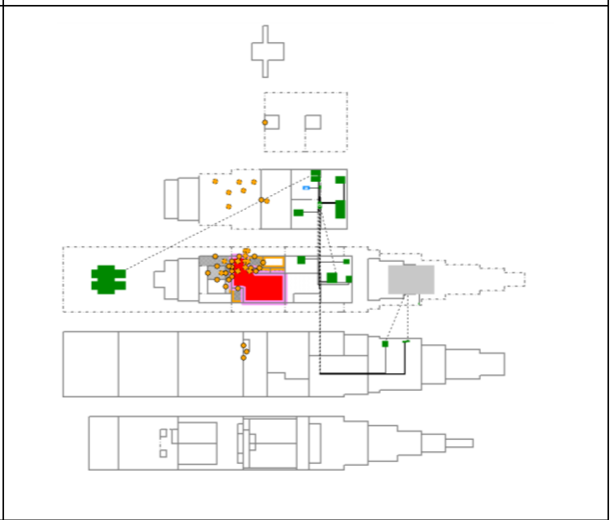
a. Initial damage area showing holes marked with orange circles



b. After 1 second the forward and aft Guns are disabled (grey)



c. After 25 seconds the forward and aft Guns are functional (green)



d. After75 seconds the forward Gun was non-functioning due to overheating

Figure 26 One IRM sample hit simulation

After the IRM simulation was completed, two BNs shown in Figure 27 were developed using the 'learning algorithm' (Koller and Friedman 2009). Figure 27 shows a sensitivity analysis of the Aft Gun. Sensitivity testing can be used to determine the relative influence of a system to another system or the vessel's operational capabilities. Sensitivity is characterised as the expected shift in variation of a selected target node due to the structure and the computational probability tables of the BN. As an example in Figure 27, all nodes in red, with arrows pointing towards the Aft Gun, indicate a high sensitivity and contribution with respect to the failure of the Aft Gun – the target node is indicated by a crosshair at the bottom right of the node. Nodes with lighter colouring, up to grey have less or zero sensitivity to the target node. It can be seen that the learning algorithm detected correctly that the aft gun is sensitive to failure of the 'Main Switchboard 1' (MSWBD1) as it supplies power directly and indirectly at the fire control console and display console.

Furthermore, although both BNs are identical in Figure 27, the BN on the right shows the sensitivity analysis on the Forward Gun, which is the target node now. Again, the main switchboard is a sensitive component, by powering the Gun Control Console. It can be concluded that the learning algorithm with the help of a sensitivity analysis model correctly identified the single point of failure that was found in the IRM model. Both these cases indicated that the operational state of the main switchboard was necessary for the guns to be operational. Investigation of the power system design showed that critical gun components for the Forward Gun and Aft Gun systems were powered from the same power panel.

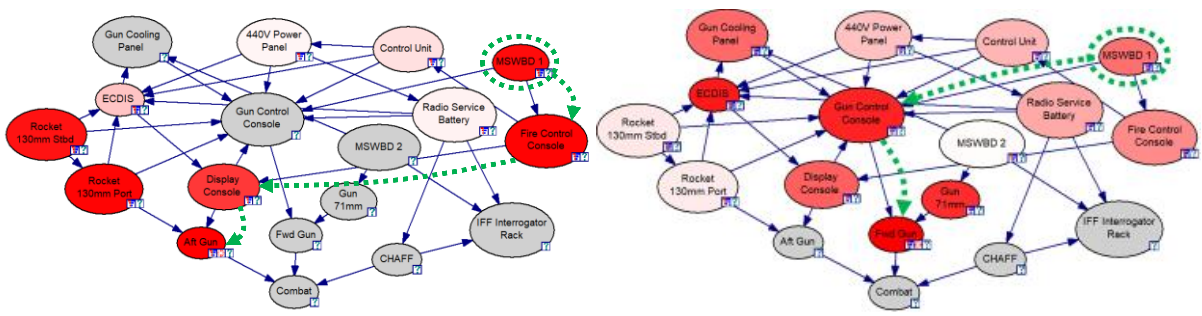


Figure 27 A reduced BN with equipment sensitive to the Aft Gun on the left and to the Forward Gun on the right

4.6.2. Model reiteration

The power network then was reconfigured so that the forward gun is provided power from Main Switchboard 2 (MSWBD 2) which is not in the pilot house, but from in compartment next to the main engine room. The MOTISS and IRM model was adjusted accordingly and re-run. As predicted, reconfiguring the power network and supplying the Forward Gun with power from MSWBD2 separated the critical equipment from the Forward and Aft Gun. The red coloured equipment shown in Figure 28 on the left and right are clearly non-identical and therefore shows that both systems are independently powered.

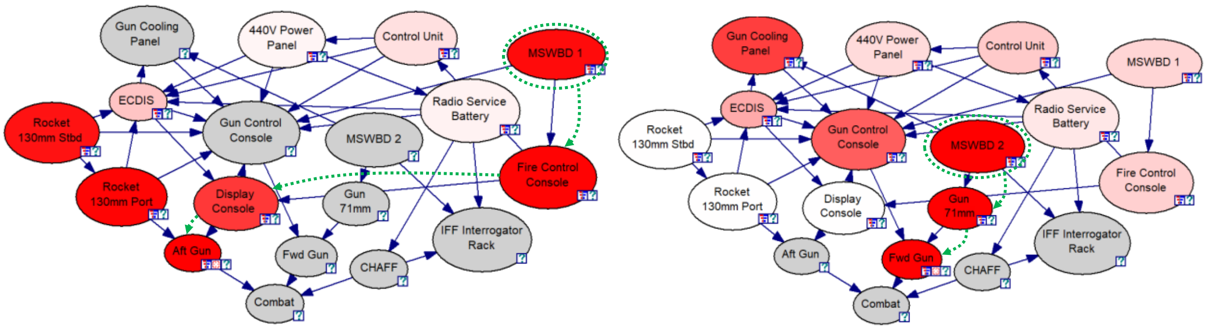


Figure 28 BNs sensitivity analysis showing the critical equipment for the Aft Gun on the left and the Forward Gun on the right

It can also be inferred from comparing the BNs on the right side in Figure 27 and Figure 28 that the main power source for the Forward Gun changed from MSWBD1 before the network reconfiguration. These are surrounded by a green dotted line on the both figures. To MSWBD2 surrounded by a green dotted line on the right figure after the reconfiguration. The different colours in Figure 28 represent a graphical interpretation of the quantified sensitivity of the critical equipment.

Sensitivity analysis helps to identify critical systems that lead to the failure of other systems or the vessel's operational capability. As an example, table 2 shows the cross-entropy values of the critical systems ranked in order of their sensitivity with respect to the Forward Gun capability. The sensitivity values show a drop for the MSWBD1 and a rise for MSWBD2, which is beneficial as the MSWBD1 is supposed to supply power only to the Aft Gun as it would be otherwise a single point of failure.

Ranked Observations	Diagnostic Value
Gun 71mm	0.261
Gun Control Console	0.069
MSWBD 1	0.040
MSWBD 2	< 0.001

Ranked Observations	Diagnostic Value
Gun 71mm	0.253
Gun Control Console	0.106
MSWBD 2	0.037
MSWBD 1	< 0.001

Table 3 Results of the quantitative sensitivity comparison for the Forward Gun before reconfiguration on the left, and after reconfiguration on the right. Values represent calculated entropy[3]; the larger the value the greater its influence on the target node

The design issues identified by the BN of the vessel were confirmed by naval experts and the combat requirement performance improved after the power system reconfiguration as shown in Figure 29. The combat system's availability improved by 0.9% from 173/220 to 175/220. The improvement of the combat system performance is attributed to the higher survivability rate of the 'Display_Console' and the 'Rocket_130mm_Component'. This improvement appears small at first sight, but it is important to note that this improvement can be achieved through connecting the power differently and does not add any cost or weight to the vessel. The demonstrated design error was not found by naval architects as the model of vessel is very complex and comprised of many systems interacting. Also, it must be noted that the magnitude of the improvement probably would change with a different hit grid resolution, which has not been investigated yet. Eventually several small improvements with similar low costs can be found for a complex design, that then could accumulate to more significant impacts.

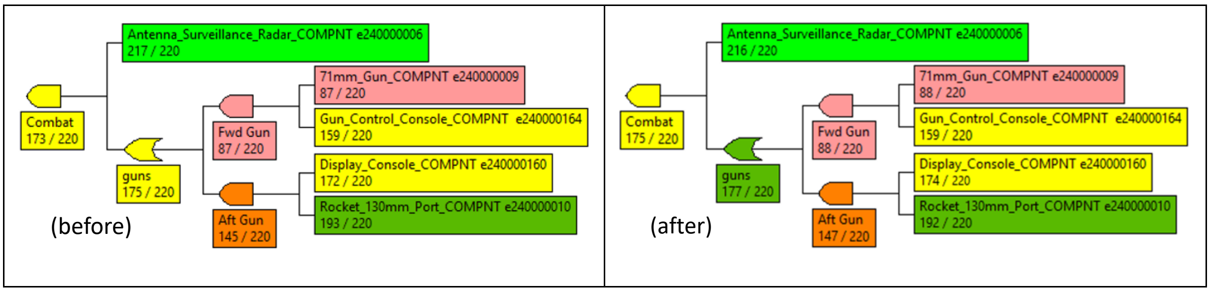


Figure 29 shows the combat performance before and after the power reconfiguration

[3] Entropy is defined as the variation *I* of a query variable *Q* due to a finding F, and is computed as $I=\sum_q \sum_f P(q,f)\log[P(q,f)/P(f)]$, where *q* is a state of *Q*, *f* a state of *F* and the summations are the total sum of all states *f* or *q* of variables *F* or *Q*.

Also, the machine learning algorithm was tested for variability and its performance to successfully build a BN that can identify the same single point of failure from the preceding sections. The machine learning algorithm was trained 20 times with the same result database and was then reduced by the least sensitive nodes to contain only the critical systems in the BN. The results in Figure 30 show that the highest success rate of identifying the design issue is if the size of BN in the range between 15 to 30 nodes. When the size of the BN is reduced to less than 15 nodes, too much valuable information is cut out and thus identifying the design issue becomes impossible. On the contrary, when BN contains too many nodes and too much information, the relative sensitive of each node diminishes and the chance of successfully identifying the design error reduces. It was found that the highest possible chance of machine learning a BN that successfully identifies the error is if the size of the BN is at 20 nodes, which corresponds to a chance of 90% success as shown in Figure 30.

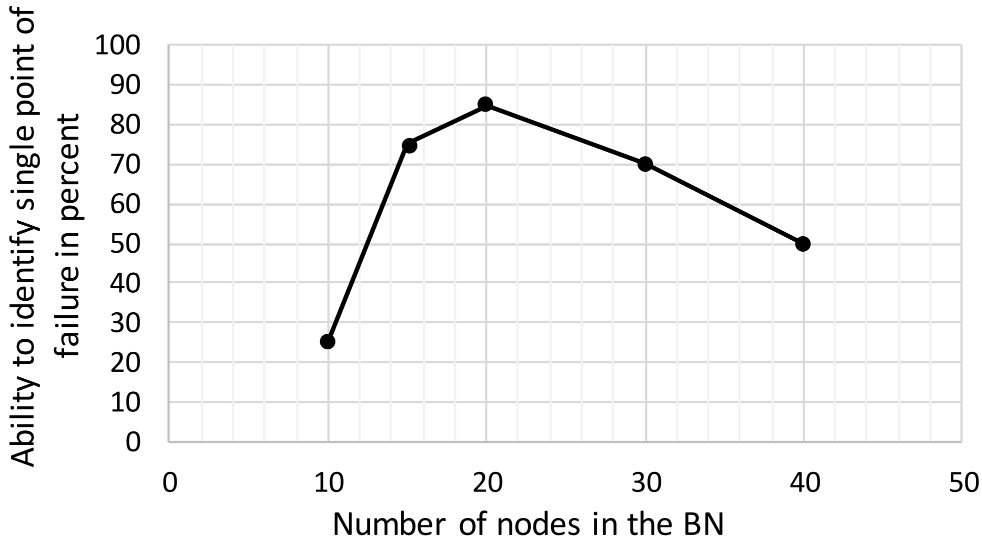


Figure 30 Percentage of machine learned BNs that successfully identify the single point of failure depending on number of nodes and/or systems in the BN

4.7. Discussion and future work

The presented study links data from different parts of survivability assessments and combined them in a naval assembly, without requiring further human input, analysed a design of an actual vessel and provided insights into design issues and consequently suggestions to improve the design. The tool to perform this analysis is the BN theory that enables naval architects not only to study the consequences of a failing system to the operational capability, but also to reason backwards as in which system caused the operational capability to fail.

The case study is a model of a patrol boat. The model was chosen to be complex enough to demonstrate that the proposed process is capable of identifying human design errors and the same time allow verification by a human expert. The beneficial effects of this process are believed to grow with the complexity of models as the developed process can be automated and should outperform any human expert in the search for single point of failures.

The damage predictions from MOTISS vary with each simulation, as the physical nature of fragmentation is probabilistic. However, in this study each hit location was simulated once only, which rendered the output deterministic. Thus, the next steps in this research are:

- to produce more simulation runs for each hit location and produce a probabilistic damage output from MOTISS for input into IRM, and
- to introduce a probability distribution at some nodes of the BN and analyse parameters of uncertainty to the systems.

4.8. Conclusion

The goal of this study was to create a framework that could improve the design of vessels through the probabilistic quantification of the failure relationships between its systems and the performance of the vessel. This resulted in the development of a framework that used a novel combination of three well-established software tools in the fields of survivability and risk assessment. Initially, the IRM and MOTISS tools were used to model an actual vessel's structure and systems and assess its operational capabilities against the effect of a weapon strike. Then a Bayesian Network model describing the association between functional survivability and vulnerability of the vessel's systems and components, was derived. This BN was able to successfully produce a recommendation for design change based on the identification of a single point of failure of the vessel. The framework was found to perform best when the BN was reduced to 20 nodes and to successfully identify the design issue in

90% of the tested cases. The design change was then used as the basis for the next design iteration and consequently resulted in an improved survivability performance of that vessel. Thus, the proposed framework was validated and has shown to be capable of improving an existing vessel's survivability through smart design changes.

It should be noted that the framework performed best at a sample size reduced to around 20 nodes as shown in Figure 30. As discussed earlier, the original number of number of nodes therefore had to be manually reduced by the least sensitive nodes with the weakest statistical correlations to achieve the final Bayesian Network. As this manual Bayesian Network reduction can be mathematically expressed and automated, it is assumed by the author that the developed framework is not bound to any limitations in its applicability with regard to the size of the naval vessel.

4.9. Acknowledgement

The author wishes to acknowledge the support of the Australian Research Council (ARC) Research Training Centre of Naval Design and Manufacturing (RTCNDM). The RTCNDM is a University-Industry partnership established under the ARC Industry Transformation grant scheme (ARC IC140100003). Also, many thanks to Dr. Jonathan Binns, Dr. Rouzbeh Abbassi, and Dr. Vikram Garaniya from the Australian Maritime College and Tim Speer from Austal.

Chapter 5

Inclusion of system reliability in survivability assessment

This chapter has been submitted to the Journal of Ocean Engineering on February 19th, 2019.

In Chapter 3 , a naval model was developed that then was enhanced in Chapter 4 to include the major and auxiliary systems of the naval vessel. Additionally, in Chapter 4 a framework to assess and improve the vulnerability performance of the model of a naval vessel was developed and demonstrated. One result of the framework from Chapter 4 was the probabilistic failure relationships between system-system and system-crew interactions.

An inherent limitation of current vulnerability assessments and the vulnerability assessments in Chapter 3 and Chapter 4 is the assumption that systems are perfectly reliable. One objective of this research is to investigate the effect of the systems' reliability on the performance of the naval vessel. To include the reliability of the naval vessel's systems, the derived probabilistic failure relationships are extended using each system's reliability function in the Bayesian Network.

The result of this work is a join vulnerability and reliability model. This enables naval architects to predict random system failure in combat situations. Which in turn provides a more realistic model of naval vessels as systems random failure doesn't have to be excluded from vulnerability assessments anymore.

Title: Inclusion of system reliability in a survivability assessment framework

5.1. Abstract

Naval vessels are designed to be survivable to protect their crew in combat. However, survivability assessments are performed under the assumption of perfectly reliable systems. This assumption may cause naval designs to be less survivable than predicted. This paper presents a proof of concept of an extension to a framework that derives the probabilistic failure relationships from a survivability assessment simulation. In the presented study, the probabilistic failure relationships are extended to include system reliability as part of the survivability assessment. The inclusion of system reliability into the survivability performance assessment of the power systems and related operational capability of the vessel provides a more realistic performance model of a naval vessel. This method also helps to predict vessel's survivability performance during combat with regards to its years in service and furthermore will ensure the safety of the life of crews and the navies assets.

Keywords: Vulnerability, Bayesian Network, Reliability, Survivability Assessment

5.2. Introduction

The design philosophy of naval vessels has significantly changed since the late 1940s and lead to a reduction of large naval vessels such as destroyers and an increase for smaller type vessels like frigates as shown in Figure 31 (Kok 2012, Stark 2016). Also, as modern naval vessels get smaller and more complex, the number of requirements on their performance increases (Waltham-Sajdak 2011). One method that can be used to manage this is called 'System Engineering', which provides a methodology to integrate the growing number of requirements into the design of vessels. System Engineering also examines the reliability, availability, maintenance and safety which are also increasingly integrated into the design of commercial and vessels (Haskins, Forsberg et al. 2006).

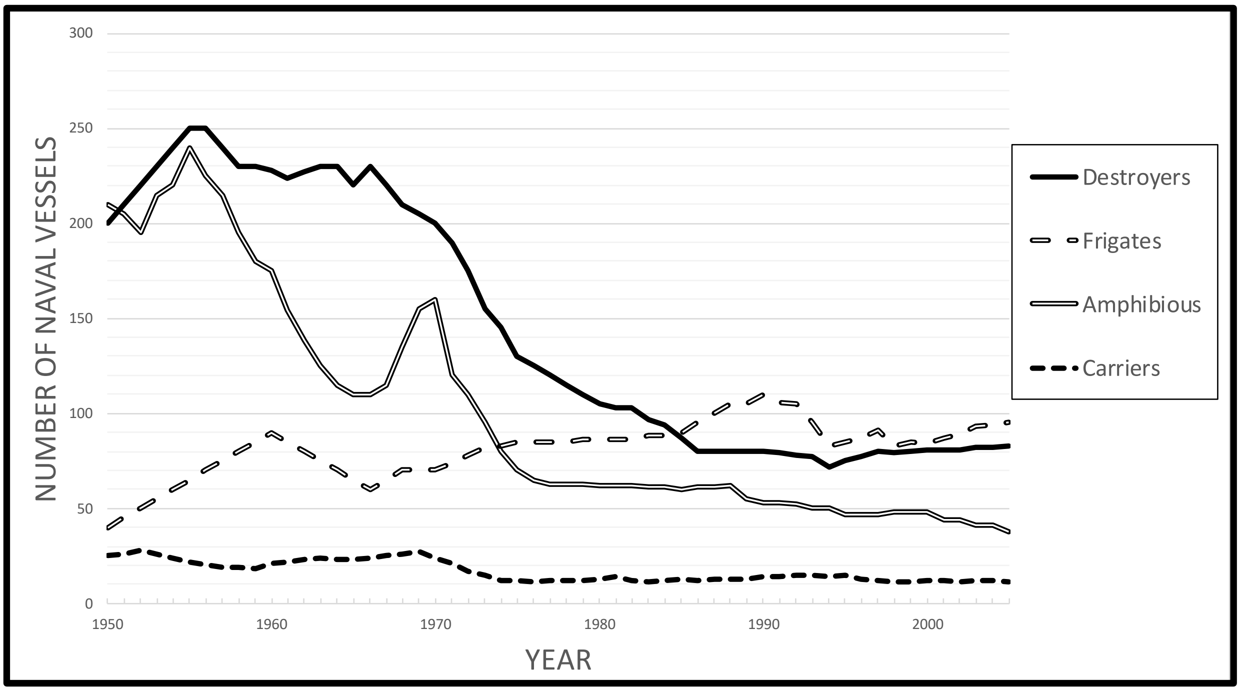


Figure 31 Number of USN Ships by Class by Decade

But, unlike commercial vessels, naval vessels require survivability (Piperakis 2013, Liwång 2015) – where survivability in this context is limited to the vulnerability aspect, which describes the amount of damage a vessel can endure and keep functioning (U.S.Navy 2012). Naval vessels are usually designed with 85-95% equipment availability requirements (Malakhoff, Klinkhamer et al. 1998), whereas survivability assessments are performed with the assumption of 100% available systems (Foos and Skahen 2008, R. Gregg Fresa, Zackary R. Stull et al. 2017) which leads to the conclusion that if the reliability of the equipment in a survivability assessment is neglected, the naval vessel might be less survivable than anticipated. To assume an only 85% reliable system to always function and never fail is a major assumption that may have a significant effect on the survivability performance in a combat scenario. Thus, the focus of this research is the inclusion of the reliability effect into the survivability assessment of an existing naval design.

There are various possible design measures to improve the reliable performance of a vessel, such as providing physical redundancies of systems or by selecting more reliable components for a system (Kim, Haugen et al. 2016). Survivable rated vessels usually provide at least one level of physical redundancies of their systems. This level of redundancy can absorb certain damage in a combat scenario, but the damaged vessel then requires the remaining system to be perfectly functional and reliable. Thus, it is important to include the effect of reliability into survivability assessments and estimate the reliability-corrected survivability performance.

Holistic assessments considering the joint effect of reliability and survivability of a vessel during operations have not been performed and is thus the objective of this paper.

5.3. Background

Survivability is generally described as the complement of the probability of being killed (Ball and Calvano 1994) as shown in Equation 3.

$$P_S = 1 - P_K \qquad \text{Equation 3}$$

With

P_S = the probability of survival and

P_K = the probability of being killed.

It can be seen from Equation 2 that a vessel, needs to be detected, aimed at, targeted and hit in order to be killed (Ball and Calvano 1994, Kwang and Jang 2012). This can be equated and written in an equation as the following:

$$P_K = P_D \times P_A \times P_T \times P_H \qquad \text{Equation 4}$$

Where

P_D = the probability of being detected;

P_A = the probability of being aimed at;

P_T = the probability of being targeted;

P_H = the probability of being hit; and

P_K = the probability of being killed.

However, engineers working in the field of survivability also need to know the effect of reliability of systems so that design choices that affect the reliability of a system such as a system's time in operation and the system and component specific Mean Time to Failure (MTTF) can be made. Fault Trees (FTs) have been used widely in the assessment of risk and fault diagnosis of equipment and reliability analysis (Khakzad, Khan et al. 2013). However, a FT's major limitation is to assess large complex systems and their inability to effectively identify causes that lead to failure. Furthermore, FTs are incapable in calculating interdependencies between branches and decision-making aspects. Also, FTs are predisposed to erroneous human input as FT relationships are built based on empirical experience (Friebe and Waltham-Sajdak 2017).

FT assessment is a deductive failure analysis that is structured top-down with the desired state at the top and a series of events combined through gates that operate by Boolean logic. The desired state in this case is the R_{RiC} which is based on the simultaneous occurrence of the system's successful survival and reliability. Since both events need to happen simultaneously, they can be expressed through an 'and-gate' as shown in Figure 32.

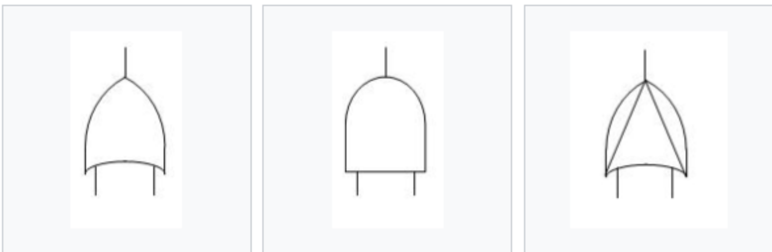


Figure 32 Example gates are 'or-gate', 'and-gate' and 'exclusive or-gate'

Recent research (Friebe and Waltham-Sajdak 2017) has shown that some of these limitations can be overcome through the application of Bayesian Networks (BN). BN is a probabilistic inference tool and has become a commonly used technique for reasoning under uncertainty conditions. The main advantage of BNs is its ability for reasoning and to update initial beliefs when new system information becomes available over time (Konovessis, Cai et al. 2013). Thus, BNs can also be used as decision making tools due to their inherent ability to calculate the difference between two probabilistic scenarios.

Another ability of BNs is its ability to link and include expert knowledge into probabilistic assessment (Khakzad, Khan et al. 2013, Yuan, Khakzad et al. 2015, Zhang and Thai 2016). However, even though BNs are powerful tools, their computational cost grows exponentially with network size (Druzdzel 1999).

Also, a BN algorithm has the capability to automatically learn causal failure dependencies between the equipment and operational capability of vessels from simulation data (Druzdzel 1999). In this study that data is obtained from survivability simulations and used to build complex BNs that can then examine failure relationships between different equipment and their effect onto the operational performance of the vessel. However, that analysis data is collected under the assumption of perfect availability of its systems and thus requires post-processing to understand the effect of equipment reliability on the survivability of the naval vessel.

5.3.1. Bayesian Network

A generic BN model comprises a set of variables representing nodes in a network. For example, in Figure 33, the nodes are 'Rain', 'Grass Wet' and 'Sprinkler', and act as a 'root node', 'intermediate node' and leaf node' respectively. Links between the nodes represent the probabilistic relationships between them, also shown in Figure 33. Nodes that are not connected represent variables that are causally unrelated, whereas arrows that proceed from one node to another represent a causal parent - child relationship. For example, in Figure 33 the relationships between 'Grass Wet' and 'Rain', 'Grass Wet' and 'Sprinkler', and 'Sprinkler' and 'Rain' are shown in the Computational Probability Tables (CPTs) next to their respective nodes with 'T' representing true and 'F' false as logical states of that node. The BN algorithm then performs backwards reasoning to identify the causes that led to the logical state of the node. For example, if 'Grass Wet' is showing wet, then the probability that 'Rain' is true can be determined, but it will be modified with the observation from the node 'Sprinkler'.

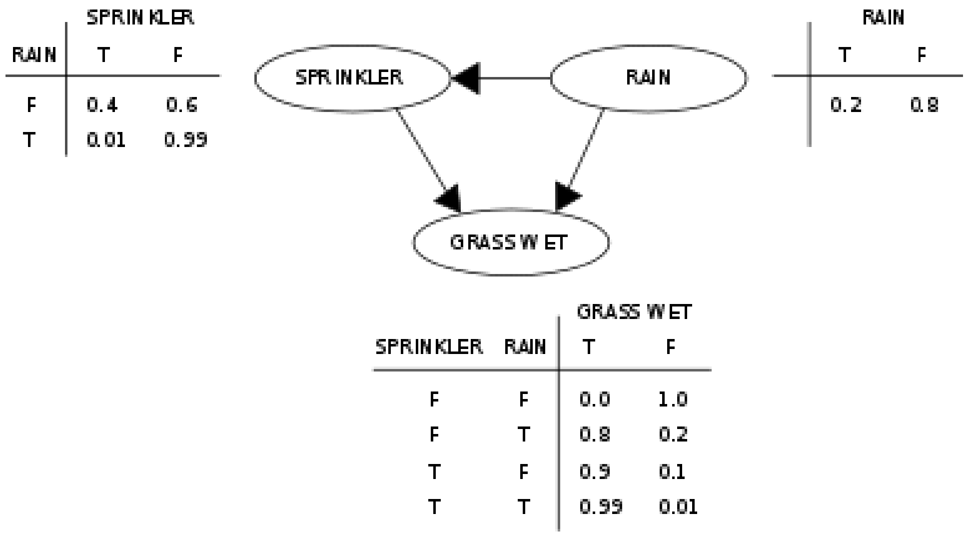


Figure 33 Exemplary BN with associated CPTs

The key feature of a BN is its capability to form a risk-knowledge model enabling reasoning about the uncertainty of each variable. Each node is associated with a probability function that uses as input a particular set of values and returns the probability of the variable represented by the node. Furthermore, BNs represent the joint probability distribution *P(U)* of each variable in the network (Friis-Hansen 2000) as shown in Equation 5.

$$P(U) = \prod_{i=1}^{n} P(A_i \mid Pa(A_i)) \qquad \text{Equation 5}$$

where $Pa(A_i)$ are the parents of A_i. BNs are also used as inference engines in accident analysis (Friis-Hansen 2000, Khakzad, Khan et al. 2013) for updating the prior occurrence probability of events given new information, called evidence *E* in Equation 6. For any two events, *U* and *E*, where *P(E)* is the probability of *E* occurring and *P(U|E)* as the probability of *U* given that *E* has been observed, the joint probability distribution *P(U|E)* is defined in Equation 6.

$$P(U \mid E) = \frac{P(E \mid U) \cdot P(U)}{P(E)} = \frac{P(U,E)}{\sum P(U,E)} \qquad \text{Equation 6}$$

5.3.2. Bayesian Network structure and parameter learning

GeNIe, the utilized software tool for this study was specifically developed for Bayesian Network applications and has a wide range of Bayesian machine learning algorithms to choose from (Druzdzel 1999). The learning algorithm applied in this study is the Bayesian Search algorithm which is commonly used, and was developed in 1992 (Cooper and Herskovits 1992).

To identify probabilistic relationships between the variables, the Bayesian Search algorithm learns the Bayesian Network structure using a set of training data and a hill climbing procedure with random start seeds (Koller and Friedman 2009). The Bayesian Search algorithm also needs a scoring function and a set of possible structures to determine which learned BN fits the training data best (Koller and Friedman 2009). The Bayesian search algorithm creates the network by testing different network operations such as edge additions, edge removals and edge reversals to maximize the scoring function. A drawback of this Bayesian search algorithm is that it often finds local maxima rather than a global maximum. Therefore, the learning algorithm must be reiterated using different seeds to find several BN’s, which are then compared and evaluated by a scoring function to find the best fitting BN (Friebe, Skahen et al. 2018).

5.3.3. Mapping Fault Trees to Bayesian Networks

The process of mapping FTs to BNs has been previously described (Khakzad 2011) and is briefly explained in the following section. FTs consist of events, whereas BNs consist of nodes as shown in Figure 33. The events of the FT are connected in the same way as corresponding nodes in the BN. The numerical mapping depends on the type of gate (Khakzad 2011) and, for each leaf and intermediate nodes, individual CPTs are developed. Whereas in the BN the occurrence probability of primary events is assigned as prior probabilities of the root nodes.

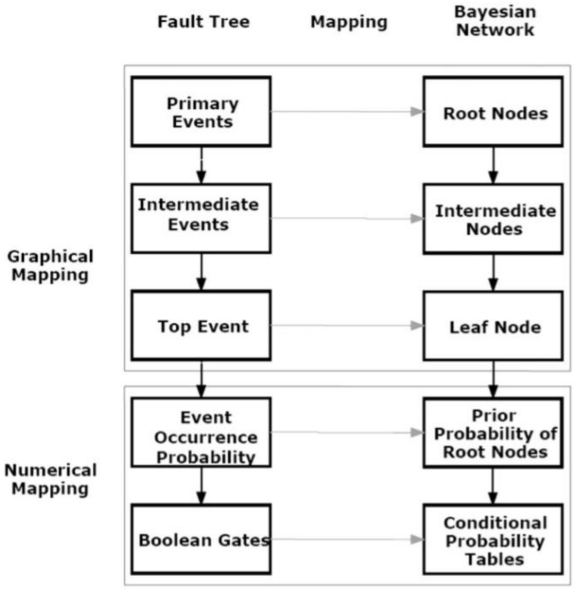


Figure 34 Mapping FT to BN (Khakzad 2011)

5.3.4. System Reliability

The reliability function is shown in Equation 7 and is an expression of a system's predicted *MTTF* and its service time, *t* (Birolini 2017).

$$R = e^{\frac{-t}{MTBF}}$$ Equation 7

Furthermore, survivability is the probability to survive an attack and reliability the probability of successful operation without accidental failure. Because both probabilities are independent of each other, they can be combined as shown in Equation 8. The combat survivability reliability including, R_{RiC}, is denoted as the product of the probability of survival and the equipment's reliability, *R*.

$$R_{RiC} = P_S \cdot R$$ Equation 8

5.4. Methodology

This paper demonstrates how a reliability assessment of a system can be inserted into a machine learned BN and thus the need of engineers to integrate reliability into survivability assessment. It demonstrates the capability of extending a previously developed framework (Friebe, Skahen et al. 2018) using a case study to show the effect on the performance of naval vessels.

A survivability assessing framework has been introduced that resulted in a BN representing the probabilistic failure relationships between systems and the operational capability of a vessel. After the survivability assessment has been performed and a BN developed the system reliability can be included into the BN.

This BN, representing the failure relationships between systems of a vessel, can then be extended by multiplying each system's individual reliability factor into each node of the BN. To multiply the reliability into the BN, the concept of a Fault Tree 'and-gate' was chosen and then converted into a BN operation. In the following subsections necessary concepts to multiply the reliability into a survivability assessment are explained.

5.4.1. Survivability assessment framework

This paper builds upon previous work where a BN learning algorithm was used to derive a BN from a survivability assessment of a naval vessel (Friebe, Skahen et al. 2018). The process of developing a BN from raw data was integral in developing a framework to improve the survivability performance of a naval vessel. This framework is presented in Figure 35. At the first step, a naval vessel is modelled in Integrated Recoverability Model (**IRM**), (Foos and Skahen 2008). This model is then imported into Measure of Total Integrated System Survivability (**MOTISS**) (Waltham-Sajdak 2011) and fragmentation and blast damage, induced by a missile, is simulated. The damage results are imported back into **IRM** where the supply and demand analysis assessment was conducted. The states of each equipment are recorded in binary format as either "working" or "failed" and then machine learned by a Bayesian Network learning algorithm in **GeNIe** (Cooper and Herskovits 1992, Koller and Friedman 2009). That machine learning algorithm makes it possible to obtain a graphical representation of the equipment failure relationships and their relationship to the survivability performance measures.

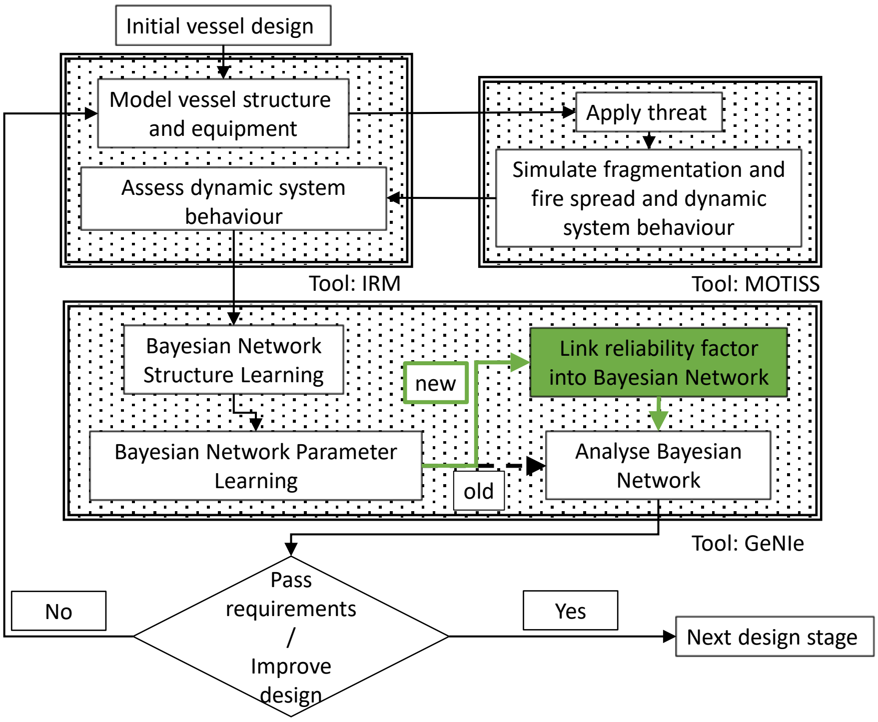


Figure 35 Framework to improve survivability through the application of a Bayesian Network (Friebe, Skahen et al. 2018) with the novel reliability extension marked with green

These failure relationships are then analysed to identify single point of failures and anomalies in the BN. If a single point of failure is identified, the original model of naval vessel is modified in the IRM and the process is reiterated until no more single point of failures are identified and the naval vessel passes its requirements.

5.4.2. Extending the Survivability Assessment Framework

In this study the previously developed framework is extended by linking the reliability factors into the framework, as shown with the green marked process step in Figure 35. This step represents a manual extension of the machine learned BN and is performed prior the evaluation of the BN. The assumption in this study is that new root nodes can be created in the BN and linked through CPTs into the assessment. This manual extension of a BN will help to study the effect of system reliability onto the vessel.

5.5. Case study

The goal of this case study is to exemplify the use of the reliability factor and the consequence to vessel's survivability. In this case study a generic vessel is used to assess the reliability of the switchboards on the operational performance of the vessel. The effects on platform survivability will also be demonstrated.

5.5.1. Learning a Bayesian Network from survivability simulation data

The vessel was initially studied and assessed under minimal survivability performance requirements, such as the maintenance of power, propulsion, combat, communication and damage control capability under the assumption of 100% reliable systems. The model of the naval vessel was comprised of 769 naval components that formed the vessel's auxiliary and major systems. The output from the previous study (Friebe, Skahen et al. 2018) consisted of a 220 hit simulations and 769 binary measurements of equipment state and operational capability. This data is then utilised within the case study, but for simplicity, only the power system and its critical relationship to the operational capability of the platform's combat performance are considered. The considered equipment that constitutes the power system are the generators, switchboards and their correspondingly connected gun resulting in the BN shown in Figure 36.

The BN in Figure 36 represents the causal failure relationships between the generators, switchboards and guns and the platform's operational requirement to perform the mission capability 'Combat' under the assumption of the equipment to be perfectly reliable. Due to the nature of the Bayesian learning algorithm, not only actual physical failure relationships between equipment are found, but the best fitting structural and numerical representation of the probabilistic relationships (Koller and Friedman 2009).

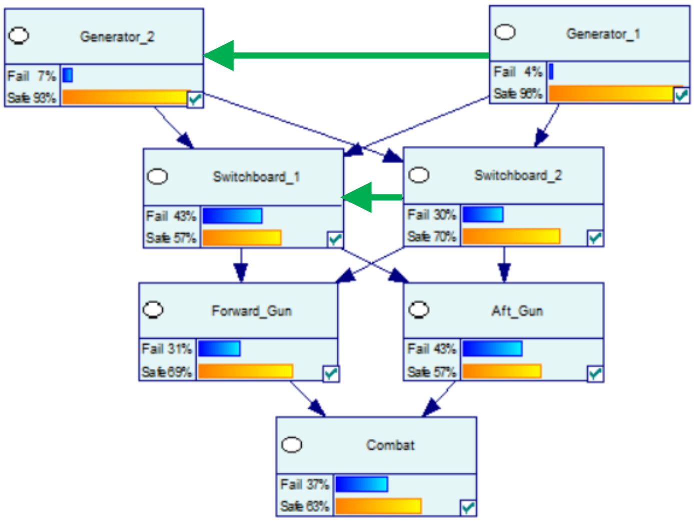


Figure 36 BN of the vessel assessed in (Friebe and Waltham-Sajdak 2017) under the assumption of the equipment to be perfectly reliable

Also, it should be noted that there is a certain variability in the algorithm's performance to find the best matching Bayesian Network for the entered simulation data. The two arcs that are affected by this variability of the learning algorithm are the one arc between Generator_1 and Generator_2, as well as the arc between Switchboard_1 and Switchboard_2 which are highlighted with green colour in Figure 36. The Bayesian machine learning process has been repeated 20 times resulting in two different BNs. In 16 out of 20 repetitions the machine learning algorithm identified the BN from Figure 36, however in 4 of 20 repetitions the two green arrows are found reversed.

5.5.2. Developing a BN reliability value

In section 5.5.1, the BN has been learnt from the relevant components and nodes, in this step the reliability of the equipment is linked into the developed BN.

At first, the reliability value for the switchboards and generator is developed using and then mapped into the existing BN in Figure 36. Two exemplary MTTF, one of 500.000h and another of 900.000h are considered for the switchboards and generators. Also, three possible scenarios of service time are considered for the generators and switchboards: 12 months, 24 months and 36 months. The resulting reliability values are then entered into the corresponding CPT, shown in Table 4.

mtbf	500.000 (poor)			900.000 (good)		
service time in months	12 (short)	24 (medium)	36 (long)	12 (short)	24 (medium)	36 (long)
unreliable	0.02	0.04	0.05	0.01	0.02	0.03
reliable	0.98	0.96	0.95	0.99	0.98	0.97

Table 4 CPT reliability values

The values in the CPT shown in Table 4 are shown in the BN in Figure 37. It can be seen the MTTF and service time are evenly distributed and result in an averaged reliability value of 0.97.

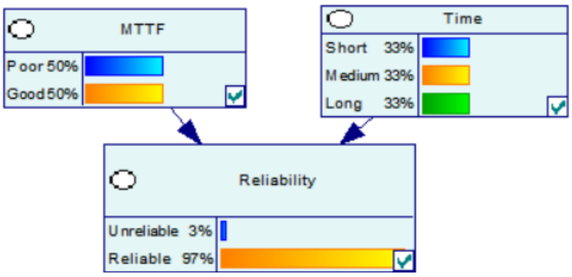
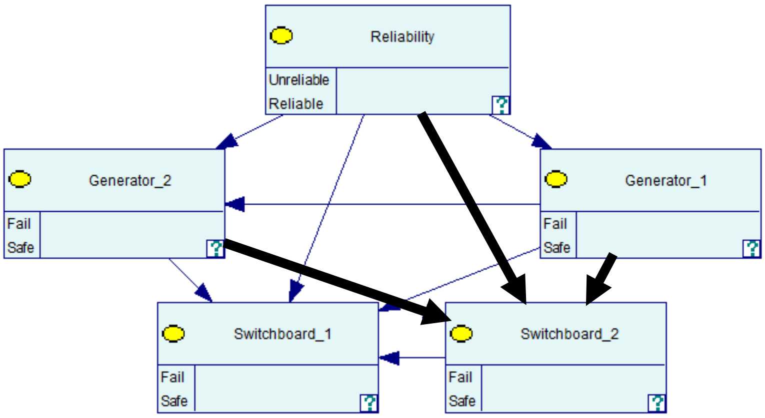


Figure 37 BN of reliability based on MTTF and service time

5.5.3. Mapping reliability to the power system BN

After the structure and the probabilistic relationship of the BN are learnt, the BN will be extended through the inclusion of the reliability node linked to both switchboards and both generators as shown in Figure 38. The reliability node has two possible states, the first is Unreliable and the second is Reliable. If the system Unreliable and fails, the state of Switchboard_1 and Switchboard_2 changes to Fail and thus a '1' is entered in the respective cell of the CPT of the switchboard. If the switchboard does not fail, the CPT value stays unchanged and thus remains unaffected by the reliability.



Genset_1	Fail				Safe			
Genset_2	Fail		Safe		Fail		Safe	
Reliability	Reliable	Unreliable	Reliable	Unreliable	Reliable	Unreliable	Reliable	Unreliable
Fail	1.000	0.252	1.000	0.245	1.000	0.547	1.000	0.285
Safe	0.000	0.748	0.000	0.755	0.000	0.453	0.000	0.715

Figure 38: Exemplary BN extension of switchboard_2 with a reliability factor and the according computational probability table for switchboard_2 and ingoing relationships marked with bold arrows

The reliability factor affects the performance of the Generator_1, Generator_2, Switchboard_1 and Switchboard_2, which cascades through the BN and reduces the combat system performance from 63% in Figure 36 to 61% as shown in Figure 39.

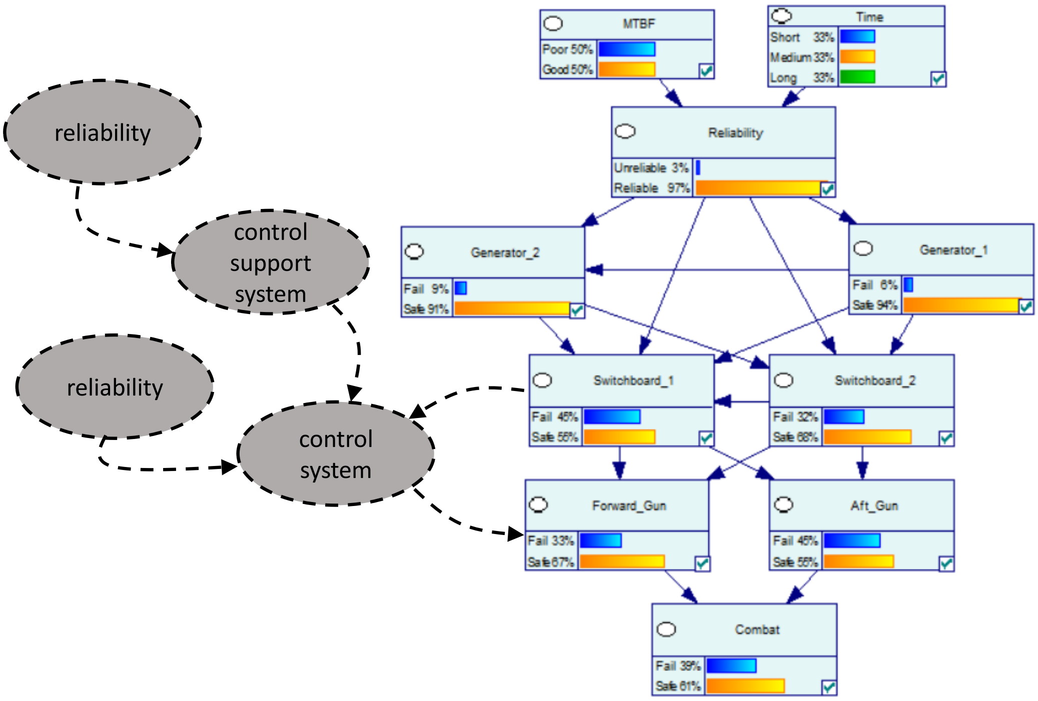


Figure 39 Effect of power system reliability on the combat system with hypothetical system functionality expansion

5.5.4. Analysing the BN

Comparing the combat system performance with a reliability factor of approximately 97% in Figure 39 and a reliability of 100% in Figure 36, it can be seen that the combat performance has dropped from 63% to 61%. This performance drop will most likely be amplified the more systems are included into the model.

Setting the observed states of the service time in the BN from Short, to Medium and to Long the combat system performance can be seen to drop over the three states from 62%, to 61% and 60% respectively. This effect is a combination of maintenance and aging of the vessel over its years of service, because with longer service time the reliability of the equipment degrades and results in a lower performance of the combat system.

5.6. Results, discussion and future work

Without the integration of the reliability factor, the survivability performance of the combat system was observed to be 63%. Linking the reliability effect onto the switchboards, the unreliability of the electric equipment propagates through the BN and results in a reduction of the operational capability of the combat system to 61%. A drop of the survivability performance of 2% is significant as often requirements are designed to exactly meet the requirement and rarely exceed them. Consequently, many vessels that are designed to meet a certain survivability criterion is very likely to not meet its requirements and pose a threat to the vessel’s crew. Considering that there are many other systems that are less reliable than generators and switchboards, the effect of reliability on the survivability is going to be even more severe as those systems are more likely to fail during combat.

Only the power system of the original survivability assessment is considered for this study. However as indicated with grey circles in Figure 39, the forward gun is not only dependent on the power supply from the switchboard, but also a control system, which also depends on its own control support system. Both, the control system and the control support system have their own reliability, which if they were considered would contribute negatively to the availability of the combat performance. The same effect applies to the aft gun as well, and the more systems are affected by their reliability, the more severe will be the overall effect onto the naval vessel’s performance. Furthermore, the longer the chain of affected system with a connected reliability node, the larger the negative effect will apply to the system and system performance overall.

Through selection of different states of the node ‘service time’, i.e. short, medium or long, the probability of the reliability is updated, and a drop of the survivability performance is observed from 62% for one year in service to 60% for three years of service. The observed effect is the degraded survivability performance of a vessel with aging systems. It should be noted that vessels are designed to meet their requirements at the time of construction as well as at any time in their service life. The reliability of the onboard systems degrades with every year and increases the risk for the crew to try to operate a failing or already failed system during combat. To counter the degrading effect and the reduction in survivability performance, the vessel’s design must be adjusted to account for the degradation and prevent the failure of an anticipated performance to protect the crew and the assets of the navy.

The true benefit of this method would amplify if the process of machine learning a BN and including the reliability parameters is automated further. This could potentially lead to the inclusion of various other uncertainty parameters that are neglected at this stage, such as weather condition, crew fatigue and sea state. A lot of these parameters are simplified and assumed to be constants, but the integration of each would enable the insight into the true nature of survivability.

This study presents a proof of concept for the inclusion of system reliability into naval survivability through BNs. To validate and verify the results of this study it is necessary to test the proposed concept with Dynamic Bayesian Networks as they allow to fully capture the time-dependent behaviour of the system.

5.7. Conclusion

The purpose of this study was to include the reliability factor naval systems into the survivability process and evaluate the effect on the mission performance of the vessel. This resulted in the extension of a previously developed framework deriving a probabilistic model of the survivability assessment of a naval vessel and extending it to integrate a reliability factor.

The reliability was linked into the assessment through the inclusion into the switchboards and generators, which led to a less reliable power system and consequently a reduction of the combat performance. The inclusion of the reliability effect provided a more realistic picture of the nature of survivability and showed that this effect reduced the performance of the combat system and the vessel. Thus, it demonstrated that under the consideration of the reliability of systems the operational requirements of the vessel are reduced and less than anticipated by the designers, which eventually could lead to negative combat outcome in real life.

Also, it was shown that the effect of aging on a naval vessel's power system can be modelled in survivability performance prediction in future. This was achieved through modelling the reliability as a function of time and the system's mean time to failure, which enabled the prediction of the system's diminishing reliability in the future. The inclusion of the reliability effect into the survivability assessment enables the prediction of the availability and survivability performance of the equipment in a combat scenario, but also helps modelling the naval vessel's future survivability performance.

Furthermore, it became clear that the assumption of perfectly reliable systems and the omission of the reliability effect in a survivability assessment is overly optimistic and puts the Navy's assets and crew in danger. Thus, the inclusion of relevant uncertainty factors of systems need to be considered in the assessment of survivability of vessels to ensure the life and safety of the crew.

Chapter 6

Summary, Conclusions and Future Work

This chapter provides a summary of the thesis and analyses the findings of the individual chapters. It concludes the findings and outcomes and discusses their impact onto the field, its limitation and recommends work for future research.

6.1. Summary

This chapter provides an overall evaluation of the results and findings and their effect to the research field. Furthermore, limitations are discussed thoroughly and future research to expand the developed methodology to increase its effectiveness and power.

Chapter 3 is a case study, designed to compare the difference between layouts and automation levels to evaluate design decisions for the optimal vulnerability performance. The purpose of this study was primarily to gain familiarity with the IRM, which is one of the leading vulnerability assessment tools; and to build the foundation for a complete model of an actual vessel that then later was assessed as part of Chapter 4 . The outcome of this comparison study filled research gaps with new knowledge about the effectiveness of valve automation on the damage control process and highlighted the importance of valve automation as part of the firemain design.

To answer the primary research question, *Can the Bayesian machine learning algorithm be used to automatically investigate the vulnerability performance of a vessel during detail design stage*?*,* a literature review was conducted on Bayesian Network machine learning and a framework to automatically investigate the design of a naval warship was hypothesized (Friebe and Waltham-Sajdak 2017). The framework was first hypothesized and published, before we refined it to successfully build the model of an actual vessel that then could be assessed through IRM, MOTISS and the Bayesian machine learning algorithm. This refinement resulted in a final framework (Friebe, Skahen et al. 2018), which enables system design issue identification, which can often be resolved through network reconfiguration. The framework had been validated and verified through a variability study, which demonstrated that the reiteration of the framework lead to similar results and quantified the performance of the framework through the alteration of process parameters

The next stage of this research aimed at the question as to *whether the developed BN and supporting Inference model also be extended by new knowledge that has not been processed in IRM*. Therefore, the developed framework in Chapter 4 had been extended to link historic information and integrate the uncertainty of the system's reliability into the assessment (Friebe 2019 under review). This study enabled the view on the interaction between the vulnerability and reliability effect, resulting in the observation of the degrading effect on the equipment subsequently onto the prediction of the vulnerability performance of vulnerability of the vessel.

6.2. Conclusions

As a result of the various studies shown as part of the thesis, the following main conclusions can be drawn:

6.2.1. General findings

The case study in Chapter 3 focused on the comparison of different firemain layouts and different levels of automation. The primary purpose of this study was to demonstrate the complex manual work a user does during a vulnerability assessment. Findings of this research showed that a firemain equipped with only manually operated valves, the vessel had almost no firefighting capability for the first 10 minutes post damage impact. It was found that partial automation on crucial points in the firemain have a significant positive effect on the availability of the firemain capability the immediate moment post damage.

It was also found and demonstrated that for larger threats (zonal damage) the intended redundancy of a horizontal main over a single main is rendered obsolete. For a relatively small threat (compartment damage) the effect of the offset loop over the horizontal loop is minimal as the damage enveloped is not enough to affect the redundancy of the horizontal main. The research resulted in the recommendation of a partial valve automation and to carefully choose the appropriate firemain layout depending on the expected hostile threat.

However, a limitation of this study was that the system configuration was quite simple and every other system outside the firemain system was omitted. To increase the accuracy of the research in Chapter 3 a fully developed naval vessel as in Chapter 4 should accommodate the same various firemain systems and repeat the same kind of analysis. Chapter 3 is a proof of concept and compared for the first time the effect of different firemain systems layouts and automation levels on naval survivability scientifically.

6.2.2. Advantages of applying a Bayesian Network to a vulnerability assessment

The purpose of Chapter 4 was to demonstrate the beneficial effects of applying BNs to vulnerability assessment. Through the application of a BN machine learning algorithm and the search for sensitive nodes and/or systems in the network it was shown that single points of failure can be detected semi-automatically. This means that no additional vessel model modifications were needed and that the machine learning algorithm independently recognized system-system and system-performance relationships.

Single points of failure present high areas of risk that can lead to system failure as the system is lacking redundancy. The single points of failure that were found by the BN in the framework were mitigated through reconnecting and reconfiguring the system, which led to a vulnerability improvement without the otherwise necessary manual and tedious search for design error and design mitigation. This demonstrates that "*Bayesian Network can be used to automatically investigate the vulnerability an early design stage"*. The framework performed best at a sample size reduced to around 20 nodes as discussed in Chapter 4.8. The original number of number of nodes had to be manually reduced by the least sensitive to achieve the final Bayesian Network. As this manual Bayesian Network reduction can be mathematically expressed and automated, the developed framework is not bound to any limitations in its applicability with regard to the size of the naval vessel.

Furthermore, the vessel's vulnerability was improved without adding weight or an additional system and thus is considered a 'smart' improvement of the naval design as it leads to design improvement, but without the usual increase in weight or drastic change in arrangement. It should be noted that the magnitude of the improvement will eventually accumulate with several small improvements and similar low costs that are found.

6.2.3. Further advantages of applying a Bayesian Network to a vulnerability assessment

The results of Chapter 4 are obtained under the assumption of perfectly reliable systems. Chapter 5 demonstrates a method to include the reliability factor into the vulnerability assessment and according BN to enable the possibility to observe the combined effect of both uncertainties. As a result of this study it was shown that the achieved vulnerability performance of the ship is less than what it had been designed for, which became quantifiable through the work in Chapter 5 . Also, the developed method demonstrates the ability to model the effect of system degradation onto the vulnerability performance over the time of the vessel's service life answering as to whether the "*developed BN and supporting Inference model also be extended by new knowledge that has not been processed in IRM*" positively.

6.3. Implications of the Research

In this thesis, machine learning and Bayesian Network analysis were conducted to investigate the ability of linking historical data and information into the assessment of actual ship designs. This allowed the interaction between reliability and vulnerability to be the core of this study, thus enabling to assess the ships more realistic performance and model the vulnerability capabilities performance for future years in service. The results will help naval architects to gain deeper insights of the systems interactions and effects on the ships performance, but also could act as a reference improve designs through the detection of single point of failures and smart design choices as otherwise making drastic design changes, which usually lead to increase in cost and weight. Overall, the results from Chapter 4 demonstrate that the framework can successfully identify probabilistic failure relationships from overly complex models and to identify critical and failure sensitive components.

In addition to the research on behalf of the BNs within this research, various firemain systems with different layouts and automation levels have been assessed and compared. As the results in Chapter 3 indicated, already a small amount of automated valves enables the vessel to fight a fire onboard immediately after the vessel has been attacked, whereas the automation leaves the vessel for at least 10min without any firefighting capability. With more automation technology becoming available in the future, this research will be a strong advocate to automate critical parts of the firemain system to achieve at least a minimum level of damage control performance for ships in combat.

Furthermore, the results of Chapter 3 and Chapter 4 show a potential cross-over benefit. The machine learning Bayesian Network from Chapter 4 has the ability to identify sensitive components and systems with regards to vulnerability, whereas the demonstrated vulnerability assessment procedure in Chapter 3 has the capability to implement and test various automation levels for that naval design then. This could lead to a cost-benefit assessment approach for existing designs. Whereas automating all components will cost more in terms of initial build but could be more effective in terms of enhancing the vessel's vulnerability. Thus, the approach enables naval architects to perform a cost-benefit assessment, but it would require a more developed method to drive the naval design towards a minimum cost solution for maximum design performance.

6.4. Contribution to knowledge

The thesis aims at researching an effective way to perform root-cause analyse to enable naval engineers to effectively design naval vessels for survivability as identified in section 1.3. As the literature and software survey suggests in Chapter 2 , the current state of art to perform root-cause analysis is achieved through a manual filtering procedure, that is time consuming and prone to human failure.

Furthermore, the literature survey suggests that the research of Bayesian Networks in the domain of naval survivability is stalling and not progressing as there are is very limited published data on the actual behaviour of naval vessels in combat scenarios (Friis-Hansen 2000, Liwång, Ringsberg et al. 2013). This is overcome through a novel approach to link MOTISS, a physics-based damage model and the IRM, a supply and demand-based representation of the physical model as demonstrated in Chapter 4 .

Both software tools are combined to create the simulating environment to assess the survivability of naval vessels. The resulting contribution to the scientific domain of naval survivability links the need the necessity to derive probabilistic functional failure relationships with industrial demand to effectively perform root-cause analysis during a survivability assessment. Both challenges are solved through a suggested novel framework

(Chapter 4) that contains a Bayesian machine learning algorithm and manages to solve both research problems at simultaneously.

This research is believed to open a wide field of possibilities to expand the developed Bayesian Network. As suggested, a Bayesian Network of an actual naval vessel, can be then expanded through expert knowledge and historical data, which up to now had not been possible. The major contribution of this research can be grouped into the following categories:

- Methodological contribution
    - The developed framework provides an automated framework to enhance naval designs through simulation and automated sensitivity analysis
    - The research gap to derive probabilistic failure relationships has been overcome and can be arbitrarily modified to the engineers focus and interest
- Industrial contribution
    - The developed methodology breaks ground to perform critical system analysis.
    - Through this research it becomes possible to effectively link design choices to the recoverability performance of the vessel and thus enable the naval engineer to make better informed design choices.

This framework, albeit developed specifically for the survivability assessment within this thesis can be used in various domains and is not restricted to the type or size of the vessel.

6.5. Future Work

The long-term goal for this research is to have an automated process of including parameters of uncertainty into the assessment of vulnerability to obtain more insight in the interaction of the probabilistic nature of vulnerability.

Extension of this research could lead to:

1. Extend the simulation setup in Chapter 3 for testing the firemain system under dynamic and progressive fire. This would shift the results as the firemain

performance delay will be penalised due to the progressive damage of a fire. Also, it would be very interesting to examine the firemain system interact with more systems on differently sized naval vessels, which was not done since the time and scope was limited.

2. One aspect that was not examined is a non-uniform hit distribution as part of the vulnerability assessment in Chapter 4 . The uniform hit distribution was assumed for simplicity, because realistic data was not available due to security classification restrictions. Through the application of a different hit distribution, a sensitivity analysis could be performed that can detect sensitive systems that are weak points in the onboard system architecture during combat.
3. Extend the BN in Chapter 5 with further empirical information with regards to operational, environmental, and human conditions. This will provide more insight into the various areas of risk of the vulnerability assessment. A lot of research on human factors has been done that is currently not part of any deterministic vulnerability assessment. Furthermore, the reliability factor for each component could be included into the assessment of the whole naval vessel, which would signify the degrading effect of the onboard systems.

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