A DATA MINING FRAMEWORK FOR RISK-BASED SHIP DESIGN

Wenkui CAI, BEng

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Department of Naval Architecture and Marine Engineering
Faculty of Engineering
University of Strathclyde

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SUMMARY

The *Risk-Based Ship Design* (RBD) methodology, advocating the systematic integration of risk assessment in the conventional design process so that ship safety is treated as an objective rather than a constraint, has swept through a wide spectrum of the maritime industry over the past fifteen years. Through this methodology, safety is situated at a central position alongside conventional design objectives, so that well-balanced design effort could be spent and consequently comprehensive design optimisation can be performed. Despite the recognition and increasing popularity, important factors that could potentially undermine its implementation arise both from qualitative and quantitative aspects. This necessitates the development of an objective, reliable and efficient methodology for risk-based ship design implementation.

The research presented in this thesis proposes a formalised methodological framework to fulfil this global objective. It comprises three interrelated stages to be performed during risk assessment, namely the development of next generation marine accident/incident database, risk modelling in Bayesian networks by deploying data mining techniques, and the integration with the framework for risk-based design decision making. Working procedures, techniques, methods and algorithms have been developed and applied to representative examples and case studies to demonstrate the applicability and the potential offered by this framework.

Each stage of the framework is a field with vast potential for further research, development and application. The ensuing findings firm the faith that an optimal approach towards risk-based design is achievable and extensive applications need to be conducted before experience and confidence can be gained. It is believed that this research has contributed positively towards the evolvement of risk-based ship design.

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GLOSSARY

Accident	:	A sudden unintended departures from normal operating conditions in which some degree of harm is caused [HSE, 2001].
Incident	:	Relatively minor accidents, i.e. unintended departures from normal operating conditions in which little or no harm was caused [HSE, 2001].
Risk	:	The combination of the frequency and the severity of the consequence [IMO, 2007b].
Risk analysis	:	The quantification of risks without making judgements about their significance. It involves identifying hazards and estimating their frequencies and consequences, so that the results can be presented as risks [HSE, 2001].
Risk assessment	:	A means of making a systematic evaluation of the risk from hazardous activities, and making a rational evaluation of their significance, in order to provide input to a decision-making process. This may be qualitative or quantitative [HSE, 2001].
Risk contribution tree	:	The combination of all fault trees and event trees that constitute the risk model [IMO, 2007b].
Risk control measure	:	A means of controlling a single element of risk [IMO, 2007b].
Risk control options	:	A combination of risk control measures [IMO, 2007b].
Risk management	:	The making of decisions concerning the risk, and the subsequent implementation of the decisions in the safety management system [HSE, 2001].

ABBREVIATIONS

ABS	:	American Bureau of Shipping
AHP	:	Analytical Hierarchy Process
AIC	:	Akaike Information Criterion
AIS	:	Automatic Identification System
BAS	:	Bridge Alarm System
BIC	:	Bayesian Information Criterion
BN(s)	:	Bayesian network(s)
BNWAS	:	Bridge Navigational Watch Alarm System
CPDAG	:	Completed Partially Acyclic Directed Graph
DAG	:	Directed Acyclic Graph
DNV	:	Det Norske Veritas
ECDIS	:	Electronic Chart Display and Information System
EM	:	Expectation Maximisation
EMSA	:	European Maritime Safety Agency
GES	:	Greedy Equivalence Search
GISIS	:	Global Integrated Shipping Information System
GLM	:	Generalised Linear Model
ISM code	:	The International Safety Management Code
IMO	:	International Maritime Organisation
KDD	:	Knowledge Discovery from Data
LCM	:	Loss Causation Model
LMIU	:	Lloyd’s Marine Intelligence Unit
LR	:	Lloyd’s Register
LSA	:	Life Saving Appliance
MAIB	:	Marine Accident Investigation Branch
MCMC	:	Markov Chain Monte Carlo

MSC	:	Maritime Safety Committee
NN(s)	:	Artificial neural network(s) / Neural network(s)
NPV	:	Net Present Value
OOW	:	Officer on watch
PDAG	:	Partially Acyclic Directed Graph
QRA	:	Quantitative Risk Assessment
RCO(s)	:	Risk Control Option(s)
SAFEDOR	:	Design, operation and regulation for safety, www.safedor.org
SMS	:	Safety Management System
SOLAS	:	The International Convention for the Safety of Life at Sea, 1974, and the 1988 Protocol
SSRC	:	The Ship Stability Research Centre, University of Strathclyde
VTS	:	Vessel Traffic Service

Chapter 1

Introduction

1.1 Preamble

Ships, one of the oldest forms of transport, have played a significant role in the development of human civilisation over thousands of years. From hollowed tree trunk ventured by tribes in ancient time to the unprecedented cross-Atlantic exploration fleet by Christopher Columbus in the 14th century, and to the recent deployment of giant cruise liners with over 6,000 passengers on board, this ancient discovery has never been as prosperous and with such profound influence on human livelihood, as it is today. It is becoming an essential mode of supplying the ever growing demand of every facet of human society. More importantly, globalisation, an unparalleled and irreversible momentum, is accelerating this process.

This consecrated history and its state of affairs have brought naval architects crowning pride and tremendous satisfaction. The connotation of naval architecture, one of the most fascinating and innovative professions, is also enriching itself over thousands of years' of discovery and accumulation, from initial trial and error on floating trunk to Archimedes' principle, from Newton's scientific foundation of mechanics to advanced computer-aided-design (CAD) software. No doubt huge achievement has been made in the longstanding history through the injection of experience, good engineering practice and science, however the traceable grievous disasters are constantly giving a twinge [Lancaster, 2005], from the loss of "unsinkable" *Titanic* in 1912 [MAIB, 1992], the rapid capsize of *Herald of Free Enterprise* in 1987 [MAIB, 1987], and the massive oil spill of *Exxon Valdez* in 1989 [EPA, 2009], etc. Continuous publicised marine tragedies, resulting in catastrophic consequences with respect to human life, property and environment, force society to revise the existing approach towards ship design and the attitude towards naval architecture.

Fortunately this situation is gradually changing. Under the philosophy of *Design for Safety*, a formalised methodology, Risk-Based Ship Design (RBD), has found fertile ground for the past fifteen years. Through systematic integration of risk assessment within conventional ship design process, safety is no longer treated as a constraint but an objective. From conceptualisation, instantiation, to preliminary implementation, risk-based design has demonstrated its brawny vitality through successive large scale research projects: HARDER [HARDER, 2003], SAFER EURORO [Vassalos and Konovessis, 2008], SAFEDOR [Barinbridge, et al., 2004] and numerous ongoing research projects: FIREPROOF [FIREPROOF, 2009], GOALDS [GOALDS, 2009], etc.

Despite the increasing recognition, important factors that could potentially undermine its quality and credibility come from both qualitative and quantitative aspects during risk assessment, which can be demonstrated by the continuous usage of subjective sources of information (e.g. expert judgement), the independent relationships assumed during risk modelling, and time-consuming nature of first-principles tools for risk quantification, etc. This is inadequate as risk-based design is moving towards a more rational approach where the utilisation of objective sources should be maximised in an appropriate and effective way so that the confidence of the study and the credibility of risk-based design as a design methodology can be assured.

In this thesis, a systematic procedure for the performance of risk assessment that incorporates objective sources of information and advanced data analysis techniques for risk models elicitation will be developed. Passenger ships have been selected for demonstrating the applicability of the proposed methodology due to the large societal impact associated with the accidents involving this category of knowledge-intensive and safety-critical ships.

1.2 The Root Conflicts

As it is argued in [Rawson and Tupper, 1976], naval architecture is both art and science. Laying particular emphasis on any one aspect independently and underestimating the other is inappropriate. According to these authors,

"Basically, naval architecture is concerned with ship safety, ship performance and ship geometry, although these are not exclusive divisions."

Considering the above, it is apparent that ship design is fundamentally a multi-objective optimisation process. It is an amazing task to design an extremely complex entity like a ship (e.g. a large system, hundreds of subsystems, and hundreds of thousands of components) by just knowing a handful of initial high-level measures, e.g. payload, speed, service route, and environment, etc. The end product is supposed to be a well-balanced compromise among the three aspects, safety, performance, and geometry. It seems one can always converge to a satisfactory balance as long as the objectives are clearly predefined and proper design procedures are followed to carry out an iterative refining process. However, when idealism encounters realism, it will, most likely, lead to an endless strives between morality and capital running by sacrificing one (e.g. safety) and maximising the others (e.g. profitability).

Capitalism, one of the most successful and bold invention in the history of humankind, has resulted in the unprecedented liberation of labour productivity, which has brought us a prosperous planet. Exactly driven by this stimulant ship design has made great strides where typical evidence could be found in the development of naval architecture in the past centuries through parameterising ship principal parameters with economical performance indicators (such as, ship resistance estimation, Net Present Value, Required Freight Rate, etc.). Nevertheless, it is apparent that capitalism is not a perfect solution: blindfolded chasing of capital maximisation has resulted in rapid technological evolution and deployment of products without full understanding and justification of the underlying physical phenomena that governs shipping operations.

The ensuing adverse impact caused by marine disasters leading to serious casualties and catastrophic environmental damage has alerted the wider public. Moral censure has forced local authorities, governmental, and intergovernmental bodies to step in by introducing stringent codes of conduct so that safety can be assured. Certainly prescriptive rules are easier to fulfil and facilitate class/flag changes; however, this paradigm has also induced inherent challenges. Assuring safety performance through rule compliance implies that the development of competitive design relies mainly on the designer's competence rather than a rational and more informed base. Potentially good and innovative designs could not progress further and, as a result, the realisation that investment in safety compromise returns dominates the industry. Moreover, this configuration places absolute trust on the prescriptive rules presuming the minimum safety level implicit is deemed appropriate. Unfortunately, this often proves to be a conjecture. The key issue here is that knowledge of the actual safety level that is provided by prescriptive rules is missing.

Through rule compliance, safety is no longer a design objective but a constraint which implies that obtaining an optimal design, which makes the best compromise among the aforementioned constituent elements, is left to chance. Though most rules have proved to serve reasonably well, it should be borne in mind that most changes have followed major high-profile accidents or significant changes in casualty statistics. Precious signals from the vast amount of less serious accidents and incidents have been underutilised and neglected.

In light of this, an important undertaking in the industry is the routine investigation of operational accidents and incidents. This is justified as historical investigations and research findings, e.g. [ABS, 1999] and [Kristiansen, 2005], always suggest that a casualty has never been the result of a single contributing factor and lessons should be learned from less severe cases in order to prevent more serious ones from occurring. The evidence could be easily traced through codes of conduct in the form of either mandatory or recommended documents at international, national, and organisational context. Internationally, consecutive resolutions concerning the investigation of marine accidents/incidents [IMO, 1997, IMO, 2000, IMO, 2005], with the latest *Casualty Investigation Code* [IMO, 2008a], have spent great effort to collect as many records as possible, with particular emphasis on serious accidents. In the UK, the relevant regulations have also been introduced and enforced pertaining to accident reporting and investigation [MCA, 1999, MCA, 2005]. Furthermore, ship operators, who probably have contributed the largest share, have to constantly update their records with respect to accidents/incidents onboard within the Safety Management System (SMS) in compliance with the International Safety Management (ISM) code [IMO, 1994].

The subsequent situation is an ever growing number of accident/incident records within each organisation over the past decade, which are of no practical use for systematic analysis. This is not surprising as the initial motivation was rule-orientated and case-specific according to SOLAS regulation I/21, while little attention has been paid on how each individual record could benefit the industry in terms of design and operational activities. Even with the ISM code section 9, which forces organisations to establish the relevant reporting schemes and to implement the procedures for adopting corrective actions, the recorded information can be hardly utilised by shipyards, designers, and regulators. Furthermore, a framework to guide the operators in the investigation procedure and the assessment of the effectiveness of the risk control options (RCOs) is currently missing.

Consequently, the deliverable of an accident/incident investigation is most likely a repetition of previous similar studies presented in the form of descriptive reports suggesting a number of possible corrective actions without knowing to which extend the organisation will benefit and the associated cost. The consequence with this open-ended scheme is reluctant implementations by the operators. The lack of incentive (i.e. tangible holistic benefits and costs) has turned such a routine into an extra load. As a result, normal practice would be periodical revision of the whole data set at an abstract level by just deriving high-level pie and bar charts to reveal trends, while the “gold” is still hidden in the descriptive text.

1.3 Risk-Based Ship Design

On the other hand, the methodology of risk-based ship design, advocating systematic integration of risk assessment in the conventional design process so that ship safety is treated as an objective rather than a constraint, has swept through a wide spectrum of the maritime industry over the past fifteen years. Through this approach, safety is situated at a central position alongside conventional design objectives so that well-balanced design effort could be taken and consequently comprehensive design optimisation can be performed.

To implement risk-based design, risk assessment needs to be continually deployed in order to quantify the risk level of the hazards under consideration. Classical techniques for risk assessment (most typically, the fault and event tree techniques) have received wide recognition in the field of Quantitative Risk Analysis (QRA), [Vose, 2008], as they offer a clear and logical form of presentation. In addition, the tree-like topology is suitable for analysing the hazards that arise from a combination and sequences of adverse circumstances. On the contrary, the intrinsic characteristics of fault and event trees have also incurred challenges, which could significantly undermine the quality of the developed risk models, both from qualitative and quantitative points of view:

- Qualitatively, due to the fact that fault and event trees adopt the tree-like topology, each branch is entirely isolated from the remaining parameters, except the ones directly next to it. For this reason, all events are treated independently, a virtue that transpires oversimplification of the approach. Moreover, it soon becomes complicated, time-consuming and difficult to follow for larger systems.

- Quantitatively, large trees could easily lead to situations where detailed historical data become unavailable and, as a result, subjective sources have to be used constantly. Moreover, in the cases where performance-based first-principles tools are needed, the iterative process at both local and global levels for probabilities derivation can be very time-consuming.

Apart from using fault and event trees, it is worth noting a promising candidate for risk modelling - Bayesian networks (BNs), [Darwiche, 2009], [Holmes and Jain, 2008], etc., due to their inherent superiority to capture sophisticated relationships among physical events. With BNs, a dependent relationship is represented by a link between the concerned parameters, whilst the probabilities are stored in a conditional probability table attached to each parameter. The probabilistic inference is governed by Bayes' theorem. Although the technique has a sound mathematical foundation, the BN is discredited due to its complexity to manipulate, which is reflected on the identification of dependent relationships and the estimation of conditional probabilities as insufficient data always leads to subjective judgement. In this respect, the field of data mining provides a promising solution.

1.4 Data Mining

Data mining, which is also referred to as Knowledge Discovery from Data (KDD), can hardly be given a unified definition as its territory is expanding at a fast pace. It is a multidisciplinary field drawing work from database technology, machine learning, pattern recognition, statistics, visualisation, and information science, in order to discover meaningful correlations, patterns and trends out of a data set. The typical process is demonstrated in the flowchart of Figure 1.1. Various tasks can be carried out by data mining techniques including among others, the identification of *association* between two or more attributes, the *classification* through prediction of the categorical labels, and the *cluster* of a set of physical objects into similar classes, [Han and Kamber, 2006] and [Sumathi and Sivanandam, 2006], etc. Equipped with these functionalities the data mining techniques have been employed across a wide spectrum of fields and applications: chemical engineering [Anand et al., 2006] and aviation industry [Nazeri et al., 2001] concerning safety assessment, retailing concerning customer shopping habit [Zheng et al., 2001], financial system concerning fraud detection [Bishop, 2006], [Chan et al., 1999], [Guo et al., 2008], etc. In contrast, limited literature and applications are observed in the maritime industry in the area of data mining.

As data mining is evolving, it becomes inevitable that a developed model needs to act as an inference platform for providing intelligent information (e.g. given a collision, whether the ship can survive), whilst, at the same time, be able to accommodate uncertain circumstances (e.g. at the time of collision sea conditions may be calm or rough, the location of the ship may be at sea or in port). In this respect, the development of data mining bias towards the integration of data analysis methods with pertinent uncertainty reasoning techniques, [Chen, 2001], which covers BNs, artificial neural networks (NNs), fuzzy logic and genetic algorithms. By doing so, the identified uncertain reasoning platform can be deployed for representing the underlying characteristic of the data (e.g. one ship collision model contains all the relevant information that is stored in the training data set of fire incident) and, in the meantime, performing inference in a probabilistic environment (e.g. given a collision, the probability that the ship will survive for a given time interval). A key advantage of such an approach is attributable to the ability of describing complex correlations among various parameters purely on the basis of available data. This implies minimised intervention of subjective estimation and no assumption on independent relationships. Moreover, if the inference mechanism is based on a probabilistic background, it will offer a promising platform for risk assessment in complement to the techniques of fault and event trees.

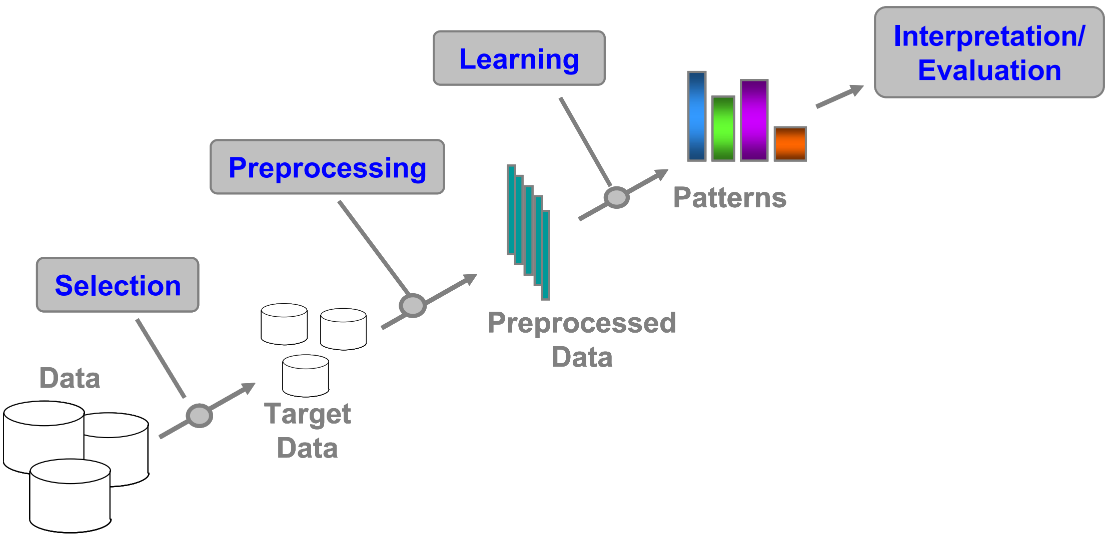


Figure 1.1: A Flowchart of Data Mining

The focus of this research is on the improvement of risk-based design methodology, by means of integrating data mining techniques with the state-of-the-art risk assessment framework in the context of risk-based ship design.

1.5 Structure of the Thesis

The thesis is structured in 10 chapters. A brief outline of the content of each chapter is given below:

- Chapter 1 (*Introduction*), the current chapter, provides the background to the research described in this thesis.

- Chapter 2 (*Aim and Objectives*), defines the problems and sets the aims and specific objectives of this research.

- Chapter 3 (*Critical Review*), reviews the current approach towards the implementation of risk-based ship design with particular emphasis on the techniques and the sources of information for risk analysis. The field of data mining and promising techniques for risk model elicitation are detailed as well.

- Chapter 4 (*Approach Adopted*), sets the fundamental assumptions made and explains the approach adopted.

- Chapter 5 (*Next Generation Marine Accident/Incident Database*), enunciates the configuration of the proposed new casualty database.

- Chapter 6 (*Data Mining*), details the theory, techniques, and algorithms for implementing pertinent data mining process for risk model derivation.

- Chapter 7 (*Risk-Based Ship Design*), elaborates a practical procedure for the implementation of risk-based design where the roles of the obtained risk models from data mining are described within the context of risk assessment. Ultimately, as a means of supplying safety relevant knowledge, the models are integrated within the decision support framework.

- Chapter 8 (*A Case Study*), demonstrates the rationality and feasibility of the proposed methodology by carrying out the three-stage procedure concerning fire safety of passenger ships.

- Chapter 9 (*Discussion*), outlines the main contribution to the field, critically discusses the outcome of the thesis on the basis of its objectives, outlines the difficulties encountered and the way in which these were addressed, and provides recommendations for further research.

- Chapter 10 (C*onclusion*), summarises the main conclusions of the research presented in this thesis.

The research to be presented in the thesis is founded on the hypothesis that the current approach towards the implementation of risk-based ship design has significant drawbacks to qualitatively and quantitatively develop interested risk models in an efficient manner, which hinder the release of the full potential of risk-based ship design. In this respect, the thesis develops a systematic and comprehensive methodological framework that is based on transparent, objective, and well-integrated principles by proposing procedures, methodologies, and techniques. The applicability of the proposed framework is demonstrated through a comprehensive case study and a number of examples addressing specific constituent components.

The logical sequence and interrelationships among the chapters of the thesis are illustrated in Figure 1.2.

1.6 Closure

Through tracing the timeline development of naval architecture and the apparent shift in the treatment of ship safety, aspects that led to the undertaking of this research has been put forward and will be scrutinised and addressed in the chapters to follow. The main drawback identified is the lack of a holistic, reliable, and effective approach towards risk assessment within the context of risk-based ship design. In this respect, this thesis will focus on the aspects relevant to passenger ship safety.

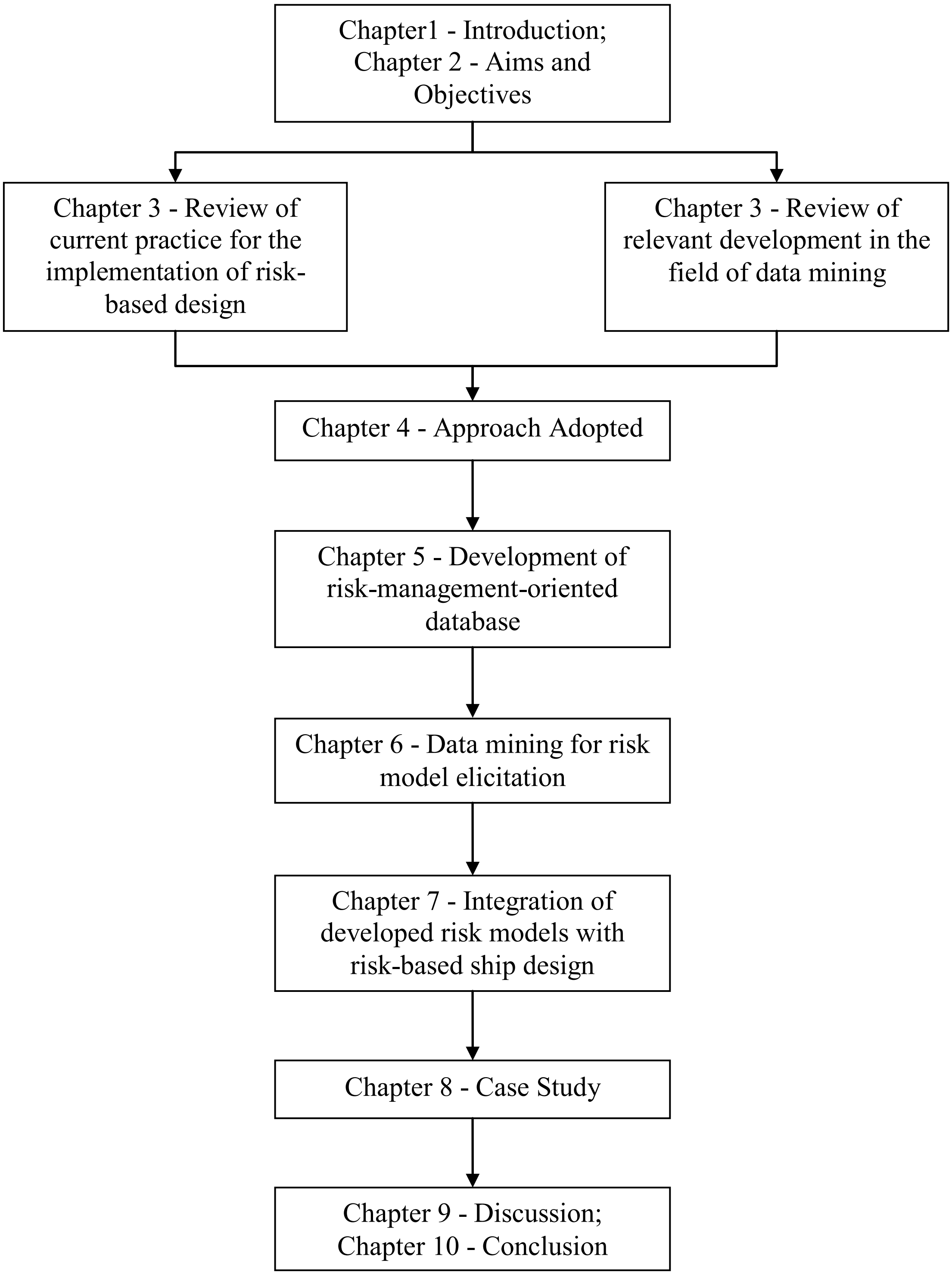


Figure 1.2: Structure of the Thesis

Chapter 2
Aim and Objectives

The overall aim of the thesis is to develop a formalised methodological procedure in the form of a framework of systematically integrating objective casualty relevant data for risk model elicitation within the implementation process of risk-based ship design. Specific objectives to realise this concept include:

- To carry out a critical review of the available literature on the state-of-the-art practice for the implementation of risk-based ship design, and to identify possible shortcomings of this process. The emphasis will be placed on sequential procedures to be followed for risk-based design, techniques for risk modelling, sources of information for risk quantification, contemporary regulatory developments concerning passenger ship safety, and promising techniques in data mining to facilitate risk assessment.

- To develop an all-embracing accident/incident database platform that is configured in such a way that it provides a comprehensive, objective, reliable, and technically feasible knowledge base to support every facet of risk assessment activities within the context of risk-based ship design. It will focus on the identification of dominant variables, which have direct impact on the risk level of passenger ships.

- To collect, assimilate and identify pertinent data mining knowledge regarding the development of probabilistic models by utilising the casualty database with minimised subjective intervention. The focal point is to qualitatively and quantitatively derive the models in the identified risk analysis tool in an objective manner.

- To propose a practical procedure for the implementation of risk-based design, through which the derived risk models can be flexibly integrated within the existing framework of risk assessment for risk-based design. The main emphasis will be put on its compatibility and the subsequent roles for decision support at the design stage.

- To develop a generic automated environment to facilitate the execution of various key components of the methodology.

- To demonstrate the adequacy of the proposed methodology through conducting a comprehensive case study containing casualty database development, data mining to derive risk models, and the subsequent decision support on the selection of optimal design alternatives.

- Finally, to offer recommendations for further research required for the realisation of a comprehensive methodological framework for implementing risk-based ship design.

Chapter 3
Critical Review

3.1 Preamble

The approach towards safety in the maritime industry is in a transitional stage. In pursuit of a rational treatment of safety at design stage, the methodology of risk-based design under the philosophy design for safety has demonstrated its brawny vitality through a series of concrete applications since its inception.

In view of the endeavour towards an effective and reliable means for risk-based design implementation, Chapter 3 provides an overview of risk-based design and associated methodologies, techniques, and tools. The in-depth consideration of each constituent element regarding risk modelling techniques and sources of information concludes with their merits and drawbacks. The field of data mining and its potential in providing an alternative for risk model derivation is also addressed, with emphasis on neural networks and BNs.

3.2 Design for Safety and Risk-Based Design

Ship design is both art and science as argued in [Rawson and Tupper, 1976]. However, it was more art than science in the past as such profession highly depends on the practical experience of naval architects. The successful designs delivered form the knowledge base of the design space. Considering the complexity of a ship, its subsystems and components, as demonstrated in Figure 3.1, and acknowledging the different focus of interests of various stakeholders, it is a difficult multi-objective optimisation task to deliver a design that successfully meets numerous requirements/constraints with respect to the expected functionality, the operational performance regarding fit for purpose, safety, etc.

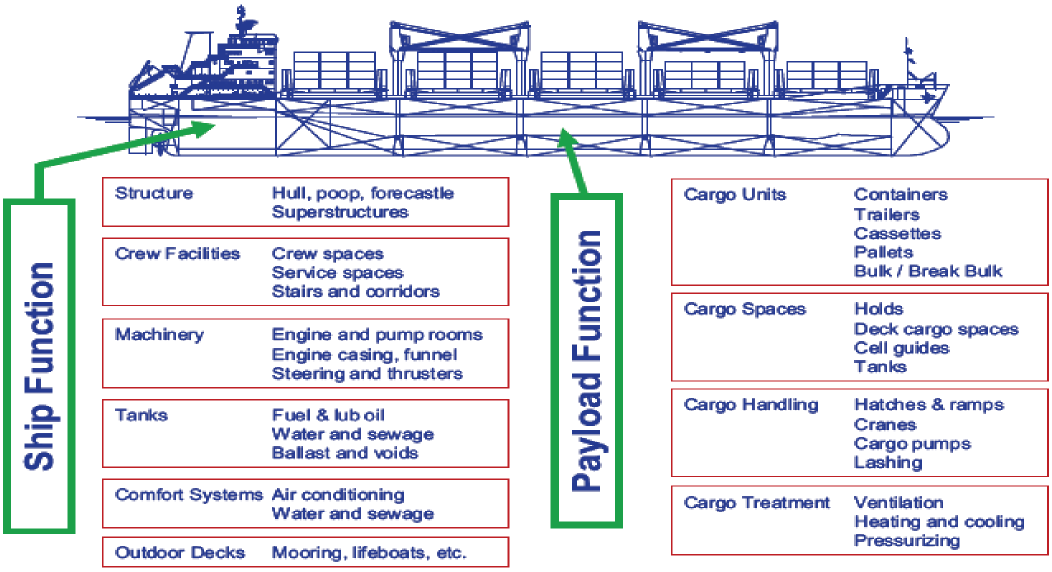


Figure 3.1: Ship Functions [Levander, 2003]

In the context of ship safety, design for safety has received significant attention in the past 20 years. The momentum amassed during this period has profoundly re-shaped the way that safety should be cognised and treated. The most noticeable distinctions between the "conventional" and the "new" approaches towards safety have been summaries in Table 3.1.

Table 3.1: Approaches to Ship Safety [Vassalos, 1999]

"Conventional"	**"New"**
Reactive	Pro-active
Regulation	Self-regulation
Deterministic	Probabilistic (risk-based)
Conformance-based	Performance-based
Compulsory	Safety Culture
Discipline-oriented (sectorial)	Total (integrated)
Experiential	First-principles (calculation/simulation)
Hardware focus	Balance of safety elements
Short-term	Life-cycle
Irrational (subjective/emotional/political)	Rational (scientific/cost-benefit analysis)

To realise the concept of design for safety, a formalised methodology, risk-based design, has been developed. A high-level definition of risk-based design is deemed to be appropriate: *Risk-based design is a formalised methodology that integrates systematically risk assessment in the design process with prevention/reduction of risk embedded as a design objective, alongside "conventional" design objectives* [Vassalos, 2006].

For the implementation of risk-based design methodology, risk assessment, particularly for the Quantitative Risk Assessment (QRA), is the premier technique as it offers a unified measure of safety and, more importantly, a wide spectrum of pertinent techniques, methods and tools are available to ensure the execution under various circumstances. With a high-level flow chart depicted in Figure 3.2, key drivers for the development of risk-based design methodology and the constituting components are contained in Appendix 1.

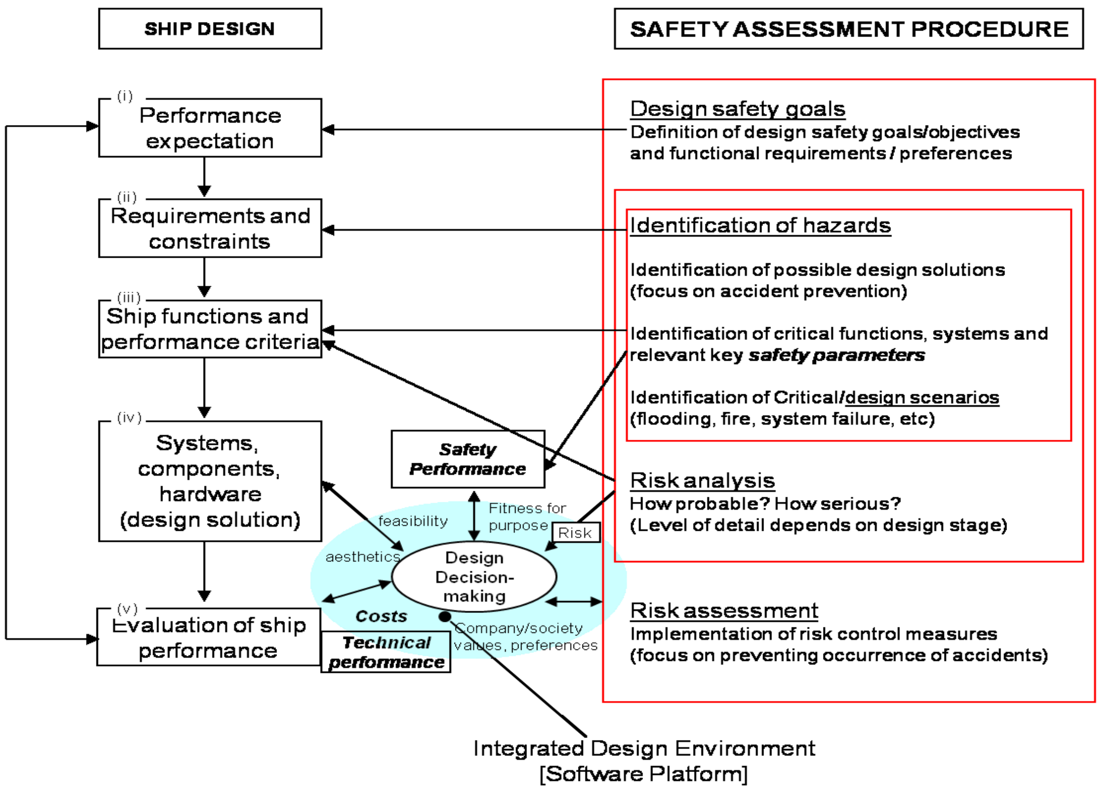


Figure 3.2: A high-level Framework of Risk-Based Design [Vassalos, 2006]

3.3 Risk Analysis Techniques for Risk Assessment

In the knowledge that fault and event trees are the most typically employed techniques for risk modelling, the key features, strength and weakness will be detailed next. Apart from the techniques adopting tree-like structures, an alternative - BNs, adopting influence network topology will be explored to examine the applicability within the context of risk assessment.

3.3.1 Fault Tree Technique

The fault tree technique is a logical representation of the failure of events and components that jointly could lead to the occurrence of a (normally, critical and undesired) top event [HSE, 2001], [Wang and Trbojevic, 2007]. Logic gates (mainly, "AND" and "OR" gates) are assigned to describe how basic events combine to cause top events.

The construction of a fault tree usually starts with a top event and works downwards. The top event should specify concisely the nature of the event within a specific domain. Events that are considered to be necessary to produce the event one level up will be included at the next immediate level. "OR" gate will be assigned if one event alone may cause the higher event and "AND" gate will be used if two or more events have to occur in combination towards the higher event. The downward development should stop once all branches have deduced to a stage where all basic events can be quantified through appropriate sources and tools.

The advantage of the fault tree technique is attributed to its clear and logical form of presentation. In the case of novel designs it is still capable of producing a systematic analysis and plausible frequency estimation. The hazards arising from both hardware (e.g. technical fault, etc.) and software (e.g. human error, etc.) aspects concerning safety generally can be covered well. This has enabled the fault tree technique to be a widely used and well accepted tool for frequency estimation of the hazard under consideration. Nevertheless, in the case of a large system it soon becomes complicated, time consuming, and difficult to follow. Also, it loses its clarity if the systems do not fall into simple failed or working state (e.g. human factor, weather condition, sea state, etc.). Moreover, it is difficult to include conditional dependencies (e.g. dependence of the visibility on the weather) and mutually exclusive events (e.g. good weather and storm) in fault tree analysis as all events in the tree are assumed to be independent, which renders a problem of over-simplifying the risk model.

3.3.2 Event Tree Technique

The event tree technique is a logical representation of the events that may follow from an initiating event, normally, an accident, a system failure, or an unintended action. It is mostly used for consequence analysis to logically and numerically examine the possible consequences following an initial single event. The branches are established at each step to show the various possibilities that may arise.

The construction of an event tree starts with an initiating event and the branches are developed step by step in a way of questioning. The answers could be binary or multiple outcomes. Each branch is conditional on the circumstances defined in the previous branches. The development of the tree should stop once each path in the tree defines a clear scenario and the consequent impact can be quantified using appropriate data and tools. Also the probabilistic information (conditional probabilities) needs to be assigned for each branch. The tree is calculated on the basis of the conditions and circumstances implied in the path linking the initiating event to its immediate consequences.

Similar to a fault tree, an event tree has a clear and logical form of presentation. Hence, it is simple and easy to understand. It is widely recognised as a powerful tool for consequence analysis. However, in case that many events must occur in combination, it may lead to many redundant branches, and it becomes inefficient. The size of an event tree also increases exponentially with the number of variables. Moreover, it is difficult to include events that the failure states are not clear (e.g. human factor, weather condition, sea state, etc.).

Both fault trees and event trees are the classical techniques for safety assessment in the maritime industry. A study as part of the joint North West European project, [DNV Technica, 1996], has developed a comprehensive safety assessment methodology, in which fault and event trees are the principal tools for risk modelling. The most noteworthy studies carried out recently are a series of formal safety assessments submitted to IMO for various types of ships, i.e. cruise ship [Nilsen, 2005, Nilsen, 2007], Ro-Ro passenger ship [Konovessis, 2007], LNG tanker [Vanem, 2006], containership [Forsman, et al., 2006], bulk carrier [IMO, 2002b], and tanker [Eliopoulou, et al., 2008], where risk modelling relies heavily on fault and event trees.

3.3.3 Bayesian Networks

Besides using fault and event trees for risk modelling, attention is also paid to BNs as an alternative [Koski and Noble, 2009]. A BN is capable of describing complex relationships probabilistically using intuitive visual representations. A BN model is normally comprised by: (i) a set of variables making up the nodes in the network, (ii) a set of directed links (with arrows) connecting the nodes representing dependencies, and (iii) a list of probability distributions (continuous or discrete) associated with each node describing the probabilistic influence of its parents on the node. The probability distribution can be continuous or discrete in principle. However, due to the BN technique is primarily oriented towards variables in discrete states and since continuous variables can be discretised easily, their formulation is restricted to the discrete case for the rest of this thesis. The key feature of a BN is the ability to form a risk knowledge model enabling modelling and reasoning about uncertainty. An example of a BN model is illustrated in Figure 3.3.

In a BN model, a variable, which dependents on other variables, is often referred to as a *child node*. Likewise, the directly preceding variables are called *parents*. The nodes without any parent are *root nodes* and the nodes without any child node are *leaf nodes*. A BN is also frequently referred to as *directed acyclic graph* (DAG) meaning one must not return to a node by following the direction of the arcs under any circumstance. As shown in Figure 3.3, each node denotes an event. The dependency is indicated by an arrow, known as an *arc*, with conditional distribution assigned in a form of conditional probability table to the down-arrow node, conditional on the combination of the values of its parents. In the case of root nodes, unconditional probability distributions are normally assigned.

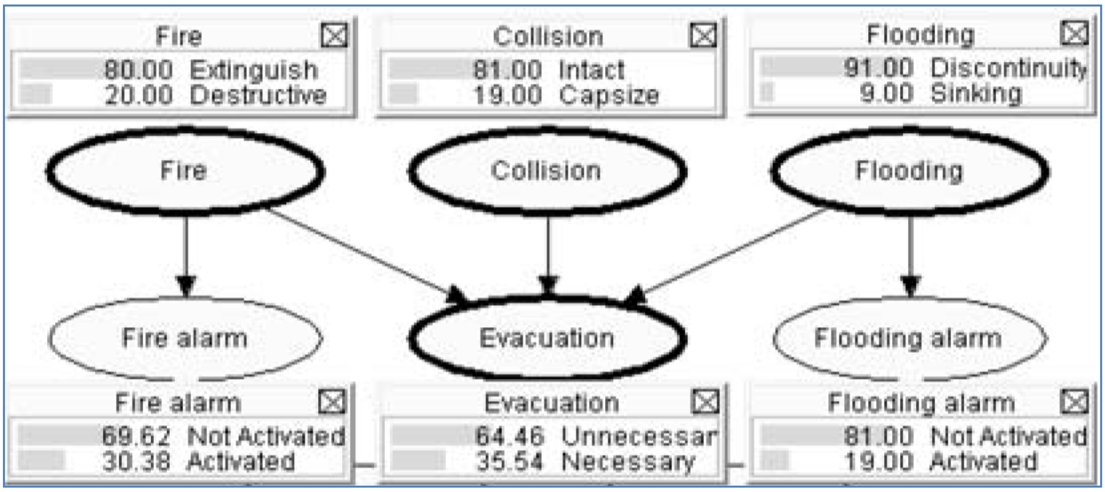


Figure 3.3: A BN Model [Eleye-Datubo, et al., 2006]

An important advantage of the BN technique is that it allows probabilistic inference in the network on the basis of the observed evidence of other nodes using the Bayes' theorem, as illustrated in equation (3.1). In the two-node BN of Figure 3.4, after initiation (meaning the probability table for the node X and the conditional probability table for the node Y are quantified given the current knowledge) and assuming that Y is observed in state y_i, equation (3.1) will enable the estimation of the probability distribution of X given $Y = y_i$, as shown in equation (3.2). Likewise, the computation can be performed for large networks in a flexible manner. Depending on the location of the evidence in the network, there are four types of inference that can be performed. That is (i) backward (diagnostic), (ii) forward (predictive), (iii) mixed and (iv) combined, as depicted in Figure 3.5.

$$P(X|Y) = \frac{P(Y|X) \cdot P(X)}{\sum_{all\ i} P(Y|X = x_i) \cdot P(X = x_i)} \tag{3.1}$$

$$P(X|Y = y_i) = \frac{P(Y = y_i|X) \cdot P(X)}{\sum_{all\ i} P(Y = y_i|X = x_i) \cdot P(X = x_i)} \tag{3.2}$$

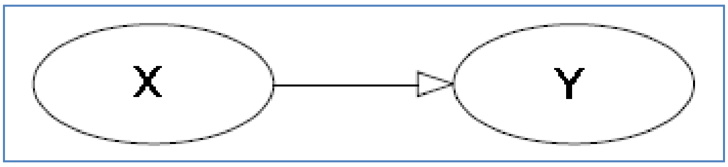


Figure 3.4: A Two-Node Bayesian Network

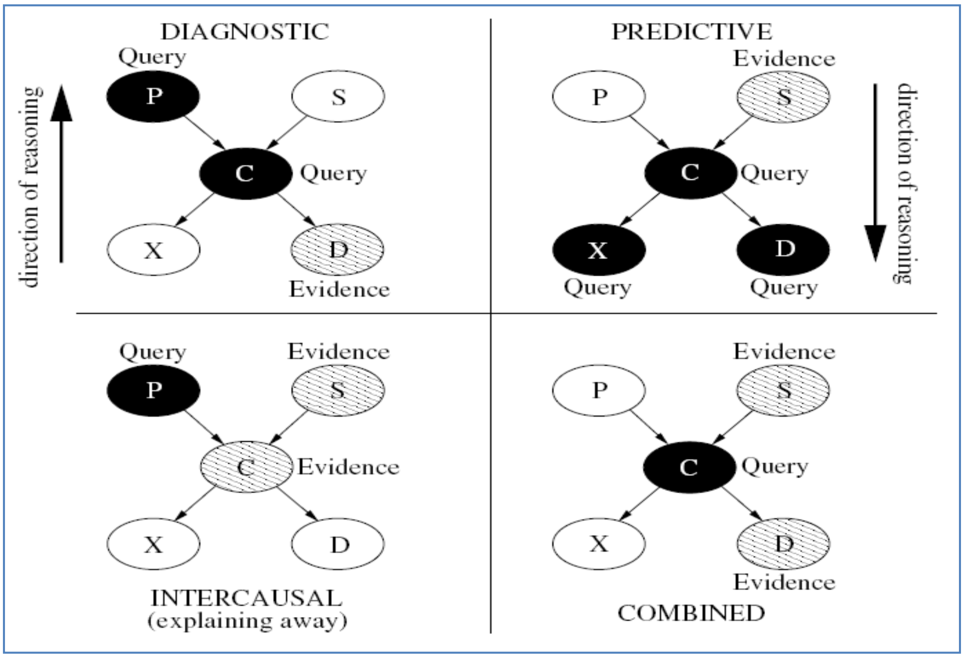


Figure 3.5: Four Types of Inference [Korb & Nicholson, 2004]

The building of a BN model starts with the qualitative development of the structure in a graphical presentation. There is a variety of software available to facilitate this process, e.g. Hugin, (http://www.hugin.com/), GeNIe, (http://genie.sis.pitt.edu/), Netica, (http://www.norsys.com/), etc. Through the identification of the nodes (variables) in the model, the level of detail will be defined. Moreover, the assignment of arrows (links with orientation) describes the model qualitatively in a manner of dependent relationships, which is often referred to as causality [Pearl, 2000]. This inherent property is desirable for pertinent probabilistic model development as standard mathematical notation is difficult to possess such characteristic [Wang and Trbojevic, 2007]. Following this, the quantification process can be performed by embracing every possible source of information to derive probabilities and conditional probabilities for each node.

BNs offer several advantages over conventional risk modelling techniques:

- It is unnecessary to assume independencies among the variables as this is inherently described by the network.
- The intuitive visual presentation depicting causal relationships facilitates a more realistic model, which is easy to interpret and validate.
- Different sources of information can be employed concurrently in a single model with minimised conflict.
- The information is computed and processed probabilistically, which is consistent with risk assessment paradigm.
- The probabilistic computation can be performed using available software, in which the implementation is fast even for large and complex networks.
- If the variables included are the key indicators/measures of the selected domain, it can be regarded as a useful tool for scenario generations and the subsequent decision support.

Disadvantages:

- The dependent (or conditionally independent) relationships can be difficult to identify in a physical environment, where such information is not explicitly available.
- The size of a conditional probability table can become large due to too many parents and their states.
- Large size of conditional probability table implies that more information is needed for the quantification of the network. This may lead to the dominance of subjective estimation as the most flexible and available sources of information.

BNs are gradually being recognised as an effective tool for risk modelling and decision support in the maritime industry [Norrington, 2008]. Earlier investigations in [Friis-Hansen, 2000] confirm their potential as a transparent and consistent modelling and decision support tool. [Faber et al., 2002] use BNs to construct a risk model of decommission activities for assessing options and identify additional safety measures necessary for the operation. From the point of view of regulatory development, MSC69 in 1998 was the first time a risk assessment based on BNs had been presented at IMO regarding "*Solo watch-keeping during periods of Darkness*" [Skjong, 2008] and [Denmark, 1998]. Moreover, the technique has been used for modelling navigational safety of the Electronic Chart Display and Information System (ECDIS) presented by DNV [IMO, 2006b]. A similar study on the ECDIS in [Kaneko and Yoshida, 2007] further ascertained the role of BNs not just for risk modelling but also for the assessment of RCOs.

In the recently finished research project SAFEDOR, [GL, 2002], [Breinholt, et al., 2009], which aimed to treat safety cost-effectively through the adoption of risk-based approaches, BNs have received strong attention. For the development of pertinent risk models concerning risk contributors, it has been deployed as a risk modelling tool to address several important hazards. That is,

- Concerning the structural integrity, a network model is developed to identify the most critical damage scenarios regarding hull girder failure [Friis-Hansen and Garre, 2007].
- For collisions and groundings, various BNs sub-models attempts to depict the behaviour of operators [Leva, 2006], to identify key causal factors affecting ship collisions both under power [Ravn, 2006a] and due to the failure in propulsion systems and steering systems [Ravn, 2006b].
- Regarding fire safety, BN models were designed to be the tool for fire screening of new layouts [Majumder, et al., 2007], and for modelling cargo fire scenarios in conjunction with the computational fluid dynamics (CFD) tools [Povel and Dausendschon, 2007].

Although BNs have been recognised as a useful tool for risk modelling, they are also blamed for the amount of information needed for establishing dependent relationships, and assigning probabilities to each node). This has significantly hindered their wider adoption. This drawback can be overcome only if proper channels are established that will allow the identification of dependent relationships and the derivation of probabilities through an objective and efficient means, as it will be described later in this thesis.

3.4 Sources of Information for Risk Assessment

In the process of risk quantification of various hazards, reliability of information sources (both qualitative and quantitative in nature) plays an important role. The current practice relies mainly on historical accident and incident data, first-principles tools, and expert judgement. As it was discussed in Section 3.3, the last approach should be deployed with care due to its inherent subjectivity. However, due to limited sources available and the lack of proper tools, expert judgement has been extensively used in practice. This situation leads to an all-around examination of the state-of-the-art sources regarding historical data and first-principles tools.

3.4.1 Marine Accident and Incident Databases

A maritime accident, similar to other service failures of engineering products, has been recognised as a priceless ground to learn and to improve the safety level of ships. This is particularly true for accidents onboard passenger ships as such casualties often lead to multiple fatalities and societal outcry. Given that the world fleet is far from casualty-free operations, the practice of learning from marine accident/incident should be appreciated as it demonstrates the attitude towards the accident by striving (both proactively and reactively) to improve safety performance.

Over the years, various theories have been proposed in order to understand the phenomenon of an accident, in which the propositions like *epidemiological theory* and *domino theory*, have received wide attention and recognition [Brown, 1990]. The former considers an accident as the conjunction between the operator (victim), the tool (agent) and the working environment (situation), which necessitates the realisation that each element, (i.e. individual, technology and working environment), is subject to improvement. The latter focuses on the sequential and multi-causal nature of an accident [Heinrich, 1980], and has received a considerable acceptance in the maritime industry. The underlying philosophy is similar to the widespread Swiss cheese model propounded in [Reason, 1990] for human errors analysis, as shown in Figure 3.6. On the basis of the precedent work, the Loss Causation Model (LCM) was developed in [Bird and Germain, 1992]. Consequently the application of *Marine Systematic Cause Analysis Technique* (M-SCAT), derived from the LCM, was advocated.

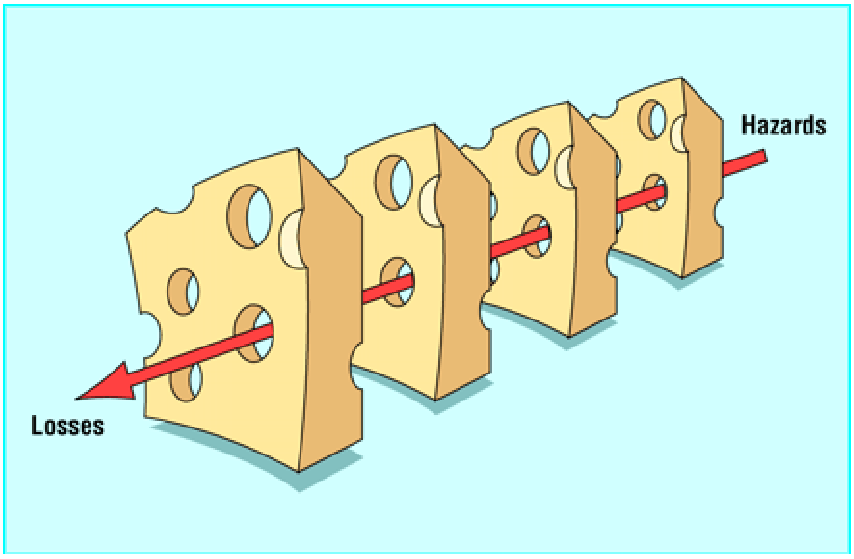


Figure 3.6: Swiss cheese model [Reason, 1990]

The fundamental principle is the postulate that the losses and the associated safety problems are the result of consecutive failures of both hardware and software safeguards, which comprise immediate, intermediate, and root causes. The *hardware* refers to physical equipments and systems, e.g. electronic navigational equipments, detection systems, lifeboats, etc., whilst the *software* is linked to human and manageable means, like safety management structures, organisational rules and regulations, etc. The difference among these factors is that the superficial ones are easy for the public to capture and to blame, e.g. human errors, whilst the remaining contributory portion is deeply implanted and difficult to perceive, e.g. management culture.

It is worth noting that great effort has been made in the past to stress the importance of correcting human errors. Statistical analysis also suggests that 75 – 85% of marine accidents involve human factors [Baker and McCafferty, 2002], [Baker and McCafferty, 2005], [Barnett, 2005]. This can be justified by the fact that almost every activity onboard needs human interference or is implemented by humans (particularly for crews). However, one should always bear in mind that equal attention should be paid to the remaining hardware and software factors as the goal is to lower the risk level by reducing the chance of experiencing an accident and mitigating the ensuing consequences.

Apart from accidents, significant effort has been devoted to prove that an accident does have precursors, which are popularly referred to as the *near-miss* or *incidents* [Tye, 1976], [Jones, et al., 1999], [Kirchsteiger, 1997], [Molland, 2008], etc. The principal assumption is that an incident is identical to the phenomenon of an accident, except that the sequence of the events is interrupted by either latent or physical safeguards before the final adverse consequences occur. Direct reference can be found in the *Star Princess* fire accident [MAIB, 2006], where the fire started by a lit cigarette butt in a balcony. Through practical experience gained in the course of the research project FIREPROOF [SSRC, 2009], the analysis of fire accident/incident data onboard passenger ships has shown an iterative nature of such events (fire started by lit cigarette in the balcony) and the effects that various safeguards (human detection, extinguisher, etc.) have on the outcome.

A number of investigations have revealed that there is a ratio between losses of different severities. [Heinrich, 1980] shows that there are about 300 no-injury incidents for every major accident, as shown in Figure 3.7, while [Bird, 1966] postulates this ratio is 600:1. In addition, [Ferguson et al., 1999] shows the ratio is 100:1 and there should be 1000 safety situations for every major accident. Certainly the exact figure varies from study to study due to several factors, however, the crucial underlying thinking is to admit that each case labelled "incident" could potentially become an "accident" and both accidents and incidents do indicate a degree of "loss of control". Reducing the number of incidents will also decrease the absolute number of accidents. Thus, it is paramount to include both valuable resources and treat accident/incident reporting and analysis as an integral part.

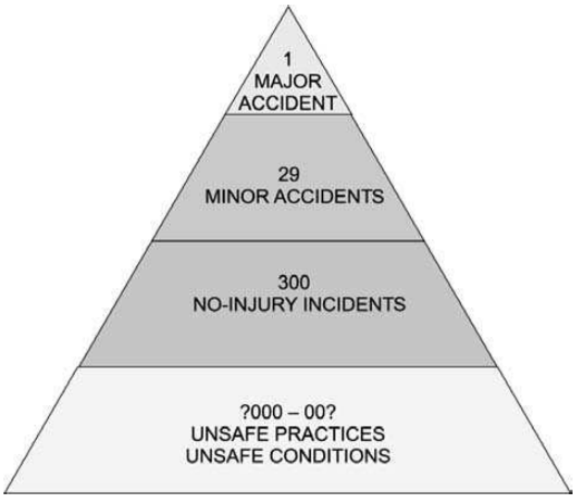


Figure 3.7: Iceberg Theory/Pyramid Model [Heinrich, 1950]

Historical Background

Casualty databases vary with respect to the marketing orientation, configuration, size, and focus. This is due to complex and mixed interests from various stakeholders, like owners, legal advisors, yards, consultants, control agencies, insurance companies, and government departments, etc. There are a number of organisations that have established casualty-related databases, such as the Lloyd's Marine Intelligence Unit (LMIU), the Marine Accident Investigation Branch (MAIB), the International Maritime Organisation (IMO), the European Maritime Safety Agency (EMSA), the Nautical Institute, the American Bureau of Shipping (ABS), etc.

The LMIU is generally recognised as the most successful organisation in commercialising and supplying electronic maritime data and information services [LMIU, 2007], and covers serious and non-serious casualties occurred after 1990. Despite the fact that its primary driver was mainly to meet the needs of insurance companies, it is still the largest casualty database in the world to date [LMIU, 2010].

It was not until the last decade that step change was observed regarding the maritime casualty database development. Technological advancement has made electronic storage of data feasible at negligible expense. For instance, the Global Integrated Shipping Information System (GISIS) – marine casualties and incidents [IMO, 2010a], was developed at the IMO to accompany a series of newly introduced resolutions [IMO, 2000, IMO, 2005]. The aim was to provide a platform where accident investigation findings classified as "serious" and "very serious" could be collected in order to facilitate learning.

The corresponding governmental agencies and flag administrations, in response to the aforementioned resolutions, have also launched regulations for accident reporting and investigation, such as the UK regulation 2005 No. 881 - the Merchant Shipping regulations (Accident reporting and investigation), [MCA, 1999, MCA, 2005], to look into casualties that occur either in its territorial waters or onboard British flagged vessels. As a result, this exercise soon became an effective means to ensure that major accidents could be investigated and stored in a central database system within each agency [NUST, 2001], [Kristiansen, 2005], e.g. the British Marine Accident Investigation Branch [MAIB, 2005], the Australian Transport Safety Bureau (ATSB), the Transportation Safety Board of Canada (TSBC), the United States National Transportation Safety Board (NTSB), the Danish Maritime Authority (DMA), the Accident Investigation Board of Finland (AIBF), etc.

As marine casualties will always entail a dimension of responsibility, the recreation of accident scenes can receive significant resistance, is treated reluctantly during the investigation, and influence the findings negatively. Therefore, various non-governmental organisations set up anonymous reporting systems, such as the Mariners' Altering and Reporting Scheme (MARS) from the Nautical Institute [MARS, 2010], etc., in an attempt to allow full reporting of accidents and free information exchange without fear of legal persecution.

Apart from the databases that have already been established at various organisations, several new databases and pertinent platforms are underway. For instance, EMSA is presently developing a European Marine Casualty Information Platform (EMCIP), [EMSA, 2010], to provide the European Commission and its Member States with objective and reliable information on maritime safety as well as to facilitate cooperation and analysis [Correia, 2010]. ABS has developed a casualty investigation database software (RootCause LEADER) to identify the root-causes of various types of accidents/incidents, and it is currently exploiting a new accident database tool to accommodate its latest casualty investigation method – Marine Root Cause Analysis Technique (MaRCAT) [ABS, 2010].

Even though marine accidents resulting in catastrophic consequences attract major attention from the industry and the wider public, the significance of marine incident data, which grows at a fast pace with the vast amount of ship operators, should not be overlooked. The data is generated primarily through the compliance of the mandatory code of conduct (Chapter 9 on reports and analysis of non-conformities, accidents and hazardous occurrence) under the SMS originated from the ISM [IMO, 1994]. For over a decade of data accumulation since the ISM became mandatory, ship operators have collected a considerable amount of operational incidental records in various formats. In fact, practical experience gained suggests that this has become a major source of firsthand and reliable marine accident/incident information, where the magnitude of the data generated is fairly comparable with the available accident data.

Characteristics of Current Generation Marine Accident/Incident Databases

The structure of the maritime industry is characterised by complex interrelationships and conflicting interests among the participating parties, e.g. regulatory bodies, class societies, shipyards, owners, operators, and insurers, etc. It is important to acknowledge that safety will be a lasting issue at the top of IMO's agenda and the occurrence of maritime casualty event is very unlikely to be eliminated in the foreseeable future. On this basis, great effort has been spent across the industry to address this issue from various perspectives. An important undertaking at IMO is the apparent shift from deterministic rule compliance to performance-based and goal-based approaches. A concurrent move is to stress the importance of casualty investigation, particularly for serious accidents in the hope that lessons could be learned in order to facilitate necessary regulatory changes. Moreover, the ISM code explicitly requires non-conformities, accidents and hazardous occurrences within the organisation to be reported and analysed to self-improve safety performance.

It is apparent that the aim is to embrace every effort to strive for better safety performance, nevertheless, the mixed signals emitted from IMO are rather confusing: on one hand, the birth place of deterministic rules has pronounced that the future is "Risk-Based" by the Secretary General of IMO, William O'Neil, in 2002 [Vassalos, 2009], whilst, on the other hand, given the clauses and the current prevailing approaches adopted for accident/incident investigation the findings will, most likely, identify the loopholes and assist the amendments by further tightening the deterministic design envelope. This leads to an ambiguous situation in the sense that although the two undertakings appear to move in the same direction, a junction point cannot be found easily.

The key issue here is that current approach concerning marine accident and incident investigation and data collection is best described as rule-oriented and case-specific. It is rule-oriented in a way that safety enhancement is sought through the legislation without clear goals and objectives. Potential revisions are carried forward within the regulatory framework itself, whilst findings hardly ever feed back to yards, operators, and designers. A similar situation has also been noticed from an organisational perspective as the lessons learnt through the SMS compliance can be difficult to circulate within the wider maritime community. It is case-specific as experience gained in the past suggests that key changes of the existing maritime safety framework have been driven by individual high-profile accidents, whilst large proportion of records are under-utilised, as it is illustrated in Table 3.2.

A short summary regarding the application of historical data for the quantification of the risk level and its components is provided next. In the case of frequency estimation for the flooding due to collisions and groundings, statistical analysis of historical accidents has been performed in the project HARDER, [Lützen and Clausen, 2001] and [Lützen, 2002], in order to investigate the probabilistic damage and collision energy distributions. On the other hand, more sophisticated probabilistic models were developed in SAFEDOR for capturing the likelihood of a collision and a grounding by taking into account ship systems failure, environmental conditions and people as it is reported in [Lepsøe, 2006], [Leva, 2006], [Ravn, 2006a, Ravn, 2006b, Ravn, et al., 2006]. A similar approach has been adopted for addressing fire safety where historical fire incident data were used for quantifying the frequencies of 14 SOLAS space categories following fire escalation [Ventikos, et al, 2010].

Table 3.2: Recent Maritime Accidents and Responses [Kristiansen, 2005]

Background	**Response**
Need to increase maritime safety, protection of the marine environment, and improve working conditions on board vessels. Flag state control is not regarded as efficient enough.	Declaration adopted in 1980 by the Regional European Conference on Maritime Safety that introduced Port state control of vessels, known as the Paris *Memorandum of Understanding (MOU).*
The loss of Ro-Ro passenger ferries *Herald of Free Enterprise* in 1987, and *Scandinavian Star* in 1990.	IMO adopts *the International Management Code for the Safe Operation of Ships and for Pollution Prevention (ISM Code):* Ship operators shall apply quality management principles throughout their organization.
Grounding of oil tanker *Exxon Valdez* in Alaska 1989, resulting in oil spill and considerable environmental damage.	US Congress passes the *Oil Pollution Act (OPA '90):* Ship operators have unlimited liability for the removal of spilled oil and compensation for damages.
The loss of Ro-Ro passenger vessel *Estonia* in 1994.	*Stockholm agreement (1995):* North-West European countries agree to strengthen design requirements that account for water on deck.
A need for greater consistency and cost-effectiveness in future revisions of safety regulations.	*Interim Guidelines for the Application of Formal Safety Assessment (FSA) to the IMO Rule-Making Process*, 1997. [IMO,2007a]
Hull failure and sinking of the oil tanker *Erika* off the coast of France, 1999.	European Commission approves a directive calling for tighter inspection of vessels, monitoring of classification societies, and phase-out of the single-hull tankers.
Oil tanker *Prestige* sinks off the coast of Spain, 2002.	The European Commission speeds up the implementation of ERIKA packages 1 and 2 to improve safety of the boats and the sea traffic

The under-utilisation of databases in the industry is mainly attributed to the lack of formalised and consistent techniques for data collection due to diverse focus points among the interested parties, e.g. root-cause analysis, human factors, hardware failures, fire fighting performance evaluations, etc. These databases can be labelled as the first generation sources of information, which are characterised by limited formatted parameters and the descriptive text still holds key information for risk assessment. Direct reference could be given to both LMIU web-based database: the Sea-Web, [LMIU, 2010], and the GISIS [IMO, 2010a]. Even with the well published serious fire accident onboard *Star Princess* cruise liner in March 2006, both databases provide formatted variables mainly on ship characteristics, general information of the event (e.g., time, location, number of passengers, injuries and fatalities), whilst more critical information regarding the fire initiation, the performance of suppression means, escalation situations, and how the fire was eventually extinguished, is not available or it is only partially recorded in the descriptive text, as shown in Figure 3.8 and 3.9.

SHIP DETAILS AT TIME OF INCIDENT

Ship Name	**STAR PRINCESS**	Flag	**Bermuda**
Ship Type	**Passenger**	Year of Build	**2002**
GT	**108977**	DWT	**6750**
Classification	**Registro Italiano Navale**	Ship Status	**In Service/Commission**
Owner	**GP3 Ltd**		

INCIDENT & CARGO

CAUGHT FIRE IN THE CARIBBEAN SEA AT 0310 HOURS LT ON 23/03/06. SUBSEQUENTLY PROCEEDED TO BREME
WERE EFFECTED. RETURNED TO SERVICE ON 13/05/06.

FIRE EXTINGUISHED BY CREW. SUSTAINED DAMAGE TO APPROXIMATELY 100 PASSENGER CABINS BETWEEN DE
THENCE TO GRAND BAHAMA FOR INSPECTION. 1 PASSENGER REPORTED DEAD FROM CARDIAC ARREST AND SE
HOSPITALISED. DAMAGE ESTIMATED AT $33-$42 MILLION.

Incident Type	**Casualty**	Casualty Type	**Fire/Explosion**	Incident Severity	**Serious**
Lives Lost	**1**	Missing	**No**		
Detail Status	**ON VOYAGE**	Cargo Status	**Loaded**	Cargo	**2,690 Passengers**
Dangerous Cargo	**No**	Pollution Occurred	**No**	Pollution Details	

VOYAGE DETAILS

Voyage From	**Grand Cayman**	Voyage To	**Montego Bay**
Removal from Scene	**Continued On Voyage**	Assistance Given	**No**

Figure 3.8: A Snapshot of Sea-Web Record of Fire Accident Onboard Star Princess in March 2006

Analysis

1. Type of Casualty:

Fire

2. Event and Consequences:

Star Princess was on passage from Grand Cayman to Montego Bay, Jamaica with 2960 passengers and 1123 crew on b
discarded cigarette end heating combustible material on a state room balcony. Assisted by a strong wind across the de
spread into the staterooms as the heat of the fire shattered the stateroom balcony doors, but was contained by each s
large amounts of dense black smoke were generated from the combustible materials on the balconies, including the ba
The dense black smoke entering the adjacent state rooms and alleyways hampered the evacuation of the passengers.
crew were treated for the effects of smoke inhalation. After the fire 79 state rooms were condemned, and a further 21

3. Contributing Factors:

The policy of allowing passengers to smoke in areas where it is difficult to control the proper disposal of cigarette ends

The relative wind speed and direction before the fire was detected and until the ship was manoeuvred to alleviate the

The balconies on board Star Princess were categorised as "open deck spaces" where the materials were not subject to

The glass doors between the staterooms and balconies were exempt from the 'A' Class Division requirements for bulkh

The glass doors between the staterooms and balconies were not required to be self-closing, which accelerated the sm

The balconies crossed main fire zone boundaries horizontally and vertically without structural or thermal barriers.

No fire detection or suppression systems were fitted to the balconies, meaning the fire was able to develop undetecte

Cabin doors were intentionally wedged ajar by crew during the passenger evacuation, accelerating the smoke saturati

A number of water mist fire suppression heads did not activate, increasing the amount of fire damage to those areas.

Figure 3.9: A Snapshot of GISIS Database Record of Fire Accident Onboard Star Princess in March 2006

Consequently, one can hardly make use of such databases as a comprehensive and standalone source of information to assist the effort in the risk assessment context [Schröder, 2005]. The main contribution of first generation database is to provide the information of specific high-profile accidents and high-level bar/pie charts that reflect the situation at an abstract level. This is inevitable as the databases have never been treated as an integral part of through-life considerations of ship safety.

3.4.2 First-Principles tools

The development of first-principles and performance-based tools is phenomenal in addressing ship safety in recent years. Due to their objectivity by following the principles of physics, these tools can be regarded as another reliable source of information after proper validation. They generally cover mathematical models, methods and numerical tools, as well as scaled model tests. Their applications have been found in addressing various phases and aspects of the casualties, in which a list of the latest development is summarised next.

In the area of consequence analysis due to collisions and groundings, the work conducted in HARDER and SAFEDOR has led to the development of an in-house simulation software PROTEUS3 at the Ship Stability Research Centre (SSRC), as illustrated in Figure 3.10. This is a dedicated tool for modelling damaged ship dynamics as it is reported in [Jasionowiski, 2002], [Jasionowiski and Vassalos, 2006], etc. In addition, the relevant study is being carried out to develop tools that are capable of simulating fire growth within various types of space onboard [Majumder, et al, 2007], [SSRC, 2009].

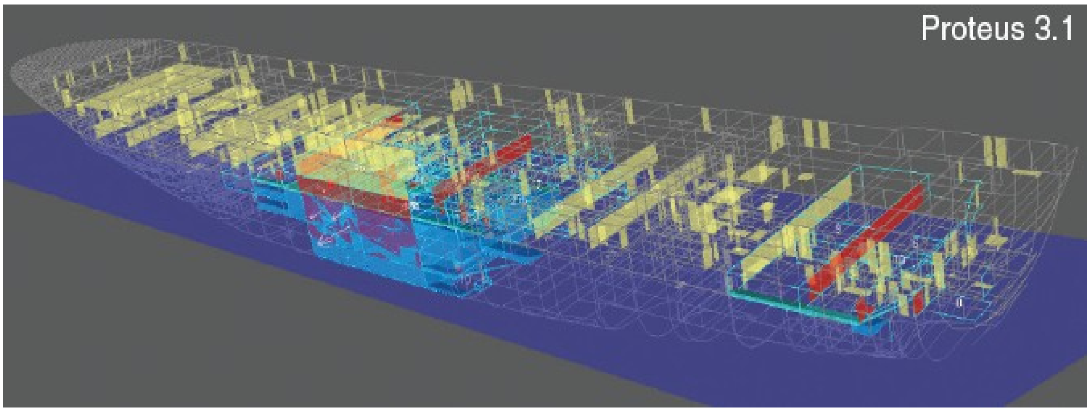


Figure 3.10: A Snapshot of PROTEUS3

The assessment of residual functional capacity following an accident that would allow a ship to seek safe haven can be achieved by examining the post-accident systems availability. This has proven to be a complex problem because it is essential to couple spatial locality and historical frequency of damage scenarios. Currently, computer software - Systems AVailability ANalysis Tool (SAVANT), is being developed to facilitate the probabilistic analysis of systems availability following collisions or groundings [Cichowicz, et al., 2009, Cichowicz, 2009], [Vassalos, 2008b].

Although there has been considerable achievement for evacuation analysis of new cruise ships and existing passenger ships on the basis of performance-based rationale [IMO, 2002a, IMO, 2007c], [Vanem and Skjong, 2006], the latest development includes crew performance and their contribution in emergencies to complement the existing definition of evacuability, as illustrated in Figure 3.11, in order to offer real “means” for enhancing evacuation performance [Dogliani, et al., 2004]. In addition, both the availability of emergency systems and the influence of the floodwater/fire must also be included in flooding/fire evacuation models [Vassalos, 2006]. The evacuation simulation software being developed at the SSRC - Evacuation model environment (Evi), aims to couple the key attributes from preceding probabilistic models, such as vessel motions and floodwater movements in the case of flooding [Vassalos, et al., 2001], visual obstructive smoke, toxic gases, and heat in the case of fire event [Guarin, et al., 2004], [Majumder, et al., 2007].

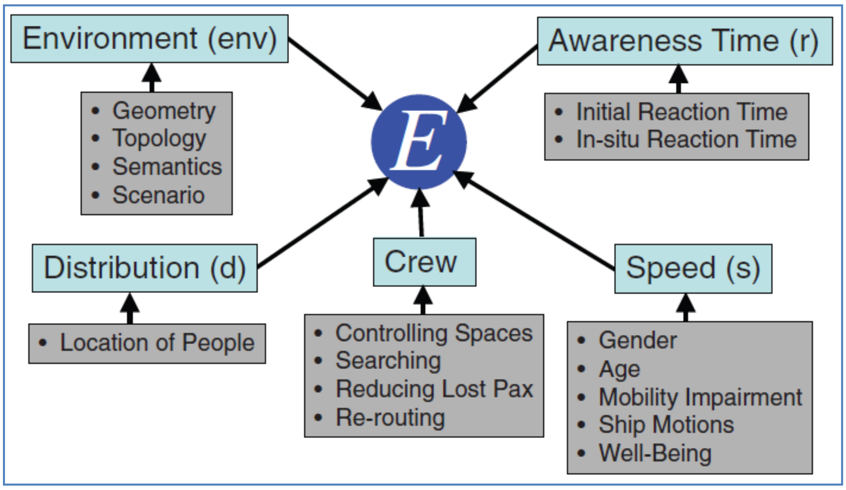


Figure 3.11: Evacuability [Vassalos, 2008b]

The key to understand the aforementioned approach for risk modelling through the deployment of first-principles tools and the risk contribution tree is to link ship design parameters with safety performance parameters. That is effectiveness of navigation equipment, manoeuvrability, time to flood, time required for abandonment, etc. These safety performance parameters play an important role in estimating the total risk of a ship.

However, cost and time consuming features associated with model tests and simulations could be a bottleneck, as illustrated in Figure 3.12, which may significantly hinder the implementation of risk-based design methodology in the early design stage. As indicated in the figure, it illustrates an engineering compromising process between the complexity/cost of application of a tool to predict a phenomenon and the prediction quality/reliability. Although the difference seems trivial in this graphic representation, one should appreciate the revolutionary difference the computer-based simulation software has brought in comparison to the model test when it comes to applications in a highly competitive industry. Similarly, an optimal approach, as shown in Figure 3.12, allowing fast-and-accurate predictions is needed so that the analysis can be performed cost-effectively.

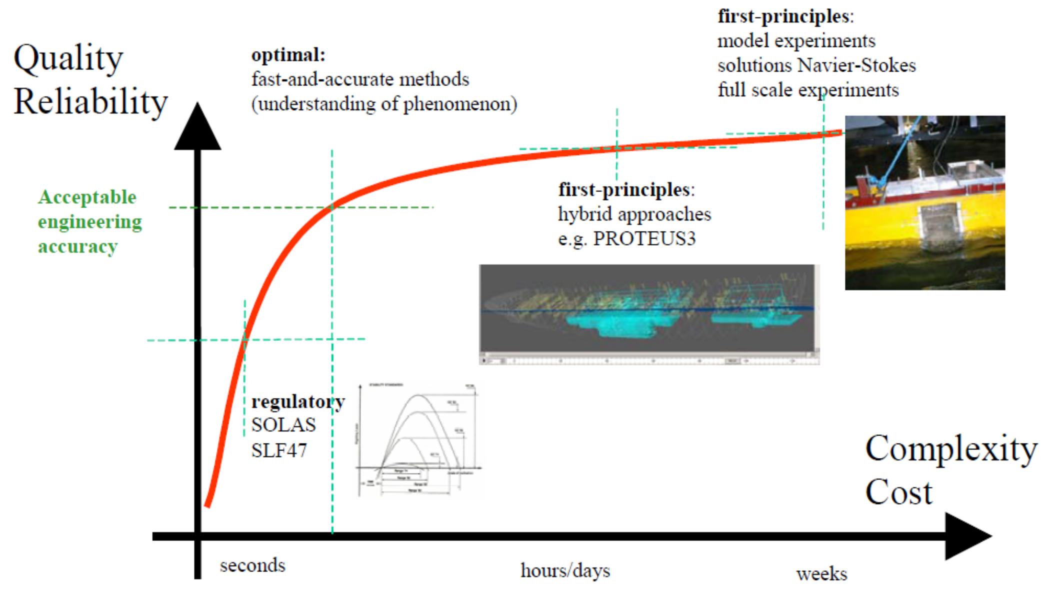


Figure 3.12: Hypothesis on Engineering Compromise between Complexity/Cost of Application of a Tool to Predict a Phenomenon and the Prediction Quality/Reliability [Castillo & Zamora, 2006]

3.5 Data Mining

As far as risk assessment is concerned, the ultimate output from various sources of information as described in the previous section will be presented in a data set for the derivation of risk models. However, with the ever increased size and number of attributes, the deployment of more sophisticated data processing techniques is also essential.

The explosive growth of the data is being collected nowadays facilitated by the technological evolution in computer science. It soon leads to a situation of "*rich in data, poor in knowledge*" in which classical statistical analysis techniques are incapable to cope with [Han and Kamber, 2006]. This has driven the birth of a new and promising field - data mining, which is also frequently referred to as the knowledge discovery from data (KDD). As suggested by the name, the key objective of data mining is to derive useful knowledge out of the data. Nevertheless, due to the diversity of subjects, data sources, storage means, quality levels, and applications, data mining draws works from multidisciplinary fields, (e.g. database technology, machine learning, pattern recognition, statistics, data visualisation, etc.).

A survey of typical data mining applications is contained in Appendix 2. The process of knowledge discovery consists of an iterative sequence of the following steps, as depicted in Figure 3.13:

1. Data cleaning (to remove noise and inconsistent data)
2. Data integration (to combine data from various sources)
3. Data selection (to select data that is relevant to the analysis)
4. Data transformation (to transform data into proper forms so as to facilitate the mining process, such as coding, summarising, pre-processing, etc.)
5. Data mining (advanced data analysis methods to process the data)
6. Pattern evaluation (only truly interested knowledge findings, such as pattern, relationships, etc, will be put forward and reported)
7. Knowledge presentation (to present the knowledge in appropriate manner)

Though still young, data mining is contributing greatly to business strategies, knowledge bases, and scientific and medical research. Nevertheless, considering the property of a generic database, tackling uncertainty in a rational manner becomes an important issue of the whole process so as to ensure the quality of the analysing results.

Naturally, the integration of data mining techniques with uncertain reasoning techniques becomes a viable solution, as illustrated in Figure 3.14. Uncertain reasoning promotes effective reasoning involving uncertainty, with particular emphasis on the underlying mechanisms for reasoning processes. The popular techniques include NNs, BNs, fuzzy logic, and genetic algorithm (GA), etc.

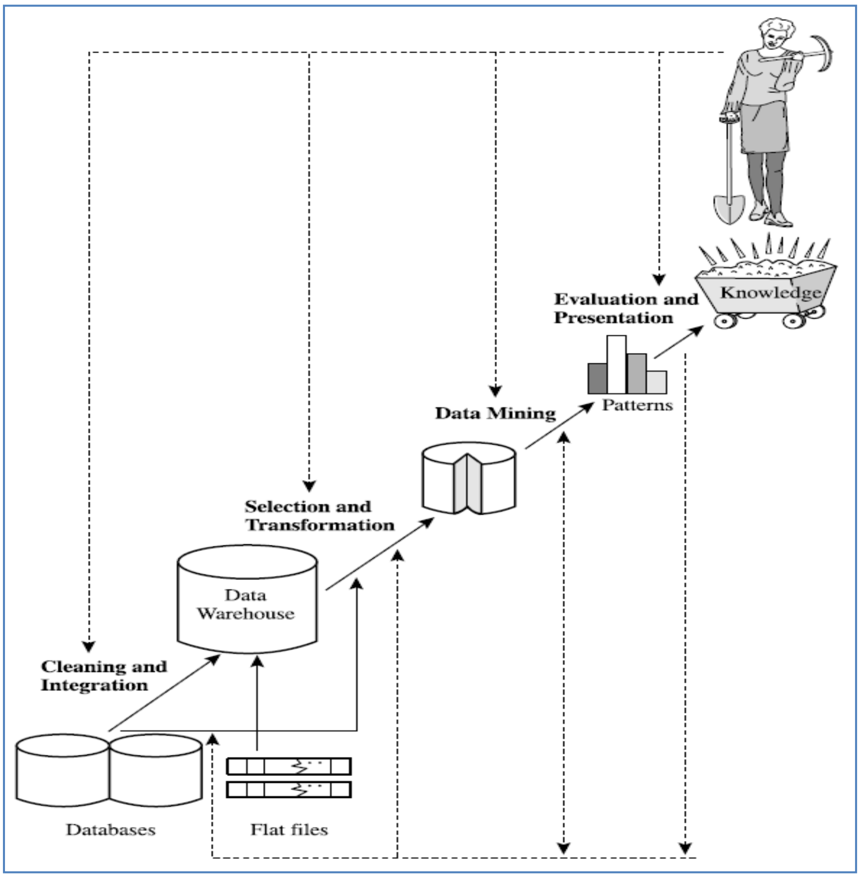


Figure 3.13: Data Mining as a Step in the Process of Knowledge Discovery [Han and Kamber, 2006]

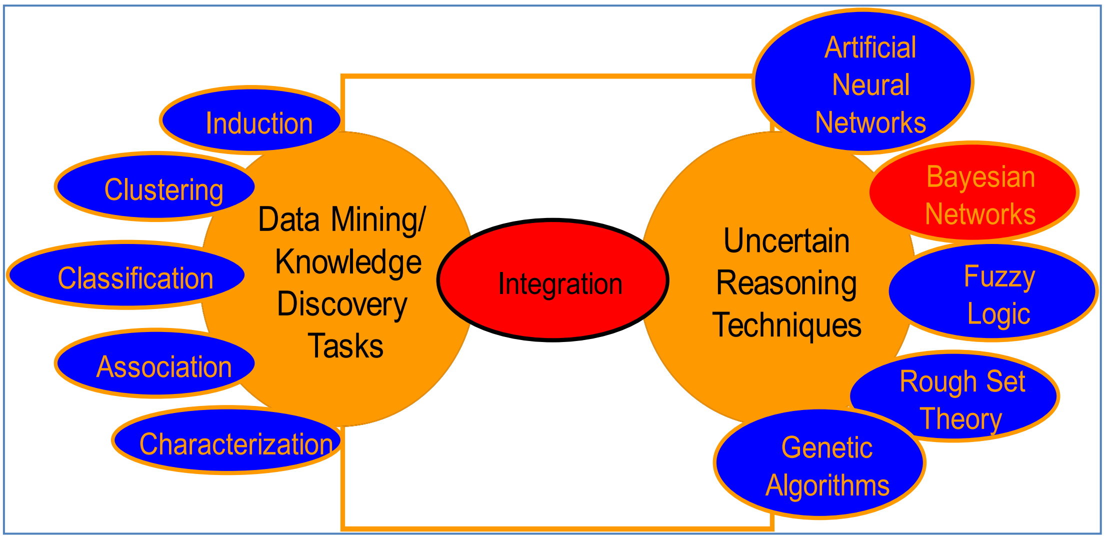


Figure 3.14: Integration of Data Mining with Uncertain Reasoning Techniques [Chen, 2001]

Data mining is an in-depth explorative analysis of the data aiming to discover knowledge patterns hidden in the data and predict future trends. In contrast, uncertain reasoning aims at developing effective reasoning methods involving uncertainty. A key advantage of integrating data mining and uncertain reasoning techniques is to transform the data into a knowledge model presented in a mechanism, which provides a platform for uncertain reasoning. By doing so, it establishes a (e.g. probabilistic) knowledge base for future application and, at the same time, quantifies and minimises the uncertainty arisen from various sources.

The application of data mining in the maritime industry is very limited comparing with the fast developing applications in other fields, e.g. business, biology, and information technology, etc. Nevertheless, there is still a few pioneer work deploying data mining techniques as will be elaborated in Sections 3.5.1 and 3.5.2. In the meantime, a noteworthy application is carried out in [Ravn, 2003], which focuses on optimising the layout of the subdivision of Ro-Ro passenger ships by considering damage stability probabilistically alongside traditional ship design activities. A Data mining technique is deployed for developing a model so that the attained subdivision index can be expressed as a function of various variables. By doing so, one can estimate the Attained Subdivision Index without detailed subdivision evaluations. This is very desirable for optimisations at early design stage.

Based on the foregoing, special attention has been paid to NNs and BNs as both techniques offer promising mechanisms to act as the risk model. They have also demonstrated the potential through a number of maritime applications.

3.5.1 Data Mining in Neural Networks

The inspiration for NNs was the recognition of complex learning systems in closely interconnected sets of neurons in animals. It starts with an input layer, where each node corresponds to a predictor variable. Each input node should connect every node in the hidden layer. It is up to the user to choose the number of hidden layers. A simple NN with a single hidden layer is provided in Figure 3.15. The nodes in the last hidden layer should connect each node in the output layer, where one or more response variables can be presented. Each connection between any two nodes has a *weighting factor* associated with it.

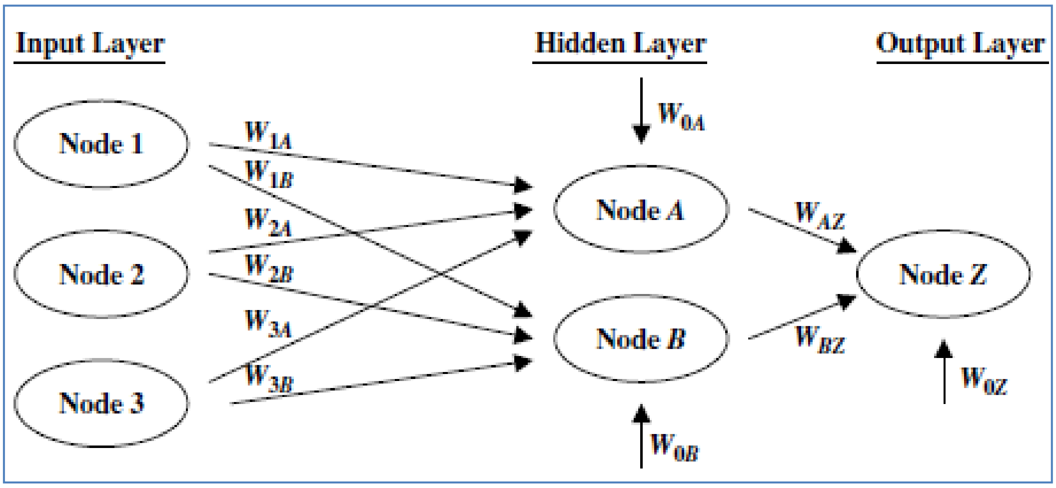


Figure 3.15: An Example of a Neural Network [Larose, 2005]

To train a NN model is a typical supervised learning method. It requires a large training set of complete records, including the target variable(s). Although the weights are assigned randomly at initiation stage, it becomes clear that to train the model is actually a process of identifying a set of model weights that minimise the prediction error, such as the Sum of Squared Errors (SSE, analogous to the residuals in regression analysis). Upon finishing the training process, the model can be used for estimation and prediction. However, as the input and output variables are always normalised to a value between 0 and 1, inversions are needed to transform the results into interpretable formats [Two Crows Corporation, 1999].

There is an increasing amount of research in the maritime industry deploying NNs as a decision support tool through training of relevant domain data, e.g. the support of steering control [Junaid, et al., 2006], the prediction of the stalling of marine gas turbines [Caguiat, et al., 2006], fault diagnosis of steam turbine flow passages [Cao, et al., 2009], etc. Nevertheless, as far as risk modelling is concerned, a limited reference is available. [Ung, et al., 2006] develops a risk prediction model incorporating fuzzy set theory and NNs. This is demonstrated by a test case evaluating the navigational safety near the port. Moreover, recent work in the project SAFEDOR attempted to use historical data on collisions and groundings to train a

NN model to predict the damages. It is concluded that this is a fast and simple technique to implement, however, the findings can be discounted if no similar training data exists [Ravn, et al., 2006].

The advantages of the NN technique:

- It is robust to deal with noisy data (uninformative or even erroneous data).
- It can be easily implemented to run on massively parallel computers with each node performing its own calculations.
- Once a model is trained, the prediction can be carried out quickly.

The disadvantages of the NN technique:

- It requires an extensive amount of training time and large data set unless the problem is very small.
- All attribute values must be normalised to a value between 0 and 1, which makes it difficult for interpretation. The situation is further complicated by too many combinations of the links between input layer, invisible layer(s), and output layer. Hence, the network serves as a "black box".
- As a result, there is no explicit rationale for decision support using NNs.

3.5.2 Data Mining in Bayesian Networks

In comparison, the integration of data mining with the BN technique leads to a totally different approach, which is also frequently referred to as the Bayesian learning. To train a risk model, there are mainly two aspects of learning: (i) structure learning and (ii) parameter learning.

Bayesian *structure learning* aims to construct the network structure by learning from the data. Considering the configuration of a BN, totally different handlings have been proposed in the field. The first proposition aims to address the structure construction from the point of view of causality discovery. Thus, through iterative dependency and conditional independency analysis using dedicated mathematical models, one can identify a diagram that entails all the relationships; on the other hand, acknowledging the fact that a BN is essentially a representation of the joint probability distribution of the entire variable domain, another strategy advocates estimating the conditional probability of how well a diagram (out of a large amount of candidate diagrams) describes the dataset.

The quantification of the network could be a very laborious and difficult process if experts' judgement is used alone. However, this is not the case if the structure is identified through Bayesian learning. A formalised method for learning from the data has been devised. For instance, the beta density function can be employed to compute the conditional probabilities for binary variables using the data alone.

The application of Bayesian learning in the maritime industry is rare and a few applications are summarised next. During the investigation of BNs as a decision support tool in marine application in [Friis-Hansen, 2000], one of the five case studies regarding preliminary ship design adopts the Bayesian learning algorithm. By using the data of main ship particulars of the existing fleet, a BN model is trained and used for answering queries. On the other hand, as far as QRA is concerned, [Hu, et al., 2007, Hu, et al., 2008] employee Bayesian learning techniques to model ship navigation safety, and attempt to analyse the interactions between human organisation factors (HOF) and vessel operation systems.

3.5.3 Comparison between Neural Networks and Bayesian Networks

Both tools are the popular fields to apply data mining techniques, however, there are three key factors affecting the decision on which one to choose for the sake of risk modelling: transparency, data treatment, and compatibility.

- NN is an interpolation tool that heavily depends on quantity and quality of data for training. On the other hand, a BN can be established and populated "manually". Also, the latter is solely based on probabilistic theory / concept.

- It is desirable to have a transparent risk modelling tool so as to facilitate model interpretation and validation. Because of the normalisation process and pure numeric information flow (training of weights) between different layers, a NN is essentially a "black box", in comparison, a BN offers a more transparent platform by having intuitive graphical representations of causal relationships and meaningful information flow (probability distribution).

- The current trend in risk-based design development is to have a tool that is capable of presenting and processing the data probabilistically. Backed up by Bayes' theorem and the subsequent deduced inference techniques, which are normally encapsulated in a software package, it is relatively easy for BNs to meet the needs; whilst, the supportive rationale for NNs is not designed for such purpose as far as the probabilistic framework is concerned, although the information is transformed to the values between 0 and 1.

- Lastly, a BN model is interchangeable with other risk models using classical techniques (i.e. fault tree, event tree, etc.) due to its transparent and probabilistic treatment of data. In contrast, this would be an extremely difficult task for NNs to perform.

3.6 Closure

The fundamental concepts, methodologies, techniques and sources of information for the implementation of risk-based ship design have been critically reviewed and analysed. An introduction of relevant promising data mining techniques has been included as well. The following are the main conclusions:

- In view of the radical shift regarding the fundamental thinking, understanding of safety, risk-based design represents a scientifically viable advancement in realising a systematic, rational, and holistic treatment of through-life safety of a ship.

- Risk assessment plays a key role in realising risk-based design, in which the techniques/methods/tools developed within the context of QRA can be readily deployed.

- The classical techniques for risk assessment, (most typically, fault and event tree techniques), still represents the mainstream in the maritime industry. Nevertheless, the inherent characteristics are undermining the quality of the study results, which can be complemented by potential techniques, i.e. BNs, having more sophisticated features.

- Both historical casualty information and the data generated through first-principles tools can be regarded as two major sources of information for risk assessment. However, in acknowledging the disorganised accident/incident database systems and time-consuming features with first-principles tools, also not forgetting that important decisions need to be made under tight schedules at early design stage, the effectiveness for the implementation of risk-based design need to be further enhanced.

- The integration of data mining and pertinent uncertain reasoning techniques represents an important achievement in developing mathematical models containing multiple variables and, at the same time, describing them in an uncertain environment.

Chapter 4
Approach Adopted

4.1 Preamble

In chapter 3 a critical review has been undertaken for the state-of-the-art risk-based ship design methodology, and promising data mining techniques for risk modelling. The deficient areas within the current techniques for risk modelling and within the main sources of information for risk quantification have been highlighted.

The objective of this chapter is to explain the methodology that will be followed throughout this thesis. Following an outline of the approach on the basis of the background knowledge reviewed in Chapter 3, the detailed procedures are elaborated next.

4.2 Outline of the Approach

The key to understand the necessity of this research is to appreciate the difficulties that are being experienced for the implementation of risk-based ship design. Classical risk modelling techniques (i.e. fault and event trees) assume all events are independent. This raises concerns over the quality of the subsequent findings due to the potentially over-simplified models. A second observation, closely relevant, is the lack of the source of information for risk quantification, which leads to routine utilisation of subjective judgement. In cases where the performance-based first-principles tools are deployed for probability derivation, it can be extremely time-consuming to perform locally. The situation can be further complicated by the globally iterative ship design process.

On the other hand, the field of data mining, which is capable of sifting through large amount of data and revealing interested domain knowledge, is evolving at a fast pace nowadays. Particular attention has been paid to the application of data mining and the consequent model learning in both BNs and NNs due to their ability to describe complex relationships and present the findings probabilistically.

On this background, the approach adopted in this thesis has the following principal characteristics:

- Development of a generic framework for the next generation marine accident/incident database. Rather than serving the development of deterministic rules, this framework is designed to be risk-management-oriented by enabling knowledge transfer from the operational phase to the design purposes. It also integrates advance first-principles tools, including physical experiments, within the database so as to establish an all-embracing casualty-related knowledge base.

- Employment of advanced data analysis techniques to transform the knowledge base into risk models in the selected uncertain reasoning environment. The contribution is attributed to the discovery of complex correlations among multiple variables and to the derived probabilistic information to quantify the models.

- The developed risk models link directly design parameters with risk indicators so that the impact of various design alternatives on the risk level can be assessed instantly.

- Integration of the developed risk models for the implementation of risk-based ship design methodology. Particular attention is paid to the role of the models for safety performance assessment, its compatibility, and the subsequent decision support for alternative selection.

In so doing, risk assessment can be carried out with minimised intervention of subjective sources within the context of risk-based ship design. Rather than expensive case-specific analysis, much effort can be saved as the developed risk models contain information at parametric level. These elements will contribute to an objective, transparent, efficient, and knowledge-based methodological framework for the implementation of risk-based design.

4.3 Implementation Process

A three-stage process describing the approach that has been adopted in this thesis is summarised in the following lines.

Stage 1: Development of the Next Generation Marine Accident/Incident Database

The first stage aims at developing a framework for the next generation marine casualty database. Compared to the current databases, the proposed concept adopts a configuration where coupling between historical records and first-principles tools as sources of information for risk assessment takes place. Following the identification of principal hazards of the ship type under consideration, a high-level database configuration will be established under the concept of total risk. Subsequently a detailed list of parameters to be recorded in the database is obtained by using the hierarchical decomposition method. By doing so, each parameter finds its corresponding place in a structure for the quantification of ship life-cycle risk.

It is worth noting an important difference between the way that first-principles tools are deployed under the risk-based design methodology and how they will be used in the proposed framework. The current practice is to iteratively perform assessment on a case by case basis so that a specific design/configuration requires extensive simulations or experiments to derive probabilistic information. In contrast, the newly proposed framework aims to collect the data that is generated from first-principles tools and store it in the database. As the data is reusable, the accumulated information can be readily extracted to derive pertinent risk models. This will facilitate a fast and reliable execution of risk assessment.

The output from this stage is an all-embracing casualty-related database that is stored in a relational database platform, which is reusable, can be updated and queried.

Stage 2: Development of Risk Models through Data Mining

At this stage, data mining techniques are employed for model learning by using the data collected at Stage 1. Considering the selection of appropriate platform for risk modelling between BNs and NNs, as it has been summarised in Chapter 3, the former is a more transparent platform having sound mathematical foundation for performing probabilistic inference. Moreover, due to its flexibility and compatibility, it is interchangeable with the classical risk modelling techniques (e.g. event trees). Hence, BNs will be deployed for assisting further data mining activities.

Having identified the risk modelling platform, the detailed learning process will be presented. Through dependency analysis, a list of dependent and conditionally independent relationships can be identified. By following the algorithm of constraint-based learning, a BN diagram that entails all the discovered relationships is obtained. Consequently, the network diagram is quantified using a formalised methodology for parameter learning from the data. Apart from constraint-based learning, the score-based learning algorithm focuses on the joint probability distribution nature of a BN model to represent a data set.
The input required for this stage is a data set of significant size containing sampled data of the interested variables. With the developed program to automate the learning process, pertinent risk models can be developed in BNs.

Stage 3: Implementation of Bayesian Networks in the Risk-Based Design Methodology

The last stage focuses on the integration of BNs in the risk-based design methodology. Following the proposition of a practical design procedure, BNs are treated as an integral part of the whole process for safety performance assessment, and the ultimate decision support on design solutions selection. In the knowledge that technical performance, cost and earning potential needs to be considered as well to achieve a well-balanced design, the Analytic Hierarchy Process is deployed for such a multi-objective optimisation process. By doing so, the applicability of the proposed approach can be demonstrated for the implementation of risk-based ship design.

It has to be appreciated that BNs can be perceived both as high-level risk models and domain risk knowledge models. This is attributed to their ability to describe sequential events probabilistically as required for the risk model and their flexibility to include design and operational parameters for direct risk analysis of various design alternatives.

4.4 Closure

The approach adopted in this thesis has been outlined. The interrelationships among the three stages and their corresponding chapters are depicted in Figure 4.1. Detailed working principles, configurations, methodologies, techniques, and illustrative applications for each stage will be presented in Chapters 5, 6 and 7 respectively.

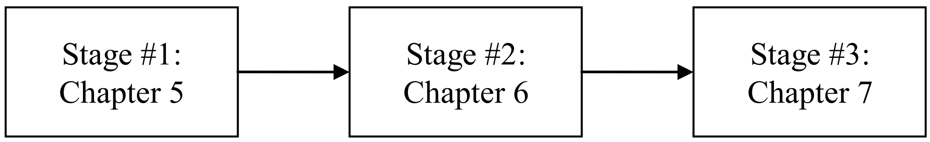


Figure 4.1: Structure of the implementation stages

Chapter 5

Marine Accident/Incident Database

5.1 Preamble

Great effort and resources have been spent across the maritime industry to investigate past accidents/incidents and to collect relevant information. The goal of this undertaking is to improve safety performance of the industry through learning from mistakes so as to prevent similar undesirable events from occurring in the future. On the other hand, the current approach concerning the investigation of marine casualties and the collection of pertinent data is rule-oriented and case-specific given the existing regulatory framework. This implies that a very limited portion of the information contained in the data is being used whilst the rest is left underutilised. Moreover, the lessons learnt, which lead to the changes of deterministic regulations, will most likely further tighten the design space. Thus, rather than a coarse deployment of this valuable resource of knowledge, a rationalised alternative utilising marine accident/incident data is needed.

In the meantime, a concurrent move of the industry is to seek a holistic and rational treatment of safety at design stage through risk-based design, by taking safety as an add-on objective and systematically integrating risk assessment in the conventional ship design process. Unsurprisingly, the ultimate goal is identical with the previous undertaking, nevertheless, rather than further reducing the design envelop this approach aims at design liberation and facilitation of innovative designs that cannot be approved under the deterministic regulatory framework.

As risk-based design methodology is still evolving, there are still a few obstacles that need to be addressed. With the emergence of an increasing number of first-principles tools which address various key issues regarding ship safety performance, the time-consuming feature has proven to be a drawback hindering risk-based design implementation at early design stage.

Based on the foregoing, this chapter focuses on the establishment of a framework for the next generation marine accident/incident database, so that it can be systematically integrated within the life-cycle consideration of ship safety. This chapter starts with the description of the main sources of information with particular emphasis on their configuration within the framework. As the core objective is to enable a reliable and objective source of information for supplying both qualitative and quantitative knowledge, the identification of dominant variables to be recorded are detailed next. Lastly, the chapter concludes with a comprehensive database platform that is dedicated for passenger ships.

5.2 Next Generation Marine Accident/Incident Database

The underlying philosophy of the proposed next generation database is in line with the current maritime accident/incident database: to learn from mistakes and to further enhance safety performance. Contrary to the rule-oriented and case-specific feature of the current approach, the next generation database will be integrated in the risk management process, with particular emphasis on the design stage. In this respect, an ideal configuration would be an all-embracing database that can be directly coupled with risk analysis and assessment, and provide a comprehensive and reliable source of safety-critical information.

The rationale for such a proposition is that the experience and the knowledge gained from operational non-conformities can be transferred and utilised for ship design, as illustrated in Figure 5.1. This is important for the maritime industry as such knowledge generally comes at a price of life loss, ships worth hundreds of millions, and considerable damage to the environment.

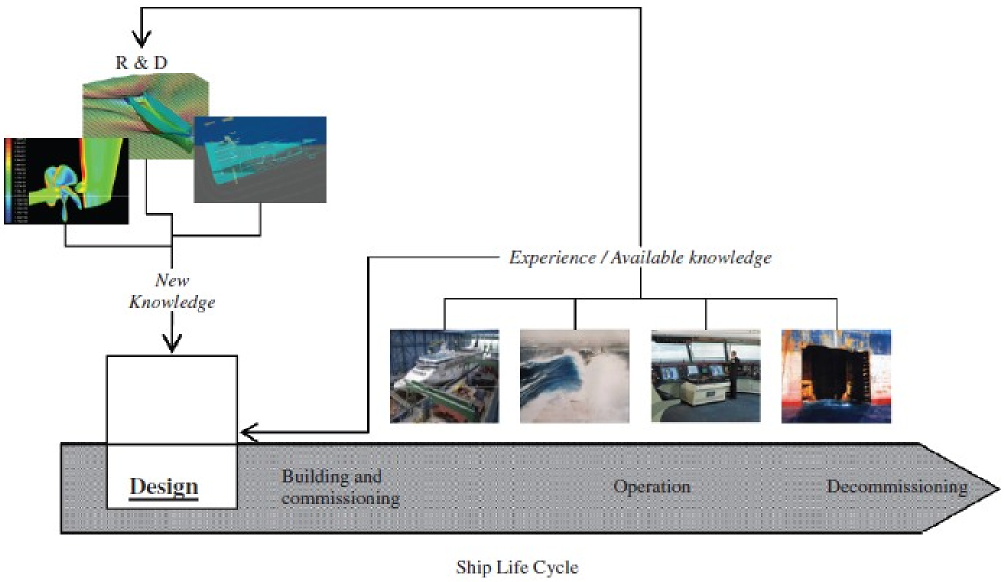


Figure 5.1: A "Common Sense" Approach to Ship Design [Vassalos, 2008b]

Moreover, it is indeed the design stage that holds the greatest freedom to make important decisions on the selection of key components that influence the ship performance, including safety, as illustrated in Figure 5.2. Hence, it has to be appreciated that analysing past casualties, deriving pertinent knowledge, and using it as early as possible in the design process should be treated as a lifecycle issue.

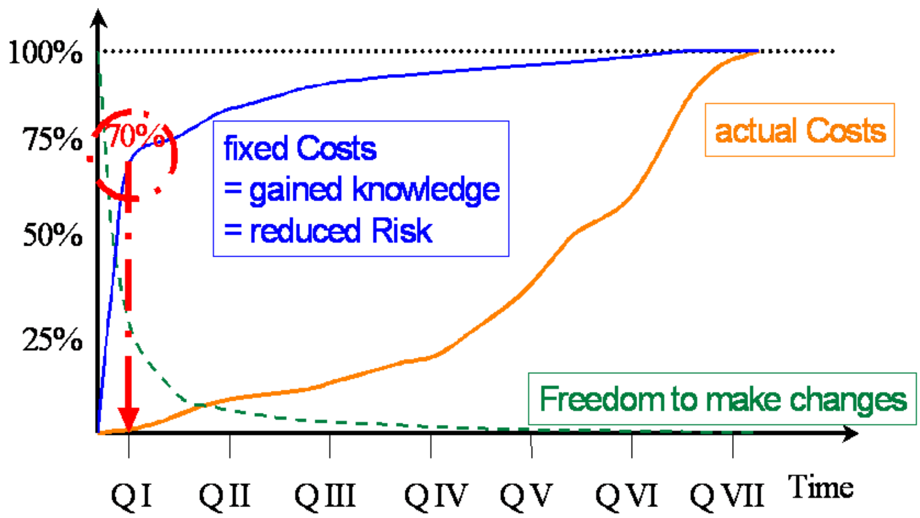


Figure 5.2: Relationships between Cost and Time in Early Design Phases [Brett, et al., 2006]

In light of the foregoing, this section focuses on the development of a high-level database framework to store casualty-related knowledge that is essential for risk assessment. It is important to remember that such source should not only provide quantitative information for the derivation of probabilistic information but also qualitative knowledge for risk model development. The emphasis is placed on the sources of information and their corresponding configurations.

In pursuit of such a database framework, the key is to identify the fields where the information is needed for risk assessment. This in turn leads to the determination of the principal hazards that are endangering the safety performance of passenger ships. As discussed in Chapter 3, historical data suggests the principal hazards of passenger ships are: collision, grounding, and fire. As a result, the risk components of each hazard need to be further investigated in order to determine the information needed.

Every accident is the result of a set of consecutive failures of both hardware and software safeguards, like technical failures, operating errors, design deficiencies, and management culture, etc., as illustrated in Figure 5.3. As far as technical safeguards are concern, there are mainly two types of them: one focuses on the prevention of accidents from happening and the other aims to mitigate the effects of their outcomes.

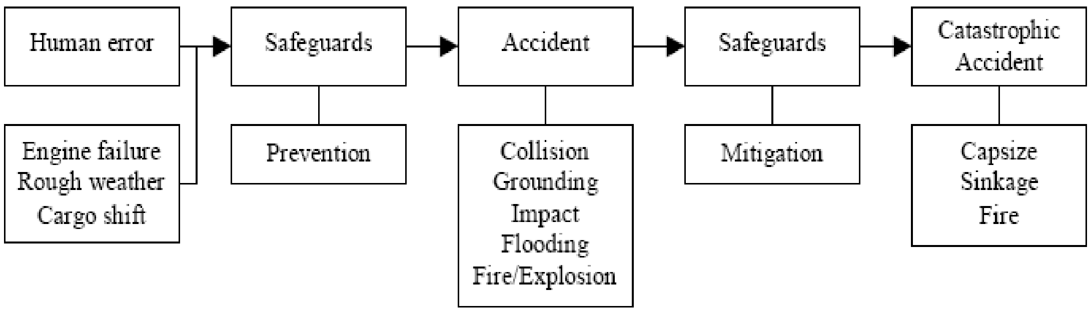


Figure 5.3: Chain of Events [Vassalos, et al., 2000]

Considering the safety level of a ship, its quantification relies on both the probability of having a certain accident, denoted by P_i, and the ensuing consequence in a quantified manner, denoted by C_i. The estimation of both probabilities and consequences requires relevant data. For instance, the data on accident causes contributes to the derivation of accidental probabilities (frequencies); the data on the consequential and evacuation process is essential for estimating the societal consequence. In this respect, it is certain that the employment of subjective resources, i.e. experts' opinion, should be minimised to assure an unbiased assessment. Fortunately, with great effort that has been devoted to the investigation of past maritime casualties, the development of first-principles and performance-based tools for analysis of the key areas affecting ship safety, and the exploitation of model experiments, the promising sources of information for the next generation maritime database with the aim of risk management embedded would be: (i) historical maritime accident/incident data, and (ii) first-principles approaches (i.e. computer-based simulations, experiment results). Both of them will be further analysed next.

5.2.1 Historical Accident/Incident Data

This source of information refers mainly to the accident records in the databases of various organisations, like international regulatory authorities, regional and national authorities, classification societies, maritime professional bodies, etc. In the knowledge that the level of detail varies in different databases, such resource should be utilised as long as proper processing can be performed for standardisation, which will detailed in Section 5.3.

On the other hand, it has been stressed in Chapter 3 that the data recorded with the aforementioned sources are mainly accidents that have significant negative consequence and the importance of incident (near-miss) data should never be overlooked. The latter source is also included within this framework in order to capture a broader picture. Such information is normally available with ship operators due to ISM requirements. A summary of the available sources of information is tabulated in Table 5.1.

Table 5.1: Sources of Historical Marine Accident/Incident Data

Categories	Organisation	Systems
International regulatory authorities	International Maritime Organisation, (IMO)	Global Integrated Shipping Information system (GISIS)
Regional/ national authorities	Marine Accident Investigation Branch (MAIB), UK	Marine Incident Database System (MIDS)
	European Maritime Safety Agency, (EMSA)	European Marine Casualty Information Platform, (EMCIP)
	United States National Transportation Safety Board, (NTSB)	Web-based platform
	Australian Transport Safety Bureau, (ATSB)	Web-based platform
	Transportation Safety Board of Canada, (TSBC)	Web-based platform
	Danish Maritime Authority, (DMA)	Web-based platform
	Accident Investigation Board of Finland, (AIBF)	Web-based platform
Classification societies	Lloyds' Register, (LR)	IHS Fairplay Sea-Web
	American Bureau of Shipping, (ABS)	RootCause LEADER
Ship operators	Cruise Liners, Ro-Ro Passenger ships, etc.	In compliance with Safety Management System (SMS), ISM code
Maritime professional body	Nautical Institute	Mariners' Altering and Reporting Scheme, (MARS)
	International Association of Independent Tanker Owners (INTERTANKO)	Tanker incidents database

5.2.2 First-Principles Approaches

Besides historical casualty information, it is important to include the data generated through computer-based simulations and model experiments. In this respect, it has to be appreciated that the key difference between the proposed approach and the usual handling. The current practice towards first-principles approaches tends to deploy it for "on-site" application on a case-by-case basis, in which the safety performance of a specific design, configuration, or feature requires a dedicated model (physical and virtual) to be developed before any computation can be performed. In contrast, the proposed approach aims to collect the data generated from first-principles approaches in a general manner in advance so that the corresponding data can be extracted and utilised directly if risk models need to be developed. In this way, the data generated in the previous studies is reusable for the future analysis of similar subject. With the progressive accumulation of data from first-principles approaches one can bypass their time-consuming features and still achieve an efficient and objective analysis.

As first-principles tools are constantly developed and fine-tuned, information from subjective sources progressively acquires a complementary role in the process. This method is inherently based on performance assessment. The deployment of properly validated first-principles tools has proven to be an important means for risk analysis as it has been discussed in Chapter 3. A list of examples of the simulation software that is capable of evaluating the performance of several mitigative measures influencing the total risk of a design is provided in Table 5.2.

Table 5.2: Examples of Computer-based Simulation Software, [Mermiris and Langbecker, 2006]

Key issues	**Engineering analysis**	**First-principles Tools**
Breach of hull following collisions/ groundings	Structural failure	ANSYS, LS-DYNA
Water ingress, flooding, capsize, sinking	Progressive flooding simulations in time domain/transient stages/in waves	NAUTICUS (DNV), WASIM (DNV), PROTEUS (SSRC)
Emergency evacuation (escapes, assembly, embarkation into LSA)	Agent-based simulation of pedestrian dynamics	EVI (SSRC), AENEAS (GL), EXODUS - Maritime (UoG)
Fire ignition, growth	Dispersion rate of smoke, oxygen levels and visibility as a function of time	Fire Dynamics Simulator (FDS), Smokeview, CFAST, CFX, Less FIRE, MRFC

These tools provide a promising environment in the sense that the casualties occurred in the past can be studied in detail by modelling and simulation without any substantial cost. The data collected through experiments is another credible source of information. This can be carried out through testing on scaled model tests in a towing tank facility or full scaled models (e.g. cabin fire test).

5.2.3 Database Configuration

It is worth noting that different data sources play distinct roles in quantifying various constituent elements within the total risk framework, as illustrated in Figure 5.4. Due to the nature of maritime accidents, historical data become progressively available in the public domain. Disregarding the "ragged" details of each record due to lack of standardised accident reporting schemes, it is relatively easy to derive the probability (frequency) by considering that the data is virtually "sampled" from the real world. However, as maritime accidents are characterised by low frequencies and high consequences, and understanding that to record the statuses of various key parameters and factors (e.g. water ingress, heeling motion, etc.) in emergency situations is a difficult task, historical data will not suffice for the analysis. The situation becomes even more difficult when it comes to post-accident system availability and evacuation analysis where extremely rare historical information is available. In contrast, data generation through first-principles approaches is a powerful avenue to complement relevant information.

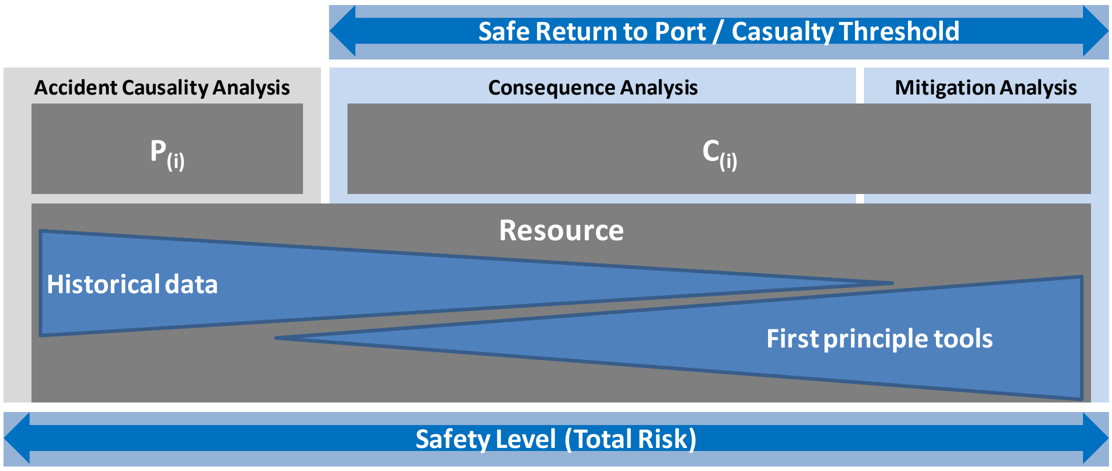


Figure 5.4: Configuration of Accident/Incident Data Sources

A further elaboration of this situation is provided in Table 5.3. With respect to the pre-casualty phase of collisions and groundings, historical accident/incident data plays a dominant role. Contrary to the breach sizes and mitigation options, where the source of information is obtained mostly by first-principles tools for post-casualty phases. A similar situation is encountered for fire events as well.

Table 5.3: Casualty Types Vs Sources of Information

Casualty type	Phases	Detail fields needs data	Source of information
Collision & Grounding	Pre-casualty	Causation	Historical data
	Post-casualty	Escalation	Historical data First-principles tools
		Flooding survivability	
		System availability after flooding	
		Evacuation & Rescue	
Fire	Pre-casualty	Causation	Historical data
	Post-casualty	Escalation	Historical data First-principles tools
		System availability after fire	
		Evacuation & Rescue	

Having identified the sources of information for various phases of casualties, the resulting situation is a set of data collected/generated from various sources, which gives rise to the configuration of the next generation database, as depicted in Figure 5.5. Historical data and first-principles tools are utilised and integrated for supplying the information on the three principal hazards concerning both pre-casualty and post-casualty phases. With respect to the mitigation analysis, such as post-accident system availability and evacuation, first-principles tools play the dominant role in providing the relevant information.

The key difference of such database in comparison to the current practice is that it is risk-management-oriented in a way that each parameter recorded has its corresponding place for risk quantification under the concept of total risk. Thus, compared to the descriptive text in the current database, the approach proposed in this chapter will be liberation for such precious resource to be utilised for exploring its full value and potential.

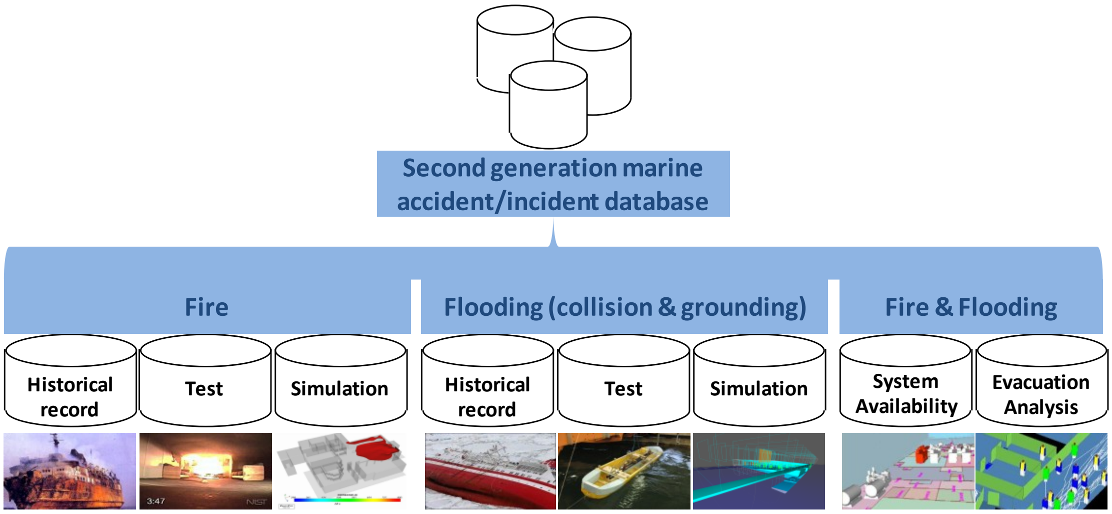


Figure 5.5: High-Level Configuration of the Next Generation Marine Accident/Incident Database

In pursuit of such a framework, the key element would be a list of parameters to be recorded in the database and to be used as the input for risk assessment. Certainly, it would not be feasible or practical to record hundreds of thousands of elemental parameters determining the exact safety level of a passenger ship. In the knowledge that the fundamental objective is to provide a transparent and well-informed platform for decision making on the selection of feasible solutions at the design stage, it will be much more efficient to focus on dominant variables and achieve a fast and accurate approximation of the estimated risk level. This will be elaborated in detail in the next section of this chapter.

5.3 Dominant Variables Identification

"Embedded in the mud, glistening green and gold and black, was a butterfly, very beautiful and very dead. It fell to the floor, an exquisite thing, a small thing that could upset balances and knock down a line of small dominoes and then big dominoes and then gigantic dominoes, all down the years across Time." [Bradbury, 1952]

The butterfly effect was first seen in [Bradbury, 1952] and ever since it is frequently used to explain the chaotic phenomenon [Smith, 2007]. A concise summary of the chaos theory is that "everything is linked", which could also be stated for the subject of ship safety. The total risk of a ship is affected by a large amount of factors, which can be grossly classified into two layers: visible and invisible, as illustrated in Figure 5.6. The visible layer refers to those variables that are physically traceable and recordable given the state-of-the-art technology. The invisible layer includes the variables which are difficult to quantify, e.g. safety culture.

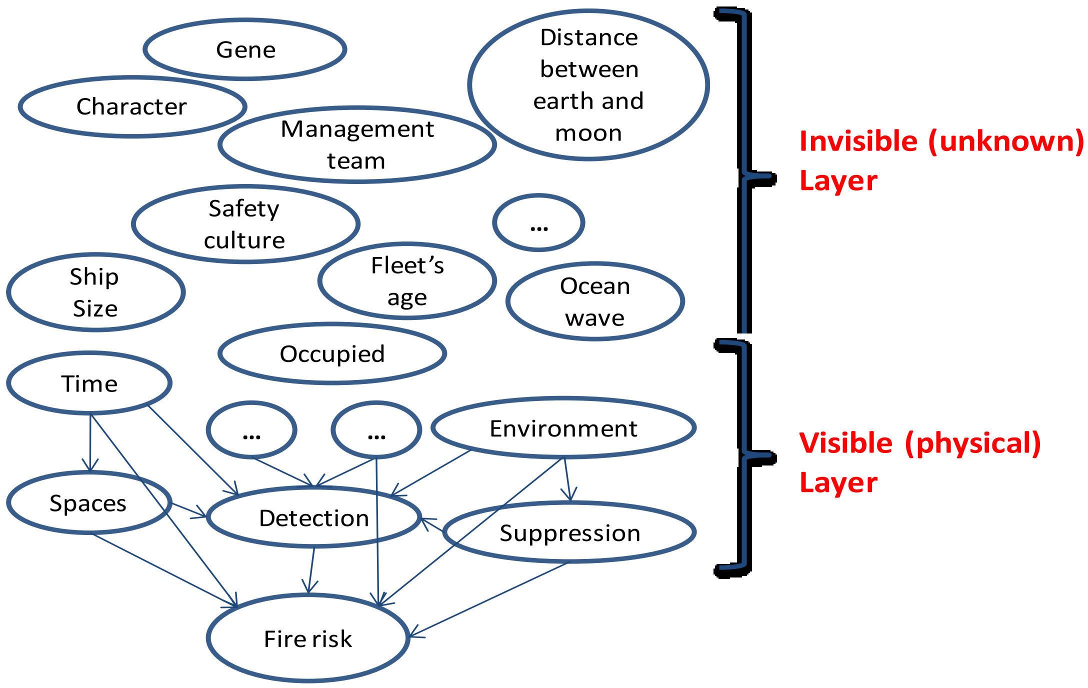


Figure 5.6: An Illustration of Visible and Invisible Layers Influencing Shipboard Fire Risk

The current practice on identifying the variables for risk assessment lies mainly in the visible layer, while the remaining factors, which in fact are the main sources of chaos, are omitted. This practice is justifiable as the available resource is always limited by a number of physical restrictions, e.g. budget, schedule, technology, etc. Moreover, with the development of mathematical theory for uncertainty quantification, the chaos can be measured and managed in a scientific manner. For instance, confidence intervals can be estimated through statistical analysis and the probabilistic distribution of interested variables can be quantified using Bayesian statistics. Hence, it is deemed appropriate to claim that any event can be modelled by a handful of variables with reasonable accuracy.

Stemming from this statement, an important and immediate task is to identify an effective means for determining a list of variables concerning the hazard under consideration. In principle, sensitivity analysis is needed to identify the variables that have more influences on the outcome than others. However, given the state-of-the-art mathematical models, which are not mature enough to accommodate smooth implementation, an alternative is needed.

In the knowledge that the up-to-date risk models developed through a number of large-scale research projects (e.g. HARDER, SAFEDOR) take the advantage of years of continuous effort and knowledge accumulation in understanding the relevant phenomena, an important assumption is that the variables included in those risk models can be regarded as a credible and well-documented pool of resources concerning the key characteristics of the interested hazards.

It is understood that one may concern the possible overlook of some potentially hazardous scenarios that are not encountered before. In this context, it is worth mentioning the following safeguards to minimise the chance of possible negligence:

- The identification of important variables through existing up-to-date risk models should be carried out in a conservative manner. This can be achieved by including those identified variables in the background material during the course of risk model development. It will be further safeguarded as the selected risk modeling tool - BNs, as an offshoot of the influence diagram [Kjaerulff and Madsen, 2008], is capable of depicting complex relationships among a diverse set of variables. This implies that the redundant variables will be excluded from the model.
- As incidents can be regarded as the precursors of similar accidents, maritime incident data should also be included so that the chance of missing those less frequent but potentially devastating scenarios can be minimized.
- Due to the flexibility offered by BNs, variables can be easily included at various stages as long as it is deemed necessary.

Hierarchical Decomposition Process

In order to facilitate the process of dominant parameters identification, a hierarchical decomposition approach is proposed for systematic break down of the total risk and its constituent elements up to a level where the physical parameters having significant importance to the safety performance of specific issues can be identified.

Through systematic decomposition of the key risk elements into various safety performance aspects and ultimately linking each one with dedicated ship design issues which are governed by only a handful of design variables, the basic ship design parameters can be linked with both safety performance parameters and the total risk, as illustrated in Figure 5.7. A unique advantage of such a structure is that the complexity of the problem under consideration can be greatly simplified as one can address a single design issue at a time.

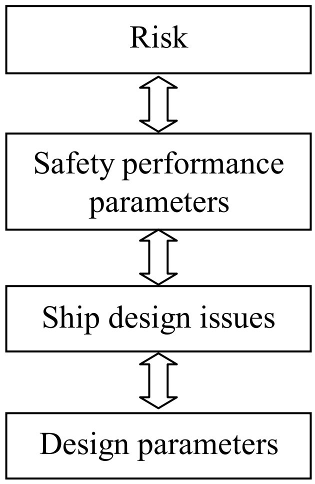


Figure 5.7: Links between Design Parameters and Ship Total Risk

To carry out the hierarchical decomposition process, the emphasis is placed on the key risk contributors. In the case of passenger ships, the total risk should be sought through analysing the principal hazards: collision, grounding and fire hazards. Moreover, on the basis of the definition of the risk, its quantification for a design concerning hazards, like collisions, groundings and fires, can be estimated through the product of a number of probabilities defining critical scenarios and the ensuing societal consequences, as illustrated below [Vassalos, 2004b].

$$R_{collision} = P_{collision} \cdot P_{water\_ingress|collision} \cdot P_{failure|water\_ingress|collision} \cdot C_{collision}$$

$$R_{ground} = P_{ground} \cdot P_{water\_ingress|ground} \cdot P_{failure|water\_ingress|ground} \cdot C_{ground}$$

$$R_{fire} = P_{ignition} \cdot P_{growth|ignition} \cdot P_{escalation|growth|ignition} \cdot C_{fire}$$

As a result, ship parameters that play important roles in quantifying the aforementioned risk components should be identified. In relation to this, it has shown that the status (values) of each risk component is dominated by a few performance parameters. The identification of pertinent safety performance parameters should be considered from the point of view of estimating the effectiveness of various preventive and mitigative measures.

For instance, in the case of collisions and groundings, the preventive measures include mainly effective navigation and manoeuvring as far as the design is concerned. This is because the performance of navigation, propulsion and manoeuvring systems is important to ensure that the action needed can be executed in time to avert a collision / grounding. On the other hand, mitigative measures include structural capacity, resistance to capsize after flooding, evacuation, etc. An example of the links between risk components and safety performance parameters concerning collisions and groundings is tabulated in Table 5.4.

Table 5.4: Links between Risk Components and Examples of Safety Performance Parameters concerning Collisions and Groundings

Risk components		**Safety performance parameters**
$P_{collision}$ P_{ground}	Probability of collision/grounding	Reliability of navigation system
		Reliability of manoeuvrability
$P_{water\_ingress\|collision}$ $P_{water\_ingress\|ground}$	Probability of water ingress due to collision/grounding	Structural capacity / crashworthiness
$P_{failure\|water\_ingress\|collision}$ $P_{failure\|water\_ingress\|ground}$	Probability of failure (capsize/sinking/collapse) due to water ingress and collision/grounding	Time to capsize/sink/collapse

$C_{collision}$ C_{ground}	Consequences	Post-accident system availability
		Time required for abandonment

In comparison, fire onboard is a much more frequent event and its occurrence is greatly influenced by local environment and conditions (e.g. usage, fire load, occupancy characteristics). In this case, the preventive means is sought through the operational aspect. As a result, mitigative measures are the main focus as far as the design is concerned. Both manual and automatic detection systems and the corresponding suppression systems are the means to contain the fire within the space of origin. Local fire containment systems (insulation boundaries, etc.) and evacuation means provide additional layers of safeguard that influence the total fire risk. An example of the links between risk components and safety performance parameters for fire event is illustrated in Table 5.5.

Table 5.5: Links between Risk Components and Safety Performance Parameters for the Fire

Risk components		**Safety performance parameters**
$P_{ignition}$	Probability of ignition	Space-specific ignition frequency
$P_{growth\|ignition}$	Probability of fire growth due to ignition	Reliability and effectiveness of detection and suppression systems
		Fire load
$P_{escalation\|growth\|ignition}$	Probability of escalation due to growth and ignition	Effectiveness of insulation
C_{fire}	Severity of consequence	Post-accident system availability
		Time to reach untenable conditions
		Time required for abandonment

As a result, the identification of dominant variables needs to be performed through modelling the influence of basic design variables with the safety performance parameters. In this respect, a number of models and tools have been developed as it is discussed in Chapter 3.

In the case of collision and grounding safety, from the design point of view the reliability of navigation is influenced mainly by the bridge layout design and the performance of navigational systems. An example of such link is tabulated in Table 5.6.

Table 5.6: Links between Safety Performance Parameters and Detailed Design Issues concerning Collisions and Groundings

Safety performance parameters	Design issues
Reliability of navigation system	Bridge layout Navigational system
Manoeuvrability	Hull shape Propulsion system Steering system
Structural capacity	Scantlings Structural material Structural arrangement
Time to capsize/sink/collapse	Watertight subdivision Tank arrangement Anti-heeling system
Post-accident system availability	Shipboard system arrangement
Time required for abandonment	Escape route Internal layout LSA

In the case of fire safety, the automatic detection system for fire hazard is linked with the selection of local detection systems (concerning reliability and effectiveness) and the layout design (concerning the density and arrangement of detectors within specific space). Table 5.7 exhibits such links between safety performance parameters and design issues for fire safety.

Table 5.7: Links between Safety Performance Parameters and Detailed Design Issues for the Fire

Safety performance parameters	Design issues
Space-specific ignition frequency	Fire fuel load and layout Heat source and layout
Reliability and effectiveness of detection and suppression systems	Detection and suppression systems selection & layout
Time to reach untenable condition	Fire load Ventilation system Insulation grade (Boundary classes)
Post-accident system availability	Shipboard system arrangement
Time required for abandonment	Escape route Internal layout LSA

The level of detail needed to produce the baseline design at early stage is limited when comparing with the detail design stage. Consequently, each design issue can be described by a handful of design parameters at a reasonable resolution. For instance, the bridge layout includes the installation of the ECDIS system, the AIS system, ergonomics, area complexity, number of work stations, and types of alarm management systems, etc.; the hull shape is determined by ship length, breadth, depth, block coefficient, presence of bulbous bow, type of stern, etc.

Apart from design parameters, it is also noted that the environmental variables, in the wider sense like sea state and traffic characteristics of the operational route, should also be included as the scenario-specific variables to assist the risk quantification process. The scenario-specific variables may cover the following aspects:

- Traffic characteristic (e.g. density)
- Sea area (e.g. depth, topography)
- Sea state (e.g. wave height, wind, current)
- Loading conditions
- Time of day
- Etc.

5.4 A New Database

In order to demonstrate the applicability of the concept for the next generation maritime accident/incident database, a software platform has been developed for passenger ships, as illustrated in Figure 5.8, with the aim that the data can be collected, stored, retrieved and integrated in the data mining system for the implementation of risk-based ship design methodology.

Considering what influences both the pre-casualty and post-casualty phases of the principal hazards of passenger ships, it is essential for the new database system to contain key information of the following seven modules:

- Vessel information
- Voyage condition
- Critical systems (Hull/Machinery/Equipment)
- Collision
- Grounding
- Fire
- Consequence

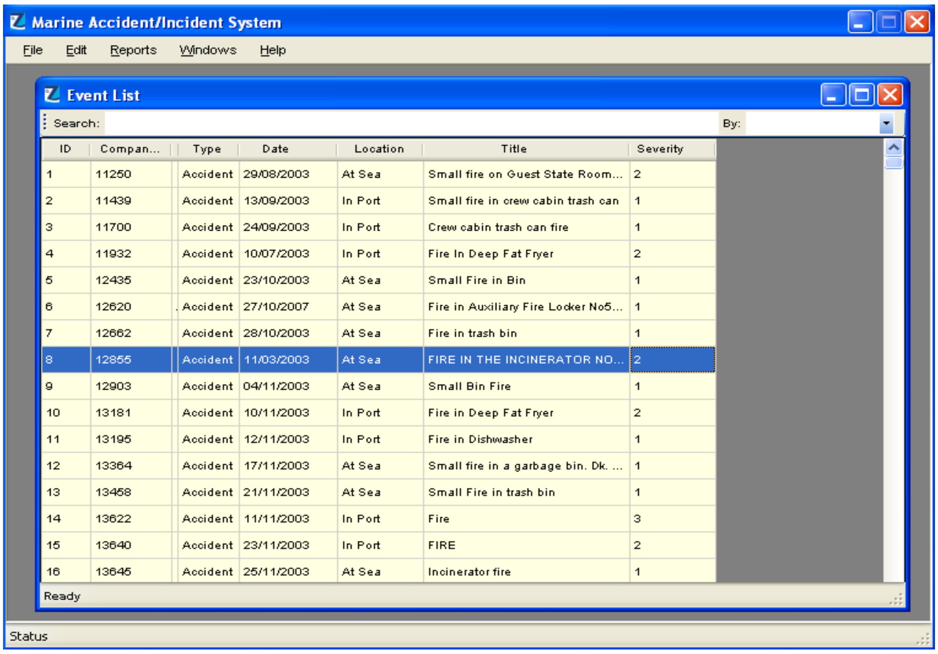


Figure 5.8: A Snapshot of the Developed Marine Accident/Incident System

Moreover, for the sake of database functioning and bearing the specially concerned safety issues in mind, another three modules are included in the system: (i) general information, (ii) root cause analysis, and (iii) human factor. A unique advantage of such a system is that most of the parameters recorded have their designated places for total risk quantification. In the meantime, it is important to ensure that the parameters are recorded in a standardised way so that data processing can be carried out easily. Due to the categorical nature of the majority of the design variables for risk assessment, most of the parameters are encoded into a predefined format where users only need to select the most appropriate option rather than to define arbitrarily.

For the functioning of the database and the subsequent data processing, technical assistance in the fields of relational database technology and distributed application architecture is discussed in Appendix 3.

The following paragraphs focus on detailed description of the variables to be recorded within the proposed framework. Particular emphasis is placed on the investigation of the principal hazards (i.e. collision, grounding, and fire) and the subsequent analysis of root-causes. Detail description of the variables and their corresponding statuses are contained in Appendix 4.

- General Information

The first module, as illustrated by the top section of Figure 5.9, is designed to cover general information that abstractly describes and classifies a record. Parameters like ID, title, etc. will not eventually contribute to the data processing phase. Nevertheless, they are included for clarity of the system.

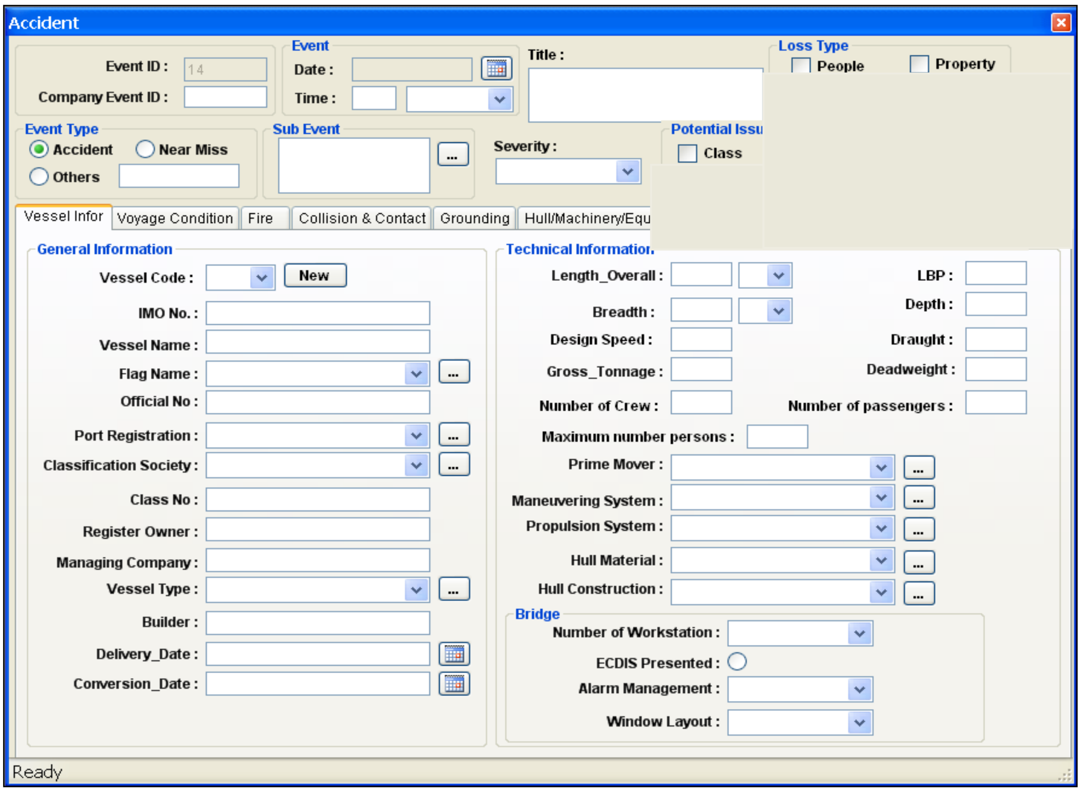


Figure 5.9: General Information and Vessel Information Modules

- Vessel Information

The vessel information module, as depicted by the bottom section of Figure 5.9, aims to record the information about ship particulars that describing the key characteristics. It contains classification statuses, physical dimensions, bridge design information, etc. This module should provide a throughout scan of the ship so that an overview can be gained and important information on ship parameters can be collected.

- Voyage Condition

Historical tragedies suggest the environmental conditions play an important role for a fully-developed accident, e.g. MV Estonia [Estonia, 1997], Salem Express [BBC, 2006], and MV al-salam Boccaccio 98 [IMO, 2010b], hence, situation-specific variables (e.g. ship location, voyage phase, visibility, sea state, and wind speed) are included to describe the conditions of the surrounding environment.

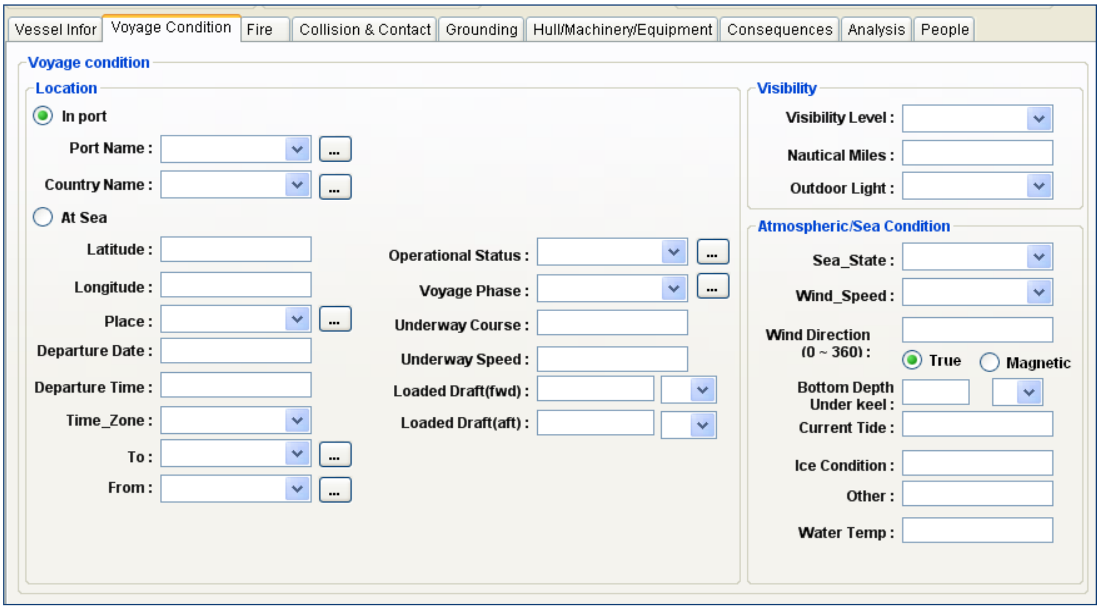


Figure 5.10: Voyage Information Module

- Critical systems (Hull/machinery/equipment)

As far as passenger ship principal hazards are concerned, the failures of critical hull/machinery/equipment can be vital initiating events to their occurrence. In this respect, the critical systems, the failure of which could potentially lead to the occurrence of the principal accidents, are included. For instance, the failure of propulsion systems can lead to a collision within intense traffic waters and the grounding in complex areas. Eventually, hull structures, propulsion systems, steering systems, navigational systems, and electrical systems are identified, as illustrated in Figure 5.11.

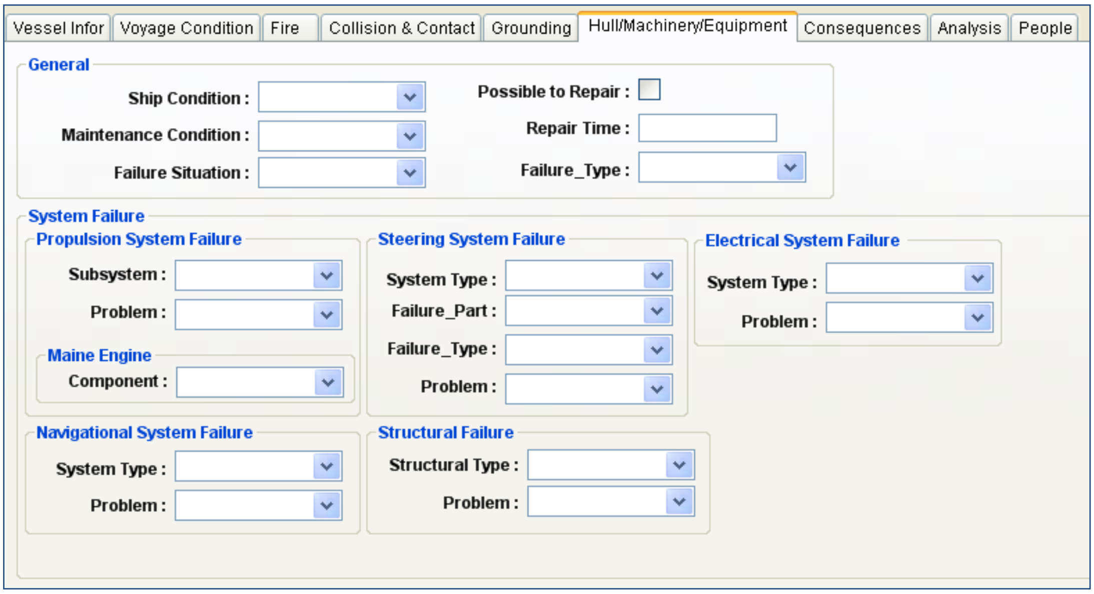


Figure 5.11: Hull/Machinery/Equipment Failure Module

- Collision

Collision is one of the major threats to passenger ships. This module, as shown in Figure 5.12, includes both collision and contact events as they share similar characteristics except that the ship is struck by another ship for a collision accident whilst the ship is struck by an external object for a contact accident. Although the contact is not among the principal hazards of passenger ships, it is included for the purpose of generalisation of the database system.

For the prevention of collisions/contacts, great attention has been paid to the bridge design. The parameters, tabulated in Table 5.8, distinguish powered collisions and drifted collisions as the energy released from the two categories varies dramatically. This can potentially influence the ensuing consequences of the accidents. Moreover, the sequence of a collision is broken into phases containing event detection, manoeuvre planning and manoeuvre execution. For collision detection, the information on both human factors and navigational aid equipments is recorded, while the manoeuvring phase focuses on the necessary timeframe to be performed.

Table 5.8: Important Parameters Recorded for the Collision

Type	To identify whether it is a powered collision or drifted collision.
Complexity, Traffic intensity	It aims to record the area complexity for navigation and the traffic intensity as they determine the number of distractions that the officer on watch (OOW) needs to be aware of.
Initial distance, speed, angle between	The initial distance that both ships are on collision courses, the speed of both ships and the angle between them would directly affect the time available for the OOW to react.
Own ship	This field indicates whether the own ship is the striking ship or the struck ship as the latter is likely to suffer more serious consequence.
Scenario	It defines the collision scenario as the own ship may collide with a meeting vessel, a crossing vessel, or an overtaking vessel.
Ship in lane (ship type, speed, size)	Information about the ship in lane, e.g. type, speed, size, which is used to record the basic facts of the ship being collided with.
Contact scenario	In the case of contacts, the object that the ship contacts with is needed, e.g. icebergs, offshore platforms, bridges, etc.
First detection	To trace how an emergency situation is firstly detected, either by visual means or navigational instruments.
Manoeuvre (time detect, time plan, time manoeuvre)	As time is the crucial factor for collision prevention, the detailed manoeuvring operations are recorded.
Officer on watch, officer number 2, pilot	Once detected, the situation is influenced by the actions taken by the crews on the bridge.
Navigational aid detection (radar system, ECDIS, AIS, etc.)	This field concerns the performance of navigational instruments/systems.
Communication between two ships	The communication between two ships is also an important factor to minimise misjudgement.
Clarity give way, give way situation, give way occur	According to the International Regulations for Preventing Collision at Sea (COLREGS) [Cockcroft and Lameijer, 1996], the give way situation is also one of the major concerns for ship collision.
Steer failure	The failure of steering systems can be critical when urgent manoeuvring operations are needed.
Tug deployed	In drifted situations the employment of tugs can be an important factor to reduce the chance of collisions.

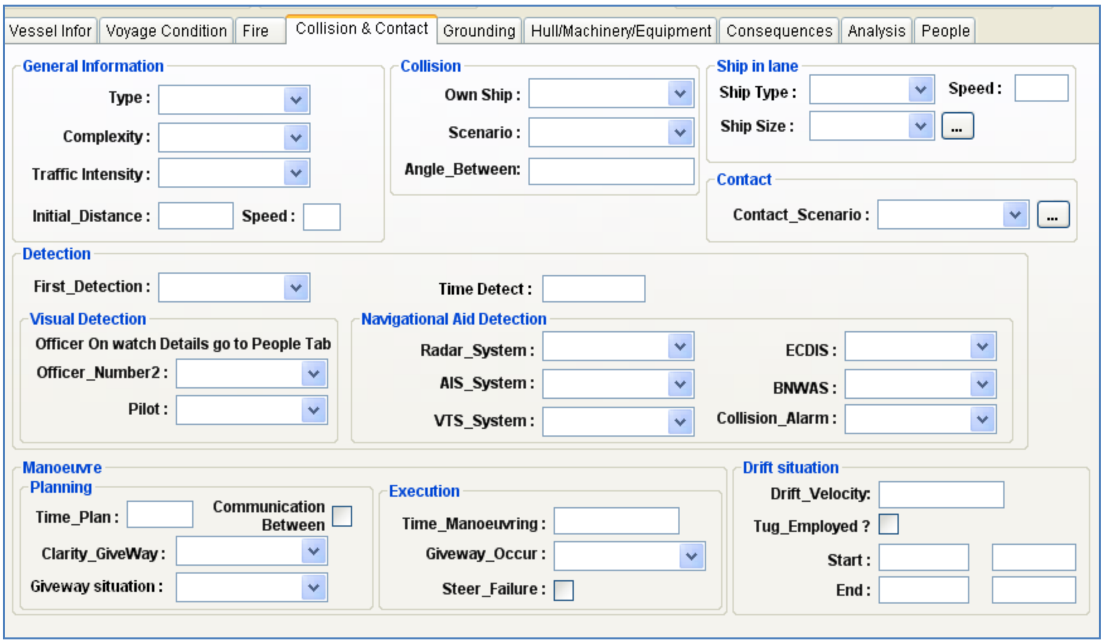


Figure 5.12: Collision and Contact Module

- Grounding

Ship grounding shares notable similarities with the collision, where early detection plays a significant role on the prevention of its occurrence. Nevertheless, the grounding is more sensitive to the safety culture of ship operators regarding route planning and updating. Furthermore, one factor needs to be taken into account is the obstacle that the ship grounds with, which may be submerge rocks or beaches (sand). Different types of obstacles may lead to significantly different damage extent, which in turn determines the time needed to sink the ship. Table 5.9 and Figure 5.13 illustrate the list of variables to be included in this module.

Table 5.9: Important Parameters Recorded for the Grounding

Grounding type	Grounding events can be categorised into powered groundings and drifted groundings.
Grounding with	The consequence of groundings is influenced by the hardness of the object that the ship grounds with, e.g. rocks, sands, large and visible obstacles, and unmarked invisible obstacles, etc.
Area complexity, traffic intensity	It records the area complexity for navigation and the traffic intensity as they determine the number of distractions that officer on watch needs to be aware of.

Update routine, passage planning	Proper and frequent update of routine and passage planning is critical in avoiding groundings, in which, on another side, it also reflects the safety culture of ship operators.
Initial distance, speed	They are important in determining the time available for the ship to respond prior to groundings.
Officer on watch, officer number 2, pilot	Once detected, the situation is influenced by the actions taken by the crews on the bridge.
Chart visibility	The chart visibility aims to record how well the obstacle is displayed on the map.
Light marked	Indicates whether the obstacle is marked by lights for visual detection at night.
First detect, time detect, time plan, time manoeuvre	To trace how the emergency situation is firstly detected, either by visual means or navigational instruments.
Navigational aid detection (Radar system, echo sounding, AIS system, ECDIS, VTS system, Bridge Navigational Watch Alarm System)	The ECHO system is employed to give an early alarm for a potential grounding accident, which is an important preventive measure for the avoidance of the grounding. Other than the ECHO system, the remaining functions of navigational aid systems/instruments are similar to those deployed for collision prevention.
Steer failure, tug employed, Start (latitude, longitude), end (latitude, longitude)	The failure of steering systems can be critical when urgent manoeuvring operations are needed.

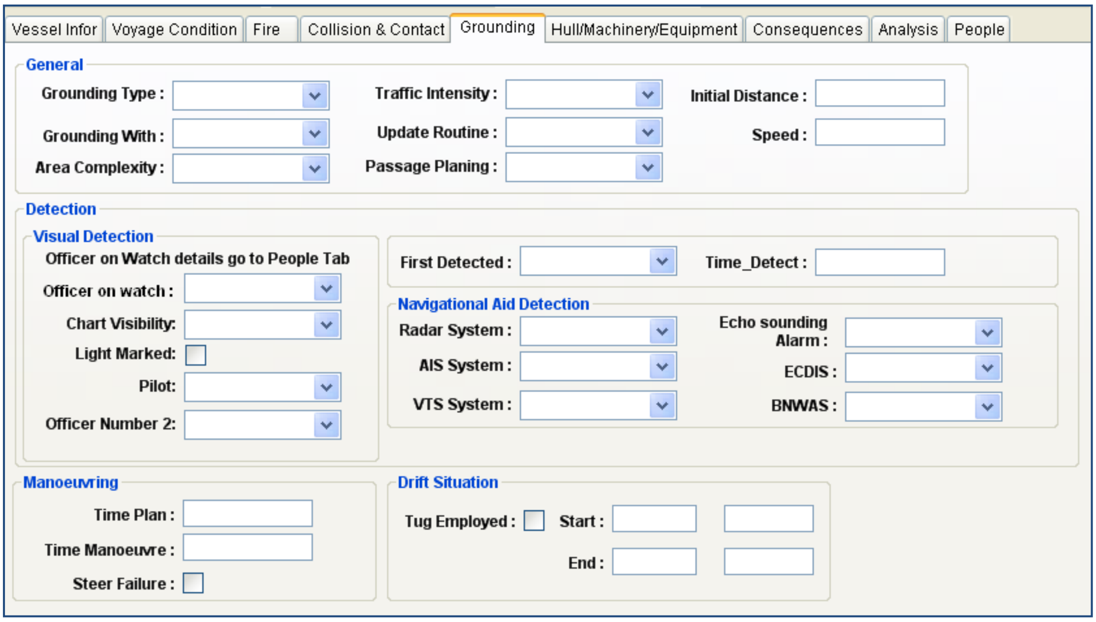


Figure 5.13: Grounding Module

- Fire

The fire event module deals with the factors influencing various phases of a fully developed fire: ignition, containment, escalation, and evacuation, as illustrated in Figure 5.14. The ignition phase addresses the likelihood of fire occurrence; the containment phase records the actions that are taken to contain the fire; lastly, the last phase contains information about the evacuation operations once the fire escalates from the space of origin. Table 5.10 exhibits the important parameters recorded in the database concerning the fire event.

Table 5.10: Important Parameters Recorded for the Fire

Location	The characteristics of local environment determine fire loads, possible causations, insulation boundaries, etc. Hence, the usage of the space onboard plays an important role.
Source of ignition, ignition mass	In this case, the source of ignition and ignition mass are useful to investigate preventive measures.
Detection means	As time is a crucial factor to mitigate the consequence, this field is designed to record by which means the fire was firstly detected. This could be fixed detectors, crew members or passengers.
Smoke detector, Heat detector (presented, activated)	Fixed detection systems are important for early alert of the bridge so that proper actions can be taken in time.
Suppression means	Fire suppression, both with fixed and portable suppression systems, is an important safeguard to contain the fire within the space of origin.
Fixed suppression system (installed, activated, contribute) Time to control and extinguish	In the case of a fixed suppression system, these fields are designed to records its corresponding reliability and effectiveness.
Crew presence	Crew members are properly trained to handle various shipboard emergencies. Hence, their presence in the first place should have positive impact to the fire fighting process.
Boundary cooling	Boundary cooling is the last safeguard to prevent the fire escalating from the space of origin.
Fire spread (number of adjacent spaces, space uses)	This field records the detail of adjacent spaces in case the fire spreads.
Evacuation zones	The number of passengers and crew in various zones and their reaction speed could be crucial for the whole evacuation process.

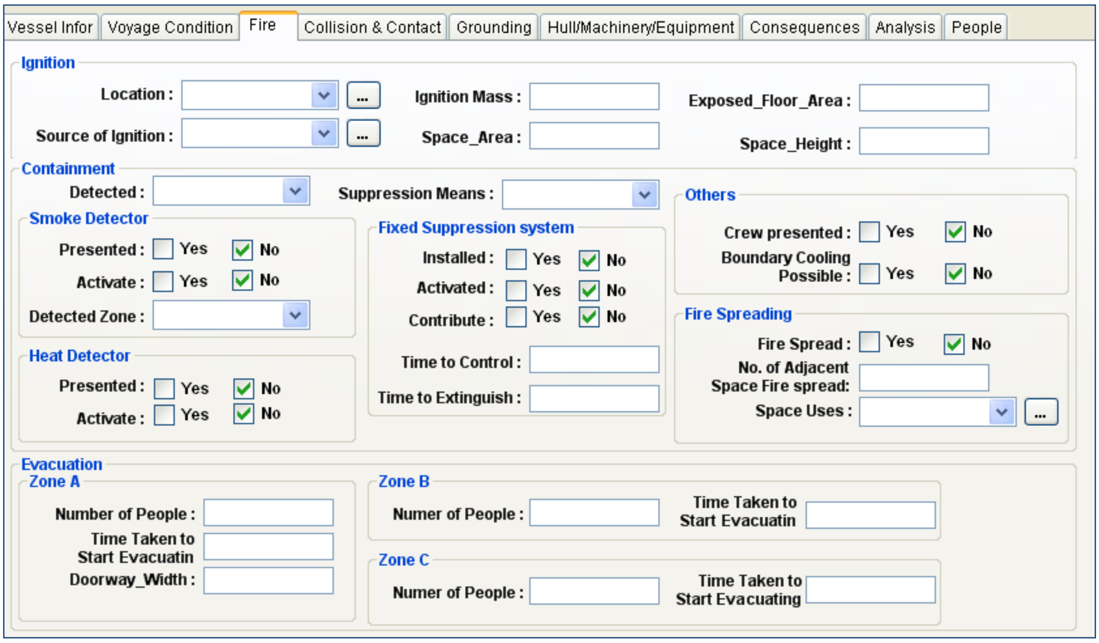


Figure 5.14: Fire Event Module

- Consequence

The consequence module is designed to capture the damages to the passengers, the crews, the environment, and the ship herself. Nevertheless, it is understood that a well-organised evacuation is an essential means in minimising the consequences. Hence, the timeline information of possible containment endeavour is included as well. Consequently, this module contains vessel status, type of flooding, mustering status, evacuation, time issues, and the quantified damages, as illustrated in Figure 5.15.

- Root-Causes analysis

In Chapter 3 it was discussed that various theories have been proposed for the root-causes analysis. These include the loss causation models developed at DNV [Soma and Rafn, 2006], the spray diagram method at Lloyd's Register [Pomeroy and Jones, 2006], and the marine root cause analysis technique at ABS [McCafferty and Baker, 2006]. A common agreement among these methods is that every casualty has more than one contributing factors and almost every factor can be traced up to the design aspect and organisational management level. In this database platform, the marine root cause analysis map developed at ABS has been adopted, where the hierarchical structure is demonstrated in Figure 5.16.

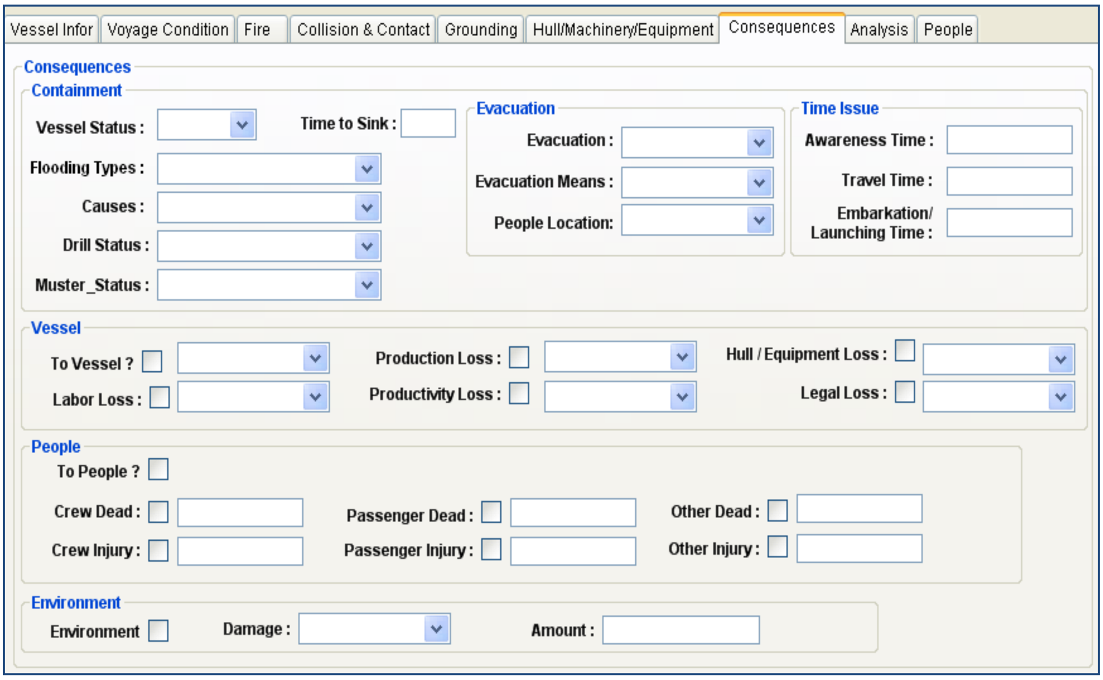


Figure 5.15: Consequence Module

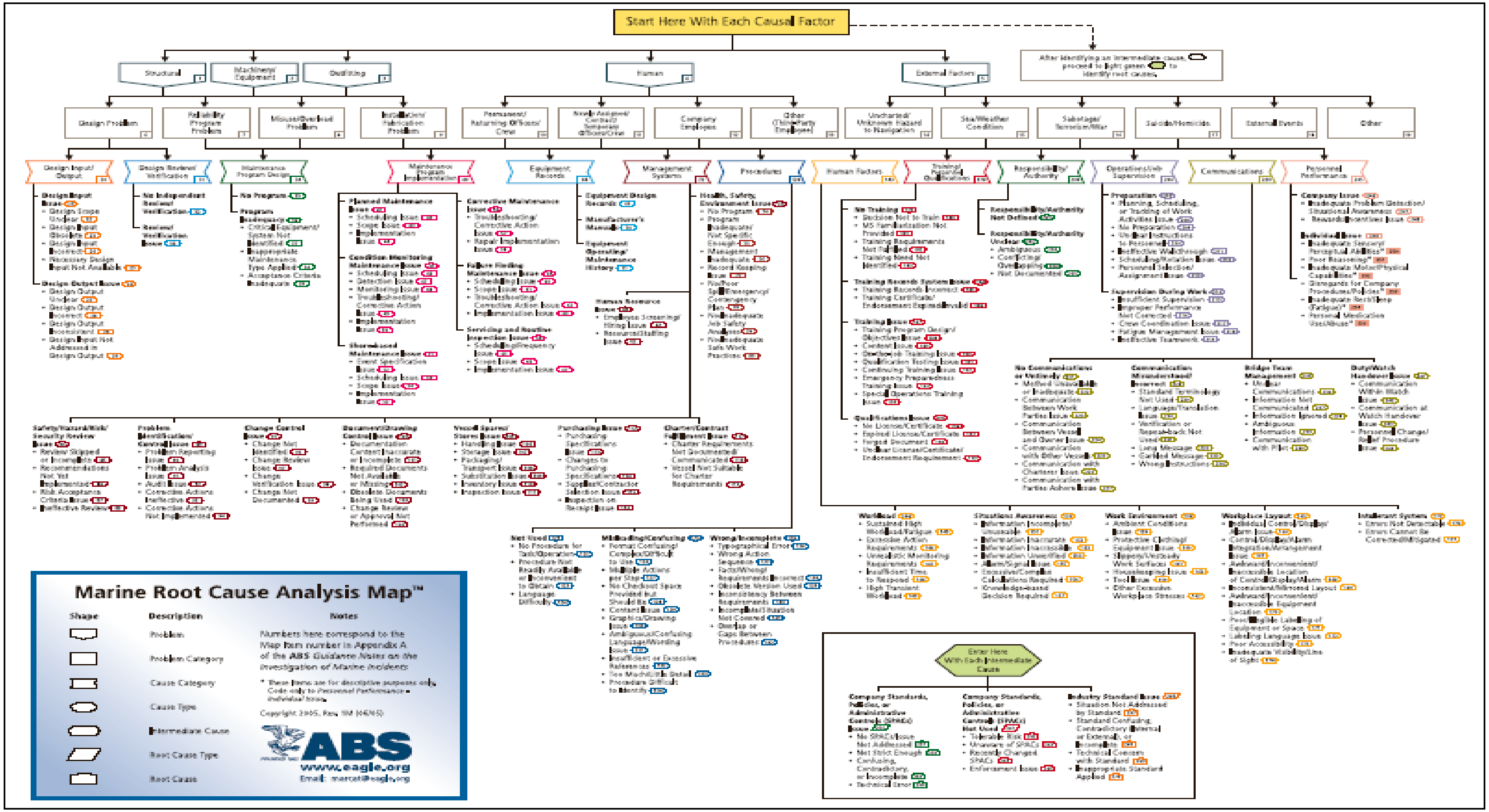


Figure 5.16: Marine Root Cause Analysis Map [ABS, 2005]

- Human-related Information

In the knowledge that the human factor has been recognised as an important contributing factor and it will be a lasting issue to be addressed in order to better manage ship safety, this module hosts the information related to human factors. Different from classical approaches, this module attempts to record the underlying factors that could lead to the underperformance of crews. It includes job titles, working experience, ages, duration of rest before work, language, education, etc., as shown in Figure 5.17.

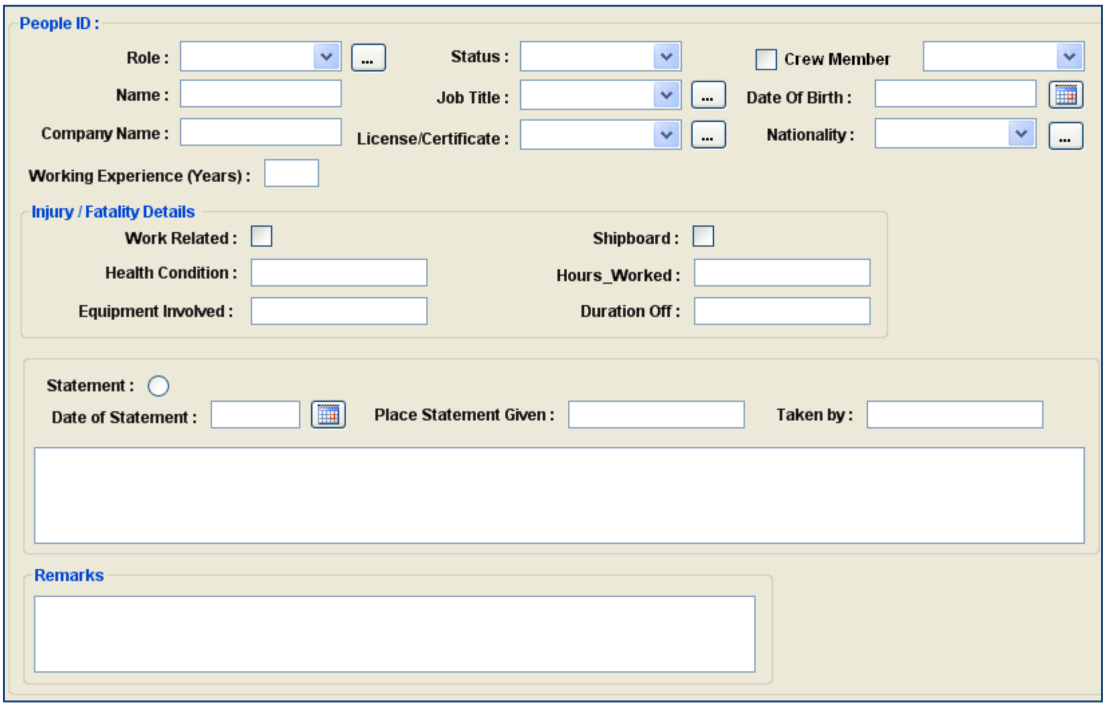


Figure 5.17: Human-Related Module

5.5 Closure

The sources of information for the next generation marine accident/incident database have been elaborated with their configurations. The proposed approach embraces major objective data sources, i.e. historical casualties and first-principles approaches. The hierarchical decomposition method for dominant variables identification has been presented and demonstrated with a newly developed database platform.

Chapter 6
Data Mining

6.1 Preamble

The need for more sophisticated data analysis techniques is derived from the difficulties that classical regression analysis becomes inefficient to cope with a mathematical model containing more than a handful of variables at a time. The situation is exacerbated by the fact that the parameters related to a physical casualty are often presented in discrete rather than continuous format, (e.g. ship types, locations, onboard spaces, etc.). This has given rise to the subject of data mining, which aims to condense a data set containing many variables into a meaningful and interpretable model with multivariate data analysis techniques.

As it has been noticed in Chapter 3 that the output from data mining can be presented in diverse forms, the identification of the most adequate platform and the associated "mining" techniques are of great importance. In this respect, BNs offer a unique platform for fulfilling the intended goals. This is attributable to its inherently adopted probabilistic regime for pertinent probability inference, which is transparent and flexible in terms of capturing complex relationships.

Hence, following a brief discussion of the links between data mining and BNs, this chapter focuses on detailing the techniques for training risk models in BNs both from qualitative and quantitative points of view. The issues of missing data and the size of data set needed will be addressed as well. Lastly, the program designed to automate the learning process is briefly highlighted. Its validation will be elaborated in Chapter 8. In addition, the issues of poor data quality and quantity along the implementation of data mining techniques are addressed.

6.2 Data Mining and Bayesian Networks

When an all-embracing database is established and populated with reliable and objective data, it is important to ensure that it can be seamlessly integrated in a risk analysis process, and in particular for the implementation of risk-based design. In this respect, the contribution of the database to this methodology would be the derivation of a risk model that is capable of addressing both qualitative and quantitative parameters. Moreover, this model will be able to evolve as the dataset is constantly updated during the life-cycle of a ship or a fleet with minimum effort as the process is automated (i.e. data updating, model updating).

The fault and event trees are the classical risk modelling techniques to present and process safety relevant knowledge probabilistically. They have gained wide popularity and acceptance by the industry, but the assumptions needed to keep their clarity and simplicity cause concern over the credibility of the estimated risk level. This can be demonstrated by independent relationships assumed between different events and the exponentially increased computational complexity if more variables are included.

BNs, as an alternative risk modelling technique, have been explored in the maritime industry as well. Early applications have demonstrated the potential due to the flexibility to describe complex relationships, the robustness to perform probabilistic inference, and the transparency. However, questions remained to be answered are brought forth: "how to rationally identify the complex causality relationships in the case of more than a few variables?" and "how to objectively quantify large conditional probability tables?"

With the progressively increased deployment of BNs, it is found that such trend inevitably leads to extensive research activities concerning the influence relationships among the variables from observational records. This is due to the practice of recording historical operational records of specific domains and transforming them into pertinent business intelligence has become an increasingly important means for modern business to obtain an informational advantage. As a result, learning techniques are developed so that a network can be constructed with minimised subjective intervention, the philosophical term of which is frequently referred to as the discovery of causality [Spirtes, et al., 2000]. Apart from eliciting the structure of a BN model from the data, formalised methods for learning the conditional probabilities have also been developed to quantify the obtained network (i.e. allocate probabilities to its nodes).

A flowchart of the elements for Bayesian network learning and their functionalities are depicted in Figure 6.1. The whole approach starts with BN structure elicitation by using collected data. This is followed by the derivation of probabilistic information for the network, which consequently delivers a specific trained BN model.

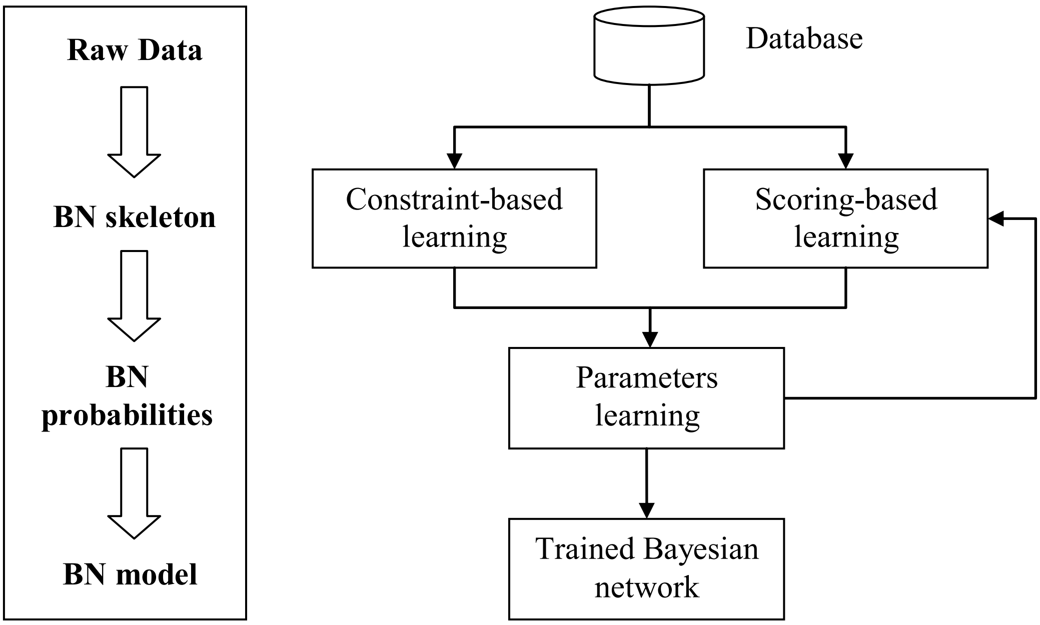


Figure 6.1: Flowchart of the Learning of Bayesian Networks

The current approaches towards the learning of a network structure have been widely classified as: *constraint-based learning* and *scoring-based learning*, in which distinct principles have been adopted. The former aims to identify a list of independent relationships from all possible two-variable combinations and conditionally independent relationships among three and more variables through statistical data analysis. A BN that entails all the discovered independent and conditionally independent relationships can then be identified. The latter approach uses a predefined scoring function so that the network structure having the highest score can be regarded as the best approximation in describing the joint probability distribution implied by the data set. As Scoring-based learning requires quantified network structures (using parameter learning techniques) for evaluation, its structure and parameters learning can be considered as an integral part.

The following sections start with a detailed elaboration of the constraint-based learning technique, followed by the parameter learning method as the scoring-based learning algorithm is carried out on the basis of quantified network structures.

6.3 Constraint-Based Learning

The technique of constraint-based learning builds on two core components: (i) discovering the skeleton of a BN through dependency tests, and (ii) creating the causal network diagram based on the obtained skeleton. With respect to the first component, it is important to identify appropriate mathematical models for dependency analysis. The hypothesis testing method is one of the major means for assisting decision making in this direction [Mendenhall, 2009]. Classical regression analysis is inefficient and unsuitable due to the following reasons: it normally applies to metric data (i.e. quantitative data), while a large portion of marine casualty data is inherently non-metric (e.g. ship types, locations, onboard spaces, etc.); the complexity of classical regression models becomes unstable with multiple numbers of parameters (e.g. over-fitting, etc.). As a result, the field of multivariate data analysis has been identified and explored [Hair, 2006].

6.3.1 Dependency Test

The selection of an appropriate mathematical model for multivariate data analysis depends on the characteristics of the parameters (e.g. metric, non-metric) and the number of dependent parameters. Due to the majority of casualty-related information being recorded in categorical (non-metric) formats, and in the knowledge that the continuous variables can be easily transformed into categorical presentations through discretisation, the Generalised Linear Model (GLM) can be used for this purpose [Dobson and Barnett, 2008].

A GLM is comprised by three components: a random component (i.e. response variables), a systematic component (i.e. explanatory variables), and a link function. An important feature of the GLM is that it contains not only standard models for continuous responses but also the models for categorical responses. In the case of analysing categorical variables, the logistic regression model and the log-linear model are commonly used [Agresti, 2002], [Perroud, et al., 2009].

For binary response variables, $\pi(x) = \{0,1\}$, with k independent variables $\mathrm{X}_1, \mathrm{X}_2$, up to X_k, a typical logistic regression model can be defined in equation (6.1). The terms, α, β_i represent the unknown coefficient parameters to be determined using the data. In order to assess the goodness-of-fit of the estimated model, the likelihood-ratio, chi-square test and Pearson chi-square test are used to compare the observed counts and the fitted values. The maximum likelihood technique is adopted for the model fitting with the estimated coefficients to be used for the examination of the significance of association.

$$logit[\pi(x)] = log\frac{\pi(x)}{1-\pi(x)} = \frac{1}{1+e^{-(\alpha+\sum\beta_i X_i)}} \tag{6.1}$$

The logistic regression model has been extensively applied in the financial sector and genetic research [Chen and Wu, 2009], [Kim, 2009], [Perround, et al., 2009]. The advantage is that the expression function (e.g. $\pi(x)$) always produces a value between zero and one along an S-shaped curve, as illustrated in Figure 6.2, which is very desirable for modelling the probabilistic functions, e.g. the cumulative normal distribution function. The determination of independent relationship between x_i and $\pi(x)$ is subject to the mean and the variance of the trained β_i. However, it should be noted that the response variable was originally designed to have binary statues, (True or False, Daytime or Night, etc.). Although the generalisation of the logistic regression model enables multi-category responses, it is still inconvenient to implement. In case of a predictor with more than two statuses, *dummy variables* need to be introduced and the quality of the trained model may be unnecessarily penalised [Kleinbaum and Klein, 2002].

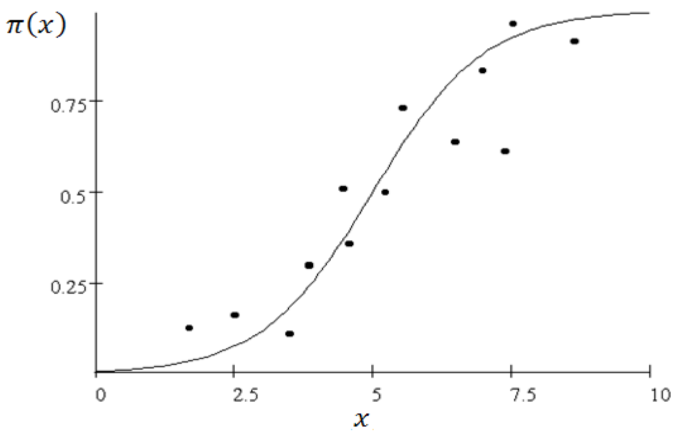


Figure 6.2: Logistic Regression Function

On the other hand, the log-linear model is a model commonly used for contingency table (i.e. a frequency distribution of the variables in a matrix format, See Table 6.1) analysis by modelling cell counts and eventually deriving the association and interaction patterns among variables. A typical Poisson log-linear model with explanatory variable x is shown in equation (6.2). Considering a contingency table with two variables x and y, representing the row and the column respectively, let mean μ_{ij} denote the product of the count at a specific cell (row i, column j) and the corresponding proportion of that count to the sum of the whole contingency table. The logarithm transformation of the mean leads to equation (6.3). Based on this, the saturated model suggesting a dependency relationship between x and y is illustrated by equation (6.4), where λ_{ij}^{XY} is the association term reflecting deviance from an independent relationship. Identical principle applies to the dependency analysis among three variables as illustrated in equation (6.5).

$$log\mu = \alpha + \beta x \tag{6.2}$$

$$log\mu_{ij} = \lambda + \lambda_i^X + \lambda_j^Y \tag{6.3}$$

$$log\mu_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY} \tag{6.4}$$

$$log\mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} \tag{6.5}$$

As a result, the identification of a dependency relationship is equivalent to the identification of the best log-linear model, which should be complex enough to fit the data, yet sufficiently simple for interpretation. To assist in this direction, the approach of backward elimination is adopted for the identification of an optimal log-linear model [Goodman, 1971]. It starts with a saturated (complex) model, and through systematically and sequentially removing a term that has least damaging effect on the model, it stops at a point that any further removal would lead to poor fit of the data. Consequently, the dependencies can be summarised when the model reaches its limit.

In order to converge to the most appropriate model, similar to classic statistical analysis, the goodness-of-fit measure can be adopted. Let's assume that the observation for a GLM is $y = (y_1, \dots, y_N)$. Let $L = (\mu; y)$ denote the log-likelihood function expressed in terms of the means $\mu = (\mu_1, \dots, \mu_N)$ and $L = (\hat{\mu}; y)$ denote the maximum of the log-likelihood of the model. When there is a perfect fit, $\hat{\mu} = y$, it indicates a saturated model. Hence, the *deviance* of the GLM is defined as:

$$-2log\frac{maximum\ likelihood\ for\ model}{maximum\ likelihood\ for\ saturated\ model} = -2[L(\hat{\mu}; y) - L(y; y)]$$

The term *deviance* is the likelihood-ratio statistic for testing the null hypothesis that the model hold against the saturated model. Thus, the process of comparing two models can be simplified to estimate the difference between the deviances of the two models, as illustrated below.

$$\begin{aligned}&-2[L(\hat{\mu}_0; y) - L(\hat{\mu}_1; y)]\\&= -2[L(\hat{\mu}_0; y) - L(y; y)] - \{-2[L(\hat{\mu}_1; y) - L(y; y)]\}\\&= D(\hat{\mu}_0) - D(\hat{\mu}_1)\end{aligned}$$

The result of the subtraction of two deviances has an asymptotic χ^2null distribution. The residual degree of freedom equals to the number of cells in the contingency table minus the number of parameters in the Poisson Log-linear model. In summary, the goodness-of-fit test can reveal not only when a fit is inadequate, but also when it is better than expected random fluctuations.

For the sake of illustration, when examining a dependency relationship between two variables, say, x and y, it is necessary to train only two log-linear models: the saturated model as illustrated by equation (6.4) and the model illustrated in equation (6.3). The latter indicates a lack of dependency between x and y. Similar principles apply to three and more variables elimination process. For instance, if the obtained model from backwards elimination for x, y, and z, is $log\mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY}$, it implies a conditional independent relationship that x and y are independent given z, which is frequently denoted as $I(x, y|z)$.

6.3.2 An Example of Dependency Test

Five variables are extracted from the database developed in Chapter 5 to demonstrate the dependency analysis process. Five selected variables are generally considered to be important factors affecting the risk level of fire hazard of passenger ships. The number of variables is preset at five as the computation complexity increases exponentially where the automation will be needed. A total of 576 cases are retrieved for the five variables:

- T denotes event time. Time of the day is commonly respected as an important factor affecting the severity (in terms of number of fatalities) of fire event onboard once it escalates from the space of origin with the smoke propagated. It is classified as *daytime* and *night*.

- L denotes vessel location. The main concern is that the situation at the evacuation stage can vary significantly if the vessel located at harbour or at sea. It is designed to have two categories: *at sea*, *in port.*

- C denotes whether the crew is present at the scene of the casualty. As the crews are regarded as the cluster of people onboard who have been trained to take proper actions under emergency circumstances, hence, the chance of putting out a fire before it escalates will exaggerate. Binary statuses are assigned for this case: *True, False*.

- H denotes the presence of human factors. Human error still accounts for about 80% of marine accident/incident, hence, it is recorded as *True* or *False*.

- S represents the severity of an event. It is classified as *minor, moderate* and *serious*.

Two-Variable Dependency Analysis

Dependency analysis between two variables is performed for all possible combinations so as to generate a list of dependency relationships. To train the logistic regression model for every combination, the corresponding contingency table needs to be summarised beforehand. An example of the contingency table for L and T is provided in Table 6.1, where the cell count (e.g. 285) indicates that there are 285 incidents out of 576 records happened at sea during the day time. The numbers in the brackets indicate the weights of specific cells to the overall count, for instance, $\frac{285}{576} = 49.48\%$.

Table 6.1: Contingency Table for L and T

		Event time		
		Daytime	**Night**	**Total**
Location	**At sea**	285	115	400
		(49.48)	(19.97)	(69.44)
	In port	143	33	176
		(24.83)	(5.73)	(30.56)
	Total	428	148	**576**
		(74.31)	(25.69)	(100.00)

To train the logistic regression model, the response variable ($\pi(x)$) and the predictor variable (x) are exchangeable for this specific application as the aim is to examine the association between L and T. Hence, the model can be presented in the form of equation (6.6) with the estimated coefficients tabulated in Table 6.2. More details on estimating logistic regression models is summarised in Appendix 5.

$$logit[P(L = at\ sea)] = log\frac{P(L = at\ sea)}{1 - P(L = at\ sea)} = \alpha + \beta T_1 \qquad (6.6)$$

Table 6.2: Summary of the Estimated Coefficients of the Logistic Regression Model Containing L and T

Parameter	Degree of freedom	Estimate	Standard error (SE)	Chi-square	P(null hypothesis being correct)
Intercept (α)	1	-1.2484	0.1975	39.96	<0.0001
β for Time ($T_1 = Daytime$)	1	0.5588	0.2225	6.31	0.012

The significance test focuses on $H_0: \beta = 0$, representing the hypothesis of independence between L and T. This can be achieved by performing the Wald test [Fienberg, 2007], $z^2 = \left(\hat{\beta}/SE\right)^2$, which is asymptotically χ_1^2, the chi-squared distribution. The probability stands at 0.012, which suggests the significance of T in the trained model if 95% confidence interval is defined (e.g. $0.012 < 0.05$). This implies a dependency relationship between L and T.

The conclusion can be checked against ordinary dependency tests for two-way contingency tables [Fienberg, 2007]. For multinomial sampling with probabilities $\{\pi_{ij}\}$ in a $I \times J$ contingency table, the null hypothesis of statistical independence is $H_0: \pi_{ij} = \pi_{i+}\pi_{+j}$ for all i and j. The Pearson X^2 statistic equals to $X^2 = \sum_i \sum_j \frac{\left(n_{ij} - \hat{\mu}_{ij}\right)^2}{\hat{\mu}_{ij}}$ and the degree of freedom equals to $df = (I-1)(J-1)$. The current practice is to treat X^2 asymptotically chi-squared. Hence, the statistics of the contingency table containing L and T can be found in Table 6.3. The result agrees well with the previous finding.

Table 6.3: Statistics of the Contingency Table Containing L and T

Parameter	Degree of freedom	Value	Probability
Pearson Chi-square	1	6.4016	0.0114

It is important to point out that the confidence interval (CI) plays a crucial role for the significance test on the hypothesis of independence. For instance, a 95% confidence interval in this specific case requires a set of β_0 for which the test of $H_0: \beta = \beta_0$ has a P-value exceeding 0.05. Practical applications suggest that the establishment of appropriate confidence intervals for dependency analysis is mainly to achieve a compromise between the size of data set and the quality of the estimation.

On the basis of the foregoing, similar studies can be performed for the remaining two-variable combinations. With confidence interval set at 90%, a list of dependency relationships is identified and tabulated in Table 6.4. The logistic regression model is adopted for binary variables analysis. As the variable *S* has three states, which is not suitable for this application, an ordinary independency test of two-way contingency tables is performed.

Table 6.4: Dependency Relationships Identification between Two Variables

Combinations	**P(null hypothesis being correct)**	**Relationship**
(L, T)	0.0120	Dependent
(T,H)	0.3305	Independent
(T, S)	0.0992	Dependent
(T,C)	0.6690	Independent
(L,H)	0.6956	Independent
(L,S)	0.6536	Independent
(L,C)	0.8782	Independent
(H,S)	0.0612	Dependent
(H,C)	0.9497	Independent
(S,C)	0.1012	Dependent (equivalent)

Three-Variable Conditional Independency Analysis

The identification of the relationships among three variables is a more complicated task due to various possible combinations. As normal dependent relationships can be explicitly identified in the previous section, the relationships among three variables are reflected through the identifications of conditional independencies. For demonstration, a list of possible combinations is examined with the log-linear model. Backward eliminations are initiated from the saturated model. For instance, the saturated model for (T, L, S) is $log\mu_{ijk} = \lambda + \lambda_i^T + \lambda_j^L + \lambda_k^S + \lambda_{ij}^{TL} + \lambda_{ik}^{TS} + \lambda_{jk}^{LS} + \lambda_{ijk}^{TLS}$, which can be denoted as (TLS).

An initial attempt is made to eliminate the three-variable association term λ_{ijk}^{TLS}. By checking the deviance (G^2) between the saturated model and the simplified model, the validity of the simplified model to fit the data can be identified. For instance, the simplified model could be $log\mu_{ijk} = \lambda + \lambda_i^T + \lambda_j^L + \lambda_k^S + \lambda_{ij}^{TL} + \lambda_{ik}^{TS} + \lambda_{jk}^{LS}$, denoted as (TL, TS, LS). As illustrated in Table 6.5, removing the term λ_{ijk}^{TLS} has limited damage effect on the saturated model with P-value stands at 0.8828.

Table 6.5: Summary Table of Backward Eliminations of the Log-linear Model containing T, L, S

Combination	**Model**	**DF**	**Likelihood ratio**	**DF**	G^2	**P-value**	**Relationship**
T, L, S	(TLS)	0	0				
	(TL, TS, LS)	2	0.25	2	0.25	0.8828	
	(TL, TS)	4	0.55	2	0.3	0.8607	$I(L, S \vert T)$
	(TL, LS)	4	4.16	2	3.91	0.1416	
	(TS, LS)	3	6.03	1	5.78	0.0162	
	(T, L, S)	7	10.79	5	10.54	0.0613	

Hence, further eliminations can be carried out by removing the two-variable association terms one by one. Through eliminating terms λ_{ij}^{TL}, λ_{ik}^{TS}, and λ_{jk}^{LS} one at a time, it leads to three distinct models: (TS, LS), (TL, LS), and (TL, TS) respectively. The subsequent analysis of the deviance suggests that model (TL, TS) has the least damaging effect to the saturated model with P-value equals to 0.8607, as shown in Table 6.5.

In order to ensure that no further simplifications are needed, the model (T, L, S) representing $log\mu_{ijk} = \lambda + \lambda_i^T + \lambda_j^L + \lambda_k^S$ is examined. This model marks the end of the backward elimination process as it indicates pure independent relationships between T and L, L and S, T and S. Nevertheless, as illustrated in Table 6.5, this model does not fit the data (i.e. $P = 0.0613$). Consequently, the process stops at the model (TL, TS), which indicates a conditionally independent relationship between L and S given T, denoted as $I(L, S|T)$.

Similar operations can be performed for the remaining combinations. However, considering that the dependent relationships, which have been identified for two-variable combinations, the number of practically possible combinations is left with only four sets: $\{T, L, S\}$, $\{T, S, H\}$, $\{T, S, C\}$, and $\{S, H, C\}$. Their conditionally independent relationships are identified and summarised in Table 6.6. It is worth noting that the conclusion of conditional independency is not drawn for $\{S, H, C\}$, as the deviance between the model (SH, SC, HC) and the saturated one (SHC) is relatively large compared with the remaining combinations.

Table 6.6: Summary Table of Conditional Independency Analysis

Combination	**Model**	**DF**	**Likelihood ratio**	**DF**	G^2	**P-value**	**Relationship**
T, L, S	(TLS)	0	0				
	(TL, TS, LS)	2	0.25	2	0.25	0.8828	
	(TL, TS)	4	0.55	2	0.3	0.8607	$I(L, S\|T)$
	(TL, LS)	4	4.16	2	3.91	0.1416	
	(TS, LS)	3	6.03	1	5.78	0.0162	
	(T, L, S)	7	10.79	5	10.54	0.0613	
T, S, H	(TSH)	0	0				
	(TS, TH, SH)	2	1.09	2	1.09	0.5810	
	(TS, TH)	4	5.43	2	4.34	0.1142	
	(TS, SH)	3	1.63	1	0.54	0.4624	$I(T, H\|S)$
	(TH, SH)	4	4.98	2	3.89	0.1430	
T, S, C	(TSC)	0	0				
	(TS, TC, SC)	2	0.58	2	0.58	0.7487	
	(TS, TC)	4	3.82	2	3.24	0.1979	
	(TS, SC)	3	0.89	1	0.31	0.5777	$I(T, C\|S)$
	(TC, SC)	4	4.85	2	4.27	0.1182	
S, H, C	(SHC)	0	0				
	(SH, SC, HC)	2	3.14	2	3.14	0.2082	

Apart from three-variable conditional independency analysis, the log-linear model containing four and more variables can be trained in a similar manner as well.

Nevertheless, such a practice to include more variables in a single analysis will destabilise the model, and ultimately jeopardise the findings. Hence, as far as the derivation of the BNs skeleton is concerned, the two-variable dependency and three-variable conditional independency analysis are generally considered to be enough to reveal the relationships among a limited amount of parameters, which also reflects the common practice for dependency analysis.

6.3.3 PC Learning Algorithm

The techniques presented in the previous section lay the foundation for the construction of the skeleton of a BN by identifying a list of independent and conditionally independent relationships. A formalised procedure needs to be followed in order to develop a BN skeleton that entails the discovered relationships. In this respect, the PC algorithm, named by its developer in [Spirtes, et al., 2000], has been regarded as a representative technique for the implementation of constraint-based learning [Neapolitan, 2004], [Korb, et al., 2004], [Jensen, et al., 2007].

PC Algorithm

1. Start with the complete graph
2. $i = 0$
3. **while** *a node has at least* $i + 1$ *neighbours*
  for *all nodes A with at least* $i + 1$ *neighbours*
    for *all neighbours B of A*
      for *all neighbour sets* χ *such that* $|\chi| = i$ *and* $\chi \subseteq (neighbours(A)\backslash\{B\})$
        If $I(A, B|\chi) = True$ **then** *remove the link* $A - B$ *and store* $I(A, B|\chi)$
  $i = i + 1$

Where: $I(A, B|\chi)$ represents the discovered relationships through statistical analysis. when χ is empty, it represents an independent relationship; when χ is not empty, it indicates conditional independent relationships.

The algorithm starts with a fully connected network. It then systematically loops through the whole network and checks the dependency relationships of the form of $I(A, B|\chi)$, where χ is a subset of A's or B's neighbours. Once such a relationship is valid on the basis of the previous dependency analysis, the link between A and B will be eliminated. It is important to notice that the subset χ can be also empty (i.e. $|\chi| = 0$), which implies two-variable dependency analysis between A and B.

With i set to be 0, the iteration at first stage focuses on the dependent relationship between two variables. Following this, with i increased to 1 and more, the conditional independencies among three variables will be included afterwards. Consequently, a network skeleton that entails all the identified independent and conditionally independent relationships can be constructed.

Having the network skeleton, it is necessary to add orientations (arrows) to transform it into a BN model. With respect to this, there are some rules need to be adhered to:

Rule 1	V -structures, also popular referred to as head-to-head orientations $(A \rightarrow \chi \leftarrow B)$, are to be introduced for $A - \chi - B$ cases that are not in the conditional independency list $I(A, B|\chi)$.
Rule 2	Apart from V-structures introduced due to Rule 1, no further new head-to-head orientation should be created
Rule 3	As Bayesian network is also known as directed acyclic diagram, the orientation should always avoid the formation of any cycle.
Rule 4	If none of the rules 1 to 3 can be applied in the graph, an arbitrary direction can be assigned for every undirected link.

It has been noted that the assignment of V-structures plays an important role during the orientation assignment process. This is because as a BN represents the joint probability distribution of a set of variables, the structure needs to fulfil the Markov condition, [Neapolitan, 2004], which implies every conditionally independent relationship, $I(X, neighbours\_of\_X|parents\_of\_X)$, needs to be presented in a way that the random variable X and its neighbours are conditional independent given its parents in the network. In the case of a conditionally independent relationship, e.g. $I(L, S|T)$, if the orientation is assigned to be head-to-head (i.e. $L \rightarrow T \leftarrow S$), it will no longer admit the conditional independent relationship as the instantiation of the variable T will not isolate the link between L and S.

Once the V-structures are assigned, the remaining links can be assigned arbitrarily as long as no more V-structure is created and no directed cycle is formed. This is mathematically valid as it will be elaborated in section 6.4, where the probabilistic inference will remain stable with identical input data. Nevertheless, due to the causality relationship associated with the assigned orientation, empirical approaches can be introduced here when applying rule 4. Regarding the assignment of orientations, the PC algorithm also proposes a process for implementation.

---

1. **for** *each triple of vertices X, Y, Z such that the pair X, Y and the pair Y, Z are each adjacent but the pair X, Z are not adjacent, orient X – Y – Z as X → Y ← Z if and only if the combination (X, Y, Z) is not in the conditional independency list* $I(X,Y|Z)$
2. **repeat**

   If *A → B, B and C are adjacent, A and C are not adjacent, and there is no arrowhead at B,* **then** *orient B – C as B → C*

   If *there is a directed path from A to B, and an edge between A and B,* **then** *orient A – B as A → B*

6.3.4 A Learning Example of PC Algorithm

The example presented in Section 6.3.2 with a list of independent and conditionally independent relationships summarised in Table 6.7 will be put forward in this example. To initiate the algorithm, a fully connected network is constructed as illustrated in Figure 6.3. With $i = 0$, the first node has more than one neighbour can be T, whose neighbours are $\{C, S, H, L\}$. From Table 6.7, it is found that the independent relationships containing T are $I(T, H)$ and $I(T, C)$, hence, the links between $T - H$ and $T - C$ can be removed as illustrated in Figure 6.4. Similarly, other independent links can be removed accordingly. The subsequent network skeleton after the loop for $i = 0$ is shown in Figure 6.5.

With $i = 1$, the identified conditionally independent relationships as listed at the bottom of Table 6.7 will be utilised, as a result, the links between $L - S$, $T - H$,

$T - C$, need to be eliminated. As these four links have already been removed due to the previous operations when $i = 0$, no further action is needed. Consequently, the PC algorithm stops with the skeleton illustrated in Figure 6.5.

Table 6.7: Summary of Independent and Conditional Independent Relationships

Combinations	**Relationship**
$I(T,H)$	Independent
$I(T,C)$	Independent
$I(L,H)$	Independent
$I(L,S)$	Independent
$I(L,C)$	Independent
$I(H,C)$	Independent
$I(L,S\|T)$	Conditional independent
$I(T,H\|S)$	Conditional independent
$I(T,C\|S)$	Conditional independent

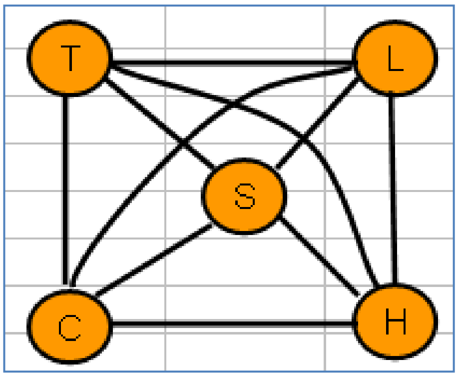


Figure 6.3: A Fully-Connected Network Skeleton

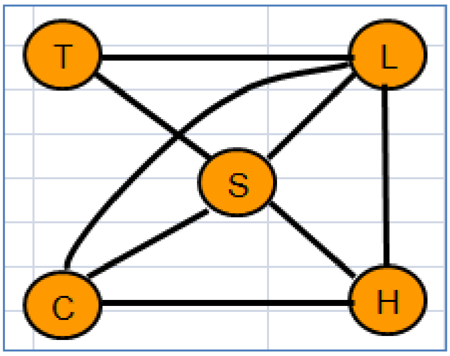


Figure 6.4: Network Skeleton (Removing the Links between $T - H$ and $T - C$)

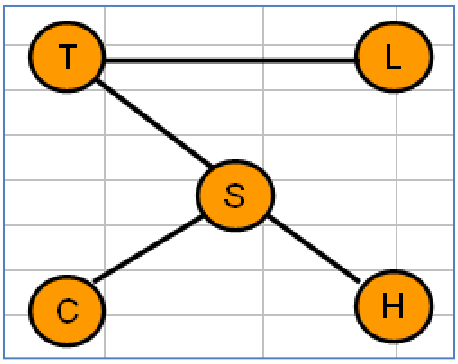


Figure 6.5: Network Skeleton with the Links removed due to Independent and Conditional Independent Relationships

Immediately following this, the orientations can be assigned for the five-node network. As discussed previously, an initial attempt should be made to orient the V-structures with head-to-head links. On the basis of the conditional independency list and the obtained skeleton, it is found that the V-structure $C - S - H$ is not in the list. Hence, the resultant head-to-head links is shown in Figure 6.6.

The remaining links can be directed in a flexible way as long as they satisfy Rules 2, 3 and 4 of the aforementioned principles for orientation assignment. As a result, the link between $S - T$ should be directed towards T to avoid making new V-structure with $C \rightarrow S$ and $H \rightarrow S$. Similar principles apply to $T - L$. Consequently, the five-node BN structure is shown in Figure 6.7.

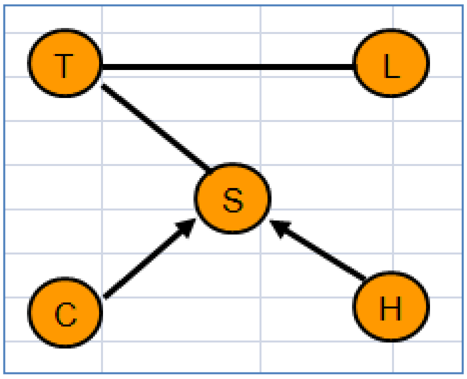


Figure 6.6: Assignment of Head-to-Head Links

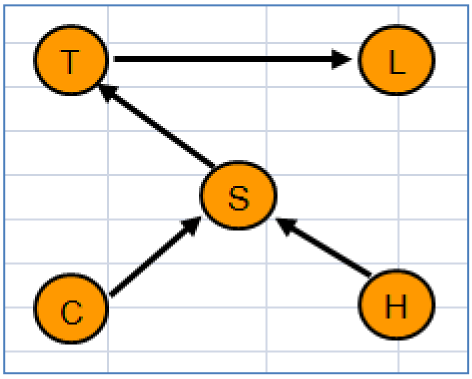


Figure 6.7: Output Five-node Bayesian Network Structure by Following the PC Algorithm

6.4 Parameter Learning

It has been stressed throughout the thesis that the current practice when employing BNs for risk assessment relies heavily on subjective experience for network structure derivation and the quantification of the associated large and complex conditional probability tables. The constraint-based learning technique is capable of objectively and rationally establishing the structure of a BN model. This section focuses on the quantification of the identified network structure.

The current practice towards the estimation of probabilities and conditional probabilities is mainly achieved through the approximation of the limit of its relative frequency in a large number of trials. Through repeating the experiment for as many times as possible and assigning the ratio between the numbers of events occurred and the total number of experiments performed, the relative frequency can be estimated using the expected value. Within the engineering context, the number of trials is restrained due to many factors, e.g. resource allocation, and characteristics of the event. Thus, proper data analysis techniques are essential to assist this transformation.

6.4.1 Beta and Dirichlet Density Functions

To express the probability containing both the prior belief and the collected evidence, i.e. the data, a properly defined density function is needed. In relation to this, both the Beta and Dirichlet density functions provide an effective means for quantifying the prior belief about the relative frequencies and updating the beliefs in light of new evidence.

In the case of binary variables, the beta density function with the parameters a, b, and $N = a + b$ is illustrated in equation (6.7), where a and b are real and positive numbers $a, b \in (0, +\infty)$. With the updated information s and t, and $M = s + t$, the updated distribution function can be written in equation (6.8). An example of the beta density function with $a = 50, b = 50$ is illustrated in Figure 6.8.

$$p(f) = \frac{\Gamma(N)}{\Gamma(a)\Gamma(b)} f^{a-1}(1-f)^{b-1} = beta(f; a, b) \qquad 0 \le f \le 1 \tag{6.7}$$

$$\frac{f^s(1-f)^t p(f)}{E(F^s(1-F)^t)} = \frac{\Gamma(N+M)}{\Gamma(a+s)\Gamma(b+t)} f^{a+s-1}(1-f)^{b+t-1} \tag{6.8}$$

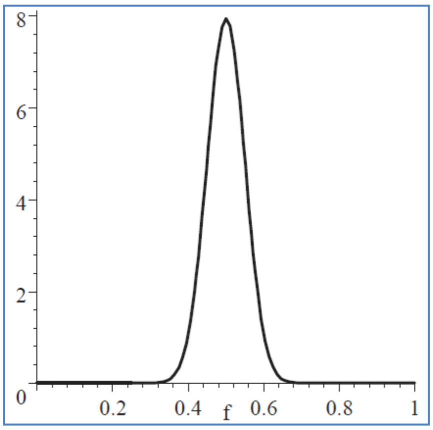


Figure 6.8: Beta(f;50,50) Density Function

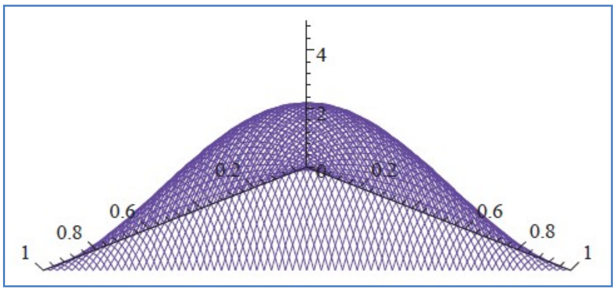


Figure 6.9: Dir(f_1, f_2;2,2,2) Density Function

Suppose a dataset of values d concerning the binary random variable x having two states: $\{True, False\}$, with s is the count in d when x is $(True)$, and t is the count in d when x is $(False)$, the probability of generating this data set by assuming the statuses are beta-distributed is shown in equation (6.9).

$$P(d) = E(F^s(1-F)^t) = \frac{\Gamma(N)}{\Gamma(N+M)} \frac{\Gamma(a+s)\Gamma(b+t)}{\Gamma(a)\Gamma(b)} \tag{6.9}$$

For illustration purpose, the variables defined in Section 6.3.2 are put forward. As the variable L has only two statuses (i.e. at sea and in port), it is reasonable to assume that its statuses are beta-distributed. In this case, let a and b be the prior believe of the two statuses. For instance, the assignment of $a = 1$ and $b = 1$ indicates that it is believed the location of the ship has equal likelihood to be "$At\ sea$" and "$In\ port$", $P(L = at\ sea) = 1/(1+1) = 0.5$, denoted as, $beta(a = 1, b = 1)$. Moreover, as it is revealed from the collected data that the suggested belief is: $s = 400$ and $t = 176$. As a result, the subsequently updated density function will be $beta(a + s = 401, b + t = 177)$. This implies $P(L = at\ sea) = 401/(401 + 177) = 0.6938$.

In the case of multinomial variables, the Dirichlet density function can be used. A Dirichlet density function with equal counts for all three statuses, e.g. $a_1 = 2, a_2 = 2, a_3 = 2$, is shown in Figure 6.9. Suppose the parameters are $a_1, a_2, \dots a_r, N =$

$\sum_{k=1}^{r} a_k$, and $a_1, a_2, \dots a_r$ are integers ≥ 1 , the Dirichlet density function is illustrated in equation (6.10).

$$p(f_1, f_2, \dots f_{r-1}) = \frac{\Gamma(N)}{\prod_{\mathrm{k}=1}^{\mathrm{r}} \Gamma(a_k)} f_1^{a_1-1} f_2^{a_2-1} \dots f_r^{a_r-1} \quad 0 \leq f_k \leq 1, \sum_{k=1}^{r} f_k = 1 \qquad (6.10)$$

Similarly, considering d as the dataset, the probability of having d by assuming all statuses are Dirichlet-distributed is shown in equation (6.11).

$$P(d) = E\left(\prod_{k=1}^{r} F_k^{s_k}\right) = \frac{\Gamma(N)}{\Gamma(N+M)} \prod_{k=1}^{r} \frac{\Gamma(a_k + s_k)}{\Gamma(a_k)} \qquad (6.11)$$

For demonstration, the variable S is considered as it has three statuses (i.e. $minor$, $moderate$, $serious$). Given the defined Dirichlet density function, the Initial priors can be assigned as $a_1 = 1, a_2 = 1$, and $a_3 = 1$ for the corresponding three statuses to reflect equal beliefs due to limited prior information, denoted as $dir(a_1 = 1, a_2 = 1, a_3 = 1)$. Furthermore, the evidence from the collected data suggests: $s_1 = 542$, $s_2 = 25$, and $s_3 = 9$. Consequently, the updated density function will be $dir(a_1 + s_1 = 543, a_2 + s_2 = 26, a_3 + s_3 = 10)$.

6.4.2 Augmented Bayesian Networks

The *augmented Bayesian networks* have been propounded in order to facilitate the process of transforming the data into probabilities and conditional probabilities [Neapolitan, 2004]. It is a BN determined by the following:

1. A network diagram $DAG\ \mathbb{G} = (V, E)$ where $V = \{X_1, X_2, \dots X_n\}$, each X_i is a random variable, and E denotes a set of ordered arcs, i.e. orientations.

2. For every i, an auxiliary parent variable F_i of X_i and a density function ρ_i of F_i. Each F_i is a root and has no edge to any variable except X_i. The set of all F_is is denoted by F. That is,

$$F = F_1 \cup F_2 \cup \dots F_n$$

3. For every i, for all values pa_i of the parents PA_i in V of X_i, and all values f_i of F_i, a probability distribution of X_i is conditional on pa_i and f_i.

For the sake of illustration, a simple BN structure with three variables x_1, x_2, and x_3 is illustrated in Figure 6.10. The corresponding augmented network is demonstrated in Figure 6.11, where the round shaded nodes are those augmented nodes designated to run enquiry from the data for the quantification of the probability tables. $\mathrm{F_{ij}}$ is a random variable whose probability distribution represents the beliefs. For instance, $\mathrm{F_{11}}$ represents the belief concerning the relative frequency with which $\mathrm{X_1}$ equals to 1, whilst, the probability distribution of $\mathrm{F_{21}}$ indicates the belief concerning the relative frequency with which $\mathrm{X_2}$ equals to 1 given that $\mathrm{X_1} = 1$. Similarly, the probability distribution of $\mathrm{F_{22}}$ represents the belief concerning the relative frequency with which $\mathrm{X_2}$ equals to 1 given that $\mathrm{X_1} = 2$.

The assignment of prior beliefs, as it is demonstrated in Figure 6.11, plays an important role for quantifying the variables in the network. Due to the additive characteristic of both the Beta and Dirichlet distributions, the consequent probabilities for each variable can be essentially regarded as the combined output from both the prior information (beliefs) and the collected evidence from the data, as it is implied in the approximated Bayes' theorem, $P(\theta|data) \propto P(\theta)P(data|\theta)$. In this respect, as the prior information is generally not available and not reliable as far as risk modelling is concerned, it would be more appropriate to deploy small values with equal priors so that the estimations can be more objective. At the same time, this will maximise the usage of the evidence from the data.

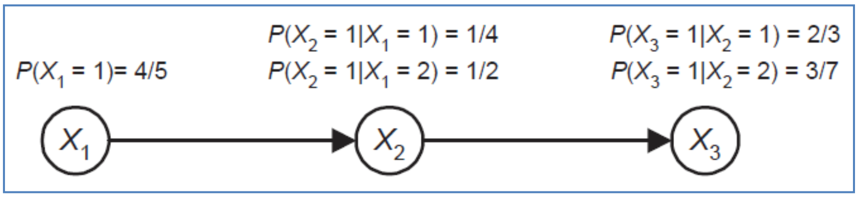


Figure 6.10: An Embedded Bayesian Network

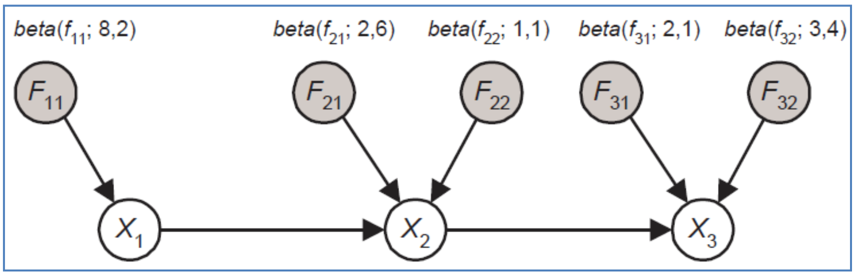


Figure 6.11: A Binomial Augmented Bayesian Network

Suppose a sample of size M with random vectors:

$$X^{(1)} = \begin{pmatrix} X_1^{(1)} \\ \vdots \\ X_n^{(1)} \end{pmatrix} \quad X^{(2)} = \begin{pmatrix} X_1^{(2)} \\ \vdots \\ X_n^{(2)} \end{pmatrix} \quad \dots \quad X^{(M)} = \begin{pmatrix} X_1^{(M)} \\ \vdots \\ X_n^{(M)} \end{pmatrix}$$

$$D = \{X^{(1)}, X^{(2)}, \dots X^{(M)}\}$$

Such that for every i each $X_i^{(h)}$ has the same space and there is an associated augmented BN. As a result, an immediate conclusion can be drawn for the probability of generating such dataset d given the probability distribution of each random variable is illustrated in equation (6.12).

$$P(d|f_1, \dots f_n) = \prod_{i=1}^{n} \prod_{h=1}^{M} P\left(x_i^{(h)} | pa_i^{(h)}, f_i\right) \tag{6.12}$$

Where $pa_i^{(h)}$ contains the values of the parents of X_i in the h^{th} case. Following the defined condition, the probability of having the data set in general is shown in equation (6.13).

$$P(d) = \prod_{i=1}^{n} \left(\int_{f_i} \prod_{h=1}^{M} P\left(x_i^{(h)} | pa_i^{(h)}, f_i\right) \cdot p(f_i)\, df_i \right) \tag{6.13}$$

Through employing Bayes' theorem, the subsequent probability distribution of random variables given the dataset d is illustrated in equation (6.14).

$$P(f_1, \dots f_n | d) = \prod_{i=1}^{n} p(f_i | d) \tag{6.14}$$

Following the previous inference, the $P(d)$ of interest can be further simplified for an augmented BN with all binary variables are shown in equation (6.15).

$$P(d) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma(N_{ij})}{\Gamma(N_{ij} + M_{ij})} \frac{\Gamma(a_{ij} + s_{ij})\Gamma(b_{ij} + t_{ij})}{\Gamma(a_{ij})\Gamma(b_{ij})} \tag{6.15}$$

With each augmented node, the probability distribution given the data can be quantified as:

$$P(f_{ij}|d) = \frac{(f_{ij})^{s_{ij}}(1 - f_{ij})^{t_{ij}}\rho(f_{ij})}{E\left(F_{ij}^{s_{ij}}[1 - F_{ij}]^{t_{ij}}\right)}$$

With each variable is beta-distributed:

$$\rho(f_{ij}) = beta(f_{ij}; a_{ij}, b_{ij})$$

The subsequent probability distribution given the prior belief and the collected evidence from the data is illustrated in equation (6.16).

$$\rho(f_{ij}|d) = beta(f_{ij}; a_{ij} + s_{ij}, b_{ij} + t_{ij}) \tag{6.16}$$

Similarly, in the case of multinomial augmented BNs, it is,

$$P(d) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma(N_{ij})}{\Gamma(N_{ij} + M_{ij})} \prod_{k=1}^{r_i} \frac{\Gamma(a_{ijk} + s_{ijk})}{\Gamma(a_{ijk})}$$

$$\rho(f_{ij1}, f_{ij2}, \ldots, f_{ij(r_i-1)}) = Dir(f_{ij1}, f_{ij2}, \ldots, f_{ij(r_i-1)}; a_{ij1}, a_{ij2}, \ldots a_{ijr_i})$$

$$\rho(f_{ij1}, f_{ij2}, \ldots, f_{ij(r_i-1)}|d)$$

$$= Dir(f_{ij1}, f_{ij2}, \ldots, f_{ij(r_i-1)}; a_{ij1} + s_{ij1}, a_{ij2} + s_{ij2}, \ldots a_{ijr_i} + s_{ijr_i})$$

With the reviewed equations, an augmented BN can be easily updated, which in turn leads to the quantification of all the associated probability and conditional probability tables of the embedded network structure.

The Assignment of Prior Belief

During the quantification process of a BN model, it has been found that the total prior belief for each variable should be equivalent [Neapolitan, 2004]. If the equivalence is not maintained, the probability inference results obtained from equivalent network diagrams (e.g. a two-node network with opposite orientation, $X_1 \rightarrow X_2$ and $X_2 \rightarrow X_1$, as illustrated in Figure 6.12) can be different. In order to avoid such circumstance, equivalent sample size should be assigned for each node. For instance, the sum of prior belief for the node X_1 is $2 + 2 = 4$, and the sum of prior belief for the node X_2 is $1 + 1 + 1 + 1 = 4$ disregarding the number of augmented nodes associated.

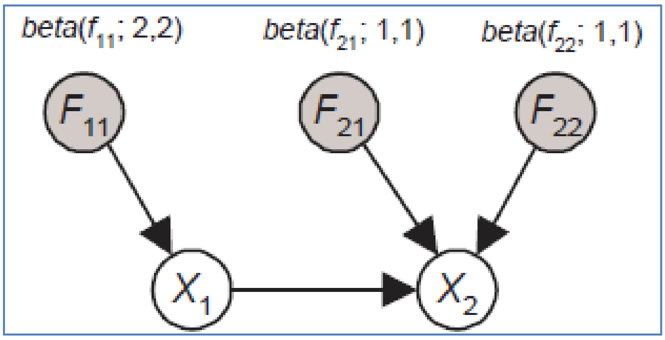


Figure 6.12: An Example of Equivalent Sample Size

In addition, during the process of prior belief assignment, the beliefs assigned for each augmented node, e.g. $F_{11}: beta(f_{11}; 2{,}2)$, does not necessarily have to be equal. The main reason for such practice is that no relevant knowledge is available concerning the value of the relative frequency. It also aims to achieve objectivity. Nevertheless, in a situation that there is clear evidence suggesting unequal prior belief for different statuses of a specific augmented node, corresponding adjustment can be made accordingly as long as the sum of prior belief of every node is equal.

6.4.3 A Parameter Learning Example

The implementation of parameter learning can be achieved in three stages: setting up the corresponding augmented network, assigning prior belief, and lastly updating the beliefs. The example takes advantage of the five-node network structure constructed in Section 6.3 through constraint-based learning.

The statuses of the parent nodes play important roles during the set up process of an augmented network. As the nodes C and H do not have any parent node, only single augmented node is needed (i.e. F_C1, F_H1) for each variable, as illustrated in Table 6.8. The statuses of the augmented nodes should be identical with the variable to which it is connected. In the case of the node S, as each parent node has two statuses, there are four ($2 \times 2 = 4$) augmented nodes associated with each one corresponding to a unique combination of the statuses of its parents, (e.g. $F_S1 \rightarrow C = False, H = False$). There are three augmented nodes assigned for the variable T as its parent S has three statuses. Following such a process, the augmented network developed on the basis of the five-node network structure is illustrated in Figure 6.13.

Table 6.8: Set up of the Augmented Network Structure

Variable	**Parent**	**Parent status**	**Augmented node**	**Statuses**
C	None		F_C1	$\{False, True\}$
H	None		F_H1	$\{False, True\}$
S	{C, H}	$C = False$ $H = False$	F_S1	$\{Minor, Moderate, Serious\}$
		$C = False$ $H = True$	F_S2	$\{Minor, Moderate, Serious\}$
		$C = True$ $H = False$	F_S3	$\{Minor, Moderate, Serious\}$
		$C = True$ $H = True$	F_S4	$\{Minor, Moderate, Serious\}$
T	{S}	$S = Minor$	F_T1	$\{Daytime, Night\}$
		$S = Moderate$	F_T2	$\{Daytime, Night\}$
		$S = Serious$	F_T3	$\{Daytime, Night\}$
L	{T}	$T = Daytime$	F_L1	$\{Sea, Port\}$
		$T = Night$	F_L2	$\{Sea, Port\}$

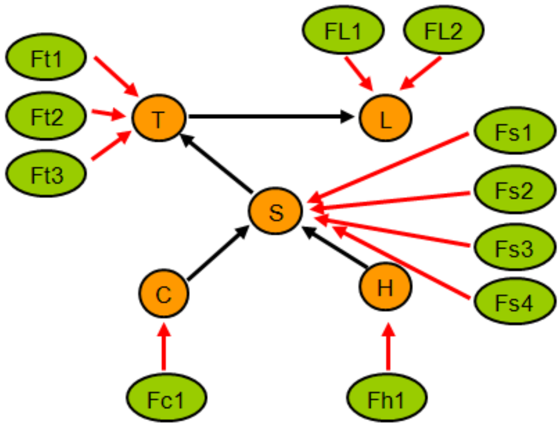


Figure 6.13: Augmented Network Structure

Following the elicitation of the augmented network structure, the prior belief can be assigned. In order to maintain objectivity, an equal prior belief is adopted to denote the probability of having one status instantiated is identical to having any other statuses. Nevertheless, in order to maintain an equivalent sample size, a balancing process is needed. If the minimum sample size is set to be a unit, denoted as 1, the equivalent sample size can be estimated through calculating the Least Common Multiple (L.C.M), as illustrated in Table 6.9. The method takes into account of the number of statuses and the number of augmented nodes that associated with every variable. As a result, the equivalent sample size for this specific case is 12.

Table 6.9: Identification of Equivalent Sample Size

Variable	Number of statuses	Number of augmented nodes	Product
C	2	1	2
H	2	1	2
S	3	4	12
T	2	3	6
L	2	2	4
		Least Common Multiple	**12**

To assign the prior belief, different handling is needed for the variables having different statuses. In the case of binary variables, i.e. C, H, T, L, the Beta function, $\rho(f_{ij}) = beta(f_{ij}; a_{ij}, b_{ij})$, is used. For instance, the augmented node F_C1 has equal prior belief for both statuses $\{False, True\}$: $beta(F_c1{:}\,6{,}6)$. In contrast, the multinomial variables, i.e. S, use the Dirichlet distribution, $\rho(f_{ij1}, f_{ij2}, \dots, f_{ij(r_i-1)}) = Dir(f_{ij1}, f_{ij2}, \dots, f_{ij(r_i-1)}; a_{ij1}, a_{ij2}, \dots a_{ijr_i})$. For instance, the augmented node F_s1 has equal prior belief for all statuses $\{Minor, Moderate, serious\}$: $dir(F_s11, F_s12{,}1{,}1{,}1)$. Consequently, the augmented BN with quantified augmented nodes is illustrated in Figure 6.14.

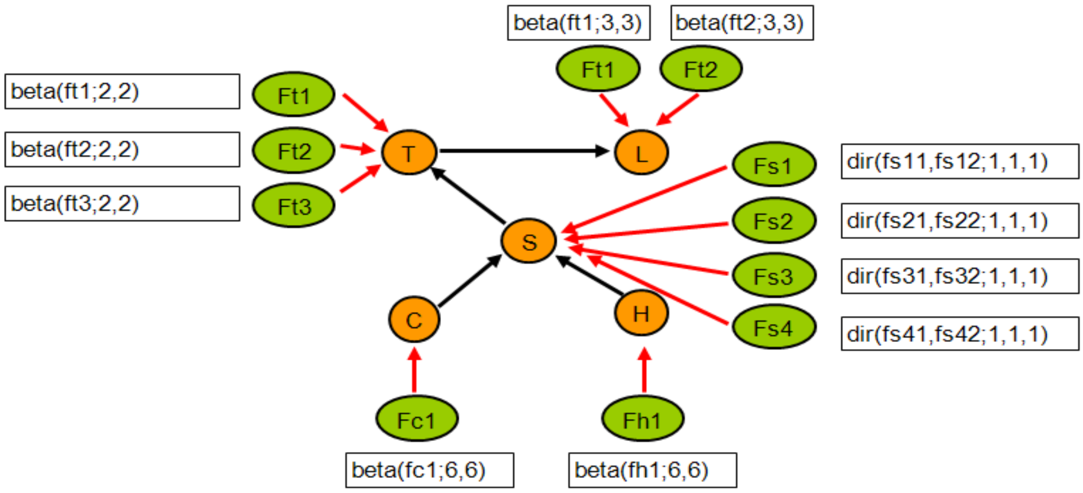


Figure 6.14: Assignment of Prior Belief with Equal Sample Size

With the aforementioned process, the last step is to update the beliefs with the collected data. With respect to this, a summary table needs to be produced and the evidence is systematically classified. In the case of root nodes, e.g. C and H, the count of the occurrence of each status in the database is recorded for each variable and tabulated in Table 6.10; whilst, the summary for ordinary nodes having parents needs to take into account of various combinations of the statuses of their parents, e.g. S, T, L.

The subsequent process is to apply the probability updating principle for both the Beta and Dirichlet distribution functions as derived in the previous section: $\rho(f_{ij}|d)$ and $\rho(f_{ij1}, f_{ij2}, \dots, f_{ij(r_i-1)}|d)$. As the computation included is pure addition, this can be performed easily with the updated augmented network presented in Figure 6.15. The updated beliefs are readily available to be transformed into probabilities and conditional probabilities to be stored in the output BN model. For instance, the probability for $C = False$ is $205/(205 + 383) = 0.3486$ and the conditional probability $P(S = minor|C = False, H = False) = 74/(74 + 9 + 5) = 0.8409$. Consequently, the five-node BN is constructed with fully quantified probability tables.

Table 6.10: Evidence Collected from the Data for Beliefs Updating

Variable	**Parent**	**Statuses**		
C		False	True	
	None	199	377	
H		False	True	
	None	245	331	
S		Minor	Moderate	Serious
	$C = False, H = False$	73	8	4
	$C = False, H = True$	151	7	2
	$C = True, H = False$	110	2	2
	$C = True, H = True$	208	8	1
T		Daytime	Night	
	$S = Minor$	407	135	
	$S = Moderate$	14	11	
	$S = Serious$	7	2	
L		At sea	In port	
	$T = Daytime$	285	143	
	$T = Night$	115	33	

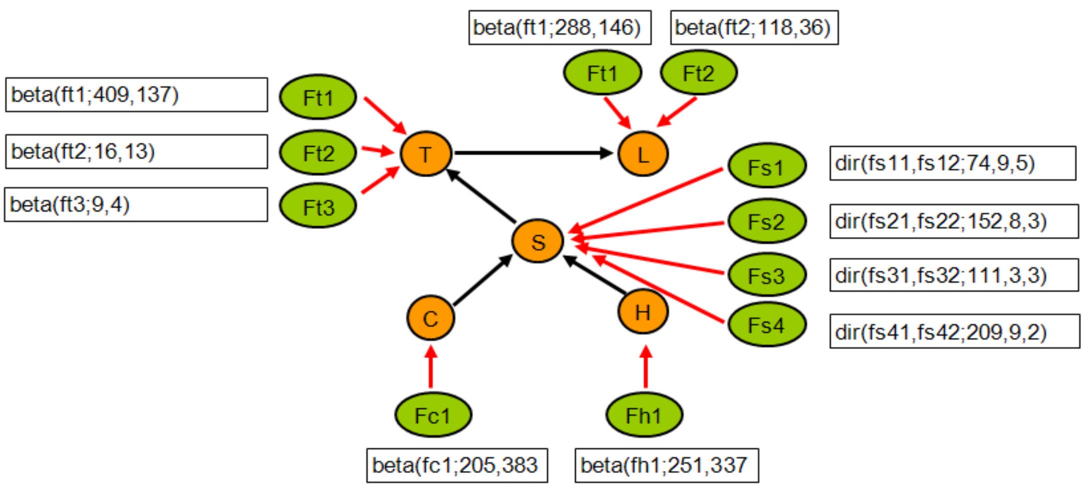


Figure 6.15: Beliefs Updating

6.5 Score-Based Learning

In contrast to constraint-based learning, score-based learning focuses on the identification of a BN structure as an integral unit. The principle of score-based learning is to evaluate the superiorities of all possible network skeletons using dedicated criterion functions and to select the one receiving the highest score. This implies that two components have to be properly addressed: the scoring criteria (merit function) and the searching algorithm.

6.5.1 Merit Functions

Classical means for judging the goodness-of-fit of a statistical model derived from the collected data is mainly through describing the spread (variability) of the data in comparison with the values estimated using the trained model, e.g. variance. With respect to a BN model, simple variance estimations become infeasible due to the complexity involved. Hence, an alternative to measure the quality of the constructed BN model in describing the sampled data is needed.

Due to its probabilistic nature, a BN essentially represents the joint probability distribution that is implied in the sampled data. As a result, it is safe to proclaim that the model is accurate if and only if its joint probability distribution matches the joint probability distribution described by the data.

Nevertheless, in most cases it is computationally infeasible to determine and use the joint probability distribution described by the sampled data. For instance, as demonstrated in [Pappas and Gillies, 2002], the matrix of the joint probability distribution for a data set containing 9 variables has 14,696,640 elements due to the combinatorial explosion, which is virtually impossible to use in practice. In this respect, the level of discretization of each variable can play a very important role. This is also the motivation for deploying BNs to present the joint probability distribution described by the sampled data.

On the other hand, considering a multinomial BN model, the joint probability distribution can be expressed in equation (6.17).

$$P(d|G) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} E\left(\prod_{k=1}^{r_i} F_{ijk}^{S_{ijk}}\right) \tag{6.17}$$

Where d represents a specific data set
G represents a specific BN model
n denotes the number of variables in the network
q_i denotes the number of different instantiations of the parents for variable i
r_i denotes the number of states of variable i

The term $E\left(\prod_{k=1}^{r_i} F_{ijk}^{S_{ijk}}\right)$ represents the joint probability distribution at each augmented node of the variable i. In the meantime, as it has been stressed during the network quantification stage, the Dirichlet distribution is assumed for the statuses recorded in the augmented node, which implies,

$$E\left(\prod_{k=1}^{r} F_{k}^{S_k}\right) = \frac{\Gamma(N)}{\Gamma(N+M)} \prod_{k=1}^{r} \frac{\Gamma(a_k + s_k)}{\Gamma(a_k)}$$

Consequently, the joint probability distribution that represented by a BN model can be calculated using equation (6.18).

$$P(d|G) = \prod_{i=1}^{n} \prod_{j=1}^{q_i} \frac{\Gamma(N_{ij})}{\Gamma(N_{ij} + M_{ij})} \prod_{k=1}^{r} \frac{\Gamma(a_{ijk} + s_{ijk})}{\Gamma(a_{ijk})} \tag{6.18}$$

On the basis of the foregoing, it is understood that the exact difference between the joint probability distributions described by both the BN model and the sampled data can be difficult to estimate, but the joint probability distribution represented by a BN can be used alone for comparative purposes as the aim to identify an optimal BN model that can best describe a data set. The defined joint probability distribution $P(d|G)$ in equation (6.18) is also frequently referred to as the Bayesian scoring criterion. Several other well-accepted criteria are summarised in Appendix 6.

With the estimated $P(d|G)$ for each candidate network, further transformation is needed by using Bayes' theorem: $P(G|d) = P(d|G) \cdot P(G)/P(d)$. Also, it is noticed that the Gamma functions within the Bayesian scoring criterion grow very rapidly due to the factorial functions. Hence, the natural logarithm of the Gamma function is adopted to greatly lower the growth rate. Moreover, in the case of combinatorial calculations, this allows adding and subtracting logs instead of multiplying and dividing very large values.

6.5.2 Heuristic Searching Algorithm

With the scoring criterion, it is possible to investigate exhaustively all possible network diagrams and to select the one that maximises $P(G|d)$. Unfortunately, this is only applicable when the number of variables is small. The difficulty arises when the number of variables increases. It becomes computationally infeasible as the possible combinations of directing arcs increases exponentially. For instance, the number of possible network diagrams (DAGs) containing n variables is illustrated in equation (6.21), [Robinson, 1977].

$$f(n) = \sum_{i=1}^{n} (-1)^{i+1} \binom{n}{i} 2^{i(n-i)} f(n-i) \quad n > 2 \tag{6.21}$$

This implies that the number of possible diagram candidates can reach 29,000 in the case of 5 variables. A similar conclusion has been derived in [Chickering, 1996], where the problem of finding the most probable DAG patterns for certain class of prior distributions is NP-complete (nondeterministic polynomial time). Therefore, it is vital to develop a heuristic searching algorithm so that the optimal one(s) can be converged efficiently.

The prevailing method for the searching algorithm of scoring-based learning was proposed in [Chickering, 2002, Chickering, 2003] and [Chickering & Meek, 2002], known as greedy equivalence search (GES). Through the introduction of score equivalent classes of the structure, the size of the searching space can be significantly reduced. Moreover, a list of logical link operations makes it easy to transform from one structural class to all possible neighbouring classes. Lastly, the score fluctuations can be calculated locally, a fact that greatly improves the computational efficiency.

Apart from the directed acyclic graph (DAG), the term acyclic partially directed graph (PDAG) was defined to contain both directed and undirected edges. As a result, the PDAG could be used to represent equivalent classes of the BN structures. Those structures admitting an equivalent class, which is denoted by $G \in Class(\mathrm{P})$, and it is true if and only if G and P have the same skeleton and the same set of v-structure. The term Completed PDAG (CPDAG) is designed to designate a PDAG that consists of directed edges for compelled edges and undirected edges for reversible edges in the equivalent class. Hence, each class has a unique CPDAG.

The CPDAG enables the heuristic searching in the GES algorithm. A searching space has three components: a set of states, a representation scheme for the states, and a set of operators. A set of states represents the sets of CPDAG that could potentially be the final solutions. Representation scheme for the states requires an efficient way to represent each state; and a set of operators are the operational procedures to be followed to transit one state to another.

The steps need to be followed is to constantly transit the obtained PDAG to a DAG after applying one of the operators. Having the DAG, the score increment can be updated easily, after which the DAG needs to be transformed to a CPDAG for the next iteration. The process is illustrated in Figure 6.16.

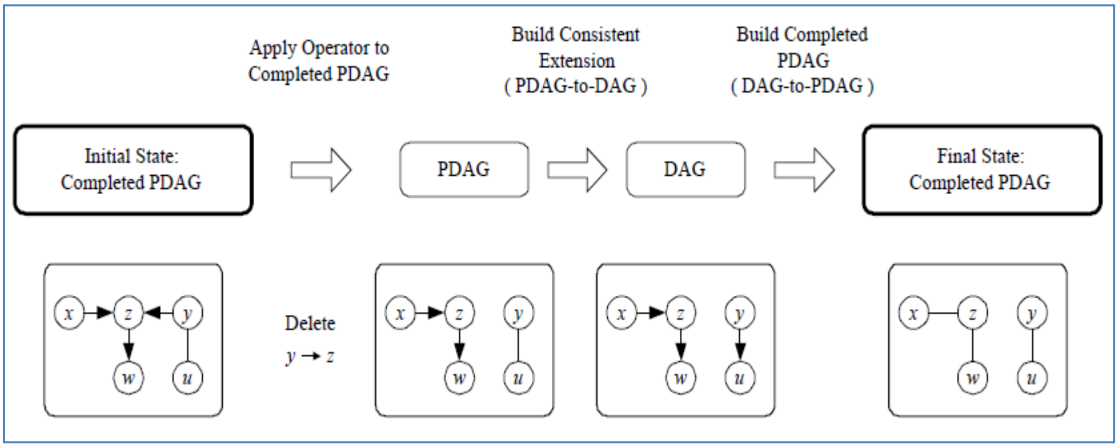


Figure 6.16: Diagram Depicting the Operational Procedure

The detailed operations of adding and removing the links are described by the two-phase GES algorithm, as shown next. For each iteration of both *Insert* and *Delete* operations, all possible operations are searched and validated through the validity test, as illustrated in Table 6.11, so that local score increment could be updated and the one giving the highest increment could be adopted for the next iteration.

$Insert(X, Y, T)$

For non-adjacent nodes X and Y in P^c, and for any subset T of the neighbours of Y that are not adjacent to X, the $Insert(X, Y, T)$ operator modifies P^c by (1) inserting the directed edge $X \rightarrow Y$, and (2) for each $T \in \boldsymbol{T}$, directing the previously undirected edge between T and Y as $T \rightarrow Y$.

$Delete(X, Y, H)$

For adjacent nodes X and Y in P^c connected either as $X - Y$ or $X \rightarrow Y$, and for any subset $\boldsymbol{H}$ of the neighbours of Y that are adjacent to X, the $Delete(X, Y, H)$ operator modifies P^c by deleting the edge between X and Y, and for each $T \in \boldsymbol{T}$, (1) directing the previously undirected edge between Y and H as $Y \rightarrow H$ and (2) directing any previously undirected edge between X and H as $X \rightarrow H$.

Table 6.11: Necessary and Sufficient Validity Conditions and (Local) Change in Score for Each Operator

Operator	**Validity Tests**	**Change in Score**
$Insert(X, Y, T)$	$NA_{Y,X} \cup T$ is a clique Every semi-directed path from Y to X contains a node in $NA_{Y,X} \cup T$	$s(Y, NA_{Y,X} \cup T \cup Pa_Y^{+X})$ $- s(Y, NA_{Y,X} \cup T \cup Pa_Y)$
$Delete(X, Y, H)$	$NA_{Y,X} \backslash H$ is a clique	$s(Y, \{NA_{Y,X} \backslash H\} \cup Pa_Y^{-X})$ $- s(Y, \{NA_{Y,X} \backslash H\} \cup Pa_Y)$

6.5.3 A Score-Based Learning Example

On the basis of the forgoing, it is clear that the candidate networks should be quantified first and a degree of automation is needed to achieve a satisfactory convergence. In this respect, a computer program has been developed to automate such a process, as will be detailed in section 6.8. On the other hand, as far as the feasibility and rationality of the technique is concerned, manual manipulation is carried out in this section with limited addition and removal of links. The emphasis is placed on the interaction between the generation of the candidates and their ensuing scoring process.

Due to the flexibility of the algorithm for candidate network generation, the jumping-off point can be either a fully empty network skeleton without any link in between or an ordinary BN model, such as the five-node network delivered through both constraint-based learning and parameter learning process as illustrated in Figure 6.15, which will be used for demonstration purposes. The process starts with the evaluation of the model using the scoring criteria. Following that, the links (e.g. $T-S$, and $S-H$) can be removed respectively, which is accompanied with re-quantification of the newly obtained networks due to the changing network skeletons. Further scoring of the two network candidates is performed and the consequential comparisons can be conducted among the three networks.

An initial attempt is made to evaluate the score for the BN model obtained in the previous section. With a_{ijk} and s_{ijk} are the prior belief and the collected evidence for every status of each augmented node, N_{ij} and M_{ij} are the summations of the prior belief and the collected evidence for each augmented node, the score for each node can be obtained first. For instance, on the basis of the probability quantification summary table for the node C, as tabulated in Table 6.12, the score for C can be calculated using equation (6.22).

Table 6.12: Summary of Prior Belief and Updated Evidence for the Variable C

Node C					
False		**True**		**Summation**	
a_{C1}	6	a_{C2}	6	N_C	12
s_{C1}	199	s_{C2}	377	M_C	578

$$\ln\left(score_{node_C}\right) = \left(\ln\Gamma(N_C) - ln\Gamma(N_C + M_C)\right) + \left(\ln\Gamma(a_{C1} + s_{C1}) - ln\Gamma(a_{C1})\right) + \left(\ln\Gamma(a_{C2} + s_{C2}) - ln\Gamma(a_{C2})\right) \tag{6.22}$$

Consequently, through estimating the score of each node the total score for the original network model is estimated to be -1.62279×10^3. The links between $T-S$, and $S-H$ are then removed one by one with the corresponding augmented BNs updated as depicted in Figure 6.17 and 6.18. Similar computations can be carried out to estimate the changes of the scores. The subsequent scores are -1.62323×10^3 and -1.62223×10^3 for the two models respectively.

During the estimation process, it is unnecessary to carry out a holistic computation for all nodes of the updated network. For instance, removal of the link between $T-S$ will affect the augmented nodes T, whilst the statues of the remaining variables are unchanged. Similar situation can be observed in Figure 6.18 for the node S.

Consequently, the obtained score is transformed into the probabilistic format from the nature of logarithm form. Furthermore, the obtained probability is equivalent to the component $P(d|gp)$ in the Bayes' theorem, which should be reverted to $P(gp|d)$, the probability of having the BN model given the collected data. As little knowledge is available concerning which network diagram is more favourable than the others, equal likelihood $P(gp)$ is assigned for the three candidates, i.e. 1/3=0.333. Moreover, due to the fact that the information about the component $P(d)$ is not known, normalisation of the results is performed.

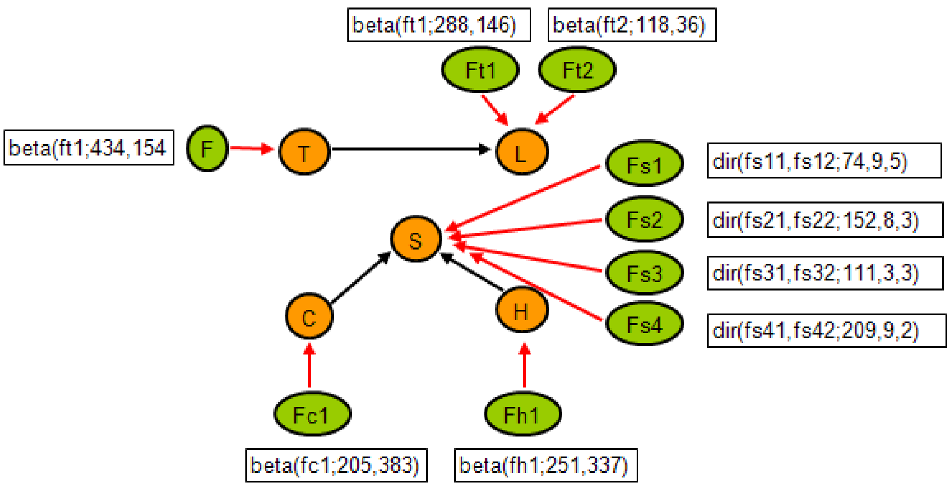


Figure 6.17: Updated Network Model with the Link between T and S Removed

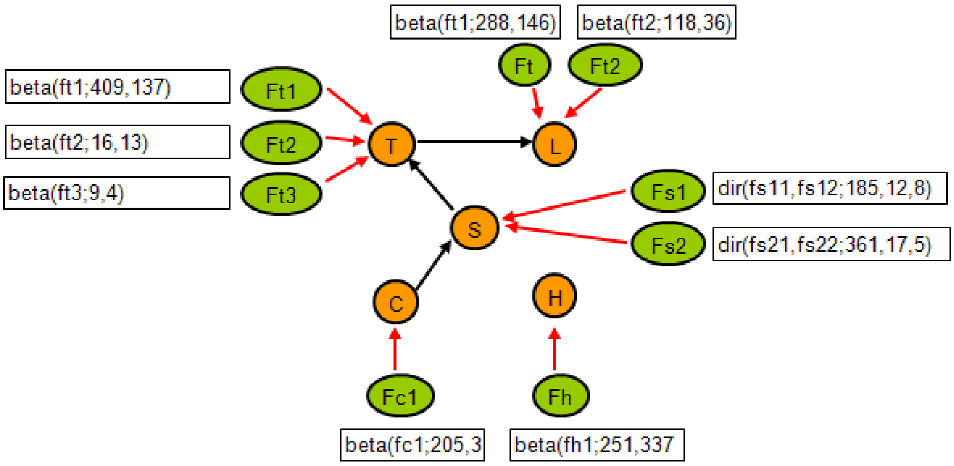


Figure 6.18: Updated Network Model with the Link between S and H Removed

The subsequent $P(gp|d)$ obtained for the three candidates is tabulated in Table 6.13. It is apparent that the original model is more favourable than model 2. Model 3 gains the highest score among the three candidates. Nevertheless, it is understood that a holistic treatment of the searching space is needed in order to identify an optimal global solution rather than the local ones.

Table 6.13: Scores of the Three Networks

Network candidates	**Description**	**Normalised probability**
Model 1	Original model	0.295
Model 2	Original model with $T - S$ removed	0.190
Model 3	Original model with $S - H$ removed	0.517

6.6 Comparisons between Constraint-based and Score-based Learning

As it was discussed above, the two methods are different regarding the underlying principles. Constraint-based learning iteratively performs statistical tests on the data to identify a list of conditional independencies and leads to a unique model that entails these relationships. Score-based learning computes the joint probabilities of different candidate models given the data and ranks the models. Distinct principles adopted lead to different advantages and preferences under various circumstances. The constraint-based method can be more susceptible to small data set as this may result in incorrect categorical decisions about conditional independencies. However, the score-based method may end up with a network model that is difficult for interpretation due to little attention being paid to the causality aspect. Hence, the constructed BNs should be scrutinised so that an optimal approximation can be achieved.

6.7 Missing Data Treatment

The ideal situation for data analysis is to possess a complete set of data that is readily available for processing. This can be difficult to achieve in practice, particularly so in the case of maritime casualty data. Despite this situation, little attention has been paid to the issue of incomplete data for risk assessment. Simple ignorance and arbitrary approximation are the standard practice to deal with such circumstances. This coarse handling will affect negatively the quality of risk assessment. Moreover, every record in the casualty database normally comes with the price of human lives, property damages, and environmental pollution. Hence, rather than wasting such priceless resource, a scientific treatment of missing data is encouraged.

Enormous development has been achieved over the last quarter of a century in general statistical methods for handling incomplete data. Notably, both the Expectation Maximisation (EM) algorithm and the Markov Chain Monte Carlo (MCMC) technique provide flexible and reliable means to address the missing-data problem [Schafer, 1997].

The EM algorithm is a technique for identifying the maximum likelihood estimates when the data are not fully observed. It utilises the interdependence between the missing data $Y_{missing}$ and the parameters θ. As $Y_{missing}$ contains the information for estimating θ, it helps in turn to identify the likely values of $Y_{missing}$. On the basis of this nature, initial $Y_{missing}$ can be filled up using initial estimate of θ, re-estimate θ based on $Y_{observed}$ and the approximated $Y_{missing}$. This process can be iterated until the estimates converge.

A short example with a small data set containing five records is tabulated in Table 6.14. The relationships between the nodes T and L can be constructed as shown in Figure 6.19. On this basis, the prior belief for the three augmented nodes can be,

$$f' = \{f_{t1}, f_{l1}, f_{l2}\} = \left\{\frac{2}{2+2}, \frac{1}{1+1}, \frac{1}{1+1}\right\} = \left\{\frac{1}{2}, \frac{1}{2}, \frac{1}{2}\right\}$$

Where f_{t1} represents the belief of the augmented node F_{t1} for node T with $T = Daytime$

f_{l1} represents the belief of the augmented node F_{l1} for node L with $T = Daytime$ and $L = In\_port$

f_{l2} represents the belief of the augmented node F_{l2} for node L with $T = Night$ and $L = In\_port$

Table 6.14: A Data Set Containing Two Empty Cells

Records	**Time**	**Location**
1	Daytime	In port
2	Daytime	?
3	Daytime	In port
4	Daytime	At sea
5	Night	?

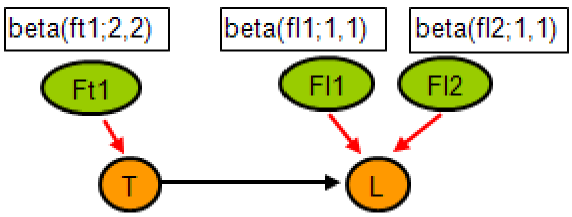


Figure 6.19: Prior Belief Assigned for both T and L

The prior belief facilitates the estimation of the collected evidence, as illustrated in Table 6.15.

Table 6.15: Updated Data using Prior Belief

Records	Time	Location	No. of occurrence
1	Daytime	In port	1
2	Daytime	In port	1/2
2	Daytime	At sea	1/2
3	Daytime	In port	1
4	Daytime	At sea	1
5	Night	In port	1/2
5	Night	At sea	1/2

Having this, it can help generate the updated beliefs.

$$s_{21} = E(s_{21}|data, f') = \sum_{case=1}^{5} P(T = Daytime, L = In\_port|data, f')$$
$$= 1 + \frac{1}{2} + 1 + 0 + 0 = \frac{5}{2}$$
$$t_{21} = E(t_{21}|data, f') = \sum_{case=1}^{5} P(T = Daytime, L = At\_sea|data, f')$$
$$= 0 + \frac{1}{2} + 0 + 1 + 0 = \frac{3}{2}$$
$$s_{22} = E(s_{22}|data, f') = \sum_{case=1}^{5} P(T = Night, L = In\_port|data, f')$$
$$= 0 + 0 + 0 + 0 + \frac{1}{2} = \frac{1}{2}$$
$$t_{22} = E(t_{22}|data, f') = \sum_{case=1}^{5} P(T = Night, L = At\_sea|data, f')$$
$$= 0 + 0 + 0 + 0 + \frac{1}{2} = \frac{1}{2}$$

Where s_{21} represents the evidence from the data concerning the augmented node F_{l1} with $T = Daytime$ and $L = In\_port$

t_{21} represents the evidence from the data concerning the augmented node F_{l1} with $T = Daytime$ and $L = At\_sea$

s_{22} represents the evidence from the data concerning the augmented node F_{l2} with $T = Night$ and $L = In\_port$

t_{22} represents the evidence from the data concerning the augmented node F_{l2} with $T = Night$ and $L = At\_sea$

Consequently, the prior belief can be further updated accordingly,

$$f_{t1} = \frac{a_{11} + s_{11}}{a_{11} + s_{11} + b_{11} + t_{11}} = \frac{2 + 4}{2 + 4 + 2 + 1} = \frac{2}{3}$$

$$f_{l1} = \frac{a_{21} + s_{21}}{a_{21} + s_{21} + b_{21} + t_{21}} = \frac{1 + \frac{5}{2}}{1 + \frac{5}{2} + 1 + \frac{3}{2}} = \frac{7}{12}$$

$$f_{l2} = \frac{a_{22} + s_{22}}{a_{22} + s_{22} + b_{22} + t_{22}} = \frac{1 + \frac{1}{2}}{1 + \frac{1}{2} + 1 + \frac{1}{2}} = \frac{1}{2}$$

Where a_{11} represents the prior belief concerning the augmented node F_{t1} with $T = Daytime$

b_{11} represents the prior belief concerning the augmented node F_{t1} with $T = Night$

s_{11} represents the evidence from the data concerning the augmented node F_{t1} with $T = Daytime$

t_{11} represents the evidence from the data concerning the augmented node F_{t1} with $T = Night$

a_{21} represents the prior belief concerning the augmented node F_{l1} with $T = Daytime$ and $L = In\_port$

b_{21} represents the prior belief concerning the augmented node F_{l1} with $T = Daytime$ and $L = At\_sea$

a_{22} represents the prior belief concerning the augmented node F_{l2} with $T = Night$ and $L = In\_port$

b_{22} represents the prior belief concerning the augmented node F_{l2} with $T = Night$ and $L = At\_sea$

With the updated beliefs, the column "number of occurrence" in Table 6.15 can be updated. This in turn leads to the updates of the probabilities estimated for the empty cells. Through six iterations, the estimated probabilities converge, as tabulated in Table 6.16, with the first empty cells have $P(L = In\_port) = 0.6$, $P(L = At\_sea) = 0.4$ and the second empty cell $P(L = In\_port) = 0.5$, $P(L = At\_sea) = 0.5$. The estimated values can be directly used for parameter learning.

Table 6.16: Six Iterations Performed for Probabilities Updating

	Number of iterations					
	1	2	3	4	5	6
f_{t1}	0.5	0.6667	0.6667	0.6667	0.6667	0.6667
f_{l1}	0.5	0.5833	0.5972	0.5995	0.5999	0.6000
f_{l2}	0.5	0.5	0.5	0.5	0.5	0.5

The computational effort needed to implement the EM algorithm depends mainly on the selection of initial priors and the defined precisions. For instance, if four decimal places are considered for the initial priors, as tabulated in Table 6.16, it needs 6 iterations to converge. In contrast, only 4 iterations are required if three decimal places are defined. Moreover, as it is depicted in Figure 6.20, the selection of initial priors has direct impact on the number of iterations needed to converge. The lowest iteration number (i.e. 2) can be achieved if the priors for f_{t1}, f_{l1}, f_{l2} are set to be 0.667 at the beginning. The main reason for such a phenomenon is that such a set of initial priors is the closest approximation to the subsequently converged one (i.e. 0.6667, 0.6000, 0.5), as tabulated in Table 6.16.

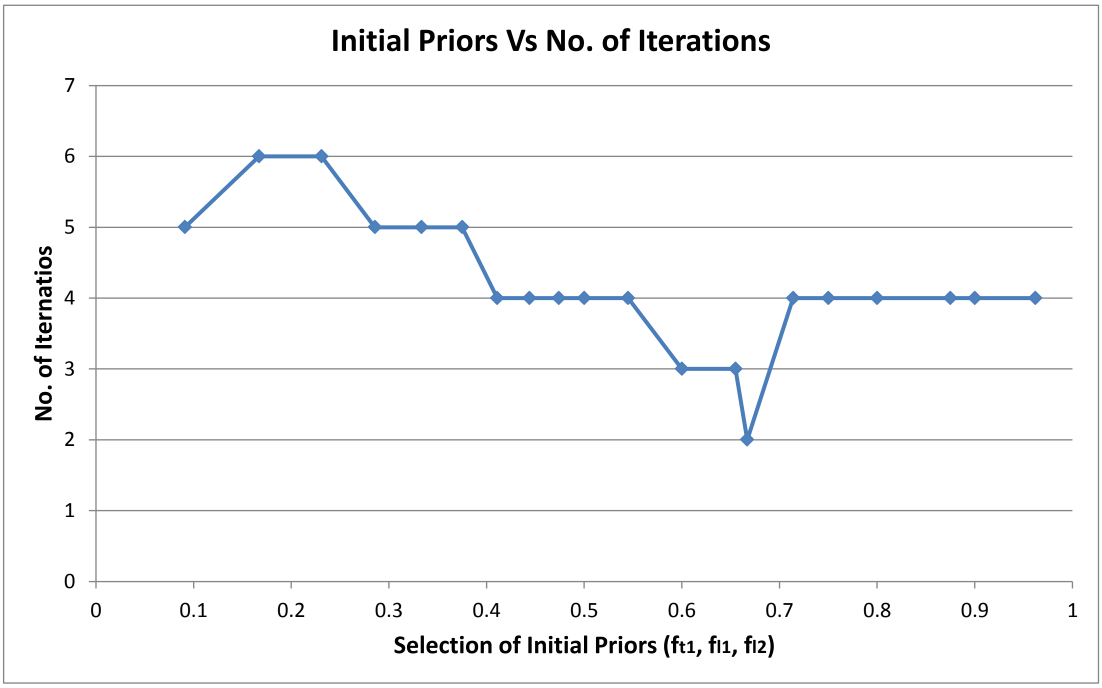


Figure 6.20: Relationship between the Selection of Initial Priors and Number of Iterations Needed

Another powerful technique is known as the Markov chain Monte Carlo, which is a collection of techniques for creating pseudorandom draws from the probability distributions. To address the issue of missing-data problem, a specific methodology has been developed in [Schafer, 1997] known as the Bayesian iterative proportional fitting (Bayesian IPF). This is a method that also adopts the log-linear model as discussed previously. The key is to train the corresponding log-linear model on the basis of the available data so as to predict the cell probabilities of the contingency table. During the model training process, a Markov chain of the predicted cell probabilities is formed through iteratively correcting the hyper-parameters of the constrained Dirichlet posterior distribution function. After a suitably large number of iterations (the burn-in period), the estimated probabilities can be regarded as a random draw from the correct posterior $P(\theta|x)$. Hence, the subsequent draws for θ represent a dependent sample from $P(\theta|x)$, which can be used for the derivation of cell probabilities.

For instance, in the case of the dataset tabulated in Table 6.14, the estimated cell probabilities for the contingency table of T and L through EM algorithm are shown in Table 6.17. Such information can be treated as the initial distribution for training the log-linear model. The subsequent estimation through the Bayesian IPF is tabulated in Table 6.18. Having such information, the statues of the missing data can be estimated accordingly for further processing. For instance, the status of T for the first empty cell is "Daytime", $P\left(L = In_{port}\right) = \frac{0.3560}{0.3560+0.2272} = 0.6104$, $P(L = At\_sea) = \frac{0.2272}{0.3560+0.2272} = 0.3896$. In the case of second empty cell, $P\left(L = In_{port}\right) = \frac{0.2208}{0.2208+0.1960} = 0.5298$, $P(L = At\_sea) = \frac{0.1960}{0.2208+0.1960} = 0.4703$.

Table 6.17: Initial Estimation of Cell Probabilities of the Contingency Table for T and L through EM algorithm

		Time	
		Daytime	**Night**
Location	**In port**	0.3	0.25
	At sea	0.2	0.25

Table 6.18: Updated Estimation of Cell Probabilities that Satisfying the Log-linear model of the Contingency Table for T and L through Bayesian IPF

		Time	
		Daytime	**Night**
Location	**In port**	0.3560	0.2208
	At sea	0.2272	0.1960

6.8 The Size of Data Set Needed

In order to gain better confidence of the developed BN model, a number of researchers have investigated the amount of data that is needed for a satisfactory analysis. Nevertheless, a definite conclusion has not been achieved and the dispute continues. The bounds on the number of records needed are developed in [Zuk, et al., 2006] to ensure a particular wrong network diagram can be avoided. Moreover, [Dai, et al., 1997] suggests a relationship between the number of nodes and the sample size needed to learn a correct network diagram, as tabulated in Table 6.19. Nevertheless, there are also some conflicting empirical results. For instance, a 37-node network is generated from 3000 pertinent records [Cooper and Herskovits, 1992], while [Neapolitan and Morris, 2003] uses 9640 cases to train an 8-node network model.

Table 6.19: Correlations between Number of Nodes and Sample Size Needed, [Dai, et al., 1997]

Number of nodes	Sample size needed
2	10
3	200
4	1000-5000
5	1000-2000

Despite of the aforementioned empirical findings, it is important to understand the current status of the marine casualty database. Due to the negative nature and the subsequent confidentiality, the difficulties encountered when approaching ship operators can significantly limit the amount of data that can be collected. Hence, as the current sample size still stands at a relative low level when considering the number of variables that needs to be considered at a time, (e.g. hundreds of records versus 10~20 variables, etc.), the emphasis should be placed on collecting as much information as possible at this stage.

6.9 Automation of Bayesian Learning Algorithms

As it can be noticed that the amount of computation needed for the implementation of key components of the BNs learning, i.e. dependency analysis, the PC algorithm implementation, parameter learning, and score-based learning, is tremendous even for a simple BN model containing a handful of nodes, hence, a degree of automation is needed in order to facilitate a smooth execution of the learning process.

The classical automation work for BNs focused mainly on the probability processing through Bayesian inference. This has now become almost standard functions to be equipped by every BN package, like Hugin (http://www.hugin.com/), Netica (http://www.norsys.com/), GeNIe (http://genie.sis.pitt.edu/), etc. In contrast, the functions allowing both the BN structure learning and the subsequent network quantification are very limited. For instance, the TETRAD project (http://www.phil.cmu.edu/projects/tetrad/) undertaken at Carnegie Mellon University is one of the few important and continuous researches focusing on the development of the principles of causality discovery, which can be applied to BN learning due to its influence diagram nature, [Spirtes, et al., 2000], [Glymour, 1987, Glymour and Cooper, 1999, Glymour, 2002].

A number of commercial BN software has also embarked on the development of relevant functions for learning BNs in recent years, e.g. Hugin. Nevertheless, these packages work in a black-box nature, which provides little information of the detailed computation process and the quality of the identified network structure. As the field of learning BNs from the data is still evolving, the maturity of these functions is doubtable. All the aforementioned factors drive the development of an independent program, which is tailored for this research and the context of risk-based ship design. The architecture of the developed program is illustrated in Figure 6.21. Raw data that is recorded in the database system developed in Chapter 5 can be selected and exported into text files (Figure 6.22). Having the data, it can be easily imported into the code developed in R (http://www.r-project.org/), as depicted in Figure 6.23. Adopting R as the platform is attributable to its well-established statistical functionality, which allows easy training of the mathematical models, e.g.

the log-linear model, the logistic regression model, and scripting flexibly. Both constraint-based and score-based learning algorithms are included. The identified BN model can be directly exported into GeNIe for facilitating future probabilistic inference, (Figure 6.24). In the meantime, the detailed computational process is recorded in the log file for further scrutinisation, as shown in Figure 6.25. In order to examine the quality of the BN model constructed through data mining, a series of investigation will be performed and discussed in Chapter 8.

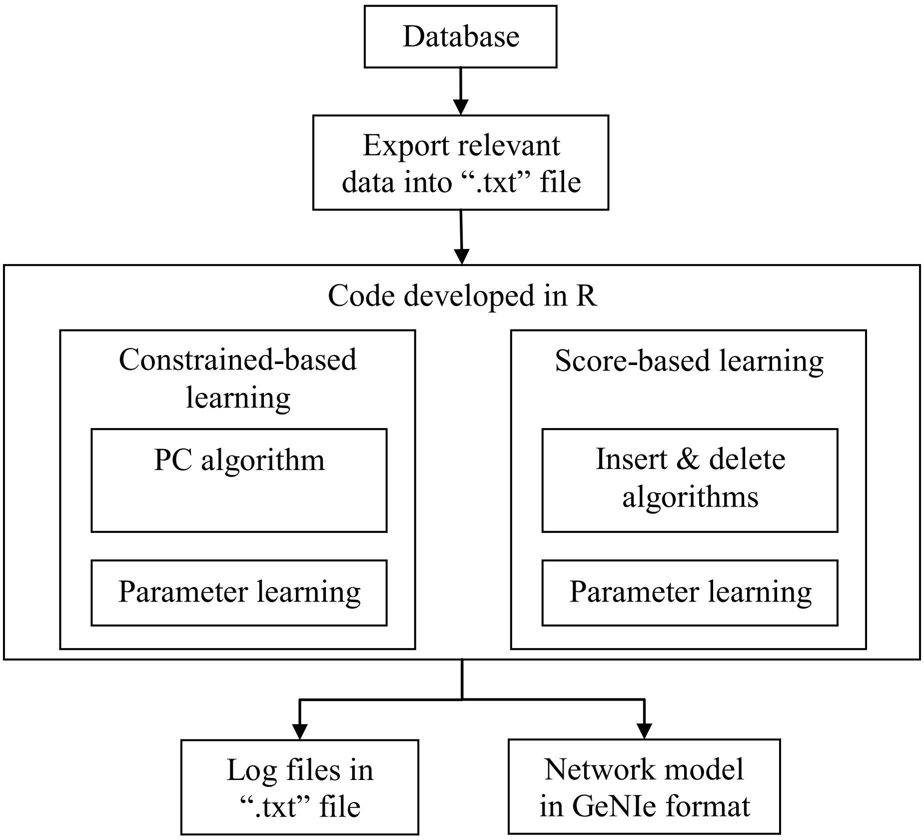


Figure 6.21: Architecture of the Developed Code for Bayesian Networks Learning

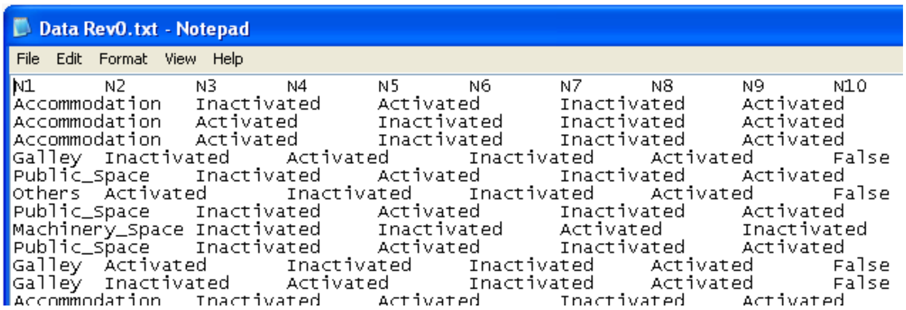


Figure 6.22: A Sample of Raw Data in Notepad

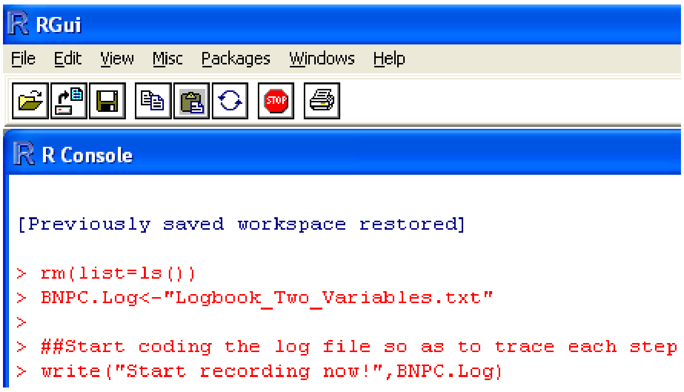


Figure 6.23: A Snapshot of R Interface

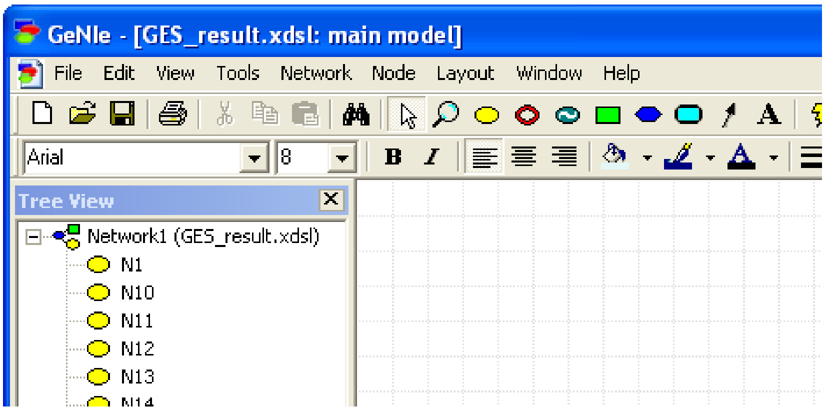


Figure 6.24: A Snapshot of GeNIe Interface

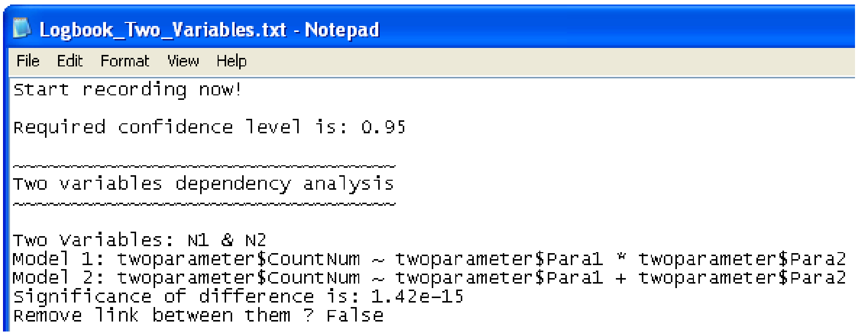


Figure 6.25: A Snapshot of a Log File

6.10 Closure

Although data mining is a broad and multidisciplinary subject, as far as the elicitation of the BN model is concerned, the two major categories of structure learning techniques: constraint-based learning and score-based learning, have been elaborated in great details, in parallel with the formalised technique for the quantification of the network structure in a scientific manner. The difficulties frequently encountered during application stages e.g. missing data, size of data set, etc. have also been explicitly addressed. Due to the tremendous computation involved, the developed program in R has been presented for facilitating the implementation process.

Chapter 7
Risk-Based Ship Design

7.1 Preamble

The value of risk-based design is attributed to a scientific methodology for the quantification of ship life-cycle risk and its constituent components. Through systematically performing risk assessment, the risk level can be revealed, when compared against pre-defined risk acceptance criteria. Moreover, as Risk-based design can offer a transparent and well-informed platform where the knowledge on technical performance, cost/earning potential, and safety is readily available for the trade-off process, it is crucial to adhere to a properly developed practical ship design procedure for the implementation of risk-based design. This entails two sequential issues need to be addressed properly: risk assessment and the subsequent decision support.

In light of the foundation that has been laid over the past fifteen years for risk-based design and on the basis of the proposed approach for the development of probabilistic models in BNs, this chapter starts with a proposition of a practical ship design procedure with particular emphasis on the safety aspect. An important feature concerns the BNs, which can be integrated with other design components as safety-relevant knowledge models. Following an elaboration of the framework, the roles of BNs will be demonstrated.

7.2 A Practical Ship Design Procedure

It can be argued that the initial design stage comprises the most creative part of a ship design process and it also possesses the largest freedom to make important decisions that will influence the overall performance of a design. It starts with a few basic requirements from the owners (specification), such as range between refuelling, payload, and speed, etc. This is accompanied by a list of restrictions arising from port approaches and route characteristics. As the design is evolving, it needs to comply with classification society's rules and international and national regulations, all of which are mainly concerned with safety features. The output from this process is an initial set of principal dimensions and a basic layout of the ship.

A theoretical presentation of the design process, which demonstrates the inherent compromise, this exercise is the well accepted concept of the design spiral, as illustrated in Figure 7.1. Nevertheless, considering the high risk associated with huge expenditure if a design is developed from scratch, the practice in the day-to-day operation of the design office is based on either of the following approaches [Konovessis, 2001]:

- The basis ship approach, through which a proven feasible design is used as the template. The principal particulars and layout of the basis ship will be used as the basis for deriving the design under consideration using simple geometrical projection formulae.

- A database approach: in which instead of using a single basis design, the main features of a series of similar designs on main dimensions, ratios and layout characteristics are collected and deployed to determine the properties of the new design.

Clearly, as the procedures of the aforementioned two approaches imply, the aim is to speed up the iterative process so that a faster convergence can be achieved, while, at the same time, not compromising the techno-economic performance. However, it should be noted that intuitive judgement is playing an important role as the design proceeds. Moreover, the two approaches do not offer an alternative nor promote the identification of a better solution. An inadequate estimation of one of the design elements can subsequently lead to a feasible design but not to an optimal one. This is because at each step the designer must satisfy limited criteria, but having them satisfied he proceeds to the next step without knowing how good the design actually is [Vassalos, et al, 2005].

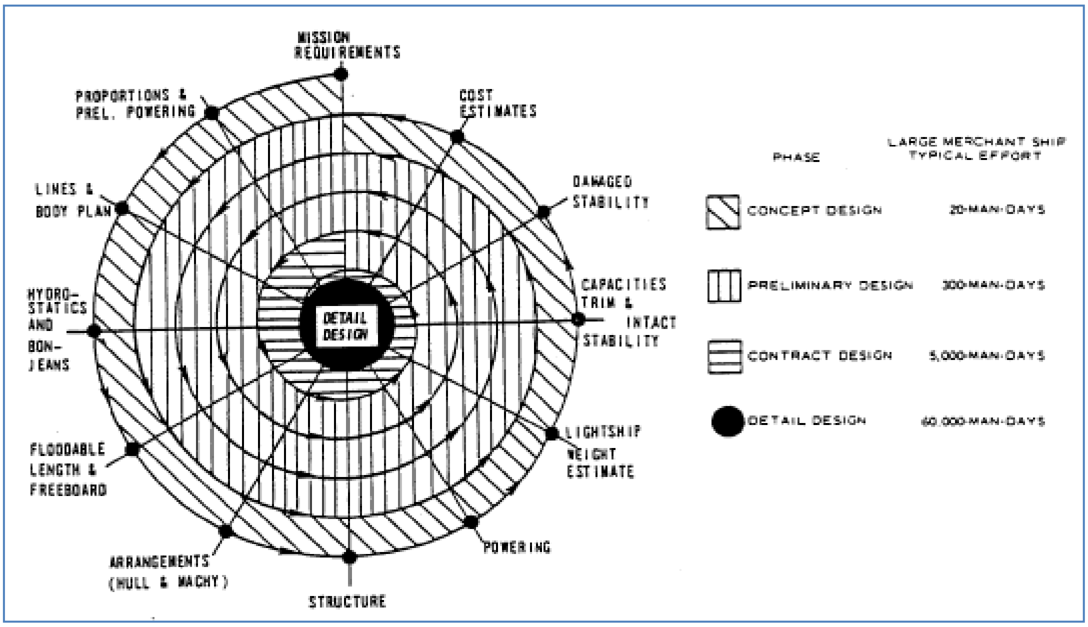


Figure 7.1: Design Spiral [Taggart, 1980]

In the knowledge that ship design is essentially a multi-objective multi-criteria optimisation process, in which technical performance, cost, and earning potential are the traditional objectives, diverse practical design approaches coupled with pertinent optimisation methodologies have been explored. One of the key features of such practice is to take advantage of the computation capability nowadays so as to exhaustively search the design space given a list of requirements and constraints. Upon completion, a set of feasible designs should be identified and is subject to a trade-off process where optimal designs can be selected. This process is illustrated in Figure 7.2.

As the aim of risk-based design is to treat safety as an add-on objective alongside conventional ship design objectives (like low resistance, etc), it becomes natural to introduce an extra set of constraints during the exploration of design space stage and an extra set of criteria for a balancing process. The high-level design concept is shown in Figure 7.3. As indicated, designs that successfully satisfy owner's requirements, technical constraints, external restrictions, and risk acceptance criteria should create a design space where a list of feasible designs is located. Having the design space, it is necessary to introduce appropriate optimisation methods which enable the selection of the favourable designs, with respect to the performance expectation of the owners.

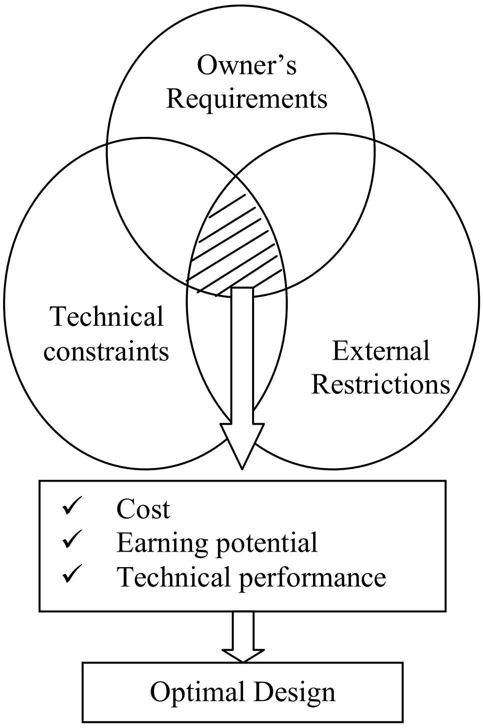


Figure 7.2: Flowchart of Design Optimisation Process

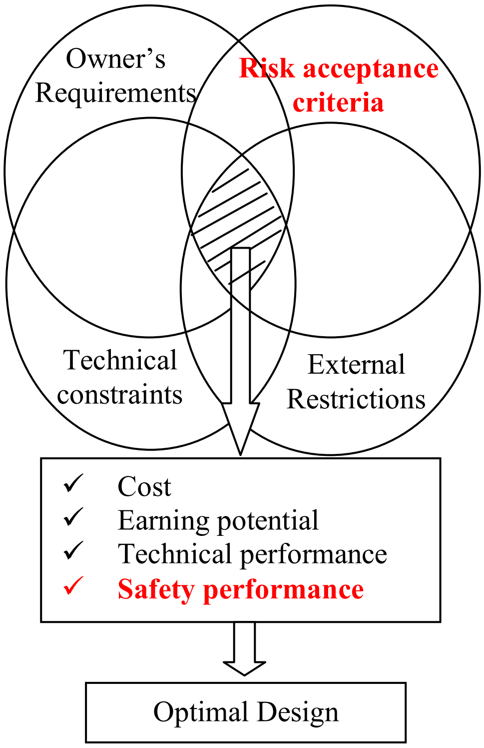


Figure 7.3: Updated High-level Flowchart of Design Optimisation Process

The key for implementing this approach is to develop a working procedure for the creation of the design space and for the execution of the multi-objective multi-criteria optimisation. On the basis of the calculation procedure for risk-based design propounded in [Konovessis, et al., 2007], a working procedure is proposed as shown in Figure 7.4, where the emphasis is placed on integrating BN models within the ship design process. The procedure consists of the following steps:

1. Define design parameters, determine their variations, and generate candidate designs.
2. Select risk acceptance criteria, as well as other design criteria, to be applied.
3. Use pertinent database and data mining techniques to develop risk models, in the form of BNs, for risk level quantification and assessment.

4. Evaluate the technical and economic performance of the new design.
5. Consider RCOs.
6. Set-up the optimisation problem
7. Iterate as many times as necessary

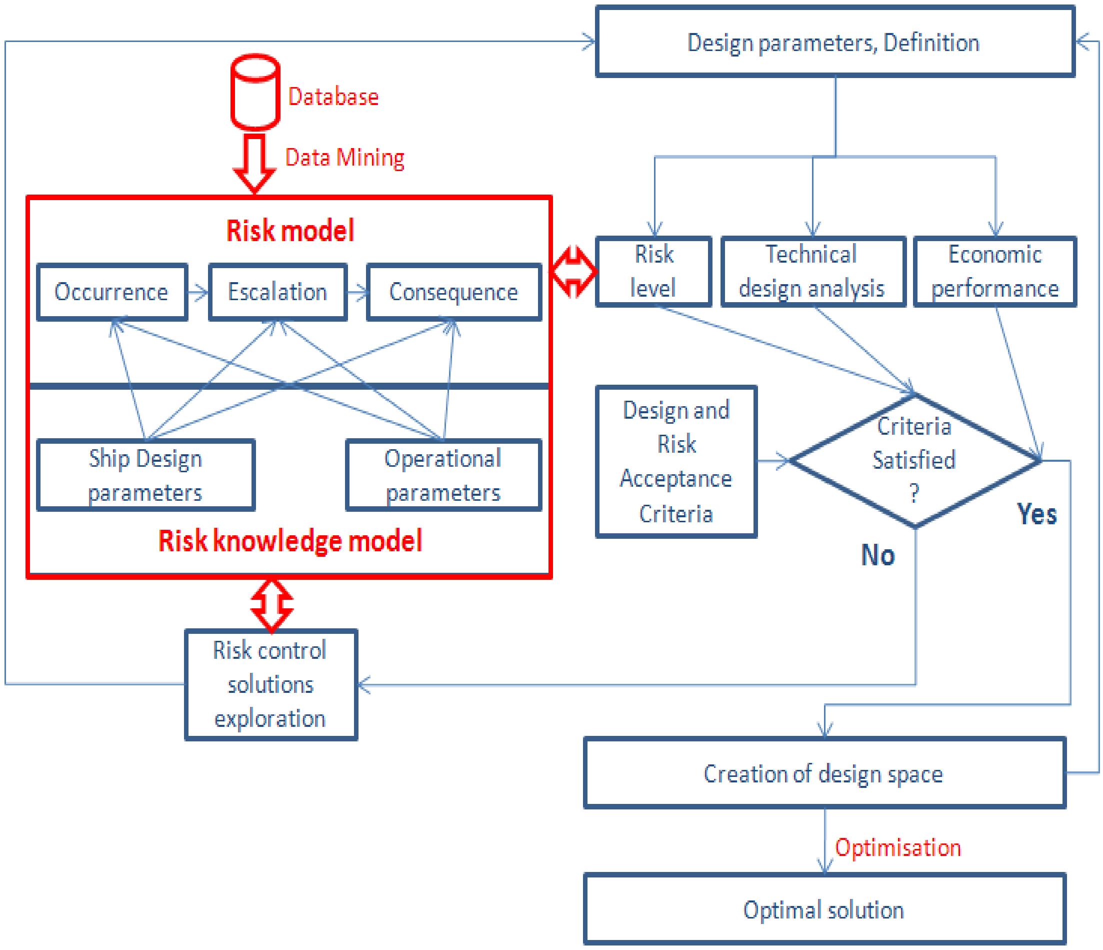


Figure 7.4: A Calculation Procedure for Risk-Based Design Implementation using the Bayesian Network Models

Definition of Design Parameters

At this stage, the dominant parameters should be identified, the variation of which need to be estimated as well. It is important to note that the classical approach tends to derive a single design out of the first iteration, while the proposed approach advocates the utilisation of the computational capability to search the design space exhaustively. The aim is to deploy appropriate local iterations and to minimise global iterations so as to achieve a faster convergence to the optimal design, [Cai and Konovessis, 2008]. However, the searching algorithm can be defined in a sparse way in order not to miss out promising design candidates yet maintain a reasonable computational effort.

To do so, the searching of the values of each parameter can be achieved by the expression (7.1). The density of possible values generated depends on the definition of the $interval$. In the case of discrete parameters, e.g. presence of a lower hold, categorical definitions can be assigned, i.e. true or false. Consequently, the generation of possible designs is just a matter of determining various combinations of the values/states of the key parameters.

$$X\ lower\ bound\ \leq X \pm n \cdot interval\ \leq X\ upper\ bound \tag{7.1}$$

In the case of passenger Ro-Ro vessels for example, the desired goal is to identify appropriate arrangements and layouts. The various characteristics/parameters to be considered can be grouped in the following broad categories, [Konovessis, et al., 2007]:

- <u>Hull-related parameter</u>, for example, principal dimensions, ratios and coefficients, height of the main vehicle deck, etc.
- <u>Internal layout and arrangement</u>, i.e. possible layouts below (for example, pure transverse subdivision, combination of transverse and longitudinal subdivision, presence of a lower hold) and above the main vehicle deck (for example, presence of centre and/or side casings, transverse or longitudinal bulkheads, combinations).

<u>Selection of Criteria</u>

For candidate designs with the risk level and the technical performance estimated, it is necessary to ensure a set of minimum requirements is met before proceeding to the optimisation process (e.g. the risk level of a candidate design must not exceed the upper bound of an ALARP region, the probabilistic damage stability requirements are met). On the other hand, it is understood that the economic performance indicators, e.g. Net Present Value (NPV), Required Freight Rate (RFR), are generally regarded as confidential information with ship operators. In this respect, minimum criteria will not be imposed for economic performance at this stage; however, they should play an important role at the optimisation stage for measuring the superiority of promising designs.

As far as safety performance is concerned, risk acceptance criteria focus mainly on individual risk and societal risk. In this respect, the latest development through SAFEDOR can be regarded as the most widely accepted criteria concerning passenger ships [IMO, 2008b]. Detailed description is supplied in Appendix 7.

Furthermore, typical technical design criteria that could be considered:

- Required payload (number of crew and passengers, private cars and trucks)
- Minimum operational speed
- Passenger comfort as expressed by hydrostatic and hydrodynamic properties (GM and acceleration)
- Etc.

7.3 Bayesian Networks for Risk Assessment

Through the deployment of the new generation database and the corresponding Bayesian learning techniques, one should be able to obtain pertinent BN models. It is important to notice that these developed models have two concurrent roles: the *risk model* and *risk knowledge model*.

The role of a risk model is to provide a high level risk quantification platform where the probabilities of key situation-specific events and their corresponding consequences are estimated, whilst, a risk knowledge model stores probabilistic information of the influence of ship design parameters, operational variables, and situation-specific factors on the components of risk models.

7.3.1 Bayesian Network as Generic Risk Models

An important component for the implementation of the risk-based design methodology is the availability of an effective and systematic way to quantify the risk level of a specific design. In relation to this, although the absolute value of the obtained risk level entails a degree of uncertainty which arises from various aspects (e.g. quality of the data input, assumption made, etc.), as far as the identification of RCOs and design prioritisations are concerned, the relative risk values provide a tangible measure to achieve design objectives optimally.

In this respect, rather than adopting the classical tools for risk quantification, a BN can be used. An important difference between the tree and network techniques is that the former adopts the concept of "logic", meaning the occurrence of one event leads to its followers, whilst the latter emphasises the "influence". That is, the fact that physical (steel material, subdivisions, etc.) and qualitative variables (culture, management, etc.) can influence the occurrence of a specific event.

As the trained BNs accommodate the sequential events that lead to the manifestation of a specific hazard (e.g. they contain the occurrence of an event, its escalation, and ultimately, the possible consequences), such models can be regarded as generic risk models for risk level estimation. From this point of view, a BN model is equivalent to a conventional risk contribution tree (i.e. fault and event trees) for risk assessment.

<u>Exchangeability between Bayesian Networks and Risk Contribution Trees</u>

Nevertheless, it has to be appreciated that both techniques are interchangeable. The risk model developed in fault and event trees can be transformed into a model in BNs, and vice versa. This exchange provides a rather flexible way for the development of risk models as the tree techniques may encounter difficulties when more than a few variables influence the occurrence of an event. In this case, it will be desirable to make use of BNs for risk modelling.

A generic fire risk model illustrated in Figure 7.5 demonstrates the interchangeability between the two approaches. The tree on the left-hand side represents a fault tree showing various spaces of origin that a fire event can occur. An "OR" gate should be assigned for the high-level fault tree to indicate an independent relationship. The event tree as shown on the right-hand side indicates how the situation progresses given a fire event starting in space *i* with certain consequences.

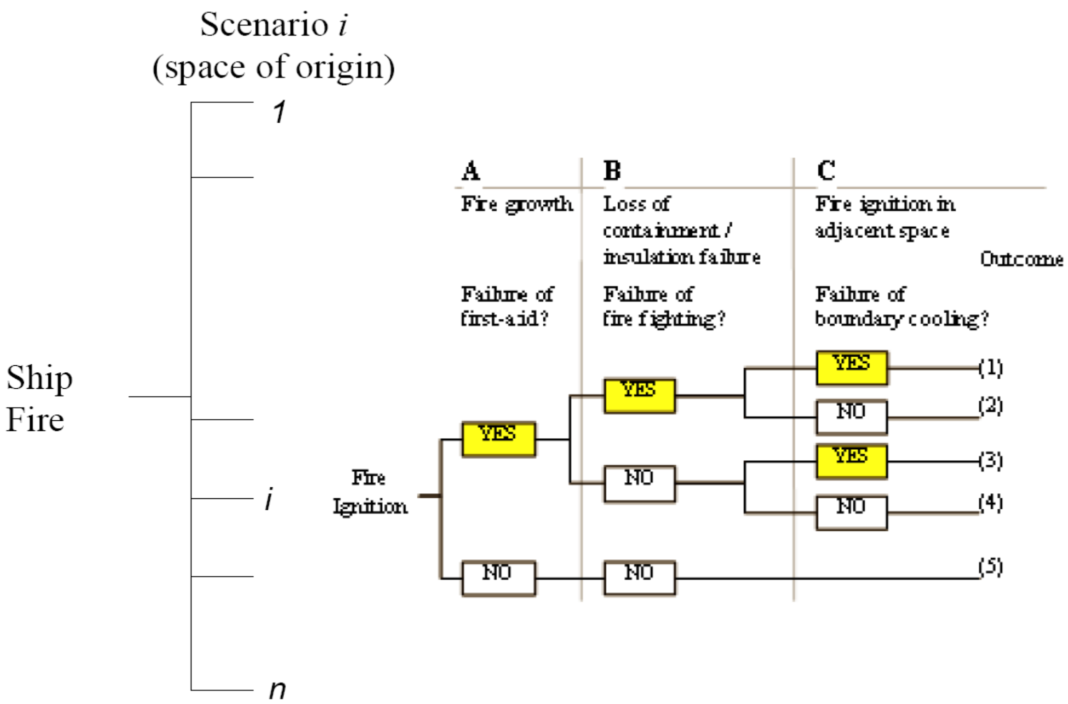


Figure 7.5: A Generic Fire Risk Model [Guarin, et al., 2007]

An equivalent BN model is illustrated in Figure 7.6, where each event is denoted by a node with the arrows showing the influences. For this specific case, the root node "*fire_location*" is equivalent to the fault tree of the fire risk model where detailed space information and their relative probability values are stored, as shown in Figure 7.7. "*Fire_growth*" is influenced by the location of fire initiation. This is justified as fire growth depends on fire load and its distribution in space, which varies for spaces of different usages. The conditional probability tables for "*fire_growth*" and "*containment_failure*" are shown in Figure 7.8 and 7.9 respectively. The outcome node, "*boundary_failure*" is conditional on the states of "*fire_location*", "*fire_growth*", and "*containment_failure*". Its conditional probability table is illustrated in Figure 7.10.

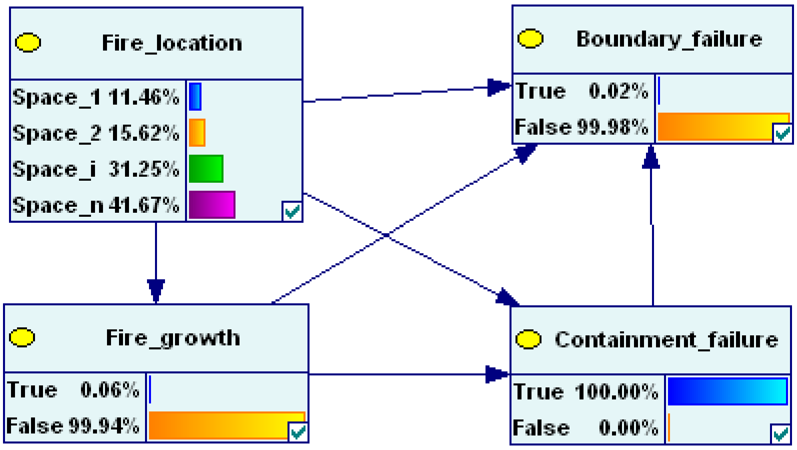
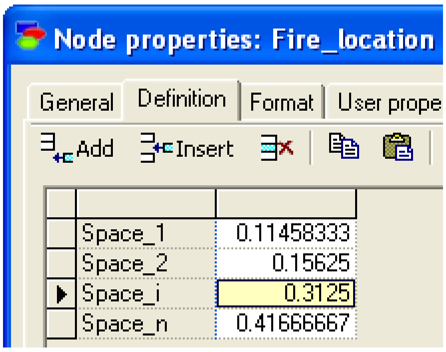
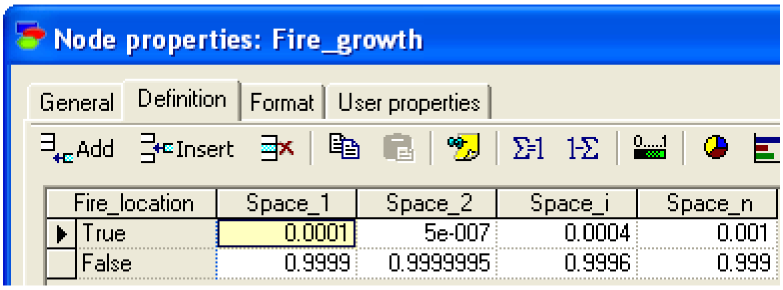


Figure 7.6: An Equivalent Fire Risk Model in Bayesian Networks



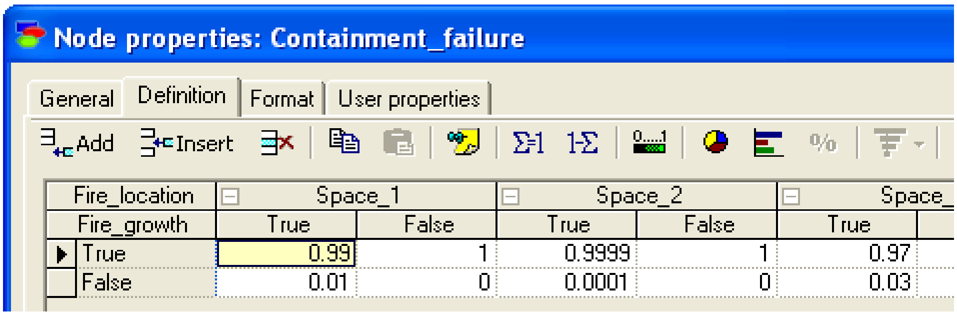
Space_1	0.11458333
Space_2	0.15625
Space_i	0.3125
Space_n	0.41666667

Figure 7.7: Probability Table for *"fire_location"*



Fire_location	Space_1	Space_2	Space_i	Space_n
True	0.0001	5e-007	0.0004	0.001
False	0.9999	0.9999995	0.9996	0.999

Figure 7.8: Conditional Probability Table for "*fire_growth*" Given "*fire_location*"



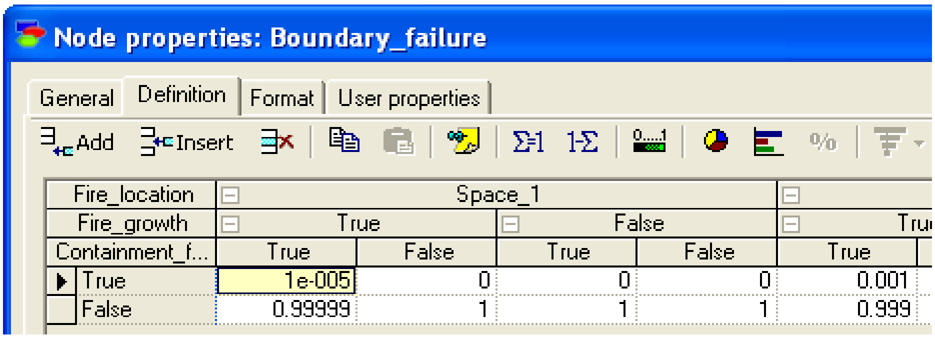
Node properties: Containment_failure

General | Definition | Format | User properties

Add | Insert

Fire_location	Space_1		Space_2		Space_
Fire_growth	True	False	True	False	True
True	0.99	1	0.9999	1	0.97
False	0.01	0	0.0001	0	0.03

Figure 7.9: Conditional Probability Table for "*containment_failure*" Given "*fire_location*" and "*fire_growth*"



Node properties: Boundary_failure

General | Definition | Format | User properties

Add | Insert

Fire_location	Space_1				
Fire_growth	True		False		Tru
Containment_f...	True	False	True	False	True
True	1e-005	0	0	0	0.001
False	0.99999	1	1	1	0.999

Figure 7.10: Conditional Probability Table for "*boundary_failure*" Given "*fire_location*", "*fire_growth*", and "*containment_failure*"

As risk quantification using the risk contribution tree (fault and event trees) is sought through the assignment of the frequencies of fault tree components, which lead to the frequency estimation of the top event, and through the estimation of the conditional probabilities at each branch in an event tree. The product of the frequency of the top event with a series of conditional probabilities following a specific branch/path gives the frequency of a specific scenario occurring. In the case of the BN model, it works in a similar manner. Through the product of probabilities and condition probabilities that a series of events occurring, the likelihood of a specific scenario can be estimated easily.

The Issue of Frequency

Nevertheless, it is noted that the frequency is not the unit for BNs because only the probability can be assigned for the sake of probabilistic inference. A solution is to introduce the "frequency" at the last stage for root nodes. For this specific application, "*fire_location*" is the only root node. Hence, it is necessary to identify the frequency of fire event only. For instance, suppose a fleet size of 90 ships with a reporting period of 3.5 years and 1000 cases of fire event onboard, the estimated fire ignition frequency would be 3.175 per ship-year. Consequently, the relative probabilities for the root node *"fire_location"* can be easily transformed into frequencies. For instance, the probability of fire occurring in SOLAS space category 1 is 0.115, then its corresponding frequency is $3.175 \times 0.115 \approx 0.365\ per\ ship - year$. Hence, a unique formulation for the frequency estimation of a BN model is summarised in equation (7.2).

$$f_{overall} = f_{root\_nodes} \cdot P_{root\_nodes} \cdot \ldots \cdot P_{end\_node} \tag{7.2}$$

The Issue of Consequence

It is also worth noting that the consequence analysis as a result of a chain of events can be addressed in a BN model as well. Conventional treatment is to attach each individual consequence to the far end of the branch of an event tree, as illustrated in Figure 7.11, where the measure of the consequence is *Fatality Rate (%)* (number of death per 10,000 people per ship year). Once a risk model can be constructed in BNs as illustrated in Figure 7.6, it should be relatively easy to tabulate the results in a similar manner in a summary table (e.g. probability of occurrence per scenario as shown in Figure 7.11). Therefore, the quantification of the consequences can be regarded as an independent part.

On the other hand, an alternative is also available if one is willing to maintain the integrity of the model. This can be achieved by simply adding another node in the network and directing arrows accordingly, as depicted in Figure 7.12. For this specific example, every remaining node plays an important role in influencing the final consequence. The conditional probability table for the node "*fatality_rate*" is illustrated in Figure 7.13.

	ID Code	Probability per fire	Frequency per year	Fatality Rates (%)
Non-fatal impact 0.92	F1.1.1	0.6359	8.2668E-04	0
Fatal impact 0.08	F1.1.2	0.0553	7.1885E-05	0.4
	F1.2	0.0202	2.6208E-05	0.7
	F1.3	0.0086	1.1232E-05	0.7
Non-fatal impact 0.93	F2.1.1	0.0670	8.7048E-05	0
Fatal impact 0.07	F2.1.2	0.0050	6.5520E-06	0.4
	F2.2	0.0056	7.2800E-06	36
	F2.3	0.0024	3.1200E-06	36
Non-fatal impact 0.57	F3.1.1	0.0980	1.2745E-04	0
Fatal impact 0.43	F3.1.2	0.0740	9.6148E-05	0.4
	F3.2	0.0224	2.9120E-05	8
	F3.3	0.0056	7.2800E-06	8
	Sum:	1.0000	1.3000E-03	

Figure 7.11: An Example of Frequencies and Consequences Estimation in an Event Tree

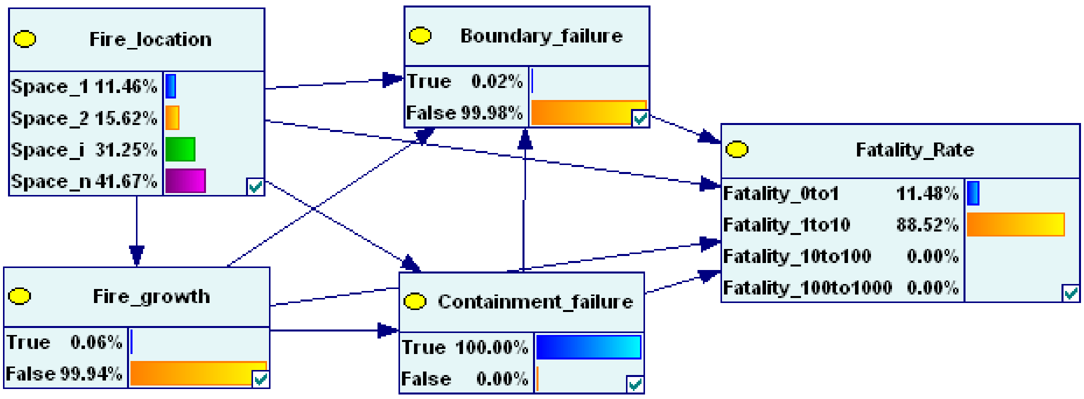
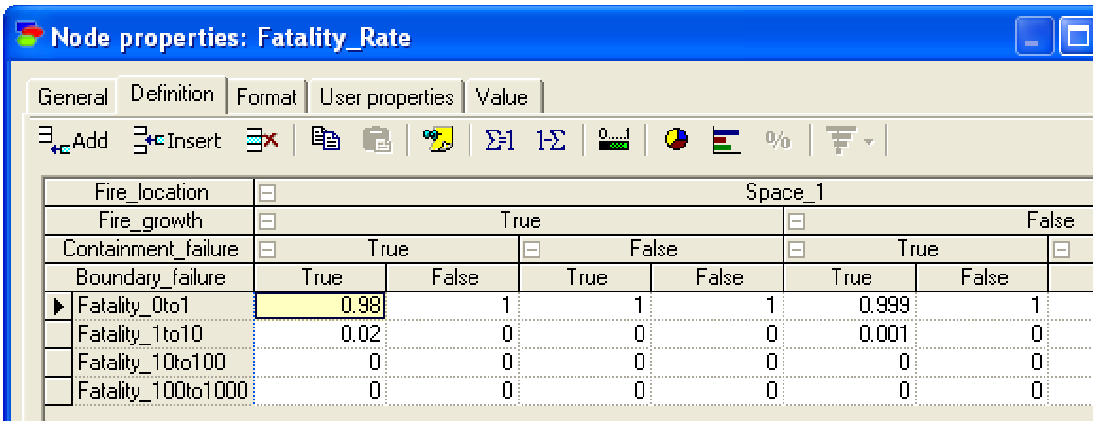


Figure 7.12: A Bayesian Network Model with the Consequences Included



Node properties: Fatality_Rate

General | Definition | Format | User properties | Value

Add Insert

Fire_location	Space_1					
Fire_growth	True				False	
Containment_failure	True		False		True	
Boundary_failure	True	False	True	False	True	False
Fatality_0to1	0.98	1	1	1	0.999	1
Fatality_1to10	0.02	0	0	0	0.001	0
Fatality_10to100	0	0	0	0	0	0
Fatality_100to1000	0	0	0	0	0	0

Figure 7.13: Conditional Probability Table for the Consequence Node

Comparing with the column "*fatality rate*" in the event tree, where the expected or averaged single value is normally assigned for each scenario, the corresponding node in a BN risk model has a higher resolution by supplying the probability distribution of the consequence. This is achieved by discretising the fatality rate into various ranges (e.g. 0 – 1, 1 - 10, 10 - 100, 100 – 1000, etc.), in which the estimation of the severity of various scenarios can be achieved. In this way, BNs offer more flexibility to present consequences in various levels of resolution depending on the analysis, and the availability and quality of data.

7.3.2 Bayesian Network as Risk Knowledge Models

In case the risk level of a candidate design needs to be reduced, the most promising RCOs should be examined. In this case, the emphasis is placed on the identification of both preventive (frequency reduction) and mitigative (consequence reduction) measures. A high level list of generic RCOs is illustrated in Figure 7.14.

A broad classification of the listed RCOs suggests that mainly design and operational parameters can be targeted. The former group refers to those parameters/features (installation of ECDIS system, watertight subdivisions, fire detection systems, suppression systems, etc.) that can be controlled at the early design stage. They determine the capability of a design to avoid and sustain accidents through preventive and/or mitigative means. In other words, there are parameters that are capable of leading to designs which are more tolerable to software (e.g. human error) and hardware failures, and more resistive to catastrophic consequences following an accident occurrence. On the other hand, operational parameters are procedures that need to be followed during the operational stage to reduce the risk exposure of the ship. For instance, scheduled maintenance, regular drilling and training of crews, establishments of contingency plans, etc., are the typical examples of operational means for safety assurance.

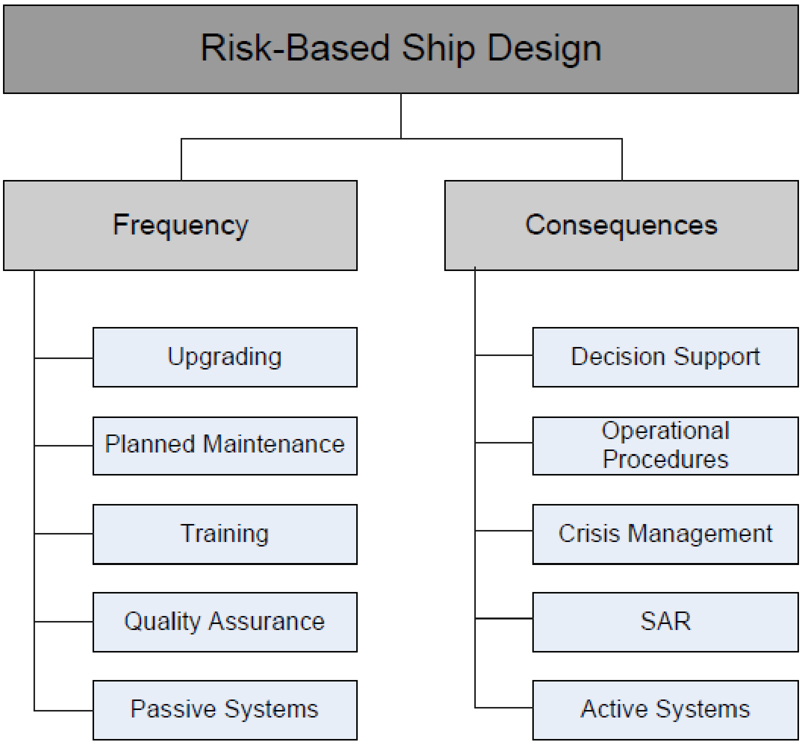


Figure 7.14: Generic Risk Control Options [Konovessis, et al., 2007]

Moreover, it is noted that apart from design and operational parameters there are certain environmental variables that are influencing the risk level as well, (traffic characteristics, geography, time of the day, sea state, etc). As a combination of different states of these parameters will evidently define a unique design scenario, they are also referred to as situation-specific parameters [Guarin, 2006].

Consequently, if the risk model for a specific hazard is constructed in a BN, its probability values are actually conditional on the statuses of these three groups of variables: design, operational, and situation-specific parameters. The high level concept is illustrated in Figure 7.15. With these three groups of parameters recorded in the database and utilised for data processing, their influences on the scenario-defining variables in the aforementioned risk models can be established. In this respect, the BN model can be regarded as a risk–knowledge model, where the knowledge of the interrelationships between manageable (physical) entities and the key risk components are stored and expressed probabilistically. In this way, the risk level of the interested hazard is ultimate conditional on the statuses of these three groups of parameters: ship design, operational, and situation-specific parameters.

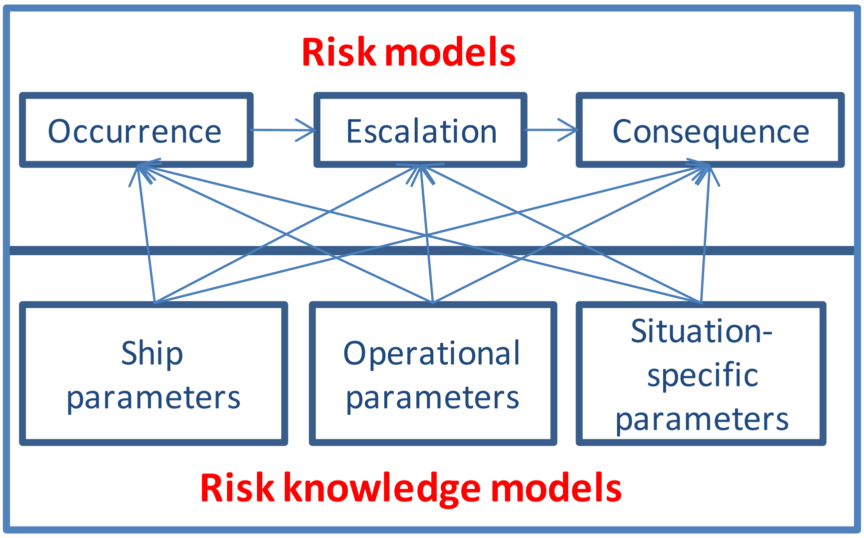


Figure 7.15: A Conceptual Bayesian Network Model

As it has been stressed in Chapter 3, the current approach for the quantification of the risk model relies heavily on first-principles tools and it is time-consuming to derive the probabilistic values. For instance, in the case of an event tree for collisions, in order to quantify the conditional probabilities of the sub-tree following the flooding of the struck ship, as indicated by the red box in Figure 7.16, the coupling between the Monte Carlo simulation and first-principles tools (e.g. time-domain simulation software Proteus 3.1 for modelling the damaged ship dynamic behaviour) can be adopted. However, such practice can take weeks to implement for a single design configuration, not forgetting this process needs to be performed iteratively at a global level during the application stage.

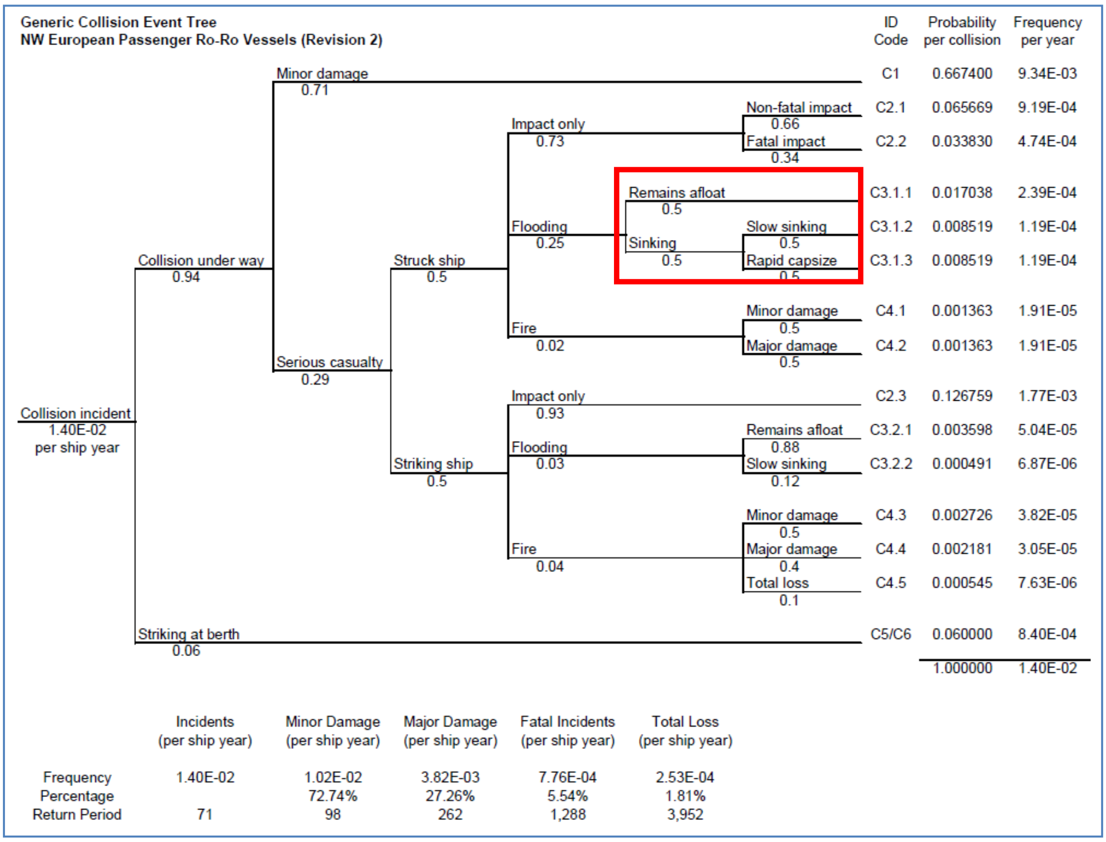


Figure 7.16: A Generic Event Tree for Collision [DNV Technica, 1996]

In this respect, BNs offer a more efficient way for the quantification of the risk models as design parameters are linking with high-level risk components directly. The immediate convenience is that there is no need for repetitive simulations on first-principles tools as the influence of specific parameters on risk components can be obtained instantly.

An example of this application is provided for the probability of fire growth given it starts in a space onboard the ship, denoted by "*fire_growth*", which is also a component of the four-node high-level fire risk model as illustrated in Figure 7.6. It is understood that the effectiveness of detection systems plays an important role on the status of "*fire_growth*", hence, a simple local risk knowledge model is constructed in Figure 7.17.

It takes into account the two main types of detection systems (smoke and heat) are installed in a space (e.g. public space). The combined effect of the reliability and the effectiveness of a smoke detection system is 0.98, while the conditional probability for a heat detection system to activate under an identical situation is 0.9, as illustrated in Figure 7.18. Nevertheless, the conditional probabilities of fire growth are not affected by the types of detectors installed, as shown in Figure 7.19. This is justifiable as once a detection system activate, the chance of fire growth mainly dependents on the performance of various suppression systems.

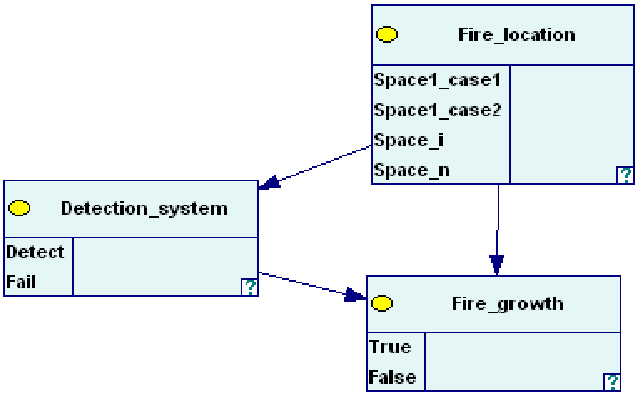
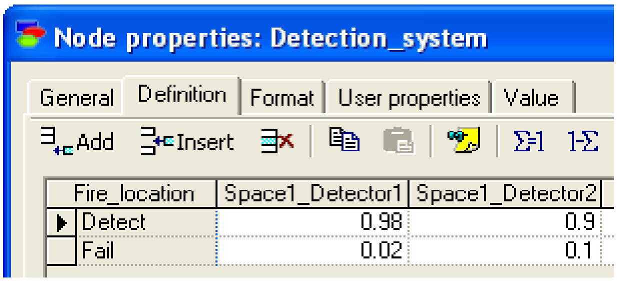
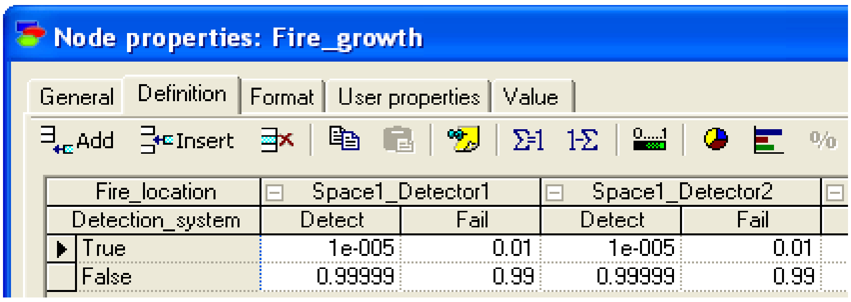


Figure 7.17: A Risk Knowledge Model Having Influence on the Risk Model Components



Fire_location	Space1_Detector1	Space1_Detector2
Detect	0.98	0.9
Fail	0.02	0.1

Figure 7.18: The Probabilistic Input for "*detection_system*"



Fire_location	Space1_Detector1		Space1_Detector2	
Detection_system	Detect	Fail	Detect	Fail
True	1e-005	0.01	1e-005	0.01
False	0.99999	0.99	0.99999	0.99

Figure 7.19: The Probabilistic Input for "*fire_growth*"

Through probabilistic inferences, these two types of detection systems are examined independently and the results are illustrated in Figure 7.20 and 7.21. The installation of the smoke detection system eventually leads to the probability of fire growth standing at 0.02% given its occurrence, while this value is about 5 time higher (i.e. 0.10%) if the heat detection system is installed. Such influence of different design solutions should propagate in the high level risk model and ultimately result in different risk levels. Although the absolute value may be doubtful, it provides a fast and plausible solution so that RCOs can be examined for comparison or prioritisation.

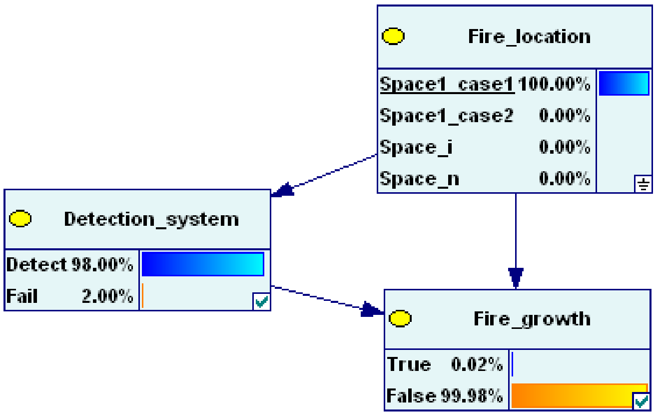


Figure 7.20: Inference Performed when Smoke Detection System is Installed

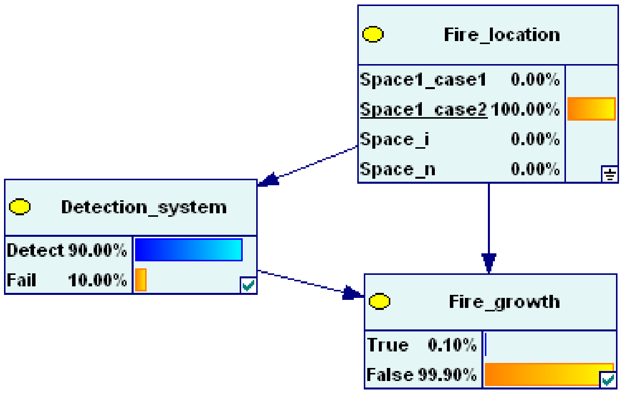


Figure 7.21: Inference Performed when Heat Detection System is Installed

The Issue of Sensitivity Analysis

As it can be seen that the knowledge about the influences of design and operational parameters can be probabilistically stored and presented in a BN model, which provides a risk knowledge base for evaluating the influence of various variables on the corresponding safety performance parameters. However, with an increasing number of design and operational parameters to be included in a model, it becomes very tedious and time-consuming to examine all possible RCOs and their combinations.

With respect to this, sensitivity analyses can be performed, in which the strength of influences of various variables can be identified and prioritised. In general, sensitivity analysis is used to determine the sensitivity of a model to changes in the states of influencing (input) parameters. This is normally achieved by performing a series of tests in which different parameter states are set to find out how a change in the input parameters causes a change in the behaviour of the output parameters. By doing so, it helps to build confidence of the trained model.

In this respect, BNs offer a premier platform compared to the classic risk modelling techniques (i.e. fault and event trees). In the case of deploying conventional risk contribution tree for risk analysis, it is tedious and complex to implement sensitivity analysis on existing tree-structured risk models by altering stepwise the states of various input parameters individually or in combination. In comparison, due to the mathematical background and maturity of BNs software, sensitivity analysis is almost a standardised function that every BNs package needs to be equipped with. As a result, sensitivity study is truly a matter of "click and go".

A sensitivity analysis is performed for the simple fire growth model, as illustrated in Figure 7.22. As far as the node "*fire_growth*" is concerned, "*detection_system*" plays a more important role than "*fire_location*" does, as highlighted in red. The physical meaning of such a finding indicates that as long as an effective detection system is installed, the probability of fire growth given it starts can be constrained disregarding the types of spaces onboard.

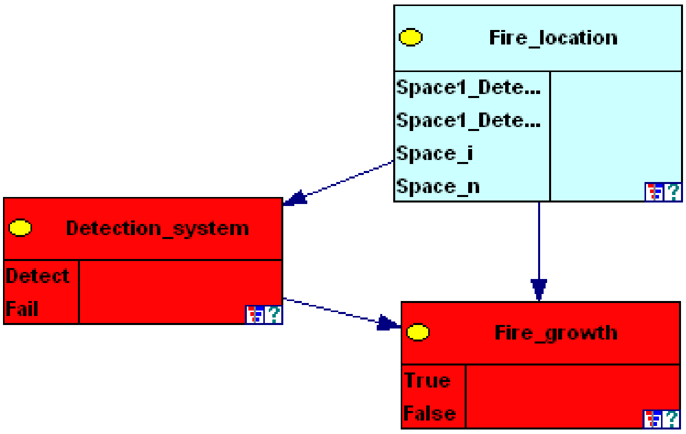


Figure 7.22: Sensitivity Analysis of the Fire Growth Model

7.3.3 Coupling between Risk Models and Risk Knowledge Models

As it has been noted above, BNs can be a promising technique for suggesting RCOs. This is achieved by linking design and operational parameters directly with risk components presented in a risk model. In the meantime, BNs can be also regarded as an effective tool for developing high-level risk models. Thus, for the sake of integrity, both risk knowledge models and risk models can be encapsulated in a single Bayesian network.

Nevertheless, considering the complexity of an overall Bayesian network model and the clarity that both fault and event trees offer, a configuration of employing the risk contribution tree as a high-level risk model and using Bayesian networks as risk knowledge models may be adopted. As Bayesian networks offer such flexibility, it is then a matter of coupling between risk knowledge models and risk contribution trees. This can be illustrated as shown in Figure 7.23. For the high level risk contribution tree, there is a need to assign probabilities at each branch. For instance, to derive the conditional probability of fire growth given the ignition as indicated in the red box, such information can be easily extracted if a pertinent risk knowledge model in a Bayesian network is available.

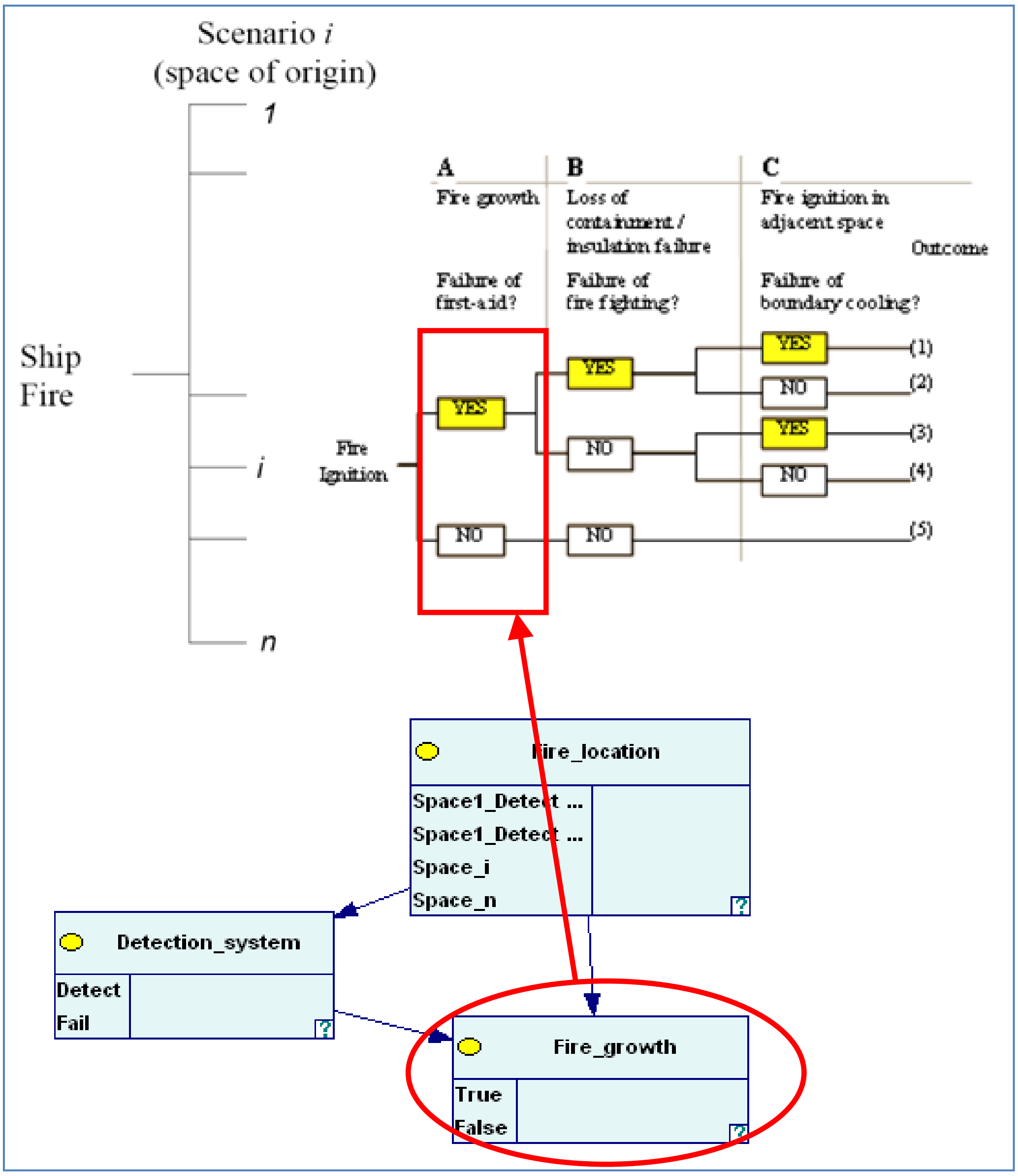


Figure 7.23: The Coupling between Risk Model in Contribution Tree and Risk Knowledge Model in Bayesian Network

By doing so, the quantification of the risk level of a specific hazard can be carried out in an efficient manner. If this is feasible for studying the fire hazard, it can be extended to other principal hazards of passenger ships as well, i.e. collision, grounding. Consequently, the knowledge discovered from the data and presented in the mechanism of BNs can be seamlessly integrated with the high-level risk models, as illustrated in Figure 7.24.

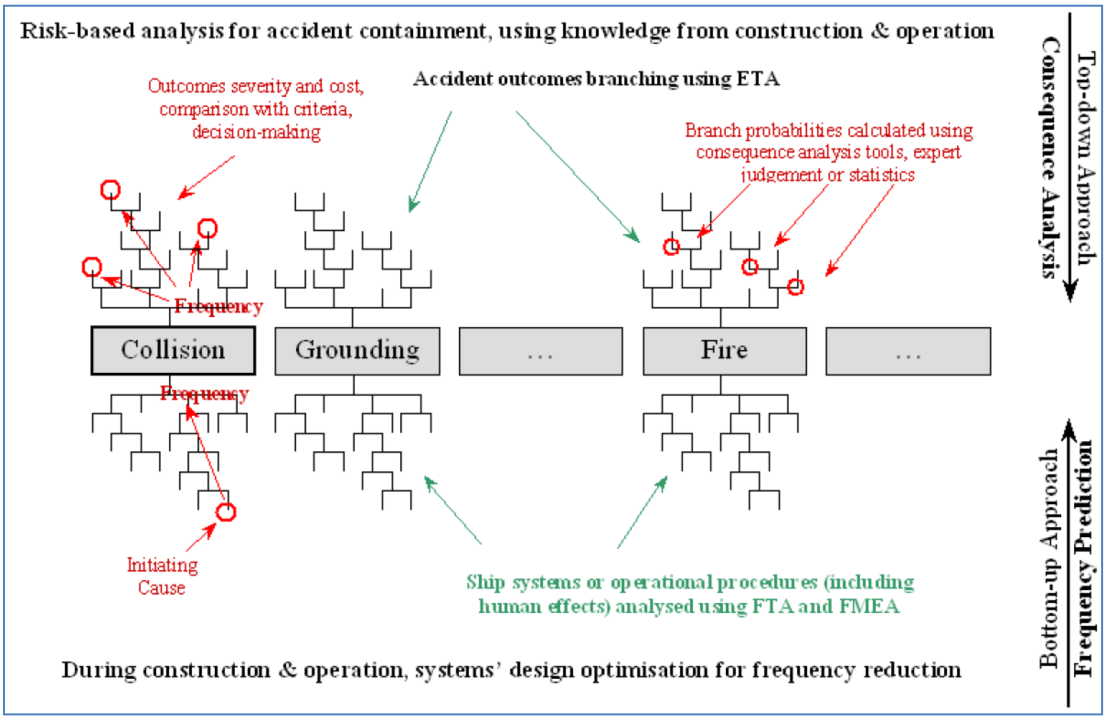


Figure 7.24: A High-level Risk Contribution Tree Model for Risk Quantification and Containment [Konovessis, 2001]

7.4 Decision Support Using Bayesian Networks

Any design activity is essentially a multi-objective optimisation process. This is particularly true for ship design, in which the decision for selecting a design solution among many others has to be made on the basis of their performance and characteristics in satisfying a set of pre-defined criteria. The emphasis was placed on single economic criterion in the past, whilst several other performance indicators, including safety, were treated as constraints. This has led to an ill-based design concept and a widely recognised perception that safety is expensive and investing on safety does not have high economic returns.

Cost-benefit analysis is one of the most widely accepted and commonly adopted approaches for decision support, in which both social costs and benefits are taken into account. It compares the benefit gained through implementing the suggested alternatives, in monetary terms, with the cost associated with such implementation. Nevertheless, it is understood that the decisions to be made at the design stage should consider not only the economic performance, but also the performance in technical and safety aspects. Hence, a formalised decision support framework allowing effective trade-offs among various performance indicators is an important component for the implementation of the risk-based design methodology.

7.4.1 Decision Support Framework of Risk-Based Design

In pursuing a rational design process that enables a scientific treatment of every facet of a ship's performance, a transparent and systematic decision support framework plays a vital role. In this respect, the approach proposed in [Konovessis, et al., 2007] is adopted, in which a structured formulation of criteria, parameters, constraints, objective functions, and mathematical models will be developed. Through the consideration of pair-wise comparisons using hierarchically decomposed objective functions that reflect and combine economic, technical performance, and safety aspects, it offers the following features:

- As one of the main objectives is to deliver optimal design solutions, the criteria should be based on performance rather than on conformance. The criteria need to be incorporated in the formulation of objective functions.

- Due to the flexibility of objective function definitions, it allows various performance indicators (e.g. economic, technical and safety) to be included in the objective function.

- Due to the performance nature of this approach, the risk model and the risk knowledge model developed in BNs can be easily incorporated in the optimisation procedure.

The approach comprises four components: criteria, design parameters, design constraints, and objective functions. A short explanation of each component is provided with particular emphasis on the development of the objective functions.

Criteria

The criteria are those entities that are capable of revealing the performances of a design solution in specific aspects, which normally cover economic performance, technical performance, and safety performance. As the identification of the criteria is closely linked with the development of objective functions, it will be considered in the last section.

Design Parameters

The performance of a ship is governed by a limited number of parameters, especially at early design stage. This is in line with the development of the risk knowledge model in BNs, in which the emphasis should be placed on the identification of dominant design parameters.

Design Constraints

Design constraints are usually requirements that cannot be included in the objective function. Such constraints come from physical limitations, regulations, owners' requirements, etc.

Objective Functions

The Analytical Hierarchy Process (AHP) will be deployed for the development of the objective function [Saaty, 2001]. It is a method developed for a multi-criteria decision making process. The key to understand the AHP is to develop a hierarchy of characteristics that the decision will be based upon. Design alternatives are compared on a pair-wise basis with respect to each specific criterion that listed in the hierarchy framework. The priority synthesis, which will be performed at the end, will provide an overall prioritisation of the various design alternatives for decision support.

The AHP starts with the definition of the problem and pertinent domain knowledge. A decision hierarchy is then developed with the goal of the decision stated at the top and the objectives defined at the intermediate levels. A set of alternatives is provided at the lowest level so that a set of pair-wise comparison matrices can be constructed. Each element in an upper level is used as the criterion to compare the elements that is immediately below it. The priorities obtained from the comparison are synthesised to produce the global priorities of the alternatives. Appendix 8 elaborates briefly on the application of the Analytic Hierarchy Process.

An example has been provided in [Konovessis, 2001], for the development of the objective functions.

Level 1	Goal	Derive effective subdivision arrangements and layouts that maximise safety, whilst minimising the incurred costs
Level 2	Selection Criteria	• Income • Building cost • Operational cost • Machinery configuration • Performance indicators • Safety indicators
Level 3	Detailed Attributes	The attributes to be included and their measures are detailed in the following
Level 4	Merit Function	Compose and iterate based on necessary improvement

Design parameters included for this study are:

- For the arrangement below the main vehicle deck.
    - Transverse subdivision: the number i and location x_i of the transverse bulkheads
    - Longitudinal subdivision: the length l_L and width W_L of longitudinal bulkheads, if such an arrangement is present.
    - Vertical subdivision: The number j and height h_j of any immediate decks below the main deck.

- For the arrangement above the main vehicle deck
  - The presence of side casing (length l_s and width w_s) should be considered in during optimisation

The combinations of various statuses/values of design parameters produce different design solutions. The performances of these designs are then evaluated on the basis of the objective functions as illustrated in Figure 7.25.

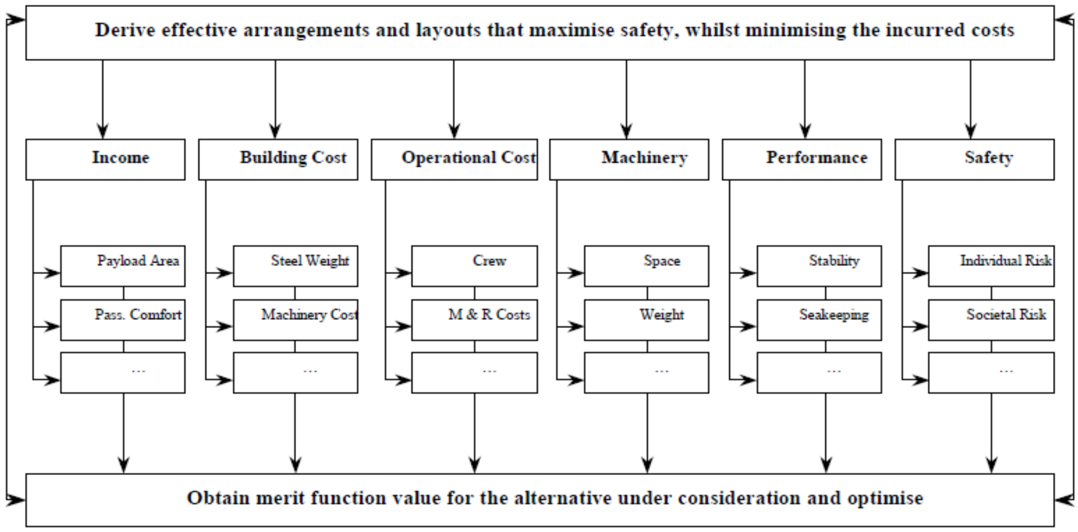


Figure 7.25: Decomposed Objective Function

7.4.2 Bayesian Networks for Decision Support

The framework presented above entails pertinent knowledge on economical, technical, and safety aspects for an objective evaluation of the design alternatives. Significant effort has been devoted to developing parametric models in the past for both economic and technical fields so as to achieve a fast and reasonable approximation, e.g. NPV estimation, ship resistance calculation. In comparison, the means for evaluating the safety performance of various designs are time-consuming and inadequate for the probabilistic inference process (due to independent assumptions made during risk modelling). As a result, the risk knowledge models developed in BNs can be regarded as unique parametric models, where ship design parameters are linked with safety performance indicators intuitively, objectively, and directly.

An important issue needs to be addressed is to integrate the BN models into the decision support process of the highlighted framework. On the basis of the structure of the AHP, the key would be to make use of the relevant BN knowledge models to systematically quantify pair-wise comparison tables with respect to safety performance.

<u>The Generation of Design Alternatives</u>

The current approach towards the generation of design alternatives is through the modification of design features/characteristics prior to feeding them into first-principles tools for performance-based evaluations. This could be a very tedious and time-consuming task. In the case of risk knowledge models in BNs, it is possible to bypass this by encompassing all possible statuses of each variable in a probabilistic knowledge base.

Due to the inherent feature that a parameter is virtually stored and presented in a manner of probabilistic distribution, every possible value/state of a parameter is captured. If design parameters are included in such a model, the instantiation of a number of design parameters will lead a unique design alternative. In the knowledge that these parameters ultimately link with safety indicators, the performance of every single design alternative can be assessed instantly with the assistance of proper Bayesian inference software. Consequently, pair-wise comparisons of various design alternatives with respect to safety performance can be carried out easily.

To demonstrate the process of the generation of design alternatives through BNs, the model developed in the SAFEDOR for analysing causal factors of ship collision under power is provided [Ravn, et al., 2006]. On the basis of the definition of ship collision risk, as illustrated in equation (7.3), [Vassalos, 2004b], this model focuses on the component: the probability of collision $P_{collision}$ for ship under power. An overview of the model is provided in Figure 7.26, where each rectangle has its corresponding detailed sub-networks.

$$R_{collision} = P_{collision} \cdot P_{water\_ingress|collision} \cdot P_{failure|water\_ingress|collision} \cdot C_{collision} \tag{7.3}$$

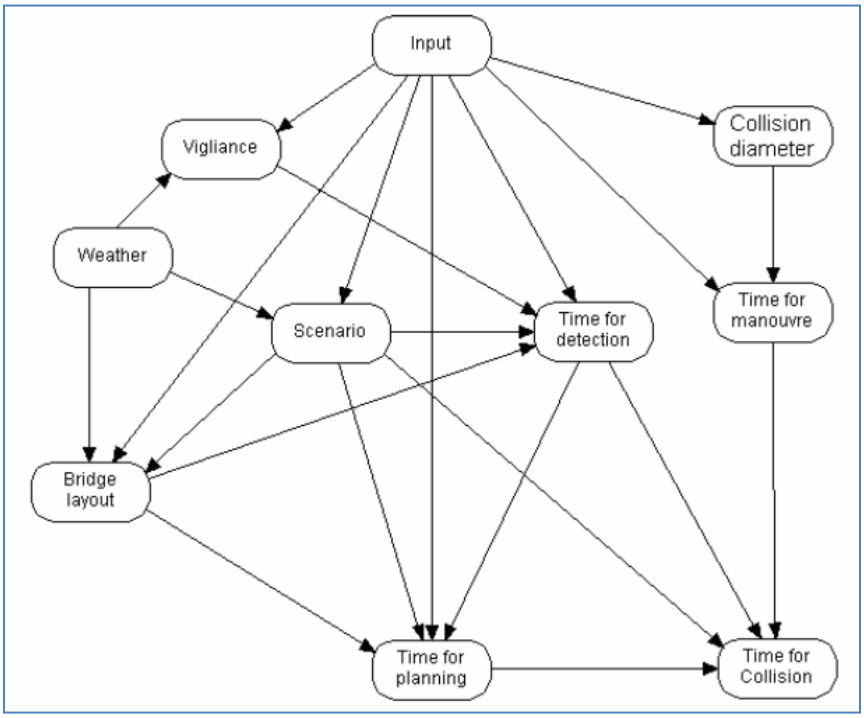


Figure 7.26: An Overview of Collision Model with Each Rectangle Representing a Sub-Network [Ravn, et al., 2006]

A list of important design parameters included in the model are summarised and tabulated in Table 7.1. In the knowledge that preventive measures of ship collision rely mainly on the actions taken on the bridge, its internal design plays an important role. In this respect, design alternatives can be generated by simply combining different values/statuses of the aforementioned design parameters. For instance, the combination of no workstation, no ECDIS installed, no alarm management system, poor window layout, no Automatic Identification System (AIS) system, and poor ergonomics of the bridge layout produces one design alternative. Conversely, a bridge having two workstations, ECDIS installed, Bridge Alarm System (BAS) installed, above standard window layout, AIS installed, and good ergonomics of the bridge layout produces another design alternative, which theoretically should be more effective in preventing ship collision under power. The differences that various design alternatives can make will be ultimately reflected through the output node "*collision*", as illustrated in Figure 7.27, in which the time for detection, interpretation, planning, and execution is subtracted from the time available to react.

Table 7.1: Design Parameters Included in the Bayesian Network Model of Ship Collision under Power

Design parameters	Description
L own	Length of own ship
Work station	The number of work stations on the bridge. {Two, One, No}.
Support for planning provided by the bridge	The way the bridge layout is organised and the equipment that it enables to be accessible can affect the performance of the operator both in terms of the time required for him to take action and the correctness of the action taken as well. For instance, the availability of ECDIS etc. ECDIS present? {True, False}
Alarm management	Types of alarm management system installed. {BAS, NAS, none}.
Window layout	{Above, Standard, Below}. A window layout that minimises blind sectors is above standard.
AIS availability and graphically displayed	AIS is onboard of own vessel and the AIS targets are graphically displayed. {True, False}
Ergonomics of the bridge layout	The way the bridge layout is organised, and the equipment that it enables to be accessible can affect the performance of the operator. A factor from 0 to 0.4 shall be used, where 0.4 represents the best ergonomics.

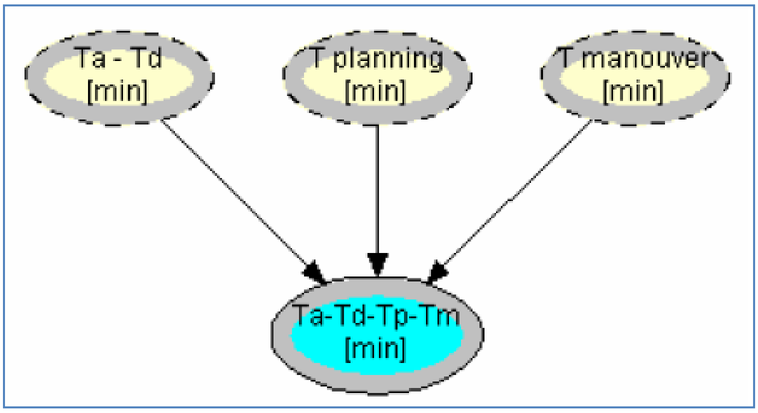


Figure 7.27: The Output Node of the Developed Bayesian Network Model for Ship Collision under Power [Ravn, et al., 2006]

Pair-wise Comparison through Bayesian Networks

As it has been noted that a BN model can be used for the generation of design alternatives, the following task is to integrate such a tool with pair-wise comparison tables for the implementation of the AHP. This can be achieved by using a matrix table to exhibit the relative superiority of one design alternative over another with respect to safety performance. By adopting appropriate scales for this comparison process, a summation of the scores obtained for each design through pair-wise comparisons produces an overall evaluation, which is referred to as the "priority". Table 7.2 exhibits an example of such comparison process.

Table 7.2: Pair-wise Comparison among Various Design Alternatives

Safety aspect						
	Design 1	**Design 2**	**…**	**…**	**Design n**	**Priorities**
Design 1	1	…	…	…	…	…
Design 2	…	1	…	…	…	…
…	…	…	1	…	…	…
…	…	…	…	1	…	…
Design n	…	…	…	…	1	…

With the evaluated priorities concerning safety aspect, this piece of information can be readily integrated into an overall performance evaluation and trade-off process. Other than the performance indicator for safety, a design should be also technically sound and cost-effective. Hence, the indicators in technical, cost, earning aspects are included as well. In this case, all available resources, including parametric formulae, empirical and computational tools, etc., should be embraced together. As the aim is to demonstrate the utilisation of pertinent BN models for assisting decision making with particular reference to safety aspect, other performance indicators will not be elaborated further. A high level summary table for an overall evaluation of various design alternatives is provided in Table 7.3.

The priorities obtained for each design with respect to various performance issues (e.g. technical, cost, earning, safety) can be tabulated. The corresponding summation produces an overall evaluation. Weighting factors can be assigned as well during the trade-off process to emphasise the importance of one or more performance indicators over the rest. Consequently, the designs can be ranked on the basis of the estimated overall priorities and ultimately assist decision making.

Table 7.3: Priorities Synthesis for Various Design Alternatives

Overall evaluation					
	Technical	**Cost**	**Earning**	**Safety performance**	**Priorities**
Design 1	...	...	...	...	...
Design 2	...	...	...	...	...
...	...	...	...	...	...
...	...	...	...	...	...
Design n	...	...	...	...	...

7.5 Closure

The implementation of risk-based design entails a practical ship design procedure to be followed, where risk assessment can be smoothly integrated. A methodology encapsulating the BN models for safety performance evaluation has been presented. Particular emphasis has been placed on the multiple roles that BNs can play: the high-level risk model, the detailed risk knowledge model. Consequently, the decision support framework for risk-based design has been discussed with particular attention has been paid to the assessment of safety performance through BNs.

Chapter 8
A Case Study

8.1 Preamble

Historical statistics suggest that shipboard fire incidents have important contribution to the casualties relating to shipping activities. This is attributed to the inherently captive nature of a ship's occupancy and the fact that water accumulated due to fire fighting can seriously affect the stability of a ship. The fire incidents comes next to flooding when the consequence is concerned, nevertheless, due to its high frequency a large number of lives has been lost due to fire incident over the past decades.

This chapter elaborates on a case study of fire safety of passenger ships by adopting the proposed data mining framework. Following the preparation of an accident/incident data set of passenger ships for the fire incident database, Bayesian learning techniques are deployed to transform the data into domain risk models, which are then integrated in the design process for the implementation of risk-based design methodology. Particular attention is paid to the decision-support process by evaluating specific safety performance parameters of various design alternatives on the basis of the developed Bayesian network model.

8.2 Introduction

The current approach towards the assurance of fire safety is achieved mainly through compliance with prescriptive requirements. However, with more designs of passenger ships demand even creative features in order to maintain its competitiveness, (e.g. a public space extends to three or more decks on "*Sovereign of the Seas*"; the atrium solution for "*Voyager of the Seas*" extends to three fire zones), this led to the adoption of the SOLAS II.2, regulation 17 allowing a performance-based methodology for alternative design and arrangement for fire safety using fire engineering methods [IMO, 2001]. A high-level process flowchart is illustrated in Figure 8.1. Nevertheless, this regulatory clause can be too open-ended and does not provide a clear basis for approval and may result in ambiguity and undefined control of safety. Moreover, the methodology highlighted provides little means of linking effectively fire safety relevant design parameters with risk performance indicators. Thus, this case study aims to embed both design parameters and risk performance indicators in a stand-alone BN model, with particular emphasis on the utilisation of this approach in decision making.

Passenger ships are more vulnerable to fire hazards due to that thousands of lives onboard could be under threat once the fire escalates from the space of origin. Furthermore, the market demands even bigger ships for more passengers. Hence, the main focus is placed on passenger ships with particular attention to cruise liners.

In pursuit of a rational treatment of fire safety at the design stage, the methodology proposed in Chapter 7 will be adopted to demonstrate its applicability. The case study starts with the development of a fire incident database. Following the application of pertinent data mining techniques for risk model developments in BNs, the effectiveness of the obtained model for decision support is explored in detail.

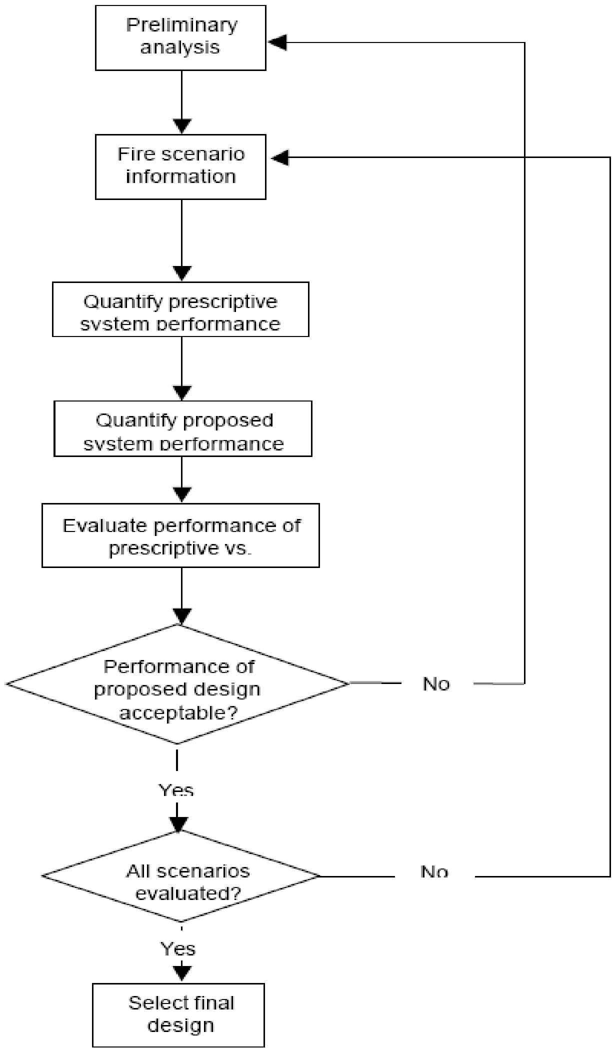


Figure 8.1: A Flowchart of Alternative Design and Arrangement Process [IMO, 2001]

8.3 Database Development

8.3.1 The Identification of Dominant Parameters

The concept for shipboard fire risk can be defined as a summation of the risk contribution from each space onboard, as illustrated in equation (8.1), in which the elemental risk can be considered as the product of probability and consequence, as illustrated in equation (8.2), [Mermiris and Cai, 2010].

$$R_F = \sum_{i=1}^{n} dR_i \tag{8.1}$$

$$dR_i = P_{ignition} \cdot P_{growth|ignition} \cdot P_{escalation|growth|ignition} \cdot C_{fire} \tag{8.2}$$

Where dR_i is the elemental risk from space i;

$P_{ignition}$ denotes the probability (frequency) of fire ignition event in space i;

$P_{growth|ignition}$ denotes the conditional probability of fire growth given fire ignition in space i;

$P_{escalation|growth|ignition}$ denotes the conditional probability of fire escalation from space of origin given fire ignition and growth in space i;

C_{fire} denotes the consequence, which was frequently referred to probability distribution function of loss of human life injuries/fatalities.

Theoretical analysis suggests that the instance of ignition is associated with locations, fuel type, and spatial distribution of fuel load, overall occupancy, ignition causes, and other factors that contribute to the ignition. Available incident data indicates that the most significant fuel sources include various pieces of furnishing, floor material, wall and ceiling coverings, fittings and other contents (e.g. oil and waste receptacles), which have been shown to have a degree of correlation with the floor area of the space [Tillander, 2004]. The exposure to a hazardous situation is conditional on the exposure to different operational factors such as the level of occupancy, the access by public and / or crew, the time of the day, etc. As all these factors are associated with the actual "use" of the space, the estimation of the frequency of ignition for a specific space type is based on the corresponding historical incidence rate per unit area (γ_i). Thus, the frequency of fire ignition in a specific space type of given area a_i and "use" type, is calculable using equation (8.3).

$$f_i = \gamma_i a_i \tag{8.3}$$

Apart from the usage of a space for $P_{ignition}$, a list of important physical variables influencing the other two risk components, i.e. $P_{growth|ignition}$ and $P_{escalation|growth|ignition}$, has also been identified and is listed next. The rationale and their corresponding importance are elaborated in Appendix 9, together with detailed statuses explained.

1. On board location (defined according to SOLAS space category, see Appendix 10)
2. Date of event
3. Time of event
4. Vessel location
5. Weather contribution
6. Detection means
7. Suppression means
8. Ventilation system status
9. Fire door status
10. Space occupancy status
11. Crew status
12. Boundary cooling status
13. Emergency response failure
14. Containment failure
15. Ignition in adjacent space

8.3.2 Data Collection and Processing

Given a list of variables to be recorded, it is important to ensure a reliable source of data, which can be collected in an objective manner. Considering the nature of these variables, it is noticed that they cover mainly the early phase of a fully developed fire event. Hence, the source of information should be sought through ship operators. To comply with the SMS of the ISM code, [IMO, 1994], it is necessary for ship operators to report and analyse non-conformities, accidents, and hazardous occurrences. Appropriate procedures should also be established for the implementation of corrective actions.

A significant amount of operational fire accident/incident data has been made available covering a reporting period of 3-4 years.

It is generally agreed that data preparation/pre-processing (e.g. summarisation, cleaning, integration, transformation, reduction, etc.) can easily consume 70-80% of the time needed for implementing a data mining task, [Han and Kamber, 2006]. Hence, significant effort has been put to properly perform data preparation to ensure the quality of the processed data. The undertaking also includes the identification of duplicated cases and irrelevant cases. The main reason of the duplication comes from different casualty reporting schemes and the subsequent merging. In order to assist data preparation, the database developed for storing marine accident/incident database is deployed. An important advantage of collecting the data and storing it in a unified format is to provide a consistent source of information. Moreover, as the descriptive text is translated into coded categorical information, it enables further mathematical computation. Lastly, it provides a reusable platform that future data can be added, in which the output of risk assessment can be further refined easily. A snapshot of the coded fire incident information of a record is illustrated in Figure 5.14 (of Chapter 5). Through the interpretation of each case in the raw data, its corresponding fields in the database platform can be identified.

The fire incident data corresponds to 463 ship-year of operation. The weighted average of fire ignition frequency is 3.2/ship-year. The expected frequency per SOLAS space category is presented in Table 8.1, in which there is no record for SOLAS space categories 1 and 11.

The derivation of historical ignition frequency is based on the collected incident data. In light of this, a comparison is performed for the spaces having the highest ignition frequencies between the existing database and the data provided in [Guarin at al., 2007]. The results are presented in Figure 8.2 and 8.3, respectively. With the exception of one case (i.e. “Corridor” and “Public space”) similar conclusions can be drawn for the spaces with the highest relative frequency of the occurrence of fire incidents. This is particularly true for the spaces, like galley, incinerator room, cabin, machinery space, laundry room, etc., despite the small variation which can be justified by the inherent data attributes and the size of the sample under consideration.

Table 8.1: Fire Ignition Frequency (per ship-year)

SOLAS space category	**Number of occurrences**	**Frequency of ignition / s-y**
1	0	0.000
2	23	0.050
3	52	0.112
4	11	0.024
5	72	0.155
6	315	0.68
7	19	0.041
8	192	0.415
9	55	0.119
10	10	0.022
11	0	0.000
12	642	1.386
13	126	0.272
14	4	0.009

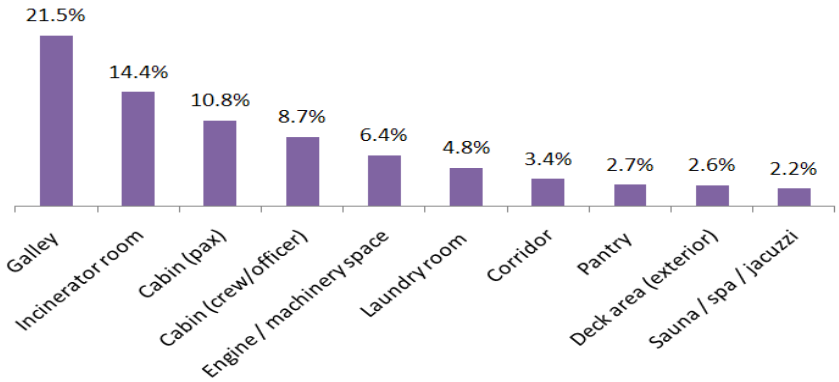


Figure 8.2: Top 10 Spaces with the Highest Frequencies of Fire Occurrence Derived from Collected Data

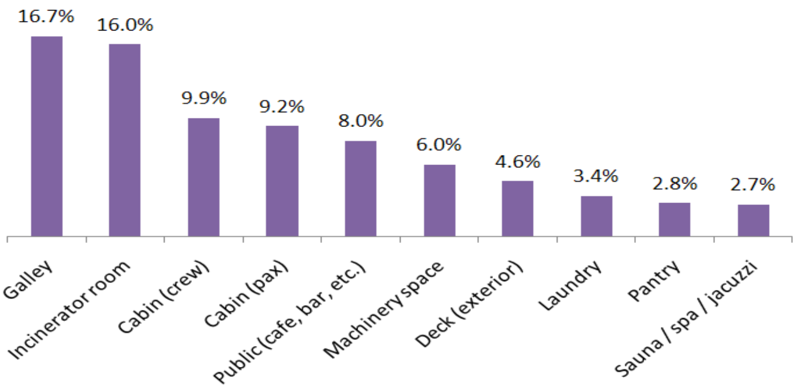


Figure 8.3: Relative Frequencies of Occurrence, Reproduced from [Guarin et al., 2007]

8.4 Bayesian Networks Model Generation

Following the preparation stage, the data is fed into the program developed for learning the BN model. In the knowledge that the amount of data is still small compared to an ordinary application of data mining, and understanding the number of variables and their corresponding states is relatively large, e.g. the ignition space originally has more than fifty states, etc., further transformation and simplification are performed to assure the quality of the results of Bayesian learning. The variables recorded and their corresponding states are tabulated in Table 8.2.

Table 8.2: Definition of Important Variables and the Corresponding Status

Variables	Notation	Status
Time	N_1	Daytime Night
Vessel location	N_2	Port (in port, at anchor) Sea
Weather contribution	N_3	True False
Ignition space	N_4	SOLAS space category 1 to SOLAS space category 14
Automatic detection activated	N_5	True False
Manual detection activated	N_6	True False
Automatic suppression activated	N_7	True False
Manual suppression activated	N_8	True False
Ventilation status	N_9	Closed Fail to close No need to close
Fire door status	N_{10}	Closed Open
Crew attended	N_{11}	True False
Guest attended	N_{12}	True False
Boundary cooling status	N_{13}	Executed Unnecessary

Emergency response failure	N_{14}	True False
Containment failure	N_{15}	True False
Ignition in adjacent space	N_{16}	True False

The data set was imported into the learning program developed in R. Both constraint-based and score-based learning algorithms are executed to examine and compare the results. Considering the size of the data set, the confidence internal was pre-set at 90% in order to minimise unnecessary removal of the links due to a relative weaker evidence of dependency for constraint-based learning. In contrast, the score-based learning approach can be initiated as long as a scoring criterion is defined.

8.4.1 Learning through the PC Algorithm

With the PC algorithm, the analyses of two-variable dependent relationships are performed first. As there are only two models, e.g. $(AB), (A, B)$, for comparison, the computation is straightforward. For instance, the comparison between the saturated model and the independent model for N_1 and N_2 as illustrated in Figure 8.4 indicates that the independent model has significantly damaged the saturated model, which implies significant association between the two variables, e.g. $0.000269 < 0.1$. In comparison, the links between $N_1 - N_3$, $N_1 - N_4$ can be removed. Consequently, a list of links which have to be removed from the fully connected network can be obtained. The computation log is provided in Appendix 11.

Following this, conditional independency analyses are performed for the combinations of three and four variables, which entail that more complicated models to be trained. For instance, in the case of N_1, N_5, N_7, as depicted in Figure 8.5, the simplified models: $(AB, BC), (AC, BC), (AB, AC)$, are compared with the saturated model (ABC). The subsequent results suggest the link between N_1 and N_7 should be removed. Consequently, it completes with a list of links to be removed from the fully connected network and the identified conditionally independent relationships, which is detailed in Appendix 11.

```
Two Variables: N1 & N2
Model 1: Twodata$CountNum ~ Twodata$Para1 * Twodata$Para2
Model 2: Twodata$CountNum ~ Twodata$Para1 + Twodata$Para2
Significance of difference is: 0.000269
Remove link between them ? False

Two Variables: N1 & N3
Model 1: Twodata$CountNum ~ Twodata$Para1 * Twodata$Para2
Model 2: Twodata$CountNum ~ Twodata$Para1 + Twodata$Para2
Significance of difference is: 0.346
Remove link between them ? True

Two Variables: N1 & N4
Model 1: Twodata$CountNum ~ Twodata$Para1 * Twodata$Para2
Model 2: Twodata$CountNum ~ Twodata$Para1 + Twodata$Para2
Significance of difference is: 0.134
Remove link between them ? True
```

Figure 8.4: A Snapshot of Two-Variable Dependency Analyses

```
Three Variables: N1 & N5 & N7
Model 1: threeparameter$CountNum ~ threeparameter$Para1 * threeparameter$Para2 *
Model 1:     threeparameter$Para3
Model 2: threeparameter$CountNum ~ threeparameter$Para1 + threeparameter$Para2 +
Model 2:     threeparameter$Para3 + threeparameter$Para1:threeparameter$Para2 +
Model 2:     threeparameter$Para1:threeparameter$Para3 + threeparameter$Para2:thre
Significance of difference is: 0.413
Model 3.1 : 1,3,0,2,3
Significance of difference is: 0.0119
Model 3.2 : 1,2,0,2,3
Significance of difference is: 0.127
Model 3.3 : 1,2,0,1,3
Significance of difference is: 2.16e-25
Model 4.1 : 1,2,0,3
Significance of difference is: 1.93e-24
Model 4.2 : 1,3,0,2
Significance of difference is: 2.61e-25
Model 4.3 : 2,3,0,1
Significance of difference is: 0.0286
Remove Link: DN1 - DN7
```

Figure 8.5: A Snapshot of Three-Variable Conditional Independency Analyses

The identified dependent and conditionally independent relationships will enable a BN skeleton. The subsequent operation is to add the orientations to the skeleton. As stressed in Chapter 6, initial effort should be put to the identification of "$head - to - head$" orientations. This is based on the conditionally independent relationships identified. Following that, the orientations for the remaining links can be assigned by adhering to the PC algorithm. The detailed operations are provided in Appendix 11.

Following the aforementioned computations, the obtained BN structure is shown in Figure 8.6. It is found that the nodes "$weather\_contributed$", "$Time$", "$Ship\_location$" are isolated from the rest of the nodes in the network. This is attributed to little evidence available suggesting a correlation between these variables with the rest based on the current data alone. It is also noted that

"$containment\_failure$" and "$Ignition\_in\_adjacent\_space$" both have no link directing to the rest. This phenomenon is mainly caused by the limited size of the data set, in which only a single fire accident in the collected data failed to contain it within the space of origin. Nevertheless, the node "$Emergency\_response\_failure$" is included in the network, which is a good indication of the status of fire growth.

As far as fire safety is concerned, if "$SOLAS\_space\_category$" is the starting point of inference, "$Emergency\_response\_failure$" can be regarded as the output node. It is not surprising to see that the influencing parameters, e.g. detection means, suppression means, crew and guest presence, etc. have complex interactions with the starting and ending nodes. Most notably, both "$Automatic\_suppression$" and "$Ventilation\_status$" have the most important and immediate influence on the probability of emergency response failure.

To examine the quality of the learning results, the influence diagram software Tetrad (http://www.phil.cmu.edu/projects/tetrad/) is deployed for similar analysis. Tetrad is one of the world's leading researches for the development of causal/statistical models. With identical input data and confidence interval, the obtained influence diagram is depicted in Figure 8.7.

As it can be seen in both Figure 8.6 and 8.7, the two networks match very well. For instance, the variables "$Time$", "$Location$", "$Ignition\_in\_adjacent\_space$", "$Containment\_failure$" are all isolated from the rest. Moreover, the remaining links and topology of the network are exactly the same. The only exception comes from the node "$Weather\_contributed$". This is because Tetrad stops the conditionally independent relationship analysis at the stage of three-variable combination, whilst, the developed R code takes one step further by analysing the conditional independencies of four-variable combinations.

In addition, it is worthwhile to compare the orientations of the established links between the two networks. As can be noted, the orientations connecting: "$Automatic\_suppression$" and "$Emergency\_response\_failure$", "$Automatic\_suppression$" and "$Ventilation\_status$" in the two models are opposite. Moreover, the links between "$Ventilation\_status$" and "$Emergency\_response\_failure$", "$Boundary\_cooling$" and "$Emergency\_response\_failure$" have no orientation in the output network from Tetrad.

The main reason for the deviance is that the algorithm for assigning orientations in the Tetrad focuses mainly on analysing causalities and plotting a diagram entails these relationships. It pays little attention to the directed acyclic feature of Bayesian networks and the subsequent probability computation (inference). Furthermore, as it is stressed previously for the principle of orientation assignment in Chapter 6, as long as the conditional independent relationships are depicted well by the V-structures in the network, the remaining orientations will not affect the results of probabilistic inference. In this respect, the reversed orientations in the two networks have very limited difference. Nevertheless, it would be still very desirable if the adopted orientations can reflect true causal relationships in reality for better interpretation.

All in all, in comparison with the diagram generated in Tetrad, the BN structure delivered through the program coded in R adopting constraint-based learning method – PC algorithm has very comparable results in terms of the network structure.

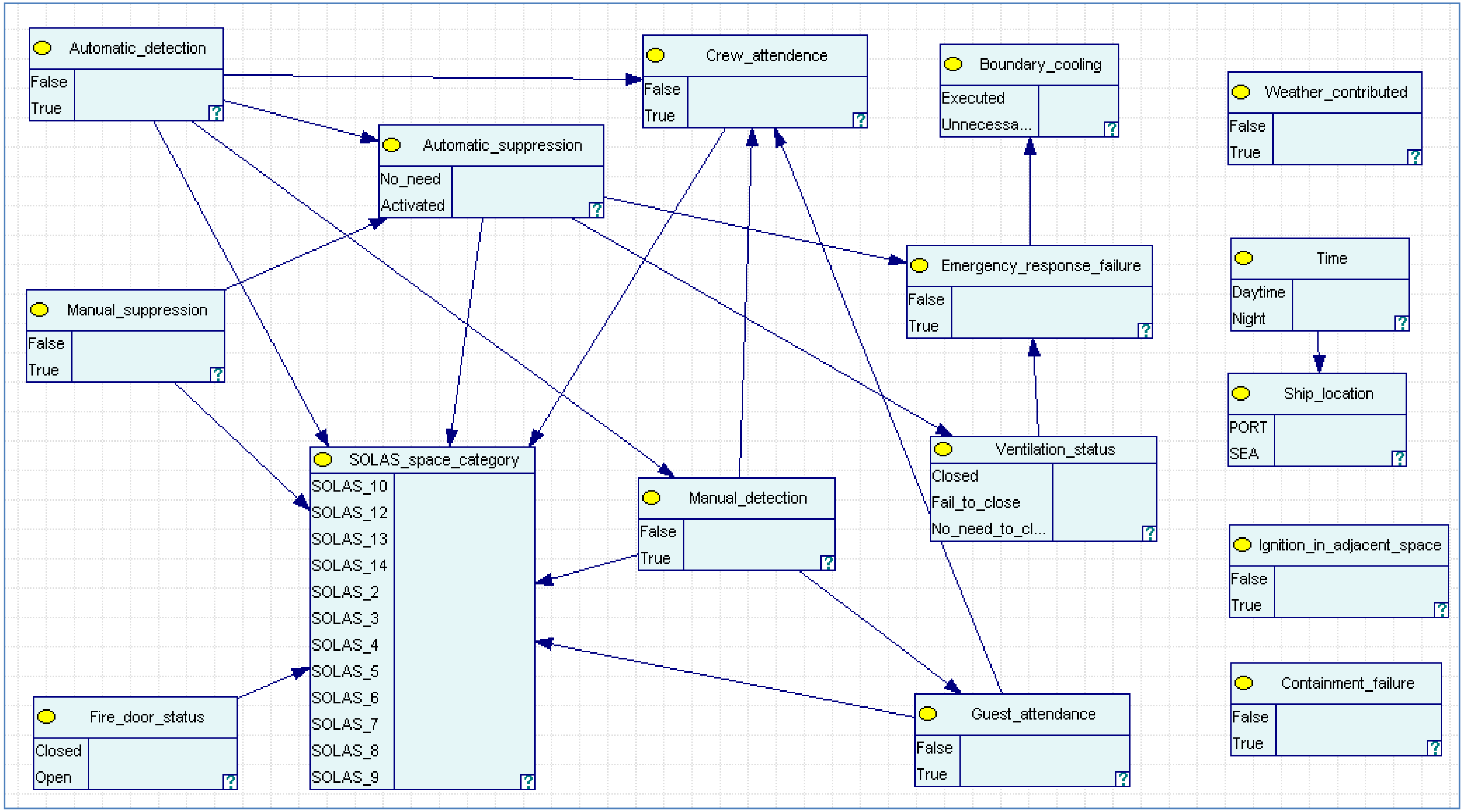


Figure 8.6: Constructed Bayesian Network Model through Constraint-Based Learning using the PC Algorithm

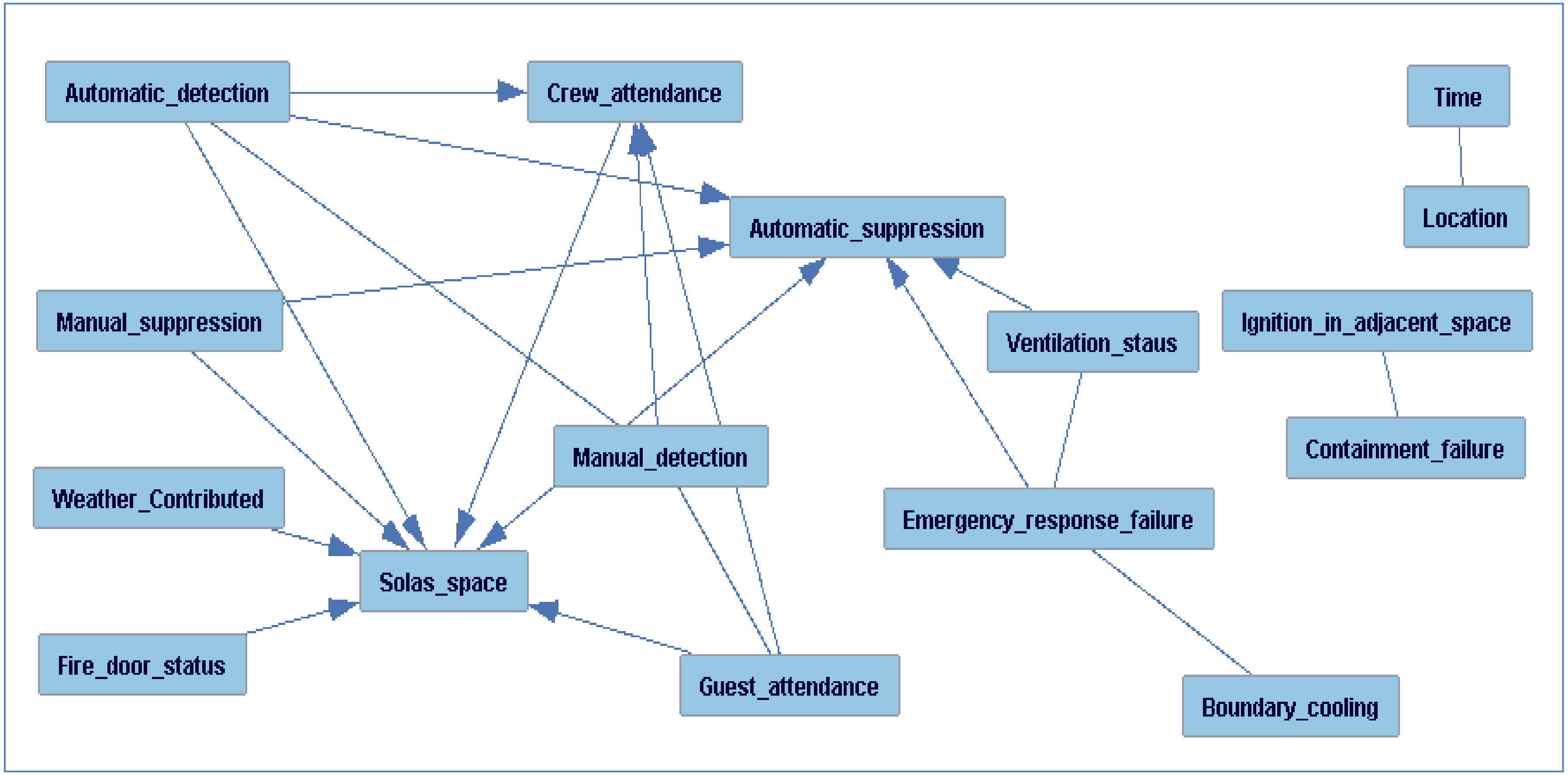


Figure 8.7: Constructed Bayesian Network Model through Constraint-Based Learning using the PC Algorithm in Tetrad

8.4.2 Learning through the GES algorithm

The components of score-based learning are the scoring function and the searching algorithm. As the Tetrad adopts a slightly modified version of the Bayesian scoring function, called the Bayesian BDeu scoring criterion, as expressed in equation (8.4), similar modification has also been made in the program in R.

$$S_{BDeu}(G,d) = log\prod_{i=1}^{n} 0.001^{(r_i-1)q_i} \prod_{j=1}^{q_i} \frac{\Gamma\left(\frac{10}{q_i}\right)}{\Gamma\left(\frac{10}{q_i}+N_{ij}\right)} \prod_{k=1}^{r_i} \frac{\Gamma\left(\frac{10}{r_i \cdot q_i}+N_{ijk}\right)}{\Gamma\left(\frac{10}{r_i \cdot q_i}\right)} \tag{8.4}$$

In contrast to the PC algorithm, the GES starts with a fully disconnected network. At the insertion stage, the computation at every iteration is to systematically examine every possible link that can be added by calculating the score increment, in which the one producing the highest increment will be adopted and taken to the next iteration. For instance, during the first iteration by systematically checking all possible links, $N_i - N_j$, the one between $N_5 - N_6$ is identified, as illustrated in Figure 8.8. The process stops once a link producing positive score increment cannot be found.

```
Loop 1

~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Highest score is: 450.7509
Between edge: 6 & 5
```

Figure 8.8: The Learning Results of Loop 1

At the second phase, similar loops are needed for the edge deletion. In contrast, this stage focuses on the systematic removal of links leading to positive score increment. The detailed computation log for this specific study is provided in Appendix 12. Ultimately, the structure of a BN is identified and presented within a matrix table, as illustrated in Figure 8.9. In the matrix, the links and orientations are denoted by "In"

and "Out", which can be transformed into the skeleton of a BN structure in GeNIe as depicted in Figure 8.10.

With respect to "$time$" and "$location$", the result obtained from the GES algorithm agrees very well with the one delivered through the PC algorithm as both nodes are isolated from the rest. Nevertheless, it is found that in terms of identifying the sequence of a fire event, the GES performs better as the links follow the logic of an ordinary growing fire: "$Emergency\_response\_failure$", "$Containment\_failure$", "$ignition\_in\_adjacent\_space$". Nevertheless, the learning algorithm underperforms in describing the interactions between the space of ignition and the remaining preventive and mitigative measures as only a single link is identified for "$SOLAS\_space$".

Similar GES learning process is performed in Tetrad and the output is illustrated in Figure 8.11. It is noted that the learning output in R matches well with the Tetrad result with respect to the topology and orientations. With all the remaining links are exactly the same, there is an extra link between "$SOLAS\_space$" and "$guest\_attendance$". Nevertheless, the variable "$SOLAS\_space$" still lacks of interactions with the rest.

Convert PDAG to DAG:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16
1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA
4	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	NA
5	NA	NA	NA	NA	NA	Out	Out	NA	NA	Out	NA	NA	NA	NA	NA	NA
6	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	Out	Out	NA	NA	NA	NA
7	NA	NA	NA	NA	In	NA	NA	In	Out	NA	NA	NA	NA	Out	NA	NA
8	NA	NA	NA	NA	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA
9	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	NA	NA	NA	NA
10	NA	NA	NA	Out	In	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
11	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	In	NA	NA	NA	NA
12	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	Out	NA	NA	NA	NA	NA
13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	Out	NA
14	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	Out	NA	NA	NA
15	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA	NA	Out
16	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA

Figure 8.9: Network Output in Matrix Table

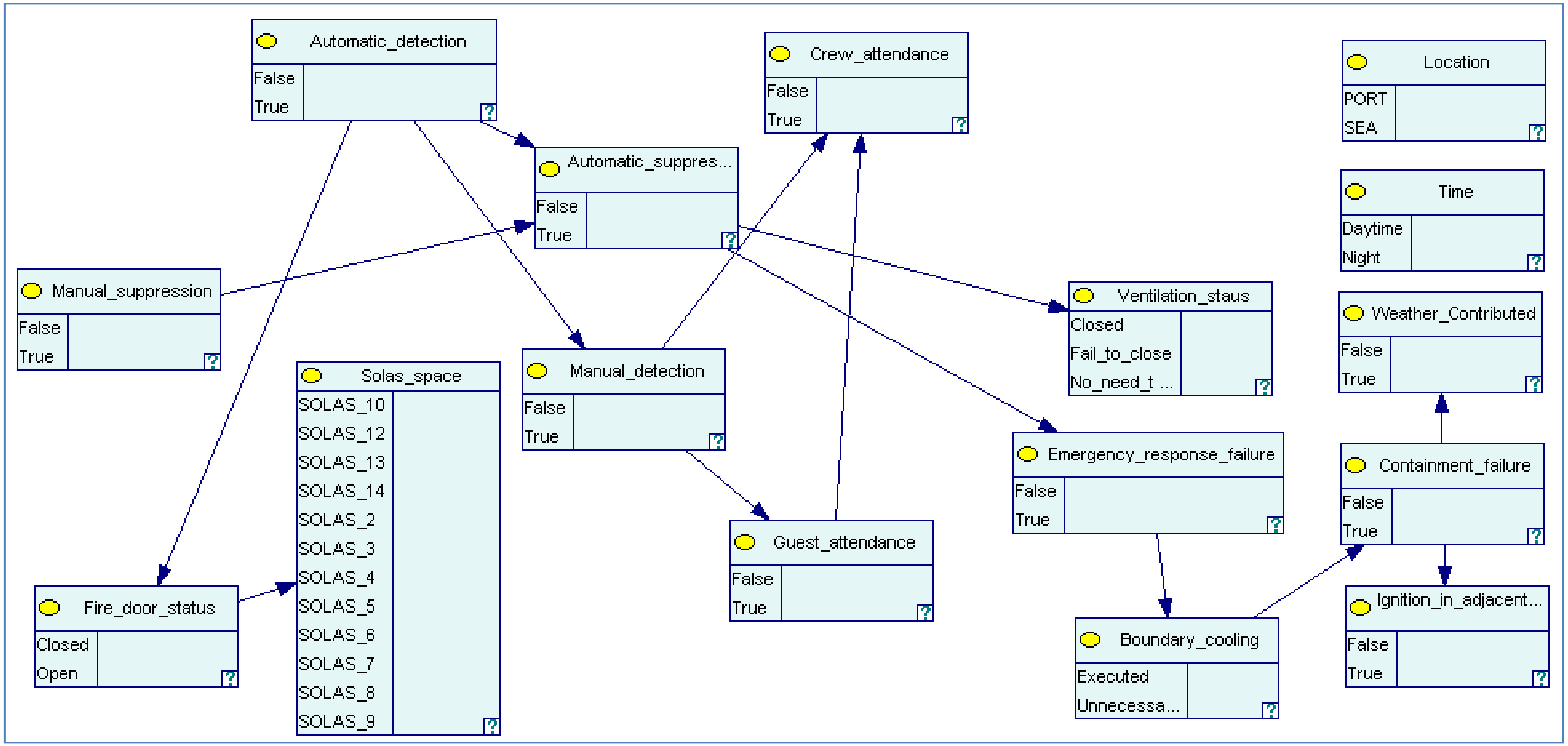


Figure 8.10: Constructed Bayesian Network Model through Score-Based Learning

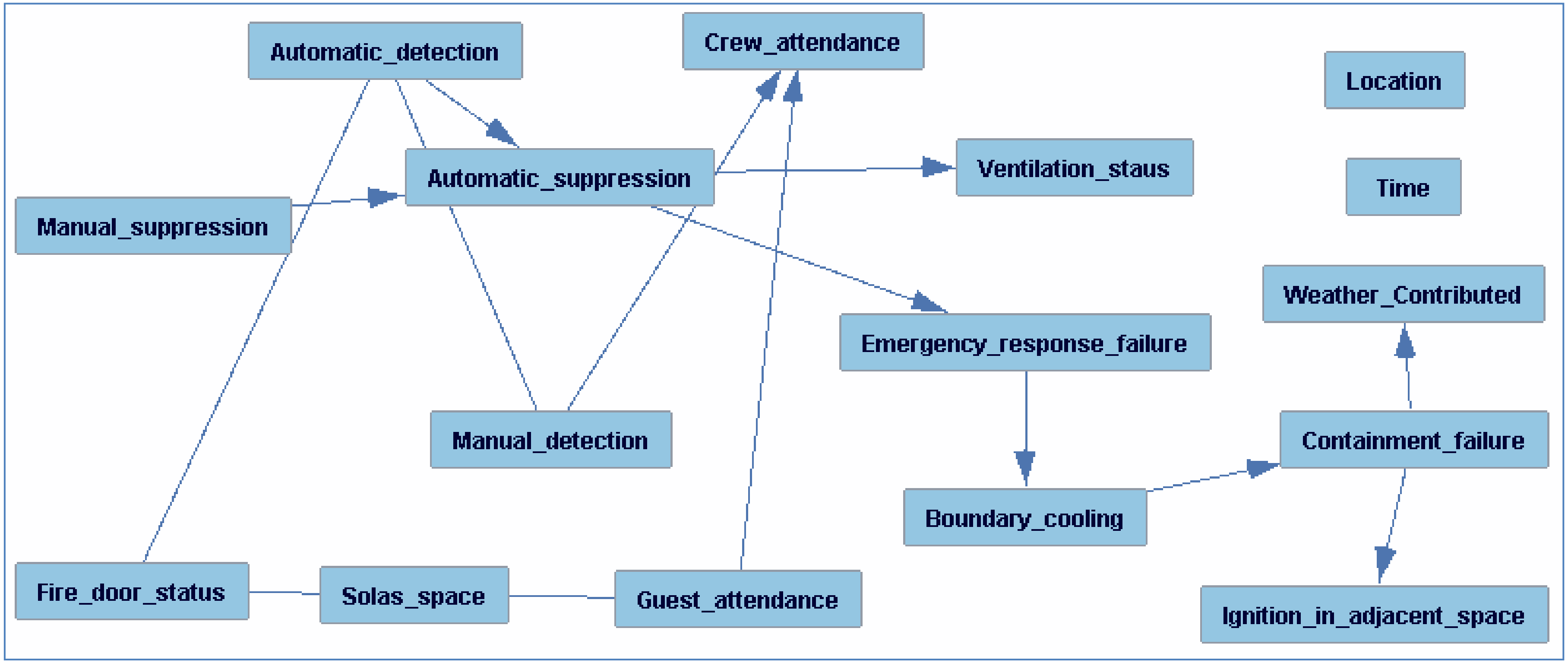


Figure 8.11: Constructed Bayesian Network Model through Score-Based Learning in Tetrad

8.4.3 Justification of Bayesian Network models

As it is noted, the topologies of the constructed networks from both constraint and score –based learning algorithms vary significantly. This is mainly attributed to distinct learning principles. The former focuses on the identification of dependency relationships, whilst the latter pays particular attention to the likelihood for the network to describe (generate) the collected data set.

As a result, the outputs from the constraint-based learning algorithm, as shown in Figure 8.6 and 8.7, are more capable of describing complex dependent relationships between various influencing variables (e.g. detection means, suppression means, and human factors). Moreover, it can be observed that the variables with more statuses (e.g. "$SOLAS\_space\_category$") are more likely to have dependent relationships with the remaining variables through statistical analysis. On the other hand, the networks constructed through score-based learning, as shown in Figure 8.10 and 8.11, are more suitable to describe the sequential events of the identified hazard. For instance, the information flow as depicted by the two networks starts briefly from Ignition spaces, detection means, suppression means, emergency response, up to ignition in adjacent spaces.

It is important to note that the quality and quantity of the collected data set plays a vital role on the obtained Bayesian networks models from both techniques. The required resolution to describe the interested hazards can be also significant in this respect. For instance, different spaces on board will have different typical scenarios of fire hazards. All these factors will ultimately affect the topology of the BN models and the stored probabilistic information.

Apart from topological judgement of the goodness of the constructed networks, the formal goodness-of-fit criteria are utilised to compare the results obtained from different means. Both the Bayesian scoring criterion and the BDeu scoring criterion are used for the comparison. The BNs models generated through both the PC and the

GES algorithms from the program developed in R and Tetrad are examined, where the scores are tabulated in Table 8.3.

Table 8.3: Goodness-of-fit Comparison Table of the Results Obtained from Various Techniques

Bayesian Network model construction means	**Bayesian Scoring Criterion**	**BDeu scoring criterion**
PC algorithm in R	-9666.545	-infinity
PC algorithm in Tetrad	-9753.706	-infinity
GES algorithm in R	-9410.066	-9764.864
GES algorithm in Tetrad	-10434.71	-10672.49

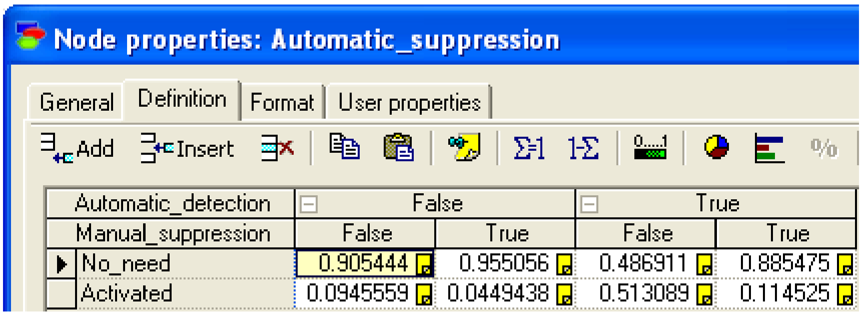
It is noted that the network models delivered through the code developed in R for both PC and GES algorithms perform better than the outputs from Tetrad, e.g. $-9666.545 > -9753.706$, $-9410.066 > -10434.71$. It is also found that the BDeu scores of the network models generated through the PC algorithms in both R code and Tetrad are $-\infty$. This is mainly caused by one of the component of the BDeu scoring criterion, $log\left(0.001^{(r_i-1)q_i}\right)$. When estimating the score contribution from "$SOLAS\_space$", which has 7 binary parents, $q_i = 2^7 = 128$ and, consequently, $log(0.001^{12\times128}) = -\infty$.

On the other hand, it is worth noting that the scores of the outputs of PC algorithm are comparable with the ones obtained through the GES algorithm. Although the results from R code for PC algorithm is lower than the one from R code for GES algorithm (e.g. $-9666.545 < -9410.066$), the output from Tetrad for the PC algorithm actually performs better than the GES algorithm as far as the Bayesian scoring criterion is concerned, (e.g. $-9753.706 > -10434.71$).

Parameter learning is performed to quantify the networks once its skeleton is developed. The outputs from both the PC and the GES algorithms are carried forward for probability quantification. As it has been stressed in Chapter 6, the conditional probability table of one node is only influenced by the combination of different statuses of its parents. Hence, the process is comprised of three steps:

construction of the augmented nodes, quantification of the augmented nodes with initial prior probabilities, update of the probabilities with the data set.

Constructing the augmented nodes is essentially equivalent to configuring the conditional probability tables. For instance, the parents of "$Automatic\_suppression$" are "$Automatic\_detection$" and "$Manual\_suppression$" in the network obtained through the PC algorithm. Hence, the conditional probability table needs the take the four possible combinations of its parents' states into account, e.g. $(False, False)$,…, $(True, True)$, as depicted in Figure 8.12. This is equivalent to four augmented nodes in the network.



Automatic_detection	False		True	
Manual_suppression	False	True	False	True
No_need	0.905444	0.955056	0.486911	0.885475
Activated	0.0945559	0.0449438	0.513089	0.114525

Figure 8.12: An Example of the Conditional Probability Table for "$Automatic\_suppression$"

The following manipulation is to input prior information for all conditional probability tables. As little prior information is available, equal prior beliefs are assigned. In the meantime, equal sample space is maintained by ensuring the sum of the prior beliefs assigned at each node is equal.

Consequently, all conditional probability tables need to be updated with the information stored in the data set by systematically summarising the data set into various contingency tables containing a specific node and its parents. Table 8.4 exhibits an example of a contingency table for "$Automatic\_suppression$", whose parents are "$Automatic\_dection$" and "$Manual\_suppression$".

Table 8.4: Updated Contingency Table for "$Automatic\_suppression$"

$\boldsymbol{Automatic\_dection}$	**False**		**True**	
$\boldsymbol{Manual\_suppression}$	**False**	**True**	**False**	**True**
No_need	316.002	595.002	93.002	317.002
Activated	33.002	28.002	98.002	41.002

With the aforementioned process programmed in R, the obtained network can be quantified automatically. The results obtained from the developed code can be readily checked by similar software using identical data and network skeleton. GeNIe is selected for performing the comparison study.

As far as fire safety is concerned, one of the interesting indicators is to estimate the probability of fire growth for a given SOLAS space category. The comparison results on the basis of various obtained models are tabulated in Table 8.5. According to the skeleton delivered through the PC algorithm, the estimated probabilities from the developed R code and GeNIe match extremely well. Similar conclusion can be drawn for the network skeleton delivered through the GES algorithm in both R code and the GeNIe. Hence, it is believed that the stability of the parameter learning algorithm can be assured.

On the other hand, it is noted that the classical regression analysis provides very poor estimation due to small size of the sample space, e.g. 0 occurrence of fire growth for SOLAS space category 2, 3, 4, 7, 10, and 14, as illustrated in Figure 8.13. In contrast, the BN models produce more realistic estimations. Nevertheless, due to the network obtained from the GES algorithm contains only a single link connecting to the node "$SOLAS\_space$" and it has limited influence on "$Emergency\_response\_failure$", the latter is not sensitive to the changing states of "$SOLAS\_space$".

Considering all the previous observations, it would be reasonable to employ the constructed BN through the PC algorithm and the associated parameters learning technique for further analysis.

Table 8.5: $P(fire\_growth|ignition)$ of the 14 SOLAS Space Categories using Various Means

SOLAS_space	**$P(fire\_growth|ignition)$ *100**				
	PC algorithm		**GES algorithm**		**Regression**
	R code	**GeNIe**	**R code**	**GeNIe**	
2	0.64	0.64	0.88	0.88	0.00
3	0.65	0.65	0.81	0.82	0.00
4	2.17	2.17	0.83	0.83	0.00
5	0.44	0.44	0.87	0.87	1.45
6	0.29	0.29	0.95	0.95	0.32
7	0.59	0.59	0.93	0.93	0.00
8	0.53	0.53	0.89	0.89	1.04
9	0.63	0.63	0.89	0.9	1.82
10	0.91	0.9	0.95	0.95	0.00
12	1.54	1.54	0.94	0.94	1.24
13	0.41	0.41	0.92	0.92	0.79
14	1.59	1.59	0.9	0.9	0.00

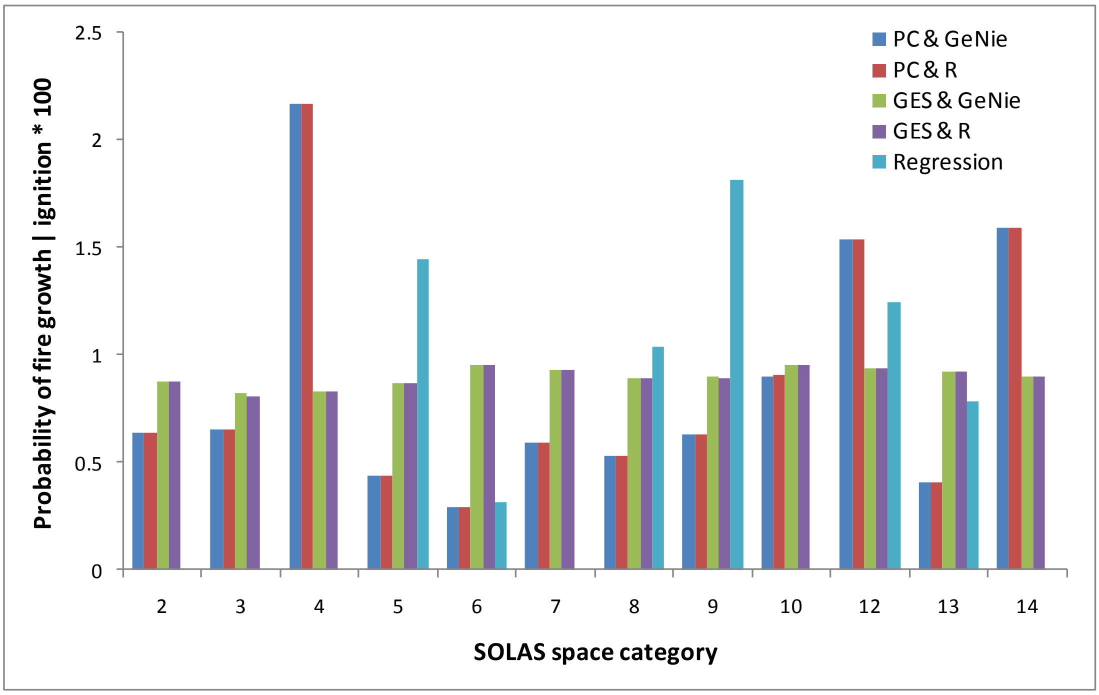


Figure 8.13: Comparison of Estimated $P(fire\_growth|ignition)$ through Various Techniques

8.5 Decision Support for RBD Implementation

8.5.1 Design Scenario Generation

On the basis of the model obtained through data mining and in the knowledge that a network can serve as a risk model and, at the same time, as a risk knowledge model, a broad classification of the variables included is performed. It is worth noting that the BN can be regarded as a risk sub-model and a risk knowledge sub-model for this specific case depicting certain phases of a fully developed fire sequential scenario, i.e. ignition, emergency response, containment, and escalation. With respect to the risk knowledge sub-model, it includes design parameters, operational parameters, and scenario-specific variables. The detailed classification is tabulated in Table 8.6.

Table 8.6: Classification of the Variables Included in the Developed Bayesian Network Model

Generic Risk model	**Variables**
	SOLAS space category Emergency response failure Containment failure Ignition in adjacent space
Risk knowledge model	**Variables**
Design parameter	SOLAS space category Automatic detection Automatic suppression Ventilation status
Operational parameter	Manual detection Manual suppression Fire door status Crew attendance Guest attendance Ventilation status Boundary cooling
Scenario-specific parameter	Weather contribution Time of the day Ship location

Concerning the implementation of risk-based design, the emphasis should be placed on the generation of design alternatives. In this respect, design parameters play an important role. In recognising that the risk of having multiple fatalities due to the fire occurring in the accommodation spaces is much higher due to large population density, SOLAS space category 6, particularly for cabin spaces, is selected for design alternatives examination.

The SOLAS space category in which a space belongs to explicitly determines the type of insulation to be installed for the sake of fire integrity. It influences mainly the risk component $P_{escalation|growth|ignition}$ through containing the fire within the space of origin. With respect to the automatic detection and suppression systems, their effectiveness depends on various aspects, which can be grossly classified as the types of systems, and their corresponding global and local layouts, etc. An example of the factors influencing design parameters are tabulated in Table 8.7, which is not exhaustive.

Table 8.7: Factors Influencing the Identified Key Design Variables

SOLAS space category	**Boundary insulation classes**
Automatic detection	System monitoring Arrangement of power supply System arrangement Location of control panel Indicating units and locations Type of detectors Choice of Positions for detectors Spacing of fire detectors Arrangement of electrical wiring Etc.
Automatic suppression	Types of suppressing agent Basic fire alarm system System arrangement (sections, isolating values, pressure indicators, etc.) Pumps and piping systems Automatic suppression system selection Power source Etc.
Ventilation status	Controls of fans for power ventilation Smoke extraction system Etc.

The current practice for achieving a minimum level of fire safety is sought mainly through the compliance with regulations. For instance, apart from the alarm system that needs to be equipped when designing the suppression system, it is also required to have an independent detection and alarm system to provide another safeguard [ABS, 2001]. Nevertheless, having satisfied such requirements, the designers actually have little knowledge of how much improvement can be achieved by designing a dual alarm arrangement.

It is apparent that the factors listed in Table 8.7 could generate a huge amount of unique design solutions through various combinations. Nevertheless, in the case of designing a fire protection system for cabin spaces of passenger ships, the design space reduces significantly due to the applicability of certain systems. For instance, the carbon dioxide system is unsuitable for the accommodation spaces. Moreover, as the aim is to demonstrate how a BN can be used as a source of information for decision support, a few design options are generated. The design factors considered and the assumptions made are explained as follows.

<u>Detection system</u>: an important factor affecting the performance of a detection system is the types of detectors installed. There are mainly two types of detectors: heat and smoke. The heat detector operates by sensing the temperature in the area surrounding the alarms, while the smoke detector will be activated once the smoke density exceeds a certain level. The heat detector is suitable for fires that involve high flames and intense heat. In contrast, the smoke detector functions better in fires that the smoke is generated before intense building up of the heat.

<u>Automatic suppression system</u>: there are numerous types of suppression agent for shipboard applications, like low-pressure water sprinkler systems, foam systems, carbon dioxide systems, etc. In the case of the accommodation spaces, the common practice is to install normal water sprinkler systems. In the meantime, more attention is being paid to the fixed high-pressure water mist system to achieve better overall performance. Traditional water sprinkler often leads to significant water damage to local furnishing and electronic equipments, while the latter uses much less water and

is able to suppress the fire efficiently as the water mist can penetrate a fire and cool the surrounding environment.

Consequently, a number of design solutions can be generated for protecting the accommodation spaces (i.e. cabin). Main attention is paid to the detection system (smoke and heat) and the suppression system (normal water sprinkler system and high pressure water mist system). The detail of various combinations for design solutions generation is tabulated in Table 8.8.

Table 8.8: Design Solutions for SOLAS Space Category 6

Design 1	Installed with normal heat detection system and low-pressure water sprinkler system
Design 2	Installed with smoke detection system and low-pressure water sprinkler system
Design 3	Installed with normal heat detection system and high-pressure water-mist system
Design 4	Installed with smoke detection system and high-pressure water-mist system

8.5.2 Bayesian Networks for Pair-Wise Comparison

In order to quantify the influence of various detection and suppression systems on the obtained fire risk model in BNs, pertinent comparative information can be obtained from the suppliers of individual systems or detailed mathematical models. Nevertheless, for the sake of demonstration of decision support using the obtained network model, the quantitative estimation is made on the basis of the qualitative information collected. It is assumed that smoke detection systems would have generally 10% improvement compared with heat detection systems in terms of the effectiveness for detecting fire incidents in cabin spaces. In the case of suppression systems, high-pressure water-mist systems are estimated to perform 10% better than low-pressure water sprinkler systems.

To take all these information into account, minor modification of the obtained model is needed. As the design solutions focus mainly on the modification of automatic detection and suppression systems, their influence to the fire safety performance is reflected mainly through the nodes "*Automatic_detection*" and "*Automatic_suppression*". As a result, a node "*Design_solution*" is added to the network with arrows directing to the two variables, as illustrated in Figure 8.14. The ultimate influences of the various design solutions can be observed through the node "*Emergency_response_failure*", as shown in Figure 8.15.

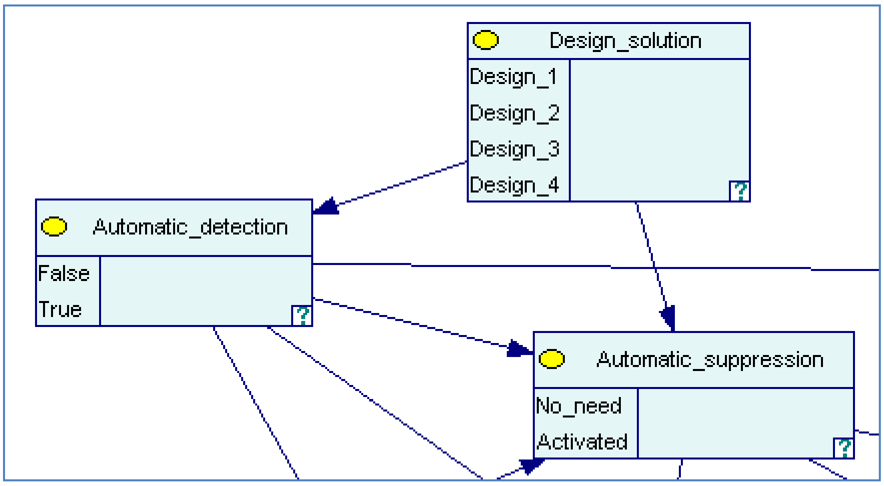


Figure 8.14: Integrating Design Solutions within the Constructed Bayesian Network Model

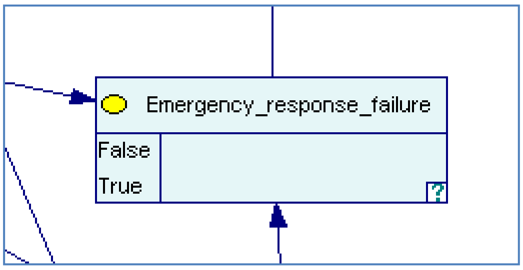


Figure 8.15: Output Node

By assuming that the states of all the remaining variables follow their nature distributions, instantiations of the design solutions are performed for SOLAS space category 6, as illustrated in Figure 8.16. The obtained probabilities of emergency response failure for the four design alternatives are tabulated in Table 8.9.

It is found design 1, which is characterised by the heat detection and low-pressure water sprinkler systems, has the highest probability of fire growth given ignition. In contrast, the modification from the heat detection system to the smoke detection system and from the low-pressure water sprinkler system to the high-pressure water sprinkler system in design 2 and 3 respectively improve their corresponding mitigative performance. It is worth noting that, although both smoke detection systems and high-pressure water mist systems have 10% improvement, their impact to the output node is different, where Design 3 (with $P_{growth|ignition}$ = 0.002199) has higher impact than design 2 (with $P_{growth|ignition}$ = 0.002781). Lastly, a combined configuration of the smoke detection system and the water mist system produces the best performance for this specific study.

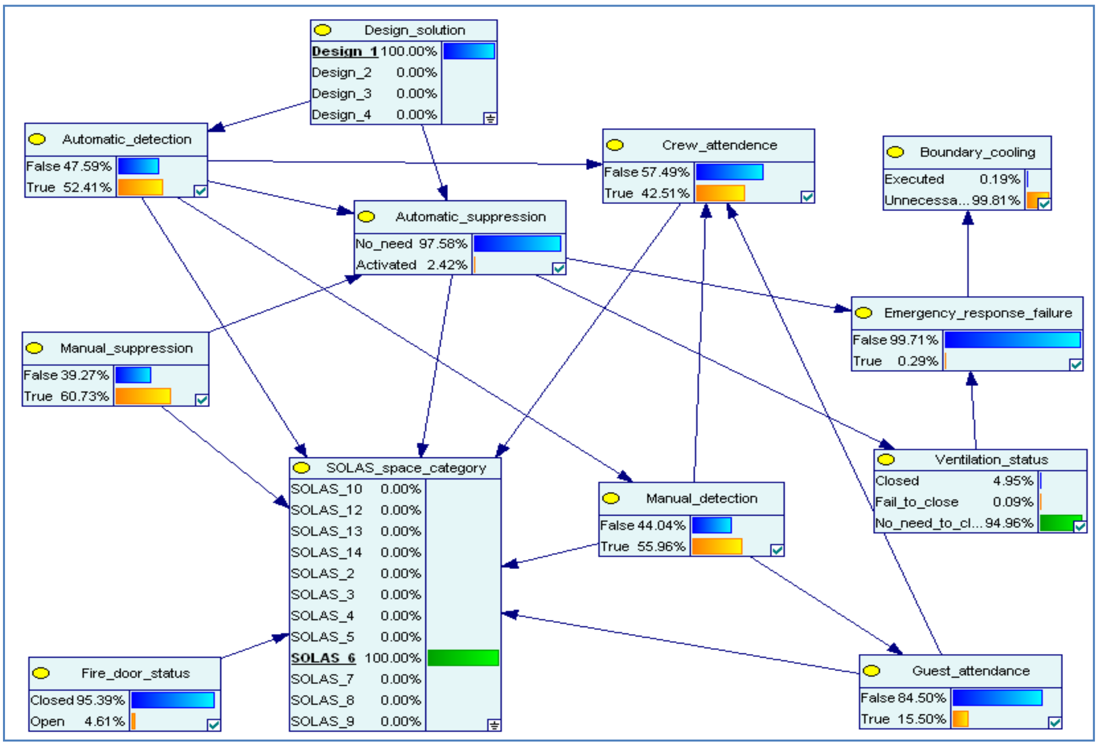


Figure 8.16: Instantiation of Design Solution 1 for SOLAS Space Category 6

Table 8.9: Results Produced by the Updated Bayesian Network Model for Various Design Alternatives

	$P_{growth\|ignition}$
Design 1	0.002928
Design 2	0.002781
Design 3	0.002199
Design 4	0.002107

In the knowledge that the fire risk of a specific space is the product of various scenario-specific probabilities and the subsequent consequences, it is assumed that other risk components (e.g. $P_{ignition}$, $P_{escalation|growth|ignition}$, C_{fire}) remain unchanged for the four design solutions. In this case, the pair-wise comparison table for fire safety in the accommodation spaces can be obtained, as tabulated in Table 8.10.

Table 8.10: Pair-wise Comparison for Fires from Accommodation Spaces

	Design 1	**Design 2**	**Design 3**	**Design 4**	**Priority**
Design 1	1	0.950	0.751	0.720	**0.209**
Design 2	1.053	1	0.791	0.758	**0.221**
Design 3	1.332	1.265	1	0.958	**0.279**
Design 4	1.390	1.320	1.044	1	**0.291**

On the basis of the pair-wise comparison, the priorities of the four design solutions can be obtained. Unsurprisingly, the priority of design1 is the lowest, while design 2 and 3 attain higher priorities. Considering the single system modification adopted by design 2 and 3, design 3 achieves better result with respect to fire safety performance for accommodation spaces. Design 4 receives a combined positive effect of design 2 and 3.

Apart from safety performance, it is also necessary to consider other aspects in measuring the merits of various design alternatives. The important indicators could be taken into account cover technical, cost and earning aspects. It is understood that other measures, such as machinery configuration, could be also important.

Nevertheless, considering the configuration difference between smoke and heat detection system, minor modification is needed. Similar situation applies to water sprinkler and water mist systems. Hence, this study focuses on the evaluation of various design alternatives with respect to the performance in safety, technical, and cost/earning fields.

For technical aspect, conventional measures are frequently referred to as: intact and damage stability, survivability, seakeeping and manoeuvring performance, structural reliability and complexity. For this specific study, the reliabilities of various detection and suppression systems are considered. The two detection systems perform relatively similar due to the maturity of both heat and smoke detection systems. As for suppression systems, it is expected that low-pressure water sprinkler systems are 10% more reliable than high-pressure water mist systems as the latter works under much severe conditions. At practical application stage, pertinent technical specifications can be collected from system suppliers.

The pair-wise comparison with respect to technical performance is carried out and tabulated in Table 8.11. As can be seen, design 1 and 2 adopting conventional low-pressure water sprinklers have higher priorities over design 3 and 4. This can be understood as the working conditions for new suppression system employing much higher pressure is more likely to experience system faults.

Table 8.11: Pair-wise Comparison regarding Technical Performance

	Design 1	**Design 2**	**Design 3**	**Design 4**	**Priority**
Design 1	1	1	1.1	1.1	**0.262**
Design 2	1	1	1.1	1.1	**0.262**
Design 3	0.909	0.909	1	1	**0.238**
Design 4	0.909	0.909	1	1	**0.238**

With respect to the cost, it consists of building and operational costs. Building cost covers design, purchasing, and installation, while operational cost includes crew and fuel cost associated with different operational systems. Commercial information of such is normally with yards, design companies, and operators. Approximations are made to demonstrate the process. Smoke detection systems are estimated to be 10% more expensive than heat detection systems. High-pressure water mist systems are expected to be 20% more costly than low-pressure water sprinkler systems. The subsequent comparison is illustrated in Table 8.12.

Table 8.12: Pair-wise Comparison regarding Cost Performance

	Design 1	Design 2	Design 3	Design 4	Priority
Design 1	1	1.1	1.2	1.3	**0.285**
Design 2	0.909	1	1.091	1.2	**0.260**
Design 3	0.833	0.917	1	1.1	**0.238**
Design 4	0.769	0.833	0.909	1	**0.217**

As far as the earning is concerned, due to the captive nature of both systems for fire protection, the selection of different systems has little impact to the earning potential. Nevertheless, it can be argued that improved safety record will positively influence the earning potential. In this respect, as the link for such influence is weak and too vague and difficult to predict in practice, the earning aspect is not taken into account in this case.

Consequently, priorities synthesis can be performed to have an overall evaluation of various design alternatives. Initial attempt is made without assigning any weighting factor, as tabulated in Table 8.13, so that equal emphasis is placed on the three performance indicators, i.e. safety, technical, cost. Figure 8.17 further exhibits the performance of the four design solutions in these aspects. The results indicate that the performance of design 3 is equivalent to design 1. It suggests high-pressure water mist systems do provide much better fire protection, however, their overall performance are penalised by their disadvantages in technical and cost aspects.

Table 8.13: Priority Synthesis with Equal Emphasis on All Performance Indicators

	Safety	Technical	Cost	Priority
Design 1	0.209	0.262	0.285	**0.2520**
Design 2	0.221	0.262	0.260	**0.2474**
Design 3	0.279	0.238	0.238	**0.2517**
Design 4	0.291	0.238	0.217	**0.2488**

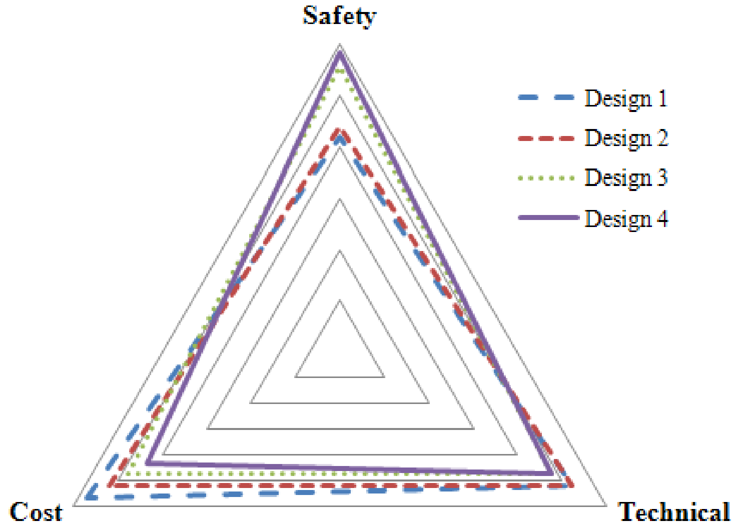


Figure 8.17: Design Solutions Evaluation Diagram (without Weighting Factors)

On the other hand, it can be argued that special attention should be placed on the safety aspect as both detection and suppression systems are dedicated to assure fire safety. Under this circumstance, weighting factors can be assigned. For illustration, the emphasis is placed on safety aspect as illustrated in Table 8.14. Figure 8.18 exhibits the performance of the four design alternatives with weighting factors included. The obtained priorities suggest design 4 is the best solution. It is also interesting to note that design 3 have very similar overall priority and its cost performance is also better than design 4, hence design 3 can be a promising solution as well.

Table 8.14: Priority Synthesis with the Emphasis on Safety Performance Indicator

	Safety	**Technical**	**Cost**	**Priority**
	0.5	0.25	0.25	
Design 1	0.209	0.262	0.285	**0.2414**
Design 2	0.221	0.262	0.260	**0.2407**
Design 3	0.279	0.238	0.238	**0.2585**
Design 4	0.291	0.238	0.217	**0.2594**

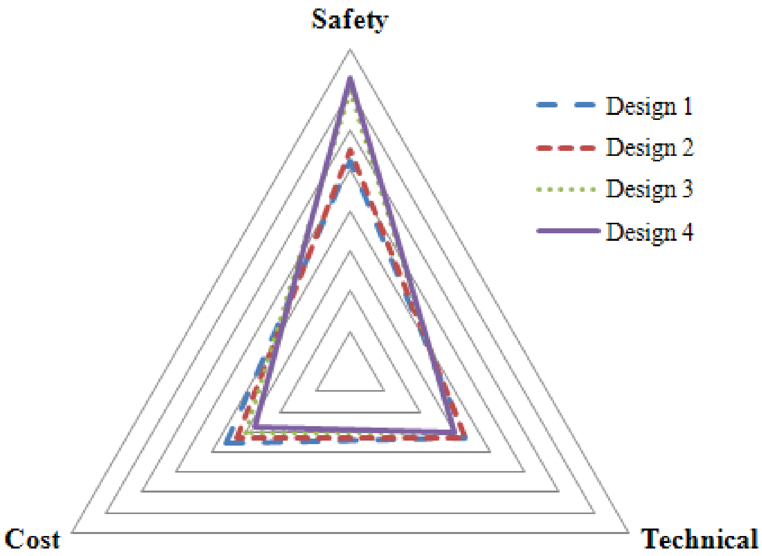


Figure 8.18: Design Solutions Evaluation Diagram (with Weighting Factors)

8.6 Closure

In view of the need to demonstrate the proposed methodological framework for the implementation of risk-based ship design, a comprehensive case study has been carried out in this chapter concerning fire safety of passenger ships. It starts with the development of a fire accident/incident database, which includes a process of identifying dominant variables and collecting pertinent data. With the database, data mining techniques have been applied for eliciting corresponding BN models. Ultimately, the validated models have been embedded into the decision support process by supplying objective and tangible safety-relevant information so that a transparent and well-balanced decision can be made. Although the exact figures may be questionable, the approach presented in this chapter does provide a systematic and transparent methodology for decision support. Particular attention has been paid to the integration of the BN model within the whole process for supplying factual information of the impact of various design alternatives on safety performance.

Chapter 9
Discussion

9.1 Preamble

In this thesis, a formalised methodology for risk-based ship design implementation has been presented. The founding hypothesis of the thesis has been that the current practice through deploying fault and event trees undermines the output of risk assessment from both qualitative and quantitative aspects. The situation becomes even more difficult due to the time-consuming feature of first-principles and performance-based tools. Such background calls for the development of a novel methodology for the implementation of risk-based design. In this respect, the emphasis has been put on the various stages constituting the working procedures and methods. The necessity of an integrated environment for data sources and data processing has been laid down, supported by an initial development of a stand-alone next generation maritime database and a data mining program developed in R. A comprehensive case study has been performed to demonstrate the validity of the methodology as a whole and its constituting components. Although the estimated risk components and figures can be questionable, the methodology presented can be regarded as a reliable means for decision support.

This chapter focuses on a discussion of the major outcomes of the thesis. Following a brief summary of the contributions of the thesis, a general discussion is presented highlighting the difficulties encountered in the development of the various components and concepts, and the manner in which these difficulties were handled. It concludes with recommendations for further research.

9.2 Contribution to the Field

This thesis proposes a novel methodology for risk-based design implementation. The initial applications demonstrate the potential of the approach to lead to a systematic implementation process. In this respect, the thesis has served the principal aim and objectives. The contribution in the field of risk-based design is the following:

1) A principle contribution of this research is a methodological framework for risk-based ship design implementation, supported by requisite concepts, tools, applicable specifically to passenger ships. In this respect, the formalisation of the proposed approach as a whole and its constituent components has been achieved. The content covered at each stage of the implementation process is believed to be comprehensive and detailed enough for allowing a systematic application.

2) A second contribution of the research undertaken is an integrated treatment of the objective sources of information, enabling an all-embracing database to facilitate the knowledge transfer from the operational phase to support the various activities to be carried out at the design stage. The emphasis has been placed on the development of a data source that is capable of supplying reliable and objective data for risk assessment. Through hierarchical decomposition processes, important parameters that are potentially influencing the risk level, specifically of passenger ships, have been identified and included. In this way, casualty-related information is readily to be employed for further risk modelling.

3) A third contribution is the introduction of tailored data mining techniques in the maritime industry, particularly within the context of design for safety. Through systematically linking the data with the risk modelling process through data mining, the underlying mathematical and probabilistic principles have been revealed. Although the BN learning algorithms are still evolving at a fast pace, the techniques and algorithms introduced in this thesis still represent the mainstream in the field.

4) A fourth contribution is attributable to the employment of the BN model as a robust platform for safety-performance evaluation and, ultimately, for decision support. Through the adoption of the framework of analytic hierarchy process for decision support, BNs can be easily integrated into the whole process for the evaluation of various RCOs from design perspective. In the meantime, it is worth noting that as operational parameters are also explicitly included for risk model development, the approach can be easily extended to the operational aspect for total risk management [Cai, et al., 2010].

9.3 Difficulties Encountered

The original aim of this research is to establish a methodology that the marine accident/incident can be properly utilised for deriving useful information. The initial effort was devoted in the promising field of data mining techniques for a generic application. However, it was soon realised that such an idea is difficult to find a practical application unless a proper framework is established. The conventional treatment of accident/incident data has been rule-oriented and case-specific, a tactic which hindered the knowledge transfer from the operation to the design phase. In direct response, the risk-based approach towards ship design is generating an unprecedented momentum in changing the way that safety is treated. With such concept, the knowledge transfer from the past experience is important. Under this background, it was decided to focus on the development of a methodology that can assist in this direction.

In realising the deficiencies of the current design practice for safety performance evaluation with respect to quality, quantity, and efficiency, the skeleton of a novel methodology for risk assessment within the context of risk-based design emerges. Through systematic processing of the available data and use of the data mining techniques, pertinent risk models can be developed, in which design parameters can directly link with safety performance measures. In the meantime, it is understood that historical data is generally not detailed enough to capture all the activities undertaken and the phenomenon of a casualty event, thus, the properly developed and validated first-principles and performance-based tools are the other means of generating reliable sources of information. Consequently, the methodology that has been presented in this thesis was shaped and materialised.

It is appreciated that a full verification of the validity of the proposed approach is beyond the scope of the present research due to limited resources available. This refers to the fact that a large amount of records on principal accidents for passenger ships and the corresponding simulations through first-principles tools should contribute to such study. However, the limited examples and the case study carried out have demonstrated the applicability of the methodology in the risk-based ship design context. The following discussion focuses on specific difficulties encountered during the course of the research at various stages.

The Issue of Data

The situation concerning current generation casualty databases is still characterised by segmentation, disorganisation, and un-standardised format. As a result, great effort is needed to prepare the data for further analysis. This data pre-processing task includes data collection, interpretation, purification and transformation.

Due to the fact that the maritime industry is a highly competitive and still segmented sector, accessing its operational records is difficult. The situation becomes even worse if the records contain sensitive information, like casualties, which implicitly links to liability and the subsequent insurance claims. Hence, the increased amount of casualty records with ship operators due to the enforcement of the ISM code has limited positive impact. The main sources of information are widely dispersed among classification societies, regional and national agencies, etc. However, it is encouraging to note that a number of changes are happening: the IMO developed a web-based casualty information platform in recent past [IMO, 2010a], and the EMSA is developing a regional centralised maritime casualty database [EMSA, 2010], etc.

On the other hand, it has been presented in Chapter 5 that the standards of the information recorded in different databases vary greatly. Even within the same company, difference can be observed within the fleet due to inconsistent onboard safety culture. The subsequent situation is ragged records in terms of format and content in the data set. Moreover, due to a lack of well-designed casualty reporting system, important information is generally recorded in the descriptive text. This in turn affects negatively the usefulness of historical data. Hence, great effort is spent at the initial stage for interpreting each case and identifying the corresponding states of the parameters recorded. This practice proves to be an extremely tedious and time-consuming task.

With respect to this, a practical solution would be the introduction of a standardised accident/reporting scheme with formatted fields to be recorded at a level of each individual ship. This could be achieved in a similar way to the casualty investigation code introduced by the IMO recently [IMO, 2008a], although the latter focuses mainly on the accidents causing serious consequences. By doing so, it is believed that this will not only benefit ship designers but also ship operators. The potential merits are:

- The amount of descriptive text can be greatly reduced and the quality and credibility of the fields in each record can be assured.
- Reduction of uncertainties for any further process, e.g. risk assessment at design stage, etc.
- Improved understanding of the sequential activities of an accident/incident.
- Facilitation of the identification of the root-causes.
- Fueling safety awareness and safety culture in the maritime community.

Fortunately, as far as this research is concerned significant assistance has been received from ship operators to transform the descriptive data into standardised and formatted records. In this way, the quality of the data source can be assured. Nevertheless, "empty cells" are still a common phenomenon that needs to be addressed properly. Hence, a scientific handling of the missing data has been proposed in this thesis so that an appropriate approximation can be achieved.

Data Mining

Similar to other data analysis applications, it is always a challenge to derive mathematical models given a limited size of data. This is particularly true for data mining as generally much more variables are included in a trained model. Classical statistical analysis allows very small number of variables that can be contained in a model (e.g. ≤ 5), in contrast, data mining can cover much larger number of variables in this case (e.g. 10 - 20). The size of the training data plays an important role on the quality of the developed BN model. In this respect, it has been discussed in Chapter 6 that although the dispute is still ongoing for the relationship between the number of variables and the size of data set needed in order to arrive at objective conclusions.

One of the most important components of constraint-based learning is the dependency and conditional independency analysis. During the course of the identification of these relationships, apart from mathematical model training, an important factor that has significant influence is the confidence level, e.g. 90%, 95%, 97.5%, and 99%. The selection of an appropriate confidence level is determined by the quality and quantity of the training data. Generally, with a larger number of records and better quality of the data, the confidence level can be increased accordingly. For this research, as it is apparent that the size of the data is at a relatively low level when considering the number of variables in the BN model and their states. Consequently, the confidence interval was set at a relatively low level (i.e. 90%) in order to avoid the removal of those links where the evidence of dependency is not very strong.

On the other hand, although the score-based learning algorithm adopts distinct principles, the quality and quantity of the data is still critical to the learning process. By considering the joint probability distribution of all the variables included, the goodness-of-fit of the model in describing the data can be obtained. As it has been noted in chapter 6 that various scoring criteria have been proposed, hence the selection of an appropriate criterion is an important task. Nevertheless, the underlying principle is to achieve a balance between the goodness-of-fit and the complexity of the network. If a faster learning process is needed, it will penalise the accuracy of the developed model to describe the data. For this research, the main emphasis is placed on the goodness-of-fit. Hence, the computation time increases significantly. For instance, the GES learning performed for the case study in Chapter 8 required approx 25 minutes to implement. Nevertheless, this is still at an acceptable level for similar study to be carried out in the context of risk assessment.

Regarding the parameter learning for network quantification, it has been noted that the prior beliefs assigned can be important. According to the Bayes' Theorem, as illustrated in equation (9.1), the prior probability $P(\theta)$ generally needs to be assigned with proper assumptions. For this thesis, equal prior beliefs are considered for each state of all the augmented nodes in the network. This is a reasonable approximation as little information is known beforehand apart from the evidence from the data. However, the magnitude of the equal prior beliefs can be also significant. With the evidence from the data contributing towards $P(data|\theta)$, if the magnitude is too big, it will overshadow the effect from the data. An initial attempt was made to assign one unit to all states of the augmented nodes and it turned out that such an approximation is too gross due to the small dataset and the subsequent smaller influence from $P(data|\theta)$. Consequently, the equal sample space is divided by 10,000. This practice leads to much better results.

$$P(\theta|data) \propto P(\theta)P(data|\theta) \tag{9.1}$$

Decision Support

Decision support for ship design has been regarded as a complex field that needs to be carefully catered. Considering the complexity of an entity like a ship, a systematic, transparent, and well-informed approach is needed. It has to be appreciated that in cases that if detailed data of the other performance measures is also available in the same way as the developed next generation accident/incident database, pertinent technical performance, cost, and earning parameters can then be included concurrently in a single BN model. This will facilitate an even faster and realistic design balancing process. Nevertheless, such concept is difficult to be realised given the state-of-the-art resources available.

The decision support framework adopted in this thesis is based on the Analytic Hierarchy Process, which was originally designed to assist a transparent decision-making process using qualitative information. In the knowledge that the decision support technique is still evolving in the context of risk-based design, the tailored decision-support framework developed in [Konovessis, et al., 2007] is a simplified technique in facilitating the necessary design trade-off. Furthermore, the main objective with respect to decision support in the thesis is to demonstrate the applicability of deploying the BN models for supplying safety performance information to assist the decision making process. Hence, it is believed Chapter 7 offers a sound basis for further development.

As it has been noted in the decision support section of the case study in Chapter 8, the information on the effective and reliability of fire detection and suppression systems is difficult to obtain. This is attributable to the current regulatory system where a suppression system is regarded to be acceptable as long as it complies with a list of clauses. But having satisfied these requirements, their performance is still missing. Hence, assumptions have to be made in the thesis regarding the performance of various fire mitigative systems. Such information at practical application stage can be sought through individual system suppliers or dedicated performance-based evaluation tools/models.

9.4 Recommendation for Future Research

The work presented in this thesis represents a formalised approach for the implementation of risk-based ship design. The methodologies, tools, and techniques as well as application on demonstrators are still evolving. With respect to these, the following are some recommendations for further research and development:

- Further complement the all-embracing next generation maritime accident/incident database, in a manner that the information can be readily deployed for design and operation for safety.

- Development of proper methodologies/techniques for root-cause analysis of the casualty information so that equal effort can be put on both preventive and mitigative measures for the sake of RCOs identification.

- Further investigate the latest trend in the Bayesian learning field so as to keep fueling the maritime industry with pertinent knowledge to further elevate the quality of risk assessment.

- Development of elemental models for assessing the safety performance of individual casualty preventive and mitigative systems.

- Development of an integrated environment that data storing, data mining, and the visualization can be performed in a stand-alone environment.

- Extensive application of the methodology proposed to gain confidence on the application of data mining, and experience on the implication of the developed approaches.

Chapter 10
Conclusion

The main conclusions drawn from the research presented in this thesis can be summarised as follows:

- A methodological framework for risk-based ship design implementation has been highlighted, in which risk assessment can be performed flexibility with minimized subjective intervention. In contrast to the traditional approaches, this approach presented in this thesis has much reduced involvement of subjective estimation and be able to make fast prediction when safety assessments of risk control options are needed.

- The structure for next generation maritime accident/incident database is presented for facilitating the knowledge transfer from the operational phase to the design phase. Moreover, as it is complemented with the data generated from first-principles tools, the new database system can be regarded as an all-embracing database supplying the necessary support for risk assessment.

- Data mining has proven to be a field that can be explored. The emphasis should be put on the probabilistic model development from the data as this resonates well with the need for a fast and objective implementation of risk assessment within the context of risk-based design. In this thesis, through systematic employment of pertinent learning methods and algorithms, the risk models can be constructed objectively.

- BNs as one of the promising risk analysis techniques are flexibly integrated within the design process by supplying safety relevant information in a fast and reliable manner.

- The coupling between the decision support framework and the BN models is established. In this research, the Analytic Hierarchy Process has been introduced and it was shown that appropriate couplings can be achieved for a transparent and well-informed decision making process.

- Both casualty database and data mining have been developed in the automated environment for facilitating data management and the subsequent elicitation of risk models.

- An initial application demonstrates the adequacy of the proposed methodological framework. Research work in this area is still at an introductory phase, more extensive applications should be conducted before experience and confidence can be gained.

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Appendix 1

Risk-Based Ship Design

A1.1 Risk-Based Ship Design

The approach of risk-based ship design is an evolutionary design paradigm, in which safety is treated as an objective rather than a constraint through rule compliance. The main driver comes from the continuously elevated society expectation with respect to the value of human life and environmental protection. The ever increased market demand for larger, faster, more complex and specialised ships implicitly contributes to the demand for higher safety. The whole initiative is fuelled by the phenomenal progress that has been made in scientific and technological fields, e.g. advance marine vehicles (Wing in Ground), advanced simulation and animation software, advanced material, and modern shipboard arrangements and layouts, as illustrated in Figure A1.1.

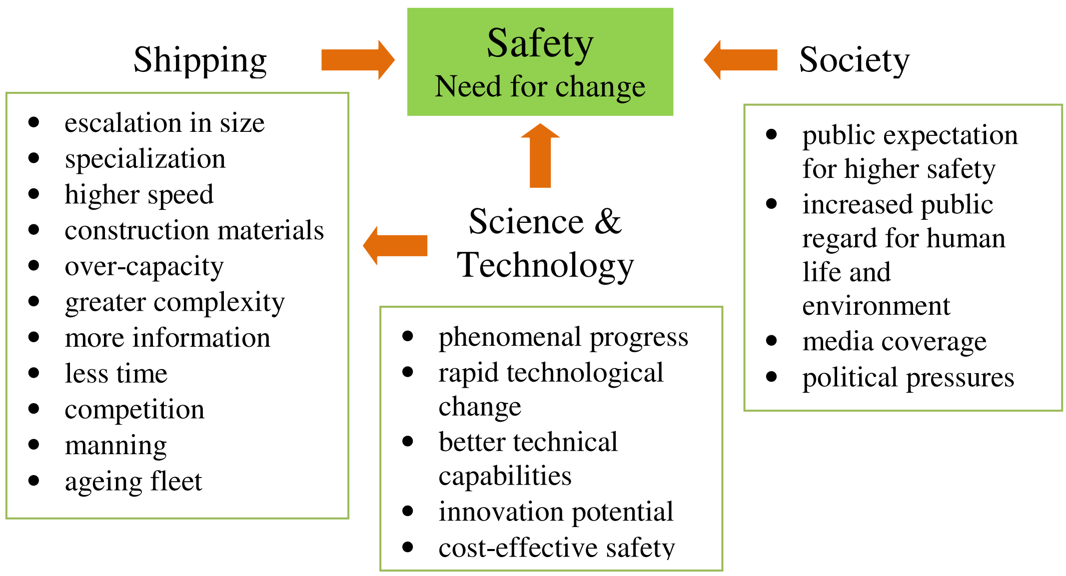


Figure A1.1: Safety Drivers [Vassalos, 2008a]

To realise the concept of design for safety, it is necessary to have a formalised methodology that is capable of embracing innovation through routine utilisation of first-principles tools, thus leading to cost-effective ways of dealing with safety. This is popularly referred to as Risk-Based Design methodology. As risk is the typical indicator of safety that can be measured, it allows, in turn, a trade-off process to balance safety performance with other design objectives. The immediate benefit is an enlarged design space offering the opportunity that a safe design, which cannot be approved under the existing regulatory framework, can be taken forward as long as, at least, an equivalent risk level is achieved and presented. Moreover, a design can be optimised either to improve safety performance with equivalent cost or to enhance earning potential without compromising safety.

The theoretical development of risk-based design and its materialisation of pertinent methods, techniques, and tools have gone through a long way [Vassalos, 1999], [Konovessis, 2001], [Oestvik, 2001], [Jasionowski, 2002], [Mermiris, 2010], [Vassalos, 2008b], etc. The establishment of a collaboration network under the theme "Design for Safety" on a European-wide basis in the late nineties marked the staging of risk-based design, although this term was not brought forward at that time. The strategic objective through the Thematic Network, SAFER-EURORO [Vassalos and Konovessis, 2008], was the development of a formalised design methodology for safer ships [Vassalos, 1997].

Through more than 25 years of research, learning, and settling, an in-depth understanding has been gained with higher resolution. The firsthand experience in the field is fuelling the conceptualisation and formalisation of the whole approach. In this process, it becomes clear that an explicit, rational and cost-effective treatment of safety will be achieved only if some fundamental principles can be adhered to [Vassalos, 2006].

1. A consistent measure of safety must be employed and a formalised procedure of its quantification should be adopted. With risk being the "currency" of safety, various risk quantification methods, within the context of risk assessment and risk management, can be used. Thus, a high level framework for risk-based design can be considered as the integration between conventional ship designs procedures with typical risk assessment process.

2. Such procedure must be integrated in the design process to allow for trade-offs between safety and other design factors by utilising the overlaps between performance, life-cycle cost considerations, functionality and safety. Ultimately,

the information obtained on safety performance through the risk assessment will be the basis of design optimisation, decision making, and innovation.

3. Considering the level of computation that might be needed, the use of parametric and knowledge-intensive models to facilitate trade-offs and access to fast and accurate first-principles tools are essential. An integrated design environment will also be required for the process to be conducted efficiently.

The key to a successful implementation of risk-based design is to strive for a balance between the integration of safety assessment with conventional design process to achieve the overall design goals and, at the same time, meeting safety-related goals and objectives through iterations.

The formal risk assessment techniques range from qualitative, semi-quantitative, and quantitative approaches as detailed in [HSE, 2001], [ABS, 2000], [Bedford and Cooke, 2001], [Mullai, 2006], etc. Selection of the appropriate technique depends on several factors: lifecycle stage, major hazard potential, and risk decision context:

- *Design stage*: the highly complex activity normally takes months or even years, thus the flexibility to change and the knowledge of design details vary along this period. Due to limited information is available at conceptual design stage coarser methods may be employed. As the design is progressively refined, risk assessment can be further detailed with updated knowledge.

- *Major hazard potential*: the potential consequence of hazards (in terms of total loss or multiple fatalities) is another important criterion for selection. The greater the potential, the less it favours conventional rule-based approach, which implicitly entails principal hazards to be the main scope of risk-based design.

- *Risk decision context*: as higher elements of novelty, uncertainty or stakeholder concern demand more thorough risk assessment, the bias of risk-based design towards high-innovation and high-value vessels.

In the context of risk-based design methodology, each component of the risk assessment process is briefly explained as follows, [DNV Technica, 1996].

Definition of Safety Goals

In parallel to the definitions of other design goals, safety goals are linked with ship's mission and purpose. Explicit safety goals are already part and parcel of the design input. Examples of design goals in relation to safety aspect include [Vassalos, 2008b]:

Generic top-level goals

- No accidents leading to total ship loss
- No loss of human life due to shipboard accidents
- Low impact to the environment

Specific Technical Goals:

- Vessel to remain upright and afloat under all feasible operational loading and environmental conditions
- Sufficient residual structural strength in damaged conditions
- Sufficient power supply to offer safety return to port in damaged conditions [IMO, 2006a]

Hazard Identification

Events and conditions that may result in the failure or loss of a ship, passenger or crew injuries and fatalities, and environmental damage should be identified through hazard identification. This is a qualitative exercise based mainly on expert judgement, it requires significant experience and, at the same time, creativity in order to determine hazards not only experienced in the past but also previously not considered. Moreover, a structured approach should be adopted in order to obtain a comprehensive coverage of relevant hazards. There are numerous techniques available to assist hazard identification, while the popular ones are listed as follows: hazard checklists, hazard and operability study (HAZOP), failure modes, effects and criticality analysis (FMECA), structured what-if checklist (SWIFT), etc. [HSE, 2001] [BSI, 2002].

Identification of Critical Design Scenarios

Considering what constitutes ship safety, it is governed only by a handful of factors (undesirable events) which, when considered individually or in combination, define a limited set of design scenarios, as illustrated in Figure A1.2. These factors represent major accident categories with calculable frequencies and consequences, which inherently control the life-cycle risk of a ship at sea.

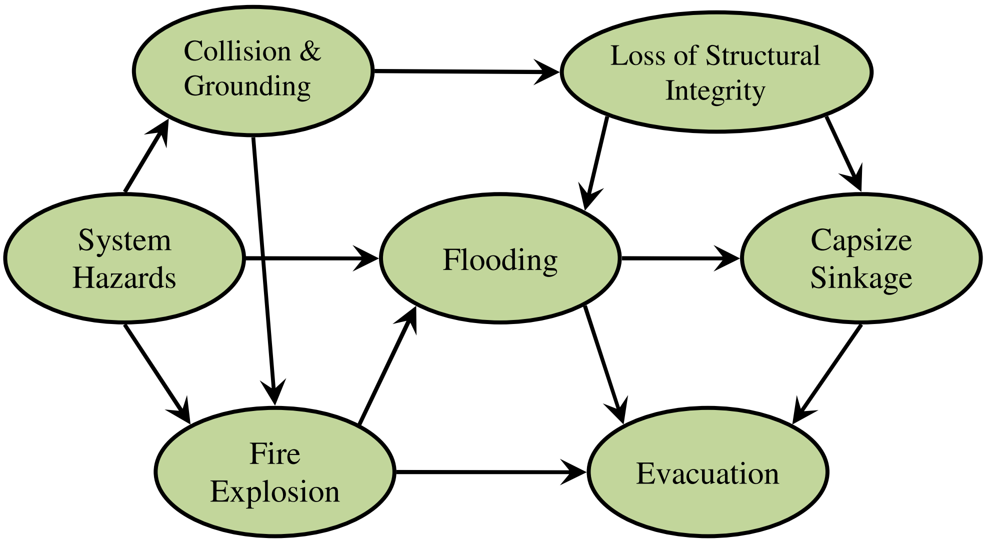


Figure A1.2: Typical Structural Links of Design Scenarios [Vassalos, 2004a]

Definition of (Safety-Related) Functional Requirements

Having identified the principal hazards and relevant design scenarios, specific functional requirements and evaluation parameters need to be formulated. Safety performance evaluation parameters should cover both preventive and mitigative aspects. For instance, in the cases of ship collision and grounding, the effectiveness of navigational equipment and proper design of bridge layouts represent preventive parameters, while structural integrity, time to flood, time to capsize, etc. denote mitigative evaluation parameters. These can be considered as an additional set of safety performance requirements. By having a consolidated list of safety-related functional requirements, alongside conventional design requirements, a base line design can be produced and disciplines requiring further evaluation will be identified (e.g. fire modelling and evacuation simulation).

Risk Analysis

The main tasks for risk analysis are root-cause and frequency analysis, consequence prediction, risk summation and presentation. These entail specific methods and techniques to be used for risk modelling. Classical techniques (most typically, fault and event trees) adopt a top-down tree structure for root-cause and frequency analysis and a bottom-up tree structure for consequence analysis. A combination of these two trees will form a conceptual risk model in a combination tree, as illustrated in Figure A1.3.

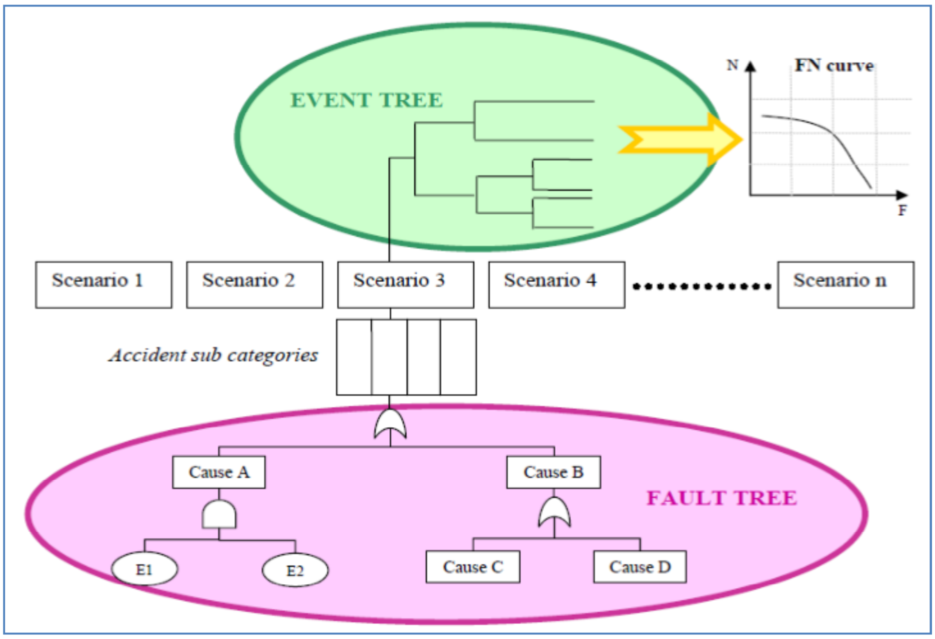


Figure A1.3: Conceptual Risk Model [IMO, 2007b]

The sources for the quantification of generic fault and event trees are expert judgement, historical data and first-principles tool (e.g. computers simulation and model test). Judgement evaluation estimates the frequencies mainly through the judgement of experienced personnel. Due to its subjectivity it should be employed for simple assessment, for frequent events, and for events where no better approach is available. Historical data is generally regarded as a straightforward and reasonable source, however, the scale, the size and characteristics of the sample space should be justified as they have significant influence on the quality of the derived frequencies. First-principles tools represent a reliable source of information. Nevertheless, the theoretical models of computer-based simulation tools have to be properly developed and validated.

Design Decision Making

In relation to design decision making, it is necessary to produce explicit safety performance and risk acceptance criteria, similar to other ship performance criteria (weight, energy efficiency, strength, etc.) and economic targets (cost effectiveness). As risk acceptance criteria is related to safety, the examination of safety performance could be integrated into the design process. By doing so, the quantified ship performance concerning technical aspects, cost and earning potential, safety performance and risk can be weighted alongside other factors (preferences, company policies, etc.) as shown in Figure A1.4. This will enable a well-informed framework for design decision making and lead to design concepts that are technically sound, fit for purpose, and more likely to meet modern safety expectation.

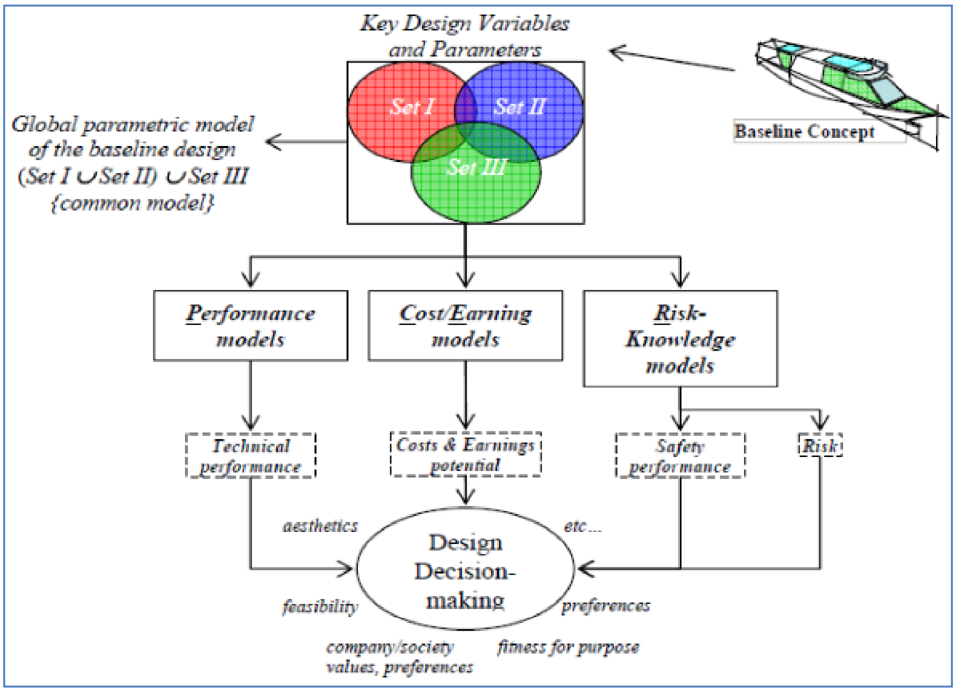


Figure A1.4: Decision-Making in Risk-Based Design [Vassalos, 2008b]

A1.2 Contemporary Developments

Apart from the methodological development for designing safer ships, the influence of the risk-based approach can be also observed in the contemporary regulatory developments concerning passenger ship safety. That is the adoption of a new "philosophy" and a working approach for developing safety standards for passenger ships, as illustrated in Figure A1.5, which is referred to as "safe return to port" [IMO, 2006a], [GL, 2009] and pertains to "zero tolerance" to loss of life. By doing so, modern safety expectations are expressed as a set of specific goals and objectives covering design, operation, and emergency situations.

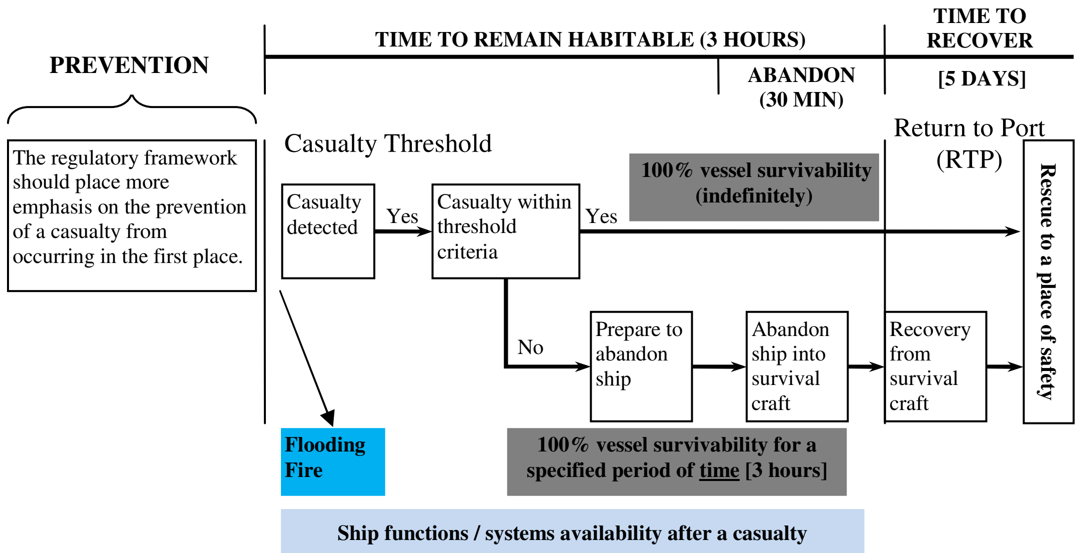


Figure A1.5: IMO Framework – Passenger Ship Safety [Vassalos, 2009]

The new approach entails explicit elements (accident timeline development, threshold definition, and system availability, etc.), for which the identified scope of work, as listed below, resonates well with the needs to concretise risk-based ship design.

- Flooding survivability analysis
- Fire safety analysis
- Post-accident (flooding or fire) system availability analysis
- Evacuation and rescue analysis

In the framework presented in Figure A1.6, the term "total risk" of a ship has been put forward in [Vassalos, 2008b]. The aim is to quantify the overall through-life safety level of a ship so that a tangible safety measure in risk lexicon can be readily employed for direct use in risk-based design.

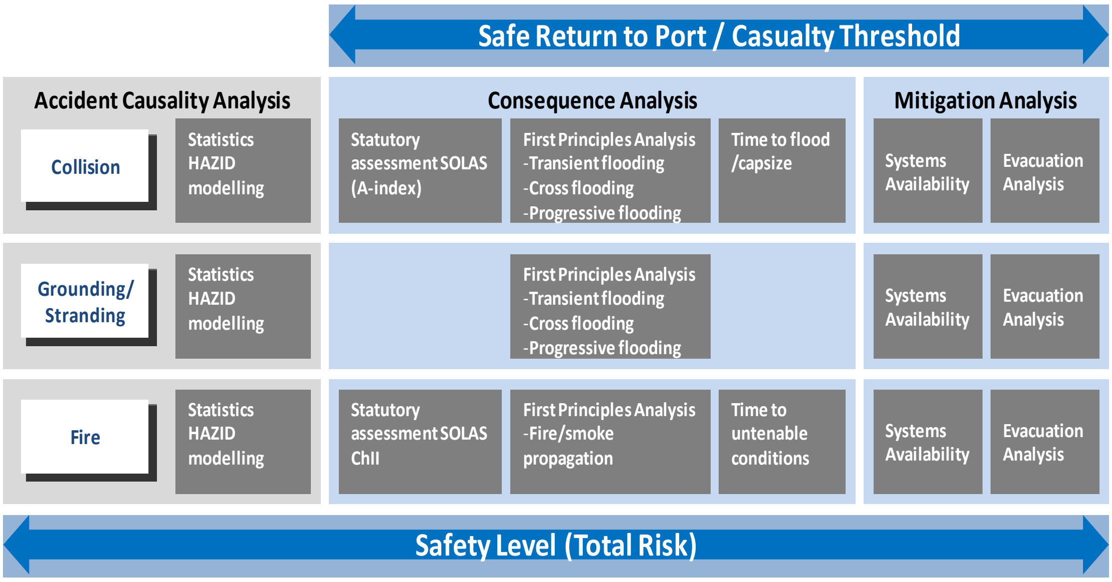


Figure A1.6: Risk-Based Design Implementation [Vassalos, 2008b]

A common way of presenting graphically the risk (in terms of fatalities) is by using the F-N diagram. While this has proven to serve reasonably well and received wide recognition, some form of aggregate information deriving from the diagram is needed for the purpose of consistent decision making. An attempt in this direction was proposed in [Jasionowski and Vassalos, 2006], in which the aggregate expected number of fatalities, $E(N)$, is used. This is often referred to as the potential loss of life, PLL, and it is expressed as follows:

$$Risk_{PLL} \equiv E(N) \equiv \sum_{i=1}^{N_{max}} F_N(i)$$

The F-N curve is given as:

$$F_N(N) = \sum_{i=N}^{N_{max}} fr_N(i)$$

where, $fr_N(N)$ represents the frequency of having exactly N fatalities per ship-year. It is obtained as follows:

$$fr_N(N) = \sum_{j=1}^{n_{hz}} fr_{hz}(hz_j) \cdot pr_N(N|hz_j)$$

where, n_{hz} is the number of loss scenarios considered, and hz denotes the principal hazard for a ship. Implementation of the foregoing framework calls for identification of the dominant hazards that endanger passenger ships so as to ensure the selected corresponding scenarios are representative in terms of operational profile and significance.

An investigation of relevant fields suggests that with passenger ships (Figure A1.7), flooding- and fire-related scenarios comprise over 90% of the risk (regarding loss of life) and almost 100% of all the events leading to decisions to abandon the ship as it is reported in [Vanem and Skjong, 2004a, Vanem and Skjong, 2004b]. Stemming from this, it becomes apparent that by addressing collision, grounding, and fire, in a consistent manner, the total risk of a passenger ship can be estimated to a large extent.

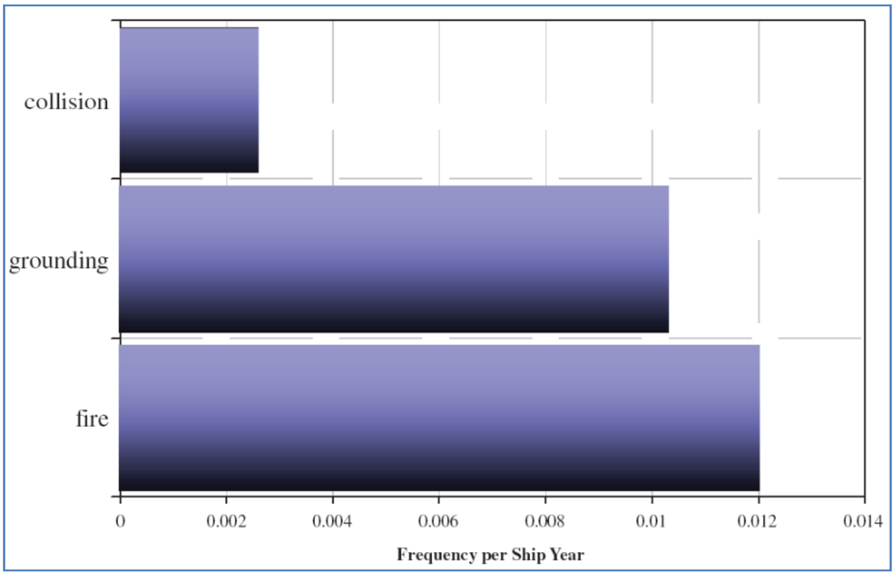


Figure A1.7: Principal Hazards of Cruise Ships – Frequency of Event Occurring [Vassalos, 2008b]

Appendix 2

General Applications of Data Mining

Apart from classical statistical analysis techniques where charts and tables are the main means of presenting the findings/patterns, there are other techniques associated with data mining:

- Association and correlation: aim to uncover rules for quantifying the relationship between two or more attributes. The logic is "*if antecedent, then consequent*", associated with a measure of support and confidence. An example of such a rule is,

$$increase(X, \text{Ship Length}) \rightarrow increase(X, \text{collision probability})$$
$$[support = 50\%, confidence = 80\%]$$

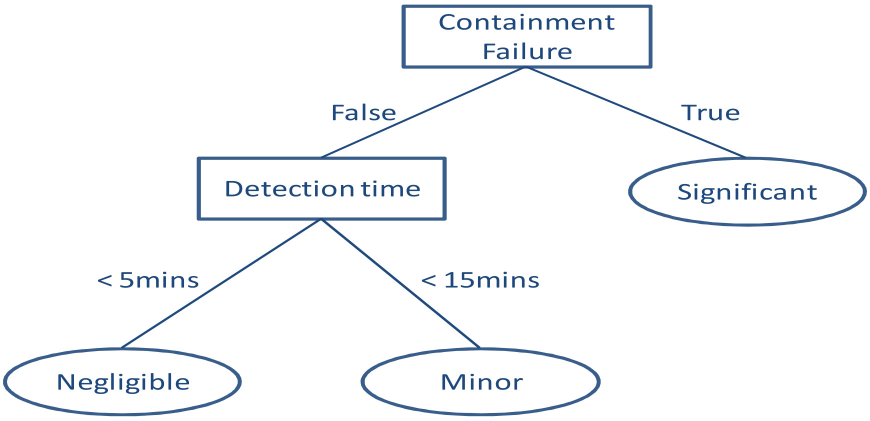
  X indicates the variables; 50% support means 50% of the data under analysis has the information on ship length and the probability of a collision; while, 80% confidence indicates 80% of the supported data indicates increasing ship length leads to the increment in the probability of a collision.

- Classification and prediction: it examines a large set of records containing both target categorical variable and a set of predictor variables. The algorithm will identify which combinations of variables are associated with the target variable. From this, the algorithm could be used to assign classifications to a new record based on the classification in the training set. An example of the assignment of severity if fire occurs onboard is demonstrated in three different forms: a) IF-THEN rules; b) a decision tree; c) influence network.

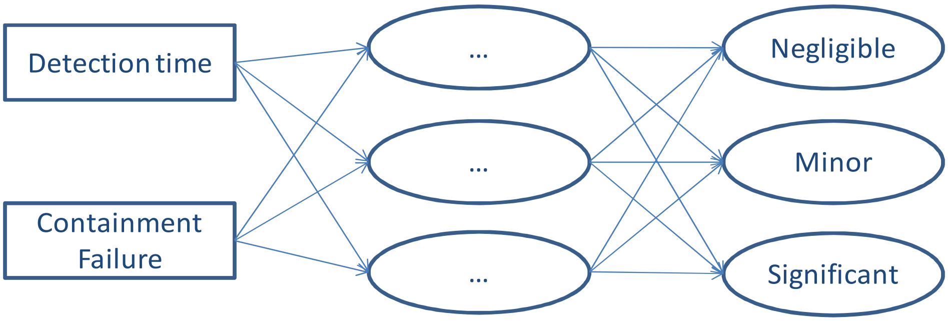
  (a) IF-THEN rules

  $containment\_failure(False)\_AND\_detection\_time(< 5mins) \rightarrow severity(Negligible)$
  $containment\_failure(False)\_AND\_detection\_time(< 15mins) \rightarrow severity(Minor)$
  $containment\_failure(True) \rightarrow severity(Significant)$

(b) Decision tree



(c) Influence network



- Clustering: it refers to the grouping of records, observations, or cases into classes of similar objects, as illustrated in Figure A2.1. The clustering differs from the classification in that there is no target variable for clustering. The clustering task seeks to segment the entire data set into relatively homogeneous subgroups or clusters, where the similarity of the records within the cluster is maximised.

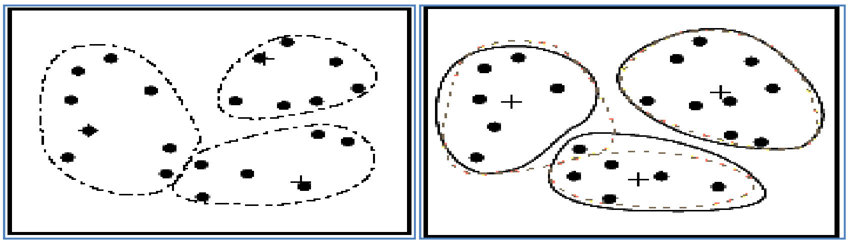


Figure A2.1: An Example of Clustering Algorithm [Han and Kamber, 2006]

Appendix 3

Technical Support for Database Development

A database is a collection of records that are organised for a particular purpose. The relational database is one of the most commonly adopted configurations to store the data. The system manages all data in tables and a typical relational database normally consists of a finite collection of tables. Each table stores information about a single subject and has fields that record the constituent information for given subject [Roman, 2002]. The advantage of a relational database system is that the tables are linked by "relations", often one-to-many relationship, as illustrated in Figure A3.1, so that they can connect to bring up a whole new subset of the data without having to store redundant information. In this way, data duplication can be avoided and integrity can be achieved [Bisset, 2005].

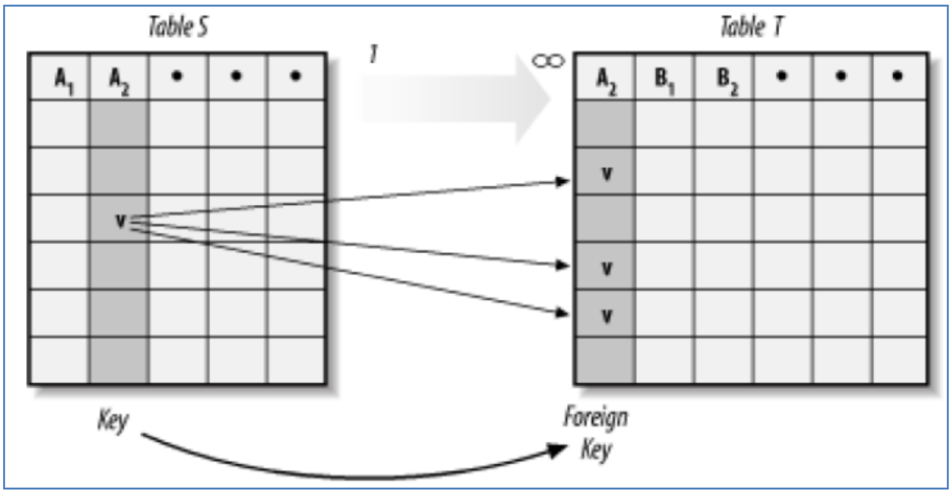


Figure A3.1: A One-to-Many Relationship between Table S and T [Roman, 2002]

In light of the aforementioned relational database, the data collected from various sources concerning every facet of the principal hazards should be grouped into entities (tables) as demonstrated in Figure A3.2. The data about ship particulars, general casualty information, voyage conditions, human factors, consequences, details about the phases of fire, collisions, and groundings, are divided into different tables and are linked with one-to-many relations through the defined key variables, e.g. "*Event_ID*", etc. By doing so, setting up of the next generation database can be technically achieved.

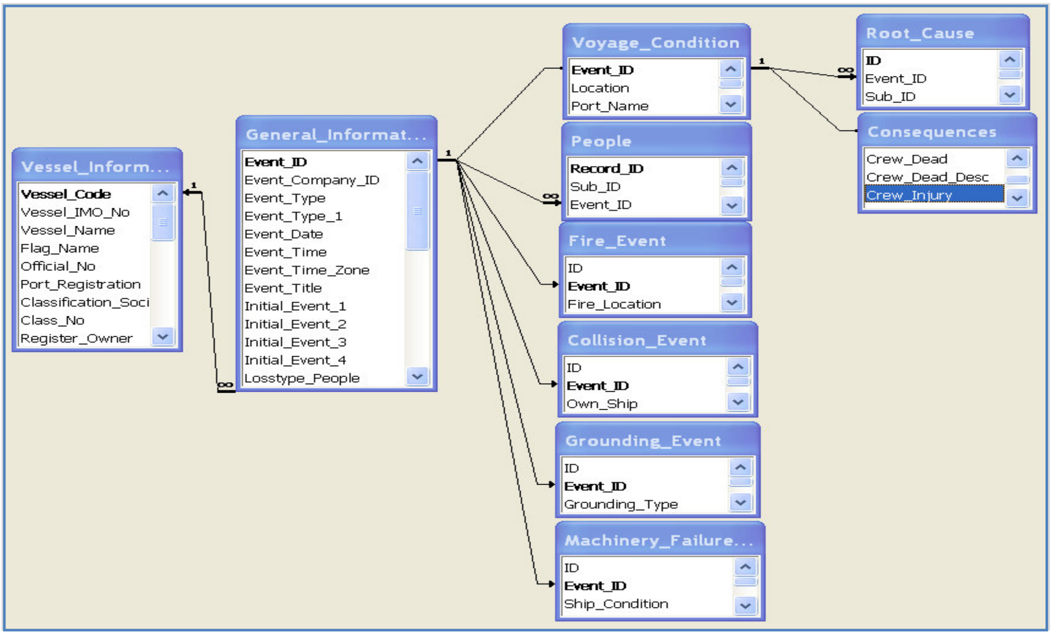


Figure A3.2: Demonstration of Marine Relational Database Structure

As one of the main goals is to retrieve the data from a database and take it further for deriving risk models for risk assessment and ultimately assisting decision making, it is crucial to identify a promising technical platform that allows flexible data retrieval, mathematical computation, and graphical presentation of the outcome. As a result, the distributed application architecture has been identified, which consists of a client interface, an intermediate business layer, and a data access layer, as shown in Figure A3.3.

As suggested by its name, the data access/storage module is in charge of data accessing and passing queried data to the adjacent layer. It is also equipped with commands to update the database with incoming information. The business logic layer deals with the workflows allowing further mathematical computation of the received data. Moreover, it is designed to pass user input and calculation output to the corresponding neighbours. Lastly, the presentation layer is responsible for graphical user interface (GUI), which, similarly, is shielded from the rest by the business logic layer. The key advantage of adopting such architecture is that the components are loosely coupled, so that possible amendments of one module have minimum impact to its neighbours, if not eliminated. Also, security, performance, and scalability are other benefits of well-designed distributed application architecture.

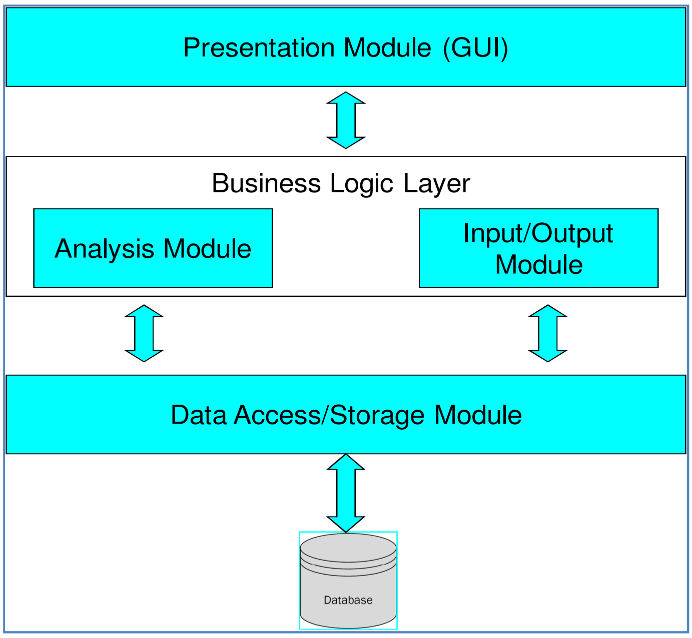


Figure A3.3: A Typical Distributed Application Architecture [Willis, 2006]

Due to the sensitivity of the information contained in marine accident/incident database, it is important to anonymously process the data. In this respect, administrative functions have been introduced so that only authorised users could access a designated portion of the database. For administrator account, it is capable of accessing any designed functions within the system including the governance of administration function; while other accounts are only allowed to access the system with restrictions, e.g. administration profile definition, etc. The examples of authentication user form and the definition of authorisation profile are illustrated in Figure A3.4 and A3.5, respectively.

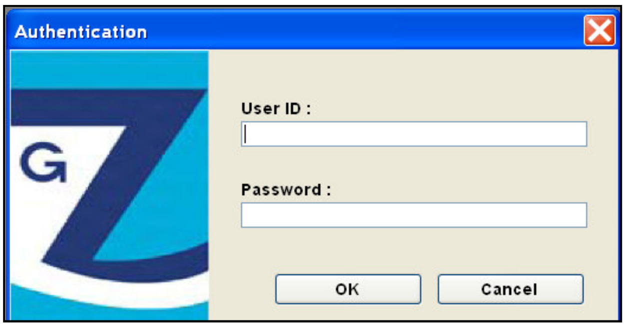


Figure A3.4: Authentication Form

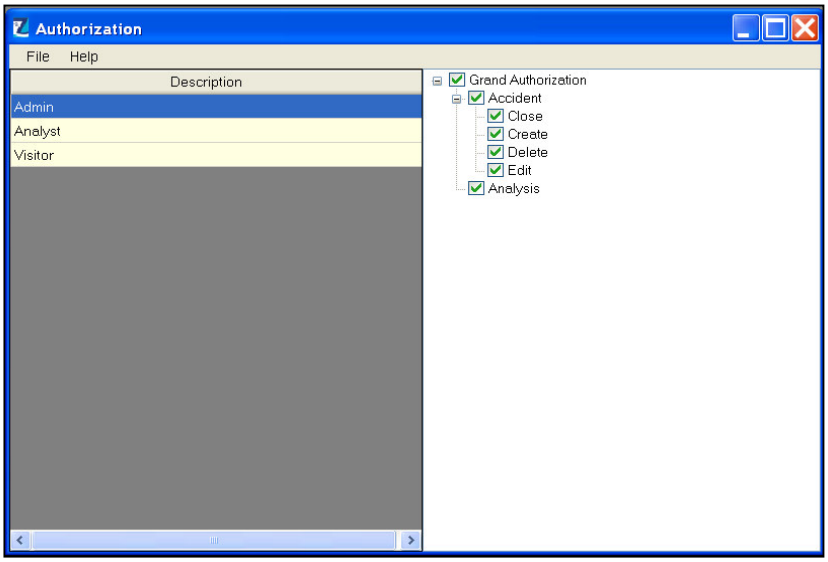


Figure A3.5: Authorisation Profile Definition

Appendix 4

Explanatory Document of Marine Accident/Incident Database

As it has been introduced in Chapter 5, the developed marine accident/incident database platform comprises ten modules: general information, vessel information, voyage condition, fire event, collision, grounding, hull/machinery/equipment, consequences, analysis, and people. Explanatory supplement to the variables recorded in each module is provided next.

A4.1 General Information

This module contains general information of an event in an abstract manner.

Event ID: is the key to access each case in the relational database and link various tables.

Company ID: the unique code assigned for each case by ship operators.

Event type: has three options: {accident, incident, and others}. The classification of accident and incident is judged on the basis of the following definitions [HSE, 2001].

- Accidents are sudden unintended departures from normal operating conditions in which some degree of harm is caused.
- Incidents are relatively minor accidents, i.e. unintended departures from normal operating conditions in which little or no harm was caused.

Event date: records the date of which the event occurs.

Event time: records the time of which the event occurs.

Time zone: records the time zone of which the event occurs.

Title: a short summary of the event.

Sub-event: records the type of the event. {fire/explosion, collision, contact, flooding/foundering, machinery breakdown, etc.}

Severity: classifies the consequence. {negligible, minor, moderate, serious, major}

A4.2 Vessel Information

This module contains information of ship particulars and key design characteristics.

Vessel code: a unique code assigned to each ship for classification purpose.

IMO number: is made up of three letters "IMO" followed by the unique seven digits number assigned for identification purpose.

Vessel name: the name of the vessel.

Flag name: the code of the country whose flag the vessel sails.

Official number: ship official number.

Port registration: the name of the port where the ship registered.

Classification society: the corresponding classification society.

Registered owner: the registered owner.

Managing company: the managing company.

Vessel Types: the type of vessels, such as cruise liner, Ro-Ro passenger ship, etc.

Builder: the name of the yard that built the ship.

Delivery date: ship delivery date.

Conversion date: the date of which the ship underwent major conversions.

Length Overall: ship overall length.

Length between PP: the length between perpendiculars.

Breadth: ship breadth.

Depth: moulded depth.

Draught: designed draught.

Design Speed: designed service speed.

Gross Tonnage: gross tonnage.

Design Deadweight: designed deadweight.

Number of Crew: the number of crews designed to accommodate.

Number of Passengers: the number of passengers designed to accommodate.

Maximum Number persons: the maximum number of persons to accommodate.

Prime Mover: records the type of prime movers installed. {diesel electric system, gas turbine, two stroke diesel engine, etc.}

Manoeuvring system: records the type of manoeuvring systems installed. {dynamic positioning system, steering gear system, tunnel thrusters system, etc.}

Propulsion system: records the type of propulsion systems installed. {fixed pitch propulsion system, controllable pitch propulsion system, etc.}

Hull material: records the material of the hull. {steel, wood, GRP, composite materials, etc.}

Hull construction: records the configuration of the hull form. {double bottom, double ended, double sided, etc.}

Number of workstation: records the number of workstations installed for traffic surveillance, navigation, and manoeuvring. There are three options:

- No workstation: IMO compliant, but without consistent attention to ergonomics
- One workstation: workstation for one operator in line with "workstation for traffic surveillance, navigation and manoeuvring".
- Two workstations: as above, but with one additional workstation in line with "Workstation for navigation support".

ECDIS presented: indicates the installation status of electronic chart display and information system (ECDIS).

Alarm management: determines the type of alarm management system installed onboard. There are three options:

- None.
- BAS: Bridge alarm system. Centralized alarm system including all bridge alarms.
- NAS: Navigation alarm system. Centralized alarm system including all navigation alarms.

Window layout: a window layout that minimizes blind sectors is above standard. Small windows with large frames are below standard. There are three options: {low, medium, and high}

A4.3 Voyage Information

Scenario-specific variables are included in this module which records mainly environmental conditions and ship surrounding conditions.

Vessel location: specifies the location of the vessel. {In port, at sea}

Port Name: the port name where the event occurs.

Country Name: the country name where the event occurs.

Latitude: the latitude where the event occurs.

Longitude: the longitude where the event occurs.

Place: the name of the water where the event occurs.

Departure date: the departure date.

Departure time: the departure time.

Time zone: the time zone where the vessel departs.

From: the location where the vessel departs.

To: the destination of the journey.

Operational status: indicates the operational status when the event occurs. {anchorage, archipelagos, at berth, canal, coastal waters (within 12 miles), inland waters, open sea course and speed, port, port approach, river, under tow}

Voyage phase: records the phase of the voyage. {pre-departure, unmooring, departure/pilotage, transit, pre-arrival, arrival/pilotage, loading, discharging, etc.}

Underway course: the underway course when the event occurs.

Underway speed: the underway speed when the event occurs.

Loaded draft (fwd & aft): the forward and aft loaded drafts.

Visibility level: the visibility level when the event occurs. {good, fair, poor}

Nautical miles: the nautical miles can be seen.

Outdoor light: the outdoor light condition. {daylight, twilight, night}

Sea state: the sea state condition when the event occurs. It includes:

- None : Sea like a mirror, calm
- 0 - 0.3 : Smooth sea : Ripples, no foam
- 0.3 - 1.7 : Slight sea : Small wavelets
- 1.7 - 4 : Moderate sea : Large wavelets, crests begin to break
- 4 - 8 : Rough sea : Moderate waves, many crests break, whitecaps
- 8 - 13 : Very rough sea : waves heap up, forming foam streaks
- 13 - 20 : High sea : sea begins to roll, forming very definite foams streaks and considerable spray
- 20 - 30 : Very high sea : Very big, steep waves with wind-driven overhanging crests, sea surface
- 30 - 45 : Mountainous seas : Very high rolling breaking waves, sea surface foam-covered
- 45 and Greater : Mountainous seas : Air filled with foam, sea surface with white spray

Wind speed: the wind speed. It includes:

- <1 knot : Calm
- 1 - 3 knots : Light air
- 4 - 6 knots : Light breeze
- 7 - 10 knots : Gentle breeze
- 11 - 16 knots : Moderate breeze
- 17 - 21 knots : Fresh breeze
- 22 - 27 knots : Strong breeze
- 28 - 33 knots : Near gale
- 34 - 40 knots : Gale
- 41 - 47 knots : Strong gale
- 48 - 55 knots : Storm
- 56 - 63 knots : Violent storm
- >64 knots : Hurricane

Wind direction: the wind direction in either true or magnetic form.

Bottom depth under keel: the depth between the keel and the sea floor.

Water temperature: records seawater temperature.

A4.4 Fire Event Information

It contains detailed information of various phases of a fire event including the performance of different preventive and mitigative measures.

Location: records detailed spaces where fire ignition occurs with its corresponding SOLAS space category.

Cabin (crew / officer)	6	Gift shop	7	Sauna / spa / jacuzzi	9
Cabin (passenger)	6	Guest Disco	8	Solarium	9

Cabin Balcony	5	Guest gym	8	Stage / backstage	8
Café	8	Ice rink	7	Stairs (interior)	2
Casino	8	Incinerator room	12	Swimming pool (area)	9
Centrum	8	Laundry room	13	Tender	4
Children / teen areas	7	Library	7	Theatre	8
Corridor	3	Lounge / bar (public)	8	Cabin Bath	6
Crew areas (other)	8	Luggage area	13	Conference Centre	8
Crew bar	7	Mess (crew / officer)	8	Gangway	4
Crew gym	6	Muster Station / life boats	4	Golf Course	5
Deck area (exterior)	5	Other		Medical Facility	14
Dining room	8	Pantry	13	Office Areas	6
Electrical room	10	Provision area	13	Specialty Restaurant	8
Elevator	2	Public Area (others)	8	Sports Deck	5
Engine / machinery space	12	Restroom (public)	9		
Galley	12	Promenade Deck	5		
Generator room	12	Salon	8		

Source of ignition: the source of ignition. It includes:

1	Cigarettes, matches, or similar smoking materials	10	Hot surface (machinery)
2	Open flames other than 1 and 8	11	Hot surface (galley)
3	Static generation	12	Overheat (Electrical)
4	Electrical other than static charges	13	Not on vessel concerned
5	Spontaneous combustion	14	Auto-ignition (store)
6	Collision	15	Pyrotechnics

7	Mechanical fault or breakdown	16	Other
8	Burning/welding/cutting	17	Not reported
9	Hot exhaust pipe or steam line		

Ignition mass: the mass of the combustible.

Space area: the area of the space of origin.

Exposed area: the exposed floor area.

Space height: the height of the space.

Detected: the means by which the fire is initially detected.

- Detection system installed and utilized.
- Detection system installed, but fire detected by personnel.
- No fire detection system installed, but fire detected by personnel.
- Not reported.

Suppression means: the fire suppression means.

- Fire resisting division
- Fire main and hydrant
- Inert gas system
- Fixed CO2 system
- Halogenated hydrocarbon system
- Foam system
- Other fixed extinguishing system (e.g. automatic sprinkler or steam smothering)
- Other protection (portable and semi-portable extinguishers)
- Not reported

Smoke detector presented: the smoke detector is installed in the space of origin. {True, False}

Smoke detector activated: the smoke detector activates in the space of origin. {True, False}

Smoke detector detected zone: indicates the zone of which the smoke detector activates. {zone A, zone B, zone C}

An illustration of the definition of various zones is illustrated is Figure A4.1.

- Zone A denotes the space of fire origin.
- Zone B denotes the adjacent spaces at the same level within the main vertical zone (MVZ).
- Zone C denotes the spaces that above the space of origin within the MVZ.

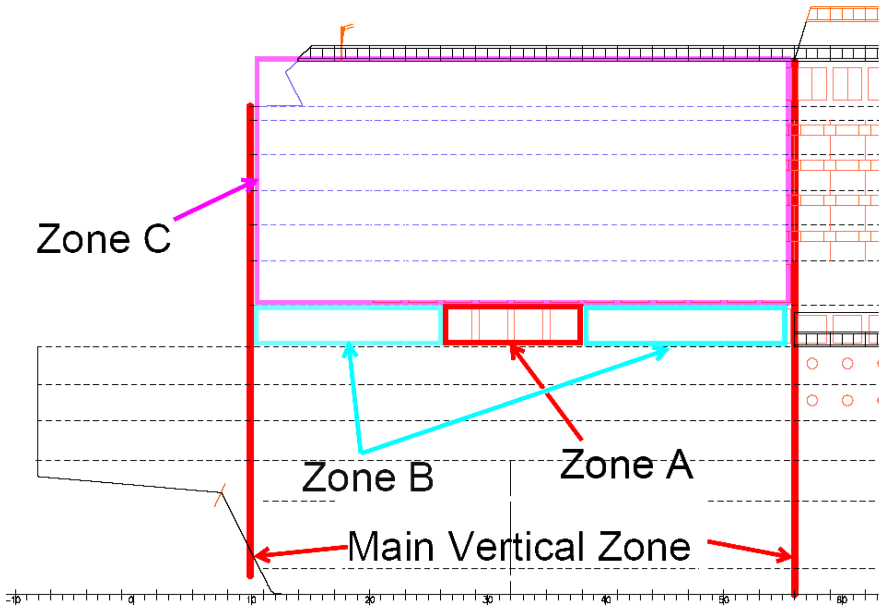


Figure A4.1 – The Definitions of Fire Zones

Heat detector presented: indicates whether the heat detector is installed in the space of origin. {True, False}

Head detector activated: indicates whether the heat detector activates in the space of origin. {True, False}

Fixed suppression system installed: records whether the fixed suppression system is installed in the space of origin. {True, False}

Fixed suppression system activated: records whether the fixed suppression system activates in the space of origin. {True, False}

Fixed suppression system contributed: indicates whether the fixed suppression system contributes to the fire fighting. {True, False}

Time to control: the time taken to control the fire from first alarm.

Time to extinguish: the time taken to extinguish the fire from the first alarm.

Crew presented: indicates whether crew members present in the space of origin. {True, False}

Boundary cooling possible: records whether boundary cooling is needed to prevent further escalation. {True, False}

Fire spread: records whether the fire spreads to adjacent spaces. {True, False}

No. of adjacent spaces fire spread: the number of adjacent spaces that catch fire. {0<integer number < 6}

Spaces uses: the usage of adjacent spaces that catch fire.

Number of people (zone A): the number of people present in zone A.

Time taken to start evacuation (zone A): the time taken to initiate evacuation from first alarm in zone A.

The Doorway width (zone A): the width of the doorway.

Number of people (zone B): the number of people present in zone B.

Time taken to start evacuation (zone B): the time taken to initiate evacuation from first alarm in zone B.

Number of people (zone C): the number of people present in zone C.

Time taken to start evacuation (zone C): the time taken to initiate evacuation from first alarm in zone C.

A4.5 Collision and Contact Event Information

It contains detailed information of various phases of a collision/contact event by following the typical sequence s.

Type: identifies whether it is a powered or drifted collision.

Complexity: indicates navigational complexity of the area. Some area regions are naturally keen to present more difficulties and hazards for navigation. {high, medium, and low}

Traffic intensity: records traffic intensity. Area with high traffic intensity (e.g. straits, channels, etc.) is exposed to higher chance of collisions.

Initial distance: the initial distance on collision course.

Speed: the speed of the own vessel.

Own ship: indicates whether the ship is a striking or struck ship.

Collision scenario: the scenario of the collision. {collision with a meeting vessel, collision with a crossing vessel, collision with an overtaking vessel}

Angle between: the collision angle.

Contact scenario: the contact scenario. {iceberg, offshore structure, bridge, harbour structure}

Ship lane type: the type of ship in lane.

Ship lane size: the size of ship in lane. {high, medium, and low}

Ship lane speed: the speed of ship in lane.

First detection: the means that the collision course was first detected. {visual detection, navigation detection, both visual and navigational detection}

Time detect: the time taken for first detection since the ship is on collision course.

Officer on watch: the actions taken by the officer on watch. {able to correct, unable to correct, not present}

Officer number 2: the reactions taken by officer number two. {able to correct, unable to correct, not present}

Pilot: the reactions taken by the pilot. {able to correct, unable to correct, not present}

Radar system: the status of the radar system. {not installed, installed but not function, function but not detected, function and detected}

ECDIS: the status of the electronic chart display and information system (ECDIS). {not installed, not function, function but does not provide extra time for detection, function and provide extra time for detection}

AIS system: the status of the automatic identification system (AIS). {not installed, not function, function but does not provide extra time for detection, function and provide extra time for detection}

BNWAS: the status of the bridge navigational watch alarm system (BNWAS). {not installed, installed but not activate, installed and activate, not applicable}

VTS system: the status of the vessel traffic services (VTS). {not present, present but not vigilant, present and vigilant}

Collision alarm: the status of the collision alarm system. {not installed, installed but not activate, installed and activate, not applicable}

Time plan: the time taken for planning avoidance actions.

Communication between: indicates whether there is any communication between the collided ships.

Clarity giveway: the clarity of the give way situation. {clear, unclear}

Giveway situation: the situation that give-way actions should be taken. {meeting and supposed to give way, crossing and supposed to give way, crossing but not supposed to give way, overtaking and supposed to give way, being overtaken but not supposed to give way}

Time manoeuvring: the time taken to execute the planned manoeuvre.

Giveway occur: the actual give way action taken. {own ship changes course, other ship changes course, neither ship changes course, both ships change course}

Steer failure: indicates whether the steering system fails. {True, False}

Tug employed: indicates whether tugs are employed in the drifted case. {True, False}

Start: the latitude and longitude that the ship starts drifting.

End: the latitude and longitude that the ship stops drifting.

A4.6 Grounding Event Information

It contains detailed information of various phases of a grounding event by following the typical sequences.

Grounding type: indicates the types of grounding. {powered grounding into sand, powered grounding into rock, drift grounding into sand, drift grounding into rock}

Grounding with: the object that the vessel collides with. {electronically marked underwater obstacle, unmarked underwater obstacle, large and visible obstacle, small and visible obstacle}

Area complexity: identical with the definition in collision module.

Traffic intensity: identical with the definition in collision module.

Update routine: indicates the status of updated routines for charts. {good, standard, poor}

Passage planning: the quality of the passage planning. {good, standard, and poor}

Initial distance: identical with the definition in collision module.

Speed: identical with the definition in collision module.

Officer on watch: identical with the definition in collision module.

Officer number 2: identical with the definition in collision module.

Pilot: identical with the definition in collision module.

Chart visibility: indicates the goodness that the ground is displayed in the map. {large, small, and not visible}

Light marked: indicates whether the ground type is marked by light for visual detection at night. {True, False}

First detected: identical with the definition in collision module.

Time detection: identical with the definition in collision module.

Radar system: identical with the definition in collision module.

Echo sounding alarm: indicates the status of the dedicated grounding detection system. {not installed, installed but not activated, installed and activated, not applicable}

AIS system: identical with the definition in collision module.

ECDIS: identical with the definition in collision module.

VTS system: identical with the definition in collision module.

BNWAS: identical with the definition in collision module.

Time plan: identical with the definition in collision module.

Time manoeuvre: identical with the definition in collision module.

Steer failure: identical with the definition in collision module.

Drift velocity: identical with the definition in collision module.

Tug employed: identical with the definition in collision module.

Start: identical with the definition in collision module.

End: identical with the definition in collision module.

A4.7 Hull/Machinery/Equipment Failure Information

This module covers the failure of critical systems including propulsion, steering, electrical, and navigational systems.

Ship condition: indicates the condition of the ship. {above expected, as expected, below expected}

Maintenance condition: the maintenance condition of the ship. {below requirement, fulfil requirement, above requirement}

Failure situation: the situation in which the ship fails. {heavy traffic, severe environment, channel, others}

Possible to repair: indicates whether it is possible to repair at the scene. {True, False}

Repair time: the time taken to repair.

Failure type: the types of failure on board. {structural failure, function system failure}

Propulsion subsystem: records whether it is the failure of propulsion subsystems. {auxiliary boiler, auxiliary engine, main boilers, gearings & clutches, main engine control system, main engine cooling system, main engine, main engine fuel system, main engine lube oil system, propeller (fixed / controllable pitch), shaft & bearings}

Propulsion problem: detailed description of the problems of propulsion subsystem.

Main engine component: indicates which component fails in the case of main engine failure. {cylinder and piston, piston rods and crossheads, connecting rods, crankshaft and bearings, bedplates and frames, camshaft and valve gear, cylinder-head mountings, turbochargers, main governor (speed regulator)}

Steering system type: the configuration of the steering system. {electrical steering gear, electro-hydraulic steering gear two ram type, electro-hydraulic steering gear four ram type, electro-hydraulic steering gear rotary vane type}

Steering failure part: indicates which part of the steering system fails. {control part, power unit part, transmission part, rudder}

Steering failure type: the failure of the steering subsystem. {steering system, rudder, others}

Steering problem: detailed descriptions of the problem of steering systems.

Electrical system type: the failure of the electrical system. {distribution, emergency systems, generators, lifts & escalators, motors & starters, switchboard, others}

Electrical problem: detailed descriptions of the problem of electrical systems.

Navigational system failure: the failure of the bridge navigational system. {bridge control equipment, communication/alarm, navigational instruments}

Navigational problem: detailed description of the problem of navigational systems.

Structural failure type: the failure of structural integrity.

- Hull structure, bow - forward of the collision/ forward most bulkhead
- Inner bottom/tank top
- Bulkhead(s) longitudinal, inboard of b/5
- Bulkhead(s), transverse
- Floor(s), wt/ot
- Deck, other
- Deck, vehicle
- Deck, weather deck
- Door side access opening
- Door, bow – inner
- Door, bow - visor, clam
- Door, stern

- Door(s), weathertight/ watertight
- Hatch(es)/coamings, access
- Hatch(es)/coamings, cargo handling
- HSC - supplementary notes
- Hull structure, bottom mid-length - between the bow and stern structure
- Hull structure, complete cross section
- Hull structure, side mid-length - between the bow and stern structure
- Hull structure, stern - aft of the aft peak/aftmost bulkhead
- Inner skin of double hull side structure
- Tanks, cargo, lose
- Tanks, non-cargo
- Window(s)

Structural problem: detailed description of the causes of structural failures.

A4.8 Consequences

It is designed to record the damages to the ship itself, passengers and crews onboard, and the environment.

Vessel status: indicates the final status of the vessel. {flooding, listing, capsize, foundering, not applicable}

Time to sink: records the time it takes to sink the vessel.

Flooding type: the type of flooding. {flooding – downflooding, flooding – other flooding, foundering – massive flooding, foundering – progressive flooding}

Causes: detailed description of the root-causes.

Drill status: the status of evacuation drill. {below requirement, fulfil requirement, above requirement}

Muster status: the status of mustering when the event occurs. {below requirement, fulfil requirement, above requirement}

Evacuation: the status of evacuation. {not initiated, successful, not successful, not possible, not applicable}

Evacuation means: evaluates the standard and location of life-saving equipments. {above requirements, fulfil requirements}

People location: indicates the location of people after the event occurs. {in the water, on lifeboat, on liferaft, onboard, not applicable}

Awareness time: the time it takes for people to react to the situation. It begins upon initial notification (e.g. alarm) of an emergency and ends when the passengers have accepted the situation and started to move towards and assembly station.

Travel time: the time it takes for all people on board to move from where they are upon notification to the assembly stations and then to the embarkation stations.

Embarkation/launching time: the sum of which defines the time required to provide for abandonment.

Loss to vessel: indicates whether there is any damage to the vessel. {True, False}

Loss to labour: indicates whether there is any loss to the crews. {True, False}

Loss to production: indicates whether there is any loss to the production. {True, False}

Loss to hull/equipment: indicates whether there is any loss to the hull, machineries, and equipments. {True, False}

Loss to legal: indicates whether there is any loss to legal aspects. {True, False}

Loss to people: indicates whether there is any loss to the passengers on board. {True, False}

Environment: indicates whether there is any loss to the environment. {True, False}

A4.9 Event Causes

This module contains detailed descriptions of the event and methods for root-causes analysis, as illustrated in Chapter 5.

Event description: the full description of the event.

Principal findings: identifies principle findings from the root-causes analysis of the event.

A4.10 Human Factor

It is designed to investigate the contributory factors to human errors.

Number of crew on board: the number of crews on board when the event occurs.

Number of passengers on board: the number of passengers on board when the event occurs.

Pilot: indicates whether the pilot is onboard. {True, False}

Role: the role of the interested person. {crew, engineer of the watch, investigation team, officer of the watch, passenger, person in charge, pilot, witness only, Others}

Status: the status of the person. {missing, injury, uninjured, dead}

Job title: the job title of the person. {chief engineer, chief mate, deck rating, engineering rating, first engineer, food service, hotel, inspector, master, other engineering officer, other navigating officer, vendor, other}

License/Certificate: the license/certificate that the person holds. {1st Engineer, 2nd Engineer, 2nd Mate/officer, 3rd Engineer, 3rd Mate/officer, 4th Engineer, 4th Mate/officer, Chief Engineer, Chief Mate/officer, Master, Ordinary Seaman, QMED, Unlicensed}

Crew Member: indicates whether the person is a crew. If so, specify whether he is on duty or off duty.

Date of birth: the date of birth.

Nationality: the nationality.

Working experience: records the years of working experience in the field.

Work related: indicates whether it is a work-related injury/fatality. {True, False}

Health condition: records the health condition.

Equipment involved: indicates whether any equipment is involved. {True, False}

Shipboard: indicates whether the injury/fatality occurs on board. {True, False}

Hours worked: records the duration of working until the event occurs.

Duration off: records the duration of the rest he has before the shift.

Statement: the statement made by the person.

Appendix 5

Estimation of Logistic Regression Models

Similar to the process of training a generic regression model, the estimation of a Logistic Regression Model starts with data collection, transformation, and the subsequent estimation of the model coefficients. Such a process will be demonstrated by using the data collected for dependency test, as it is presented in Section 6.3.2, concerning variables L, denoting vessel location, and T, denoting time of the day. The estimated model can be presented in the form of equation (A5.1).

$$logit[P(L = at\ sea)] = log\frac{P(L = at\ sea)}{1 - P(L = at\ sea)} = \alpha + \beta T \tag{A5.1}$$

Given the collected 576 records, it is noted that the statuses of the interested variables are presented in categorical formats (i.e. non-metric). Hence, it is essential to transform them into numerical values to facilitate the model training process and the ultimate employment. As both L and T have only binary statuses (e.g. $At\ sea$ or $In\ port$), the common practice is to transform them into 0 and 1 to represent different situations.

Concerning the assignment of numerical values (i.e. 0, 1) for representation, the decision on which status is to be represented by 0 or 1 will affect the numerical values of the estimated model coefficients. However, it is important to understand that such variations will not affect the subsequent decision making on identifying dependent relationships, and also the prediction outcomes. For instance, with "$Night$" and "$Daytime$" denoted by 0 and 1, respectively for T, and "$At\ sea$" and "$In\ port$" denoted by 0 and 1, respectively for L, the model can be fitted by employing the maximum likelihood technique. The coefficients are summarised in Table A5.1.

Table A5.1: Summary of the Estimated Coefficients of the Logistic Regression Model Containing L and T

Parameter	**Degree of freedom**	**Estimate**	**Standard error (SE)**	**Chi-square**	**P(null hypothesis being correct)**
Intercept (α)	1	-1.2484	0.1975	39.96	<0.0001
β for Time ($T_1 = Daytime$)	1	0.5588	0.2225	6.31	0.012

Similarly, if the denotations for "$At\ sea$" and "$In\ port$" are changed to 1 and 0, respectively for L, while the ones for variable T remain unchanged, the updated estimation is tabulated in Table A5.2. As it can noted, the changes of denotation have direct impact on the estimated coefficients, nevertheless, the subsequent significance tests are still able to reach identical conclusions as far as dependency test is concerned.

Table A5.2: Summary of the Updated Estimated Coefficients of the Logistic Regression Model Containing L and T

Parameter	**Degree of freedom**	**Estimate**	**Standard error (SE)**	**Chi-square**	**P(null hypothesis being correct)**
Intercept (α)	1	1.2484	0.1975	39.96	<0.0001
β for Time ($T_1 = Daytime$)	1	-0.5588	0.2225	6.31	0.012

Appendix 6

Bayesian Network Scoring Criteria

The Bayesian scoring criterion provides a computationally traceable method for estimating the relative goodness-of-fit of a specific BN model. However, during the learning process for identifying the optimal one(s) that produces the highest $P(d|G)$, it is found that the complexity of the network structure (model) influences the learning efficiency, which is a function of the computation complexity. Hence, further modification of the criterion through the Taylor expansion of $P(d|G)$ was made in order to balance the accuracy and the complexity of the structure.

The Bayesian information criterion (BIC) is one of the techniques aiming to achieve such a balance [Schwarz, 1978], as illustrated in the following equation. The first term measures how well the data fits the model, while the second term accounts for the model complexity. Similar concept has been adopted for the Akaike Information Criterion (AIC), [Akaike, 1974].

$$BIC(d,G) = ln\big(P(d|G)\big) - \frac{size(G)}{2} ln(d)$$

$$size(G) = \sum_{i=1}^{n} q_i(r_i - 1)$$

Where $Size(G)$ denotes the size of the structure

Another formalism that has been developed to examine the accuracy of a BN is known as the Minimum Description Length (MDL) [Rissanen, 1987], [Friedman and Goldszmidt, 1996], which was originated from the Minimum Message Length (MML) developed in [Wallace and Boulton, 1968]. The MDL was inspired by the information theory, which aims to minimise the length of a joint description of the model and the data. One of the measures propounded by Lam and Bacchus is illustrated in equation (6.20) [Korb and Nicholson, 2004] [Lam and Bacchus, 1994].

$$I_{LB}(h) = \sum_{i=1}^{N} \left(k_i logN + d(s_i - 1) \prod_{j \in \pi(i)} s_j \right)$$

Where N denotes the number of nodes

k_i denotes the number of parents the variable i

d denotes the word size of the computer being used in bits

s_i denotes the number of statuses of the variable i

It is important to notice that the MDL focuses on the entropy of the data set to examine the accuracy of the model rather than on the joint probability distribution. With respect to the BIC and the AIC, the term for accounting for the structure complexity is merely to reduce the computational effort, which may unnecessarily undermine the identified BN model. Hence, the pure joint probability distribution criterion - Bayesian scoring criterion, is employed as the criterion of score-based learning.

Appendix 7

Risk Acceptance Criteria

The risk acceptance criteria to be elaborated draw the latest development through the SAFEDOR, which have been submitted and agreed at the IMO [Skjong, et al., 2007]. The criteria for both *individual risk* and *societal risk* have received wide recognition within the maritime industry.

The purpose of individual risk acceptance criteria is to limit the risks to people due to shipping activities. It can be expressed as:

- A risk of death per year for a specific individual.
- A Fatal Accident Rate (FAR), which is defined as the number of fatalities per 100 million person-hours at sea.

The criteria agreed at IMO are:

Maximum tolerable risk for crew members	10^{-3}	annually
Maximum tolerable risk for passengers	10^{-4}	annually
Maximum tolerable risk for public ashore	10^{-4}	annually
Negligible risk	10^{-6}	annually

Nevertheless, as it is noticed that the tolerable risk proposed are not particularly strict, more stringent criteria have been proposed in [Norway, 2000] and agreed at IMO.

Target individual risk for crew members	10^{-4}	annually
Target individual risk for passengers	10^{-5}	annually
Target individual risk for public ashore	10^{-5}	annually

In the case of societal risk acceptance criteria is to limit the risk to groups of people due to shipping activities, e.g. whole crews, groups of passengers, or the society as a whole, etc. It can be expressed as:

- The Annual Fatality Rate (AFR), which is defined as the long-term average number of deaths per ship year.
- The F-N curve, which relates the frequency and number of fatalities in accidents.

The use of F-N curve is proposed. The criteria for passenger cruise ships and Ro-Ro ships are illustrated in Figure A7.1 and A7.2, respectively.

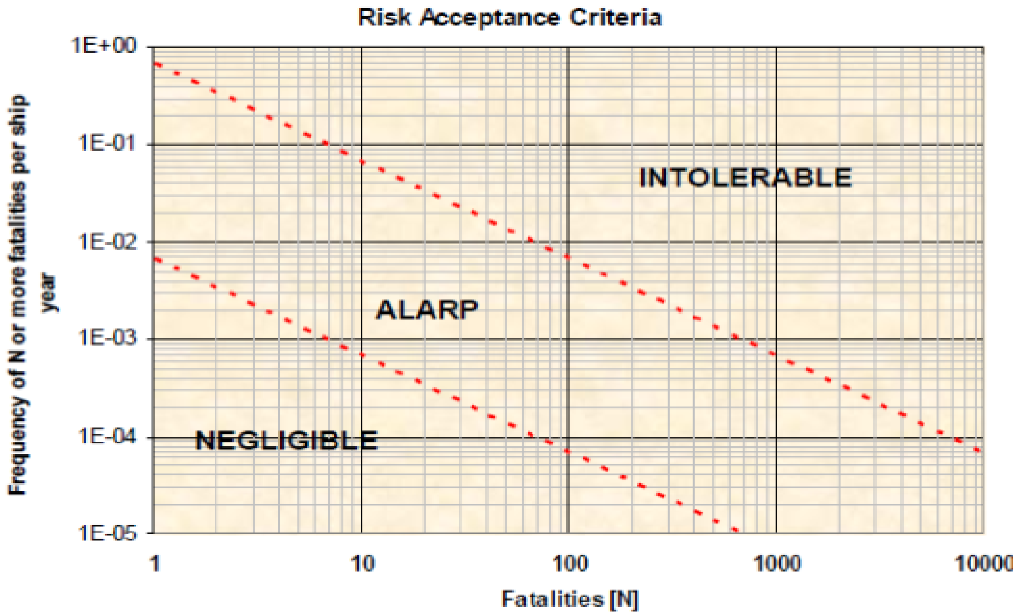


Figure A7.1: Society Criteria for Cruise Liner [IMO, 2008b]

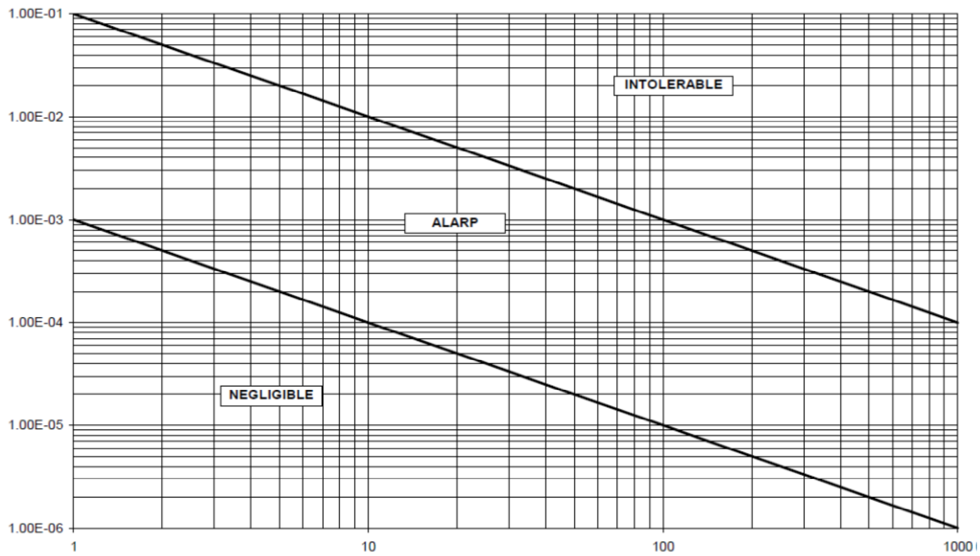


Figure A7.2: Society Criteria for Passenger Ro-Ro ships [IMO, 2008c]

The candidate designs that satisfying these risk acceptance criteria fulfil global safety objectives. It is also necessary to consider specific safety performance parameters. For instance, there is a need to demonstrate the design satisfies the required subdivision index for passenger and cargo ships, etc.

Appendix 8

Pair Wise Comparisons using the Analytic Hierarchy Process (AHP)

Dealing with multiple objectives concurrently when designing a ship in order to reach a satisfactory solution is a pervasive challenge needs to be addressed properly. The approach through the aggregate objective function (AOF) provides the most intuitive means in this direction. Nevertheless, through simple aggregation of more than a few objectives' measure in a single measure-of-merit is not appropriate in solving a complex decision problem such as selecting design solutions for a ship due to the complex relationships inherent in the situation.

An alternative method that can be readily deployed is through pair-wise comparison of available design solutions employing valid criteria. On this basis, a methodology, known as the Analytic Hierarchy Process (AHP), has been developed in [Saaty, 2008]. Fundamentally, the AHP is a general theory of measurement, which is used to derive ratio scales from both discrete and continuous paired comparisons in multi-level hierarchic structures.

The key elements for the deployment of the AHP are:

- Decomposition
- Comparative judgment
- Priority synthesis

The decomposition process aims to structure the decision in a hierarchical form. The goal of the decision is stated at the top level, whilst objectives from a broad perspective are listed in the next level, and probably, if necessary, a series of successive levels can be attached contains more specific criteria. The design alternatives are measured by the degree of how they satisfy the goals. The lowest level usually contains a set of alternatives.

Comparative judgement starts with a set of pair wise comparison matrices. The relative importance can be established among the elements on a given level with respect to the shared criterion in the level immediately above. To assist the comparison process, a scale of numbers to reveal the relative importance or dominance one element is over another has been proposed, as shown in Table A8.1, where the absolute measurement on a scale of 1 to 9 is used to score the paired comparison.

Table A8.1: The Fundamental Scale of Absolute Numbers

Intensity of Importance	*Definition*	*Explanation*
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favour one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
Reciprocals of above	If activity *i* has one of the above non-zero numbers assigned to it when compared with activity *j*, then *j* has the reciprocal value when compared with *i*	A reasonable assumption
1.1–1.9	If the activities are very close	May be difficult to assign the best value but when compared with other contrasting activities the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities.

The underlying theory for priority synthesis is to transform the obtained pair wise comparison tables into square matrices and employ the characteristic equation for matrix algebra. Hence, the problem of prioritisation of design alternatives is equivalent to estimate the eigenvalues and the eigenvectors of a matrix, as illustrated below:

$$\begin{pmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & & \frac{w_2}{w_n} \\ \vdots & & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = n \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix}$$

Where the first component represents the pair wise comparison values and second one indicates the priorities with respect to a single criterion. The solution is generally obtained by raising the matrix to a sufficiently large power, and summing over the rows, normalising to obtain the priority vector $w = (w_1 \quad \cdots \quad w_n)$. Through iteratively performing this process until the difference of the priority vectors obtained at kth power and at the $(k+1)$st power is less than some predefined small value. Nevertheless, the priority vector can be approximated by normalising the elements in each column of the comparison matrix and then averaging over each row.

The variance of the error incurred for the estimation process is expressed as $(\lambda_{max} - n)/(n-1)$, which is also known as the consistency index (C.I.). λ_{max} is the largest or principal eigenvalue and n is the order of the matrix. On this basis, it is apparent that the closer λ_{max} is to n, the more consistent is the result. It has been proposed to compare the C.I. value with the consistency index of the randomly generated matrixes of the same size, as illustrated in Table A8.2. The ratio of the C.I. above the averaged R.I. is defined as the consistency ratio (C.R.). If the value is less or equals to 0.10, it is considered to acceptable.

Table A8.2: Average Random Consistency Index (R.I.)

N	1	2	3	4	5	6	7	8
Random consistency index	0	0	0.52	0.89	1.11	1.25	1.35	1.40

On the basis of the above principles, the priorities of design alternatives can be obtained for each criterion. The normalised eigenvectors forms a matrix of local priorities, which is subject to further multiplication of the priority vector of one level up, i.e.

$$[Local\ priority\ matrix] \times [Priority\ vector] = [Result\ vector]$$

Through repetitively performing such multiplication, the final product is a vector that the priorities of various alternatives are ranked. Consequently, proper decisions can be made.

Appendix 9

Explanatory Document of Dominant Variables Identification for Fire Safety

- On board location

An important variable influencing the frequency of fire ignition is “on board location”. Hence, it is necessary to provide clear definitions of the spaces with their corresponding usages, which are tabulated in Table A9.1. It is understood that the fifty-three spaces detailed appoints high resolution to the analysis. However, considering the applicability and for the sake of consistency, the fourteen spaces scheme defined at SOLAS Chapter II-2 regulation 9 for ships carrying more than 36 passengers is adopted, which is summarised in Table A.2. The detailed definition is provided in Appendix 10.

Table A9.1: “Use” of Spaces onboard Passenger Ships and Corresponding Space Category According to SOLAS Chapter II-2 Regulation 9

Cabin (crew / officer)	6	Gift shop	7	Sauna / spa / jacuzzi	9
Cabin (passenger)	6	Guest Disco	8	Solarium	9
Cabin Balcony	5	Guest gym	8	Stage / backstage	8
Café	8	Ice rink	7	Stairs (interior)	2
Casino	8	Incinerator room	12	Swimming pool (area)	9
Centrum	8	Laundry room	13	Tender	4
Children / teen areas	7	Library	7	Theatre	8
Corridor	3	Lounge / bar (public)	8	Cabin Bath	6
Crew areas (other)	8	Luggage area	13	Conference Centre	8
Crew bar	7	Mess (crew / officer)	8	Gangway	4
Crew gym	6	Muster Station / life boats	4	Golf Course	5
Deck area (exterior)	5	Other		Medical Facility	14
Dining room	8	Pantry	13	Office Areas	6
Electrical room	10	Provision area	13	Specialty Restaurant	8
Elevator	2	Public Area	8	Sports Deck	5

		(others)			
Engine / machinery space	12	Restroom (public)	9		
Galley	12	Promenade Deck	5		
Generator room	12	Salon	8		

Table 8.2: Fourteen Spaces Defined in SOLAS Chapter II-2 Regulation 9 for Ships Carrying more than 36 Passengers [IMO, 2004]

Code	**Space defined**
1	Control station
2	Stairway
3	Corridors
4	Evacuation stations and external escape routes
5	Open deck spaces
6	Accommodation spaces for minor fire risk
7	Accommodation spaces for moderate fire risk
8	Accommodation spaces for greater fire risk
9	Sanitary and similar spaces
10	Tanks, voids and auxiliary machinery spaces having little or no fire risk
11	Auxiliary machinery spaces, cargo spaces, cargo and other oil tanks and other similar spaces of moderate fire risk
12	Machinery spaces and main galleys
13	Store-rooms, workshops, pantries, etc.
14	Other spaces in which flammable liquids are stowed

- Date of event

It provides basic information of the reporting period, which is important for the estimation of frequencies (per ship-year). The date of event is also an interesting factor for revealing trends in statistical analyses. The format of date is: *dd/mm/yyyy*.

- Time of event

Time is one of the crucial factors having complex links with various types of fire event at different spaces. For instance, experience suggests that the chance of fire occurring in both passenger and crew cabins at evening times (18:00 – 20:00) is much higher than the rest of the day. Similarly, the analysis performed in [Majumder, et al., 2007] concerning the impact of time on the consequences (in terms of fatalities) due to fire escalation shows significant dependence. The time is categorised as daytime (08:00 – 00:00) and night (00:00-08:00) for this study, however, higher resolution can be introduced if it is deemed necessary.

- Vessel location

Generally vessel location is not of great importance to fire safety as limited evidence from historical records supports this argument for cruise liners. However, lessons still can be learned from other accident types and ship types. For instance, under emergency situations, when abandonment and evacuation is needed, the difference in consequences between the fire accidents onboard *Sally Star* [MAIB, 1995] and *Al Salam Boccaccio 98* [MSUO et al., 2006], as illustrated in Figure A9.1 and A9.2, is tremendous. It is understood that such difference is under the influence of many factors; nevertheless, vessel location is still respected as an important variable affecting the effectiveness of emergency operations. The statuses are defined as: *In port* and *At sea*.

Figure A9.1: Fire onboard *Sally Star* Resulting in No Injury and No Loss of Life on 25th August 1994

Figure A9.2: Fire onboard *Al Salam Boccaccio 98* Claimed over 1,000 Lives on 2nd February 2006

- Weather contribution

Severe environmental condition has been regarded as one of the main contributing factors to marine disasters. It is included to indicate whether environmental factors, e.g. wind, sea state, visibility, etc., influence any stage of a fire accident. The statuses are: *True*, *False*.

- Detection means

As highlighted in [Guarin, et al., 2007], the probability of first-aid failure can be estimated through equation (A9.1).

$$P(A) = P(A_1) \cdot [P(A_2) + P(A_3) - P(A_2)P(A_3)] \quad \text{(A9.1)}$$

Where $P(A_1)$ denotes the probability of failure of the automatic (fixed) suppression system

$P(A_2)$ denotes the probability of failure of manual first-aid

$P(A_3)$ denotes the probability of failure of first-aid by an on-duty staff

It is noted that $P(A_1)$, $P(A_2)$, and $P(A_3)$ imply a two-stage process, that is detection and suppression by either hardware or software mitigative defenders. As far as the detection means is concerned, it includes automatic detection systems, manual detection systems by crews or guests. Hence, statuses of the detection means are tabulated in Table A9.3.

Table A9.3: Definition of the Detection Means

Detection system installed and utilized
Detection system installed, but fire detected by personnel
No fire detection system installed, but fire detected by personnel
Not reported
Other
Both automatic and manual detection system detected
Fail to detect

- Suppression means

On the basis of equation (A9.1) and the previous discussion, definitions of the suppression means are similar to the detection means. It can be performed through fixed suppression systems and manual extinguishers. This field is designed to specify the tools/equipments deployed for fire fighting, as illustrated in Table A9.4.

Table A9.4: Definition of the Suppression Means

Fire resisting divisions
Fire main and hydrants
Inert gas system
Fixed CO2 system
Halogenated hydrocarbon system
Foam Extinguisher
Other fixed extinguishing system (e.g. automatic sprinkler or steam smothering)
Other protection (portable and semi-portable extinguishers)
Other
Not reported
Powder extinguishers
CO2 Extinguisher
Self extinguished
Water Extinguisher
Water (Not Extinguisher)
Fire blanket
Fixed water mist system
Both fixed and portable means

- Ventilation system status

In the case of fire, the ventilation system is supposed to be shut down immediately and the fire dampers should be closed to prevent the circulation of smoke within the ventilation system and to reduce the amount of oxygen provided to the space of origin. Nevertheless, more often than not, such practice is unnecessary if the fire is discovered at an early stage. This field records whether the ventilation is closed: *True* and *False*.

- Fire door status

The fire door refers to an opening connecting the space on fire with an adjacent space, as illustrated in Figure A9.3, which does not have to be the fire door defined in SOLAS II-2 for a fire zone [IMO, 2004]. Such fire door is one of the primary barriers to contain the fire within the origin and to minimise smoke propagation. It is designed to indicate whether the fire door is closed: *True* and *False*.

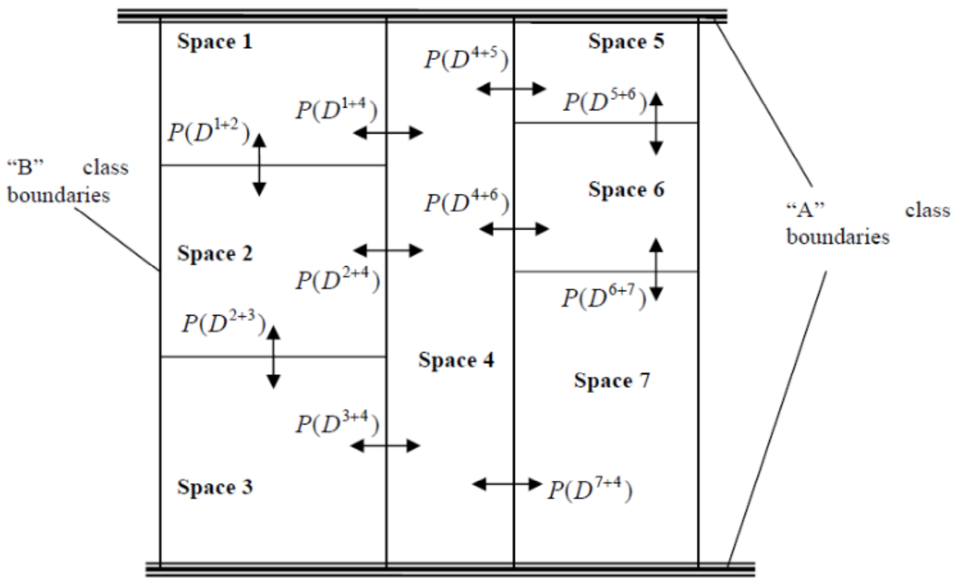


Figure A9.3: Openings Connecting Different Spaces [Majumder, et al., 2007]

- Space occupancy status

Historical experience suggests that the severity of a fire event can be significantly reduced with the presence of passengers or crews within the space on fire. This is because it has crucial impact on the detection time, the response time, and eventually the consequences. This field is marked as *True* and *False* to denote whether the space is occupied by either crews or passengers when the fire happens.

- Crew status

As implied in equation (A9.1), special attention has been paid to on-duty staff through $P(A_3)$, as crews are specifically trained to deal with various emergency situations on board including the procedures to be followed when the fire occurs. The presence of crew members should have positive impact on the probability of extinguishing a fire. In fact, historical data proves that the crew is more likely to take appropriate actions when attempting to extinguish a fire and at the same time to alert the bridge. It is designed to record whether the crew is present: *True* and *False*.

- Boundary cooling status

Boundary cooling is one of the last few operations that crews can take to contain the fire within the space of origin by lowering the temperature of the boundaries from adjacent spaces. Such practice is normally adopted when tackling a fire in machinery spaces. Still, it can be used in combination with fixed extinguishers to minimise the consequences. The options are: *Executed*, *Impossible*, and *Unnecessary*.

- Emergency response (first-aid) failure

Emergency response failure refers to the performance of both fixed automatic and manual fire suppression systems. Its status is influenced by many physical parameters, e.g. detection means, fire fighting tools, the presence of crews, etc., all of which are explicitly recorded so as to capture generic fire escalation characteristics within a known space.

The failure of emergency response is the result of the failure of three components: the failure of automatic (fixed) suppression systems, the failure of manual first-aids by either passengers or crews, and the failure of manual first-aids by on-duty staffs. It should be noted that coincidence may occur for the latter two components. It is understood that each component is a function of multiple physical variables; however, the failure of any one of the aforementioned systems is mathematically the result of the unity minus the combination of their reliabilities and the corresponding effectiveness. Hence, a key measure of judging the successfulness of emergency response is time. As presented in Figure A9.4, the failure of any of these systems would result in fire growth to flashover situations. Moreover, each space is characterised by a unique energy releasing curve, which makes the task of assigning a unified criterion of *emergency response failure* even more difficult. Thus, the following definitions for the first-aid failure are deemed to be appropriate:

(i) The fire lasts for 5 or more minutes (T_{fire}: the duration before the fire is extinguished). In this case, the definition is as follows:

First-aid failure → TRUE means $T_{fire} \geq 5$ minutes

First-aid failure → FALSE means $T_{fire} < 5$ minutes

(ii) The fire achieves a stage where other protection means in the vicinity of the space of origin start acting (e.g. insulation, boundary cooling). In this case, the definition is as follows:

First-aid failure → TRUE means insulation or boundary cooling becomes active

First-aid failure → FALSE means insulation or boundary cooling remains inactive

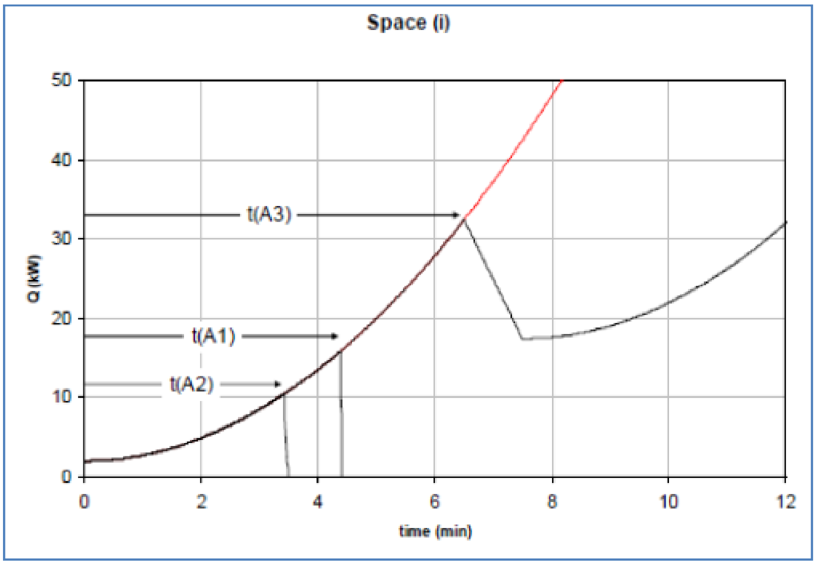


Figure A9.4: The Impact of Emergency Response on Fire Energy Timeline

- Containment failure

This is evaluated in accordance with the performance criteria implicit in SOLAS regulation 3.2, 3.4 and 3.10 for insulation class A, B and C respectively. The insulation types are depicted in Table A9.5 and A9.6. These criteria refer to the times at which the temperature at the unexposed side of the bulkhead exceeds certain limits. If the criteria are exceeded, it is assumed that loss of containment, conditional to emergency response failure, will occur. It is understood that the temperature may not be recorded in the available data, thus the following definitions are deemed to be appropriate:

(i) Boundary cooling becomes active. In this case the definition is as follows:

Insulation failure → TRUE <u>means</u> that boundary cooling is active

Insulation failure → FALSE <u>means</u> that boundary cooling remains inactive

(ii) Smoke and flame passage of "A" and "B" class divisions. In this case the definition is as follows:

Insulation failure → TRUE <u>means</u> that (a) smoke and flame passes an "A" class division sooner than 60 minutes **and / or** (b) flame passes a "B" class division sooner than 30 minutes.

Insulation failure → FALSE means that (a) smoke and flame does not pass an "A" class division sooner than 60 minutes **and / or** (b) flame does not pass a "B" class division sooner than 30 minutes.

- Ignition in adjacent space

This field aims to indicate whether the fire escalates from the space of origin if the situation reaches such a stage that the insulation fails to contain the fire within the original space. It is important as different statuses would lead to distinct scenarios and totally different consequences (in terms of fatality). The statuses are: *True* and *False*.

Table A9.5: Bulkheads Not Bounding Either Main Vertical Zones or Horizontal Zones [IMO, 2004]

Spaces		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Control stations	(1)	B-0[a]	A-0	A-0	A-0	A-0	A-60	A-60	A-60	A-0	A-0	A-60	A-60	A-60	A-60
Stairways	(2)		A-0[a]	A-0	A-0	A-0	A-0	A-15	A-15	A-0[c]	A-0	A-15	A-30	A-15	A-30
Corridors	(3)			B-15	A-60	A-0	B-15	B-15	B-15	B-15	A-0	A-15	A-30	A-0	A-30
Evacuation stations and external escape routes	(4)					A-0	A-60[b,d]	A-60[b,d]	A-60[b,d]	A-0[d]	A-0	A-60[b]	A-60[b]	A-60[b]	A-60[b]
Open deck spaces	(5)						A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0
Accommodation spaces of minor fire risk	(6)						B-0	B-0	B-0	C	A-0	A-0	A-30	A-0	A-30
Accommodation spaces of moderate fire risk	(7)							B-0	B-0	C	A-0	A-15	A-60	A-15	A-60
Accommodation spaces of greater fire risk	(8)								B-0	C	A-0	A-30	A-60	A-15	A-60
Sanitary and similar spaces	(9)									C	A-0	A-0	A-0	A-0	A-0
Tanks, voids and auxiliary machinery spaces having little or no fire risk	(10)										A-0[a]	A-0	A-0	A-0	A-0
Auxiliary machinery spaces, cargo spaces, cargo and other oil tanks and other similar spaces of moderate fire risk	(11)											A-0[a]	A-0	A-0	A-15
Machinery spaces and main galleys	(12)												A-0[a]	A-0	A-60
Store-rooms, workshops, pantries, etc.	(13)													A-0[a]	A-0
Other spaces in which flammable liquids are stowed	(14)														A-30

Table A9.6: Decks Not Forming Steps in Main Vertical Zones nor Bounding Horizontal Zones [IMO, 2004]

Space below ↓	Space above →	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Control stations	(1)	A-30	A-30	A-15	A-0	A-0	A-0	A-15	A-30	A-0	A-0	A-0	A-60	A-0	A-60
Stairways	(2)	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-30	A-0	A-30
Corridors	(3)	A-15	A-0	A-0[a]	A-60	A-0	A-0	A-15	A-15	A-0	A-0	A-0	A-30	A-0	A-30
Evacuation stations and external escape routes	(4)	A-0	A-0	A-0	A-0	-	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0
Open deck spaces	(5)	A-0	A-0	A-0	A-0	-	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0
Accommodation spaces of minor fire risk	(6)	A-60	A-15	A-0	A-60	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0
Accommodation spaces of moderate fire risk	(7)	A-60	A-15	A-15	A-60	A-0	A-0	A-15	A-15	A-0	A-0	A-0	A-0	A-0	A-0
Accommodation spaces of greater fire risk	(8)	A-60	A-15	A-15	A-60	A-0	A-15	A-15	A-30	A-0	A-0	A-0	A-0	A-0	A-0
Sanitary and similar spaces	(9)	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0
Tanks, voids and auxiliary machinery spaces having little or no fire risk	(10)	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0	A-0[a]	A-0	A-0	A-0	A-0
Auxiliary machinery spaces, cargo spaces, cargo and other oil tanks and other similar spaces of moderate fire risk	(11)	A-60	A-60	A-60	A-60	A-0	A-0	A-15	A-30	A-0	A-0	A-0[a]	A-0	A-0	A-30
Machinery spaces and main galleys	(12)	A-60	A-60	A-60	A-60	A-0	A-60	A-60	A-60	A-0	A-0	A-30	A-30[a]	A-0	A-60
Store-rooms, workshops, pantries, etc.	(13)	A-60	A-30	A-15	A-60	A-0	A-15	A-30	A-30	A-0	A-0	A-0	A-0	A-0	A-0
Other spaces in which flammable liquids are stowed	(14)	A-60	A-60	A-60	A-60	A-0	A-30	A-60	A-60	A-0	A-0	A-0	A-0	A-0	A-0

Appendix 10

Definitions of the Fourteen SOLAS Space Categories

For the sake of consistency, the fourteen spaces scheme defined at the SOLAS Chapter II-2 regulation 9 concerning "*fire integrity of bulkheads and decks in ships carrying more than 36 passengers*" is adopted in this thesis for the development of pertinent fire risk models. Detailed definitions are provided next [IMO, 2004].

1. *Control stations*

   Spaces containing emergency sources of power and lighting.
   Wheelhouse and chartroom.
   Spaces containing the ship's radio equipment.
   Fire control stations.
   Control room for propulsion machinery when located outside the propulsion machinery space.
   Spaces containing centralized fire alarm equipment.
   Spaces containing centralized emergency public address system stations and equipment.

2. *Stairways*

   Interior stairways, lifts, totally enclosed emergency escape trunks, and escalators (other than those wholly contained within the machinery spaces) for passengers and crew and enclosures thereto.
   In this connection, a stairway which is enclosed at only one level shall be regarded as part of the space from which it is not separated by a fire door.

3. *Corridors*

   Passenger and crew corridors and lobbies.

4. *Evacuation stations and external escape routes*

   Survival craft stowage area.
   Open deck spaces and enclosed promenades forming lifeboat and liferaft embarkation and lowering stations.

Assembly stations, internal and external.

External stairs and open decks used for escape routes.

The ship's side to the waterline in the lightest seagoing condition, superstructure and deckhouse sides situated below and adjacent to the liferaft and evacuation slide embarkation areas.

5. *Open deck spaces*

Open deck spaces and enclosed promenades clear of lifeboat and liferaft embarkation and lowering stations. To be considered in this category, enclosed promenades shall have no significant fire risk, meaning that furnishings shall be restricted to deck furniture. In addition, such spaces shall be naturally ventilated by permanent openings.

Air spaces (the space outside superstructures and deckhouses).

6. *Accommodation spaces of minor fire risk*

Cabins containing furniture and furnishings of restricted fire risk.

Offices and dispensaries containing furniture and furnishings of restricted fire risk.

Public spaces containing furniture and furnishings of restricted fire risk and having a deck area of less than 50 m^2.

7. *Accommodation spaces of moderate fire risk*

Spaces as in category (6) above but containing furniture and furnishings of other than restricted fire risk.

Public spaces containing furniture and furnishings of restricted fire risk and having a deck area of 50 m^2 or more.

Isolated lockers and small store-rooms in accommodation spaces having areas less than 4 m^2 (in which flammable liquids are not stowed).

Sale shops. Motion picture projection and film stowage rooms. Diet kitchens (containing no open flame).

Cleaning gear lockers (in which flammable liquids are not stowed).

Laboratories (in which flammable liquids are not stowed).

Pharmacies.

Small drying rooms (having a deck area of 4 m^2 or less).

Specie rooms.

Operating rooms.

8. *Accommodation spaces of greater fire risk*

Public spaces containing furniture and furnishings of other than restricted fire risk and having a deck area of 50 m^2 or more.

Barber shops and beauty parlours.

Saunas.

9. *Sanitary and similar spaces*

Communal sanitary facilities, showers, baths, water closets, etc.

Small laundry rooms.

Indoor swimming pool area.

Isolated pantries containing no cooking appliances in accommodation spaces.

Private sanitary facilities shall be considered a portion of the space in which they are located.

10. *Tanks, voids and auxiliary machinery spaces having little or no fire risk*

Water tanks forming part of the ship's structure.

Voids and cofferdams.

Auxiliary machinery spaces which do not contain machinery having a pressure lubrication system and where storage of combustibles is prohibited, such as:

> ventilation and air-conditioning rooms; windlass room; steering gear room; stabilizer equipment room; electrical propulsion motor room; rooms containing section switchboards and purely electrical equipment other than oil-filled electrical transformers (above 10 kVA); shaft alleys and pipe tunnels; and spaces for pumps and refrigeration machinery (not handling or using flammable liquids).

Closed trunks serving the spaces listed above.

Other closed trunks such as pipe and cable trunks.

11. *Auxiliary machinery spaces, cargo spaces, cargo and other oil tanks and other similar spaces of moderate fire risk*

Cargo oil tanks.
Cargo holds, trunkways and hatchways.
Refrigerated chambers.
Oil fuel tanks (where installed in a separate space with no machinery).
Shaft alleys and pipe tunnels allowing storage of combustibles.
Auxiliary machinery spaces as in category (10) which contain machinery having a pressure lubrication system or where storage of combustibles is permitted.
Oil fuel filling stations.
Spaces containing oil-filled electrical transformers (above 10 kVA).
Spaces containing turbine and reciprocating steam engine driven auxiliary generators and small internal combustion engines of power output up to 110 kW driving generators, sprinkler, drencher or fire pumps, bilge pumps, etc.
Closed trunks serving the spaces listed above.

12. *Machinery spaces and main galleys*

Main propulsion machinery rooms (other than electric propulsion motor rooms) and boiler rooms.
Auxiliary machinery spaces other than those in categories (10) and (11) which contain internal combustion machinery or other oil-burning, heating or pumping units.
Main galleys and annexes.
Trunks and casings to the spaces listed above.

13. *Store-rooms, workshops, pantries, etc.*

Main pantries not annexed to galleys.
Main laundry.
Large drying rooms (having a deck area of more than 4 m^2).

Miscellaneous stores.

Mail and baggage rooms.

Garbage rooms.

Workshops (not part of machinery spaces, galleys, etc.).

Lockers and store-rooms having areas greater than 4 m^2, other than those spaces that have provisions for the storage of flammable liquids.

14. Other spaces in which flammable liquids are stowed

Paint lockers.

Store-rooms containing flammable liquids (including dyes, medicines, etc.).

Laboratories (in which flammable liquids are stowed).

Appendix 11

Logbook of Two-Variable Dependency Analysis

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Variables analysed
~~~~~~~~~~~~~~~~~~

N1	Time
N2	Vessel location
N3	Weather contribution
N4	Ignition space
N5	Automatic detection activated
N6	Manual detection activated
N7	Automatic suppression activated
N8	Manual suppression activated
N9	Ventilation status
N10	Fire door status
N11	Crew attended
N12	Guest attended
N13	Boundary cooling status
N14	Emergency response failure
N15	Containment failure
N16	Ignition in adjacent space

~~~~~~~~~~~~~~~~~~~~~~~~~~~
Attributes of each variable
~~~~~~~~~~~~~~~~~~~~~~~~~~~

N1		N6	
	Daytime		False
	Night		True
N2		N7	
	PORT		False
	SEA		True
N3		N8	
	False		False
	True		True
N4		N9	
	SOLAS_10		Closed
	SOLAS_12		Fail_to_close
	SOLAS_13		No_need_to_close
	SOLAS_14	N10	
	SOLAS_2		Closed
	SOLAS_3		Open
	SOLAS_4	N11	
	SOLAS_5		False
	SOLAS_6		True
	SOLAS_7	N12	
	SOLAS_8		False
	SOLAS_9		True
N5		N13	
	False		Executed
	True		Unnecessary

N14 False True N15 False True	N16 False True

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Two variables dependency analysis
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

To investigate the dependent relationships between any two variables, the saturated model 1 (indicating association) is compared with model 2 (indicating independent relationship). The significance of the difference between the two models can be revealed.

Model 1: Twodata$CountNum ~ Twodata$Para1 * Twodata$Para2
Model 2: Twodata$CountNum ~ Twodata$Para1 + Twodata$Para2

Two Variables: N1 & N2 Significance of difference is: 0.000269 Remove link between them ? False	Two Variables: N1 & N12 Significance of difference is: 0.0827 Remove link between them ? False
Two Variables: N1 & N3 Significance of difference is: 0.346 Remove link between them ? True	Two Variables: N1 & N13 Significance of difference is: 0.626 Remove link between them ? True
Two Variables: N1 & N4 Significance of difference is: 0.134 Remove link between them ? True	Two Variables: N1 & N14 Significance of difference is: 0.423 Remove link between them ? True
Two Variables: N1 & N5 Significance of difference is: 0.0288 Remove link between them ? False	Two Variables: N1 & N15 Significance of difference is: 0.108 Remove link between them ? True
Two Variables: N1 & N6 Significance of difference is: 0.049 Remove link between them ? False	Two Variables: N1 & N16 Significance of difference is: 0.108 Remove link between them ? True
Two Variables: N1 & N7 Significance of difference is: 0.376 Remove link between them ? True	Two Variables: N2 & N3 Significance of difference is: 0.258 Remove link between them ? True
Two Variables: N1 & N8 Significance of difference is: 0.155 Remove link between them ? True	Two Variables: N2 & N4 Significance of difference is: 0.0121 Remove link between them ? False
Two Variables: N1 & N9 Significance of difference is: 0.322 Remove link between them ? True	Two Variables: N2 & N5 Significance of difference is: 0.109 Remove link between them ? True
Two Variables: N1 & N10 Significance of difference is: 0.289 Remove link between them ? True	Two Variables: N2 & N6 Significance of difference is: 0.238 Remove link between them ? True
Two Variables: N1 & N11 Significance of difference is: 0.41 Remove link between them ? True	Two Variables: N2 & N7 Significance of difference is: 0.674 Remove link between them ? True

Two Variables: N2 & N8
Significance of difference is: 0.346
Remove link between them ? True

Two Variables: N2 & N9
Significance of difference is: 0.23
Remove link between them ? True

Two Variables: N2 & N10
Significance of difference is: 0.689
Remove link between them ? True

Two Variables: N2 & N11
Significance of difference is: 0.0169
Remove link between them ? False

Two Variables: N2 & N12
Significance of difference is: 0.00289
Remove link between them ? False

Two Variables: N2 & N13
Significance of difference is: 0.334
Remove link between them ? True

Two Variables: N2 & N14
Significance of difference is: 0.102
Remove link between them ? True

Two Variables: N2 & N15
Significance of difference is: 0.437
Remove link between them ? True

Two Variables: N2 & N16
Significance of difference is: 0.437
Remove link between them ? True

Two Variables: N3 & N4
Significance of difference is: 0.000604
Remove link between them ? False

Two Variables: N3 & N5
Significance of difference is: 0.13
Remove link between them ? True

Two Variables: N3 & N6
Significance of difference is: 0.304
Remove link between them ? True

Two Variables: N3 & N7
Significance of difference is: 0.143
Remove link between them ? True

Two Variables: N3 & N8
Significance of difference is: 0.139
Remove link between them ? True

Two Variables: N3 & N9
Significance of difference is: 0.582
Remove link between them ? True

Two Variables: N3 & N10
Significance of difference is: 0.132
Remove link between them ? True

Two Variables: N3 & N11
Significance of difference is: 0.236
Remove link between them ? True

Two Variables: N3 & N12
Significance of difference is: 0.642
Remove link between them ? True

Two Variables: N3 & N13
Significance of difference is: 0.834
Remove link between them ? True

Two Variables: N3 & N14
Significance of difference is: 0.766
Remove link between them ? True

Two Variables: N3 & N15
Significance of difference is: 0.954
Remove link between them ? True

Two Variables: N3 & N16
Significance of difference is: 0.954
Remove link between them ? True

Two Variables: N4 & N5
Significance of difference is: 1.14e-18
Remove link between them ? False

Two Variables: N4 & N6
Significance of difference is: 2.61e-15
Remove link between them ? False

Two Variables: N4 & N7
Significance of difference is: 3.22e-32
Remove link between them ? False

Two Variables: N4 & N8
Significance of difference is: 7.01e-08
Remove link between them ? False

Two Variables: N4 & N9
Significance of difference is: 0.0927
Remove link between them ? False

Two Variables: N4 & N10
Significance of difference is: 1.19e-62
Remove link between them ? False

Two Variables: N4 & N11
Significance of difference is: 7.97e-35
Remove link between them ? False

Two Variables: N4 & N12
Significance of difference is: 5.21e-31
Remove link between them ? False

Two Variables: N4 & N13
Significance of difference is: 0.672
Remove link between them ? True

Two Variables: N4 & N14
Significance of difference is: 0.943
Remove link between them ? True

Two Variables: N4 & N15
Significance of difference is: 0.891
Remove link between them ? True

Two Variables: N4 & N16
Significance of difference is: 0.891
Remove link between them ? True

Two Variables: N5 & N6
Significance of difference is: 5.4e-204
Remove link between them ? False

Two Variables: N5 & N7
Significance of difference is: 4.72e-25
Remove link between them ? False

Two Variables: N5 & N8
Significance of difference is: 0.662
Remove link between them ? True

Two Variables: N5 & N9
Significance of difference is: 0.000229
Remove link between them ? False

Two Variables: N5 & N10
Significance of difference is: 7.99e-07
Remove link between them ? False

Two Variables: N5 & N11
Significance of difference is: 5.52e-80
Remove link between them ? False

Two Variables: N5 & N12
Significance of difference is: 0.00011
Remove link between them ? False

Two Variables: N5 & N13
Significance of difference is: 0.234
Remove link between them ? True

Two Variables: N5 & N14
Significance of difference is: 0.108
Remove link between them ? True

Two Variables: N5 & N15
Significance of difference is: 0.37
Remove link between them ? True

Two Variables: N5 & N16
Significance of difference is: 0.37
Remove link between them ? True

Two Variables: N6 & N7
Significance of difference is: 3e-18
Remove link between them ? False

Two Variables: N6 & N8
Significance of difference is: 0.582
Remove link between them ? True

Two Variables: N6 & N9
Significance of difference is: 0.0383
Remove link between them ? False

Two Variables: N6 & N10
Significance of difference is: 2.7e-06
Remove link between them ? False

Two Variables: N6 & N11
Significance of difference is: 1.22e-104
Remove link between them ? False

Two Variables: N6 & N12
Significance of difference is: 4.07e-07
Remove link between them ? False

Two Variables: N6 & N13
Significance of difference is: 0.276
Remove link between them ? True

Two Variables: N6 & N14
Significance of difference is: 0.0733
Remove link between them ? False

Two Variables: N6 & N15
Significance of difference is: 0.456
Remove link between them ? True

Two Variables: N6 & N16
Significance of difference is: 0.456
Remove link between them ? True

Two Variables: N7 & N8
Significance of difference is: 1.57e-20
Remove link between them ? False

Two Variables: N7 & N9
Significance of difference is: 2.39e-17
Remove link between them ? False

Two Variables: N7 & N10
Significance of difference is: 0.000172
Remove link between them ? False

Two Variables: N7 & N11
Significance of difference is: 0.000138
Remove link between them ? False

Two Variables: N7 & N12
Significance of difference is: 3.25e-06
Remove link between them ? False

Two Variables: N7 & N13
Significance of difference is: 2.33e-07
Remove link between them ? False

Two Variables: N7 & N14
Significance of difference is: 5.82e-10
Remove link between them ? False

Two Variables: N7 & N15
Significance of difference is: 0.0468
Remove link between them ? False

Two Variables: N7 & N16
Significance of difference is: 0.0468
Remove link between them ? False

Two Variables: N8 & N9
Significance of difference is: 0.262
Remove link between them ? True

Two Variables: N8 & N10
Significance of difference is: 0.0695
Remove link between them ? False

Two Variables: N8 & N11
Significance of difference is: 0.557
Remove link between them ? True

Two Variables: N8 & N12
Significance of difference is: 0.225
Remove link between them ? True

Two Variables: N8 & N13
Significance of difference is: 0.891
Remove link between them ? True

Two Variables: N8 & N14
Significance of difference is: 0.987
Remove link between them ? True

Two Variables: N8 & N15
Significance of difference is: 0.375
Remove link between them ? True

Two Variables: N8 & N16
Significance of difference is: 0.375
Remove link between them ? True

Two Variables: N9 & N10
Significance of difference is: 0.0753
Remove link between them ? False

Two Variables: N9 & N11
Significance of difference is: 0.795
Remove link between them ? True

Two Variables: N9 & N12
Significance of difference is: 0.00269
Remove link between them ? False

Two Variables: N9 & N13
Significance of difference is: 2.75e-05
Remove link between them ? False

Two Variables: N9 & N14
Significance of difference is: 7e-09
Remove link between them ? False

Two Variables: N9 & N15
Significance of difference is: 0.946
Remove link between them ? True

Two Variables: N9 & N16
Significance of difference is: 0.946
Remove link between them ? True

Two Variables: N10 & N11
Significance of difference is: 0.00123
Remove link between them ? False

Two Variables: N10 & N12
Significance of difference is: 0.935
Remove link between them ? True

Two Variables: N10 & N13
Significance of difference is: 0.809
Remove link between them ? True

Two Variables: N10 & N14
Significance of difference is: 0.43
Remove link between them ? True

Two Variables: N10 & N15
Significance of difference is: 0.636
Remove link between them ? True

Two Variables: N10 & N16
Significance of difference is: 0.636
Remove link between them ? True

Two Variables: N11 & N12
Significance of difference is: 1.62e-44
Remove link between them ? False

Two Variables: N11 & N13
Significance of difference is: 0.113
Remove link between them ? True

Two Variables: N11 & N14
Significance of difference is: 0.0359
Remove link between them ? False

Two Variables: N11 & N15
Significance of difference is: 0.13
Remove link between them ? True

Two Variables: N11 & N16
Significance of difference is: 0.13
Remove link between them ? True

Two Variables: N12 & N13
Significance of difference is: 0.722
Remove link between them ? True

Two Variables: N12 & N14
Significance of difference is: 0.93
Remove link between them ? True

Two Variables: N12 & N15
Significance of difference is: 0.0252
Remove link between them ? False

Two Variables: N12 & N16
Significance of difference is: 0.0252
Remove link between them ? False

Two Variables: N13 & N14
Significance of difference is: 9.21e-22
Remove link between them ? False

Two Variables: N13 & N15
Significance of difference is: 0.00136
Remove link between them ? False

Two Variables: N13 & N16
Significance of difference is: 0.00136
Remove link between them ? False

Two Variables: N14 & N15
Significance of difference is: 0.00225
Remove link between them ? False

Two Variables: N14 & N16
Significance of difference is: 0.00225
Remove link between them ? False

Two Variables: N15 & N16
Significance of difference is: 5.05e-05
Remove link between them ? False

The summarisation of the links to be removed from the fully connected network due to two variable dependency analyses is listed as follows.

Table A11.1: Summary of Independent Relationships Identified as a Result of Two variables Dependency Analysis

Links to be removed		Links to be removed	
N1	N3	N4	N13
N1	N4	N4	N14
N1	N7	N4	N15
N1	N8	N4	N16
N1	N9	N5	N8
N1	N10	N5	N13
N1	N11	N5	N14
N1	N13	N5	N15
N1	N14	N5	N16
N1	N15	N6	N8
N1	N16	N6	N13
N2	N3	N6	N15
N2	N5	N6	N16
N2	N6	N8	N9
N2	N7	N8	N11
N2	N8	N8	N12
N2	N9	N8	N13
N2	N10	N8	N14
N2	N13	N8	N15
N2	N14	N8	N16
N2	N15	N9	N11
N2	N16	N9	N15
N3	N5	N9	N16
N3	N6	N10	N12
N3	N7	N10	N13
N3	N8	N10	N14
N3	N9	N10	N15
N3	N10	N10	N16
N3	N11	N11	N13
N3	N12	N11	N15
N3	N13	N11	N16
N3	N14	N12	N13
N3	N15	N12	N14
N3	N16		

Following three variables conditional independency analysis among three variables, the overall list of links to be removed from the fully connected network is summarised as follows.

~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
Summary of links to be removed
~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~

Table A11.2: Summary of Links to be Removed Following Dependency and Conditional Independency Analyses

Links to be removed		Links to be removed	
N1	N10	N3	N6
N1	N11	N3	N7
N1	N12	N3	N8
N1	N13	N3	N9
N1	N14	N4	N13

N1	N15	N4	N14
N1	N16	N4	N15
N1	N3	N4	N16
N1	N4	N4	N9
N1	N5	N5	N10
N1	N6	N5	N12
N1	N7	N5	N13
N1	N8	N5	N14
N1	N9	N5	N15
N10	N11	N5	N16
N10	N12	N5	N8
N10	N13	N5	N9
N10	N14	N6	N10
N10	N15	N6	N13
N10	N16	N6	N14
N11	N13	N6	N15
N11	N14	N6	N16
N11	N15	N6	N7
N11	N16	N6	N8
N12	N13	N6	N9
N12	N14	N8	N10
N12	N15	N8	N11
N12	N16	N8	N12
N2	N10	N8	N13
N2	N11	N8	N14
N2	N12	N8	N15
N2	N13	N8	N16
N2	N14	N8	N9
N2	N15	N9	N10
N2	N16	N9	N11
N2	N3	N9	N12
N2	N4	N9	N13
N2	N5	N9	N15
N2	N6	N9	N16
N2	N7	N13	N15
N2	N8	N13	N16
N2	N9	N14	N15
N3	N10	N14	N16
N3	N11	N7	N10
N3	N12	N7	N11
N3	N13	N7	N12
N3	N14	N7	N13
N3	N15	N7	N15
N3	N16	N7	N16
N3	N4	N15	N16
N3	N5		

A list of conditional independent relationships is generated due to three variables analysis.

~~~~~~
Summarisation of three variables conditional independencies: I(X,Y|Z)
~~~~~~

Table A11.3: Summary of Conditional Independencies

X	Y	Z	X	Y	Z
N2	N10	N1	N3	N11	N4
N2	N5	N1	N3	N12	N4
N2	N6	N1	N3	N14	N4
N2	N7	N1	N3	N5	N4
N3	N5	N10	N3	N6	N4
N4	N9	N10	N3	N7	N4
N1	N5	N11	N3	N8	N4
N1	N6	N11	N3	N9	N4
N10	N12	N11	N5	N10	N4
N10	N14	N11	N5	N12	N4
N12	N14	N11	N6	N10	N4
N2	N10	N11	N6	N7	N4
N2	N5	N11	N7	N10	N4
N2	N6	N11	N7	N12	N4
N2	N7	N11	N8	N10	N4
N5	N14	N11	N8	N11	N4
N6	N14	N11	N8	N12	N4
N7	N10	N11	N8	N9	N4
N1	N11	N12	N9	N10	N4
N1	N9	N12	N9	N12	N4
N11	N14	N12	N1	N10	N5
N11	N15	N12	N1	N11	N5
N11	N16	N12	N1	N12	N5
N2	N10	N12	N1	N6	N5
N2	N11	N12	N1	N7	N5
N2	N14	N12	N1	N9	N5
N2	N15	N12	N10	N11	N5
N2	N16	N12	N10	N12	N5
N2	N5	N12	N10	N14	N5
N2	N6	N12	N11	N14	N5
N2	N7	N12	N2	N10	N5
N2	N9	N12	N2	N6	N5
N4	N9	N12	N2	N7	N5
N5	N15	N12	N4	N14	N5
N5	N16	N12	N4	N9	N5
N5	N9	N12	N6	N10	N5
N6	N14	N12	N6	N14	N5
N6	N15	N12	N6	N7	N5
N6	N16	N12	N6	N9	N5
N6	N7	N12	N7	N10	N5
N6	N9	N12	N7	N12	N5
N7	N11	N12	N9	N10	N5
N8	N10	N12	N9	N11	N5
N8	N9	N12	N1	N10	N6
N9	N10	N12	N1	N12	N6
N9	N11	N12	N1	N5	N6
N14	N15	N13	N1	N7	N6
N14	N16	N13	N10	N11	N6
N7	N15	N13	N10	N12	N6

N7	N16	N13	N11	N14	N6
N9	N15	N13	N2	N5	N6
N9	N16	N13	N5	N12	N6
N11	N13	N14	N7	N11	N6
N11	N15	N14	N7	N12	N6
N11	N16	N14	N9	N10	N6
N12	N13	N14	N9	N11	N6
N13	N15	N14	N10	N12	N7
N13	N16	N14	N10	N13	N7
N4	N13	N14	N10	N14	N7
N5	N13	N14	N11	N13	N7
N7	N13	N14	N11	N14	N7
N7	N15	N14	N11	N15	N7
N7	N16	N14	N11	N16	N7
N8	N13	N14	N12	N13	N7
N9	N13	N14	N12	N14	N7
N9	N15	N14	N2	N14	N7
N9	N16	N14	N2	N9	N7
N12	N13	N15	N3	N14	N7
N12	N14	N15	N3	N9	N7
N12	N16	N15	N4	N13	N7
N13	N16	N15	N4	N14	N7
N14	N16	N15	N4	N9	N7
N7	N16	N15	N5	N12	N7
N9	N16	N15	N5	N13	N7
N12	N13	N16	N5	N14	N7
N12	N14	N16	N5	N15	N7
N12	N15	N16	N5	N16	N7
N13	N15	N16	N5	N9	N7
N14	N15	N16	N6	N13	N7
N1	N10	N2	N6	N14	N7
N1	N11	N2	N6	N15	N7
N1	N12	N2	N6	N16	N7
N1	N3	N2	N6	N9	N7
N1	N4	N2	N8	N10	N7
N1	N5	N2	N8	N12	N7
N1	N6	N2	N8	N13	N7
N1	N7	N2	N8	N14	N7
N1	N8	N2	N8	N15	N7
N1	N9	N2	N8	N16	N7
N1	N10	N4	N8	N9	N7
N1	N3	N4	N9	N10	N7
N1	N7	N4	N9	N11	N7
N1	N8	N4	N9	N12	N7
N10	N12	N4	N10	N14	N9
N10	N14	N4	N11	N14	N9
N12	N14	N4	N12	N13	N9
N2	N10	N4	N12	N14	N9
N2	N12	N4	N2	N14	N9
N2	N14	N4	N4	N14	N9
N2	N3	N4	N5	N12	N9
N2	N5	N4	N5	N13	N9
N2	N6	N4	N5	N14	N9
N2	N7	N4	N6	N13	N9
N2	N8	N4	N6	N14	N9
N2	N9	N4	N7	N12	N8

~~~~~~~~~~~~~~~~~~~~~~~~~
PC algorithm orientation
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By removing the links that have been listed in the summary list, the BN structure can be identified and presented in the following matrix, where T denotes a link and F denotes no link.

Table A11.4: Identified Bayesian Network Structure Presented in a Matrix Table

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16
N1	F	T	F	F	F	F	F	F	F	F	F	F	F	F	F	F
N2	T	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F
N3	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F
N4	F	F	F	F	T	T	T	T	F	T	T	T	F	F	F	F
N5	F	F	F	T	F	T	T	F	F	F	T	F	F	F	F	F
N6	F	F	F	T	T	F	F	F	F	F	T	T	F	F	F	F
N7	F	F	F	T	T	F	F	T	T	F	F	F	F	T	F	F
N8	F	F	F	T	F	F	T	F	F	F	F	F	F	F	F	F
N9	F	F	F	F	F	F	T	F	F	F	F	F	F	T	F	F
N10	F	F	F	T	F	F	F	F	F	F	F	F	F	F	F	F
N11	F	F	F	T	T	T	F	F	F	F	F	T	F	F	F	F
N12	F	F	F	T	F	T	F	F	F	F	T	F	F	F	F	F
N13	F	F	F	F	F	F	F	F	F	F	F	F	F	T	F	F
N14	F	F	F	F	F	F	T	F	T	F	F	F	T	F	F	F
N15	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F
N16	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F	F

Following the PC algorithm for orientation, “head-to-head” orientations are assigned on the basis of the list of conditional independent relationships.

Head-to-Head link
N5 -> N4 <- N8
Head-to-Head link
N6 -> N4 <- N8
Head-to-Head link
N7 -> N4 <- N11

Head-to-Head link
N10 -> N4 <- N11
Head-to-Head link
N7 -> N5 <- N11
Head-to-Head link
N5 -> N7 <- N8
Head-to-Head link
N5 -> N11 <- N12

Hence, the updated matrix with the head-to-head links is shown as follows.

Table A11.5: Identified Bayesian Network Structure Presented in a Matrix Table with Head-to-Head Orientations Assigned

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16
N1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N4	NA	NA	NA	NA	In	In	In	In	NA	In	In	NA	NA	NA	NA	NA
N5	NA	NA	NA	Out	NA	NA	Out	NA	NA	NA	Out	NA	NA	NA	NA	NA
N6	NA	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N7	NA	NA	NA	Out	In	NA	NA	In	NA	NA	NA	NA	NA	NA	NA	NA
N8	NA	NA	NA	Out	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA
N9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N10	NA	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N11	NA	NA	NA	Out	In	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA
N12	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Out	NA	NA	NA	NA	NA
N13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N14	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N15	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N16	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

The PC Algorithm for the remaining links
Repeat:

(1)for each uncoupled meeting x->Z-Y
    Orient Z-Y as Z->Y
(2)for each X-Y such that there is a direct path from X to Y
    Orient X-Y as X->Y
(3)for each uncoupled meeting X-Z-Y such that X->W,Y->W, and Z-W
    Orient Z-W as Z->W

Start looping

Loop Number: 1
Action in (2) solve acyclic case: Add N12 -> N4
Action in (2): Add N5 -> N6
Action in (3): Add N6 -> N11

Loop Number: 2
Action in (2): Add N6 -> N12

Loop Number: 3
Action in (2): Add N7 -> N9
Action in (2): Add N7 -> N14

Loop Number: 4
Action in (2): Add N9 -> N14

Loop Number: 5
Action in (2): Add N14 -> N13

Loop Number: 6
Action in (2): Add N1 -> N2

The output BN structure can be presented as follows.

Table A11.6: Identified Bayesian Network Structure Presented in a Matrix Table with All Orientations Assigned

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16
N1	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N2	In	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N4	NA	NA	NA	NA	In	In	In	In	NA	In	In	In	NA	NA	NA	NA
N5	NA	NA	NA	Out	NA	Out	Out	NA	NA	NA	Out	NA	NA	NA	NA	NA
N6	NA	NA	NA	Out	In	NA	NA	NA	NA	NA	Out	Out	NA	NA	NA	NA
N7	NA	NA	NA	Out	In	NA	NA	In	Out	NA	NA	NA	NA	Out	NA	NA
N8	NA	NA	NA	Out	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA
N9	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	NA	Out	NA	NA
N10	NA	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N11	NA	NA	NA	Out	In	In	NA	NA	NA	NA	NA	In	NA	NA	NA	NA
N12	NA	NA	NA	Out	NA	In	NA	NA	NA	NA	Out	NA	NA	NA	NA	NA
N13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA	NA
N14	NA	NA	NA	NA	NA	NA	In	NA	In	NA	NA	NA	Out	NA	NA	NA
N15	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N16	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Appendix 12

Logbook of the GES Learning Process

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Variables analysed
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N1	Time
N2	Vessel location
N3	Weather contribution
N4	Ignition space
N5	Automatic detection activated
N6	Manual detection activated
N7	Automatic suppression activated
N8	Manual suppression activated
N9	Ventilation status
N10	Fire door status
N11	Crew attended
N12	Guest attended
N13	Boundary cooling status
N14	Emergency response failure
N15	Containment failure
N16	Ignition in adjacent space

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Greedy Equivalent Search (GES) algorithm
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Inserting process starts with a fully disconnected network. By investigating all possible single link inserting operations at each loop, the one producing the highest score increment is adopted.

Loop 1:

The score increment for every single link is summarised in the following table.

Highest score is: 450.7509
Between node: N5 & N6

Table A12.1: Summary of Score Increment of Each Single Link in Loop 1

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15	N16
N1	NA	-2.90	-7.65	-91.69	-6.89	-7.23	-8.70	-8.37	-14.65	-8.33	-8.91	-7.60	-7.22	-7.15	-5.98	-5.98
N2		NA	-7.64	-87.91	-8.13	-8.66	-8.97	-8.95	-14.47	-8.99	-6.59	-4.97	-6.91	-6.18	-7.16	-7.16
N3			NA	-67.25	-7.40	-7.65	-7.35	-7.43	-9.66	-7.39	-7.62	-5.57	-1.75	-2.57	0.87	0.87
N4				NA	-44.97	-52.61	-7.78	-72.92	-159.91	64.27	-4.95	-8.75	-79.69	-83.09	-75.40	-75.40
N5					NA	450.75	44.06	-9.33	-7.84	2.53	169.03	-2.01	-6.93	-6.52	-7.32	-7.32
N6						NA	29.17	-9.17	-12.54	1.19	225.46	2.52	-6.69	-5.82	-7.09	-7.09
N7							NA	33.90	24.17	-2.94	-1.55	-0.71	6.31	12.03	-4.01	-4.01
N8								NA	-14.86	-7.59	-9.18	-8.01	-7.75	-7.89	-7.31	-7.31
N9									NA	-13.72	-15.89	-10.63	1.94	9.37	-6.66	-6.66
N10										NA	-4.24	-8.49	-7.07	-7.57	-5.99	-5.99
N11											NA	87.51	-6.17	-5.39	-6.35	-6.35
N12												NA	-5.80	-6.64	-2.35	-2.35
N13													NA	41.33	5.63	5.63
N14														NA	4.39	4.39
N15															NA	9.73
N16																NA

The identified links producing the highest score increment at each loop is summarised as follows.

Loop 2:
Highest score is: 225.4595
Between edge: 11 & 6

Loop 3:
Highest score is: 162.1013
Between edge: 12 & 11

Loop 4:
Highest score is: 64.2687
Between edge: 10 & 4

Loop 5:
Highest score is: 44.0577
Between edge: 7 & 5

Loop 6:
Highest score is: 41.3299
Between edge: 14 & 13

Loop 7:
Highest score is: 37.0048
Between edge: 8 & 7

Loop 8:
Highest score is: 24.167
Between edge: 9 & 7

Loop 9:
Highest score is: 12.0333
Between edge: 14 & 7

Loop 10:
Highest score is: 9.7261
Between edge: 16 & 15

Loop 11:
Highest score is: 5.6305
Between edge: 15 & 13

Loop 12:
Highest score is: 2.5255
Between edge: 10 & 5

Loop 13:
Highest score is: 2.5245
Between edge: 12 & 6

Loop 14:
Highest score is: 0.871
Between edge: 15 & 3

The output BN structure following the insert operations can be presented as follows.

Table A12.2: Obtained Bayesian Network Structure Following Insert Operations Presented in a Matrix Table

	N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	N11	N12	N13	N14	N15
N1	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N2	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N3	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In
N4	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA
N5	NA	NA	NA	NA	NA	Out	Out	NA	NA	Out	NA	NA	NA	NA	NA
N6	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	Out	Out	NA	NA	NA
N7	NA	NA	NA	NA	In	NA	NA	In	Out	NA	NA	NA	NA	Out	NA
N8	NA	NA	NA	NA	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA
N9	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	NA	NA	NA
N10	NA	NA	NA	Out	In	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
N11	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	In	NA	NA	NA
N12	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	Out	NA	NA	NA	NA
N13	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	Out
N14	NA	NA	NA	NA	NA	NA	In	NA	NA	NA	NA	NA	Out	NA	NA
N15	NA	NA	Out	NA	NA	NA	NA	NA	NA	NA	NA	NA	In	NA	NA
N16	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	In

The deleting operation cannot identify any link having positive score increment, hence no further operation is needed.