ACCIDENT ANALYSIS, RISK AND RELIABILITY MODELING OF MARINE TRANSPORTATION SYSTEMS

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DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

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Shahrzad Faghih Roohi

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This thesis is dedicated with love and respect to my mother, father, and my beloved family

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SUMMARY

The purposes of this thesis are to propose a quantitative analysis of human and organizational factors (HOF) in marine accidents; to optimize hazardous material (hazmat) transportations considering marine accident risk and cost; to propose an accident risk model for the marine transportation systems; and to assess the availability of these systems in a developed dynamic model for further availability and cost based design of marine transportation systems.

Human and organizational factors are one of the most important contributing aspects to the cause of accidents. The proposed model of this thesis regarding to HOF analysis is made up of two phases. The first phase is the qualitative analysis of HOF responsible for marine accidents, which utilizes human factors analysis and classification system (HFACS). The second phase is a quantitative analysis using Bayesian network (BN) to enhance the ability of HFACS by allowing investigators or domain experts to measure the degree of relationships among the HOFs. In order to estimate the conditional probabilities of BN, fuzzy analytical hierarchy process and decomposition method are applied in the accident model. This quantitative accident model will provide help on improving safety and preventing marine accidents.

Accident risk minimization in transportation of hazardous materials (hazmat) has been an active area of study with remarkable improvements in route selection domains. Most of the works optimized transportation of hazmat in roads or railways; hence marine transportation of hazmat considering the associated marine accident risks has

not been studied yet. In this thesis, we propose a bi-objective optimization model for transportation of hazardous materials with the concern on accident risk and cost of transportation. Moreover, prevention of marine transportation systems from accidents requires the use of risk models. Current accident risk models contain many safety factors which make the risk analysis complicated. Therefore, another attempt of this thesis is to propose a general approach of risk modeling which would be applicable without having information on safety factors and for all types of accidents. This approach is based on Markov model incorporating with Markov chain Monte Carlo (MCMC) simulation.

The availability/reliability of a marine transportation system is dependent upon the structure of the system. Multi-state weighted *K*-out-of-*N* structure is a commonly observed structure for marine transportation systems. For this type of system, a dynamic model is developed for the availability assessment of these systems. For availability assessment, universal generating function (UGF) and Markov process are adopted in this thesis. Besides availability assessment, the design of a dynamic multi-state marine system is optimized by using Genetic algorithm (GA). The optimization problem is to minimize the expected total system cost subject to system availability requirements. The objective is to find the optimal design of the systems when state probabilities and costs of components vary in time.

The applications of the proposed models of this thesis are illustrated using real-world marine transportation systems. The models can be extrapolated to be applied in other sectors such as oil or gas industry, and other systems such as the railways, road transportation systems, and network systems.

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LIST OF ABBREVIATIONS

HOF	Human and Organizational Factors
HFACS	Human Factor Analysis and Classification System
Hazmat	Hazardous Material
BN	Bayesian Network
CPT	Conditional Probability Table
AHP	Analytical Hierarchy Process
MC	Markov Chain
MCMC	Markov Chain Monte Carlo
GA	Genetic Algorithm
UGF	Universal Generating Function
BNP	Best Non-fuzzy Performance
COA	Center of Area
IMO	International Maritime Organization
MAIB	Marine Accident Investigation Branch
MSDS	Material Safety Data Sheet
VCM	Vinyl Chloride Monomer
PPE	Personal Protective Equipment
ESD	Emergency Shut-Down
EVC	Electric Vehicle Company

CHAPTER 1: INTRODUCTION

This dissertation focuses on accident analysis, risk and reliability modeling of some marine transportation systems. Different kinds of marine transportation systems based on their application and structures are investigated. The organization of this introduction chapter is as follows. First, some background is provided in the introductory part in section 1.1, and then the motivations of research are declared in section 1.2 which highlights the aims of study. In section 1.3, some important methods and models are briefly presented, which includes human factors analysis and classification system, Bayesian network, fuzzy analytic hierarchy process, Markov chain, Markov chain Monte Carlo simulation, and genetic algorithm. The research scope and the organization of this dissertation are introduced in Section 0.

1.1. Background

Over the last decade, marine systems played as an important role as highway, rail and air systems in international commerce and transportation. Marine transportation systems are often comparable with other modes of transportation in relieving congestion, and producing more fuel-efficient and economic transportation. Although transportation on water is relatively economical and costless, the occurrence of accidents and incidents at sea is increasing leading to loss of lives and environmental effects. Therefore, it is so important to keep the marine transportation system safe. However, the desirable safety of marine transportation systems requires extensive investigations into the marine accident risk and reliability of these systems.

Among commonly underlined factors leading to marine accidents, Human and Organizational Factors (HOF) are leading causes of most accidents. A report of United States Coast Guard also points out that 75-96% of casualties are due to some forms of human errors (Rothblum 2000). In this aspect, it is emphasized that human factor is one of the most important contributory aspects to the causation and avoidance of accident.

The human factor analysis becomes much more important when a system transports hazardous materials (hazmat). Hazardous material transportation is an economic activity with increasing volume and potential risk for environment and mankind. Most hazmats, such as gasoline, fuel oil, and petroleum, are an integral part of our daily lives and industrial development. Flammables, explosives, poisonous and infectious substances, radioactive materials, and hazardous wastes are common examples of materials in the category of hazmats (Verter and Kara 2008; Jaffin 2012). Transportation of hazardous materials in sea comes with some accident risks and the possibility of incidents such as spill to sea, fire, and/or explosion. The safe transportation of ships containing hazmat is of the utmost concern to researchers that has conducted many studies on accident analysis and risk modeling of marine transportation systems.

The concept of risk is used to assess and evaluate uncertainties associated with an event. Risk can be defined as a combination of the probability and the degree of the possible human injury, damage to property, and damage to environment. Hence, risk can be measured as a pair of the probability of occurrence of an event and the consequences associated with the event's occurrence. The appropriate estimation of this probability is a matter of great significance. According to Liu and Zhang (2012), accident risk analysis is a process to identify a functional relationship between the probability distributions of causes (factors) and accidents using information.

The risk of marine transportation system's accident is related to the reliability/availability of the system. Reliability is the probability that the system will perform a required function under stated conditions for a stated period of time. And, availability is the probability that the system is in its intended functional condition and therefore capable of being used in a stated environment. Availability deals with the duration of up-time for operations and is a measure of how often the system is alive and well.

The availability of marine transportation systems is dependent upon the structure of the systems. It can be evaluated by reliability block diagram, which is a graphical representation of the logic connections of the system's components within the system. Some common structures that can be observed as a structure of marine transportation system are:

- Single component systems such as a rudder of a ship or considering a vessel as a single whole unit.
- Parallel systems such as the three parallel generators rated at 270 kW each; if all generators fail the power generation system in the ship fails.

- Series systems such as the different parts of a tanker or ship hull; if any part is holed or cracked deeply, it causes to system's drowning.

- K-out-of-N systems, in which at least K components of the system should work properly for its operation, such as a 2-out-of-3 high-speed ship engines in which at least 2 engines of the 3 available engines should work.

Sometimes there is a combination of above structures such as series-parallel systems. And, sometimes the components of a system have different states, make it as multi-state systems. A marine transportation system with $M + 1$ different states $(0,1, \dots, M)$ is considered as multi-state system, where state M is the perfect functioning state and state *0* is the completely failure state. The states between 0 and M are partial failures and do not necessarily cause the system's shutdown.

1.2. Motivations

1.2.1. Contribution of human and organizational factors in marine accidents

It has been widely recognized that human and organizational factors are leading causes of most marine accidents (Hetherington et al. 2006; Ren et al. 2008; Trucco et al. 2008). The prevalence of HOF in accidents warrants the need to incorporate HOF analysis in accident investigations, so that valuable measures to prevent similar accidents from recurring can be derived. After the review of different models, Human Factor Analysis and Classification System (HFACS) model is selected for HOF analysis in this thesis.

Human factor analysis and classification system is a validated and reliable human error model (Wiegmann and Shappell 2001), which is utilized intensively in investigating accidents (Shappell et al. 2007; Olsen and Shorrock 2010). However, HFACS is a qualitative model and would not be enough for accident risk analysis. Therefore, adding quantification analysis to this model is a motivation of this study for investigating the contribution of HOF in marine accidents. In this thesis, HFACS model is integrated with Bayesian Network (BN) and fuzzy sets as a new approach to model quantitative accident risk and deal with uncertainty regarding the observed evidences.

1.2.2. Accident risk in marine hazardous material transportation

Hazardous materials (hazmat) are potentially dangerous to people and environment because of the toxic ingredients they include (Verma 2011). The public is very sensitive to the dangers of hazmat transportation activity due to the potential magnitude of accidents to the population and the environment. Therefore, the risk associated with accidents involving hazmat shipments has found considerable attention from the government, encouraging research on hazmat transportation (Caramia et al. 2010).

The risk involved in hazmat transportation has generally been analyzed in the literature from the perspective of potential or future occurrences of release accidents (Diaz-Banez et al. 2005; Clark and Besterfield-Sacre 2009). However, most of the accident risk analysis and optimization models for hazmat transportations are for transportations in roads or railroads and rarely in sea and waterways. Thereupon, in this thesis, we are motivated to develop an optimization model for accident risk analysis of hazmats in marine transportation.

1.2.3. General accident risk model for marine transportation

Quantification and analysis of accident risk plays an important role for the evaluation of maritime transportation system reliability. Many factors such as human errors contribute to the failure and accident of this kind of systems. Li et al. (2012) had an overview on maritime quantitative risk assessment studies. These studies have been done to investigate the associations between marine accident risks and the effective safety factors (Soares and Teixeira 2001; Toffoli et al. 2005; Attwood et al. 2006; Aven et al. 2006; Yip 2008; Kujala et al. 2009; Wang et al. 2011). In the risk estimation models of these studies, many safety factors are involved in models that make these methods complicated.

In practice, we should look for a comprehensive method of risk estimation that it is even applicable without having enough information on impacting safety factors. In addition, most of the recent risk models were proposed for a specific type of accident (e.g. collision) or marine system (e.g. tanker) (Friis-Hansen and Simonsen 2002; Chen 2003; Gucma and Przywarty 2007; Vanem et al. 2008; Mou et al. 2010; Goerlandt and Kujala 2011). In this thesis, we aim to propose an approach which has the potentials to consider any marine accident or marine transportation system.

1.2.4. Availability assessment and design of marine transportation system

Some recent research works have been devoted to model the availability/reliability and design of marine transportation systems due to the importance and wide application of these systems (Kwang Pil et al. 2008; Gamidov et al. 2009; Young et al. 2010; Prabhu Gaonkar et al. 2011; Thies et al. 2012).

In spite of vast reliability research, less attention was paid to the reliability-based structure of a marine transportation system, while the availability/reliability of marine transportation system is dependent upon the structure of the systems. Multi-state *K*-out-of-*N* structure is commonly observed for marine transportation systems. As a result, the aim of this thesis is to assess availability of multi-state *K*-out-of-*N* structured marine transportation systems. In addition, the weights or utilities are considered for the components of these systems in different states.

Most reliability/availability studies of multi-state weighted *K*-out-of-*N* system pre-assumed that the state probability of system/component does not change throughout system lifetime. However, complex systems are often subject to aging process which implies that the system/component state probability may gradually change with time (Kolowrocki and Kwiatuszewska-Sarnecka 2008). Therefore, it is of large practical value to model the availability as a function of time. Our purpose is to assess availability for a dynamic model of multi-state weighted *K*-out-of-*N* marine transportation systems.

In this thesis, besides availability assessment, we also investigate the best design of a dynamic multi-state marine system in a case for each component some weights are assigned in different states. Li and Zuo (2008a) presented a study on reliability optimal design of multi-state weighted *K*-out-of-*N* systems for a non-dynamic model. In their work, the objective was to select the component choices to minimize the system cost subject to requirement on system availability. In this thesis, we modify the objective function presented by Li and Zuo (2008a) to optimize the cost and find the optimal system design in dynamic model.

1.3. Some important methods and models

1.3.1. Human factors analysis and classification system

Human factors analysis and classification system (HFACS) is a reliable human error model that is able to assist investigators in the identification of human and organizational factors (HOFs) and their relationships in an accident. Human error is usually defined as any deviation from the performance of a specified or prescribed sequence of actions (Leveson 2004). HFACS describes human error at four levels:

1) The unsafe acts of operators,
2) Preconditions for unsafe acts,
3) Unsafe supervision
4) Organizational influences.

In other words, the HFACS framework goes beyond the simple identification of what an operator did wrong to provide a clear understanding of the reasons why the error occurred in the first place. In this way, errors are viewed as consequences of system failures or symptoms of deeper systemic problems; not simply the fault of the employee working at the "pointy end of the spear" (Wiegmann and Shappell 2003).

1.3.2. Bayesian network

A Bayesian network (BN) is a Directed Acyclic Graph (DAG), where $N = \{(V, E), P\}$. V and E are the nodes and edges respectively. P is the joint probability distribution over V (Williamson 2005). The nodes represent discredited random variables and arcs represent probabilistic dependencies between the variables. As they handle uncertainty explicitly, they are suitable for examining systems containing complex and uncertain interactions (Helle et al. 2011).

Each of the nodes in V represents a variable and the directed edges in the set E that connect nodes represent the probabilistic dependency. Each node has a number of possible values called "states". Also, each of the nodes in the network is quantified with a Conditional Probability Table (CPT), which consists of the conditional probabilities given the states of the parent nodes. For each possible state of a node, conditional probability is specified with respect to all possible combinations of states of its parent nodes. The probabilities describing these relationships between the nodes were obtained through structured expert elicitations (Stiber et al. 2004).

1.3.3. Fuzzy analytic hierarchy process

Analytic hierarchy process (AHP) is extensively used as a relative weight estimation technique in many areas (Vaidya and Kumar 2006). AHP has the additional advantage of being easy to explain to the experts who need assess the different alternatives in a systematic way (Aragones-Beltran et al. 2009). However, AHP involves human subjective evaluation that necessitates the use of decision making under uncertainty. Due to the complexity and uncertainty involved in real world, it is sometimes unrealistic or even impossible to require exact judgments. Experts usually find that it is more confident to give interval judgments than fixed value judgments (Kahraman et al. 2003).

Inability of AHP to deal with the imprecision and subjective in the pair-wise comparison process has been improved by fuzzy AHP. Fuzzy AHP, which is an extension of AHP, is a useful tool for calculating the priority weight. Fuzzy AHP allowed experts to use linguistic expressions or fuzzy numbers to reflect the vagueness of human thought (Kahraman et al. 2009). There are many fuzzy AHP methods, among which the newest modified fuzzy logarithmic least squares method is adopted in this dissertation.

1.3.4. Markov Chain

Markov chain is about a sequence of random variables which corresponded to the states of a certain system. In such a sequence, the state at one time period depends only on the one in the previous time period (Ching and Ng 2006).

Consider a system (S) with m possible states, represented by the set $I = \{1,2,\dots,m\}$. Let the system S evolves randomly in discrete time ($t = 0,1,2,\dots,n,\dots$), and let J_n representing the state of the system S at time n. Then, from Janssen and Manca (2006):

- The random sequence $(J_n,\ n \in N)$ is a Markov chain if and only if for all $j_0, j_1, \dots, j_n \in I$,

$$P(J_n = j_n | J_0 = j_0, J_1 = j_1, \dots, J_{n-1} = j_{n-1}) = P(J_n = j_n | J_{n-1} = j_{n-1}) \quad (1\text{-}1)$$

A Markov chain $(J_n,\ n \geq 0)$ is homogeneous if and only if the above probabilities do not depend on *n* and is non-homogeneous in the other cases.

For more details about Markov chain, Markov process, and Markov models, one can refer to Janssen and Manca (2006) and Ross (2010).

1.3.5. Markov chain Monte Carlo simulation

Origination of Markov Chain Monte Carlo (MCMC) was in statistical physics, but has been applied in many areas, corresponded to a variety of techniques and methods (Kendall et al. 2005). MCMC refers to the utilization of Markov chains for random sampling and approximating the number of states. In other words, MCMC simulation is an algorithmic procedure for sampling from a statistical distribution. As a result of MCMC sampling, the sequence of points in the parameter space reconstructs the target distribution (Aver 2012).

The underlying principle in MCMC simulation is:

1) Write a computer program to simulate the Markov chain to sample randomly from a specific probability distribution,
2) Design a Markov chain whose long-time equilibrium is that distribution,
3) Run the programmed chain for a time long enough to be confident that approximate equilibrium has been attained,
4) Finally, record the state of the Markov chain as an approximate draw from equilibrium.

1.3.6. Genetic algorithm

An evolutionary algorithm is a stochastic process that operates iteratively on a set of individuals called population. Each individual is a potential solution candidate of the problem. Among the evolutionary algorithms, the genetic algorithm (GA) is the most extended applied method that relies on the use of a selection, crossover and mutation operators (Fogel 1998).

Holland (1992) described how to apply the principles of natural evolution to optimization problems and built the first genetic algorithms in the year 1975.

Figure 1-1 shows the process of simple GA in a flowchart. GA starts with a population of possible solutions. Each solution is represented through a chromosome. . Each chromosome has an associated value corresponding to the fitness of the solution it represents. Selection is done by using a fitness function or cost function that corresponds to an evaluation of how good the candidate solution is. The optimal solution is the one, which maximizes the fitness function or minimizes the cost function.

The initial population is generated randomly. Then, the genetic algorithm loops over an iteration process to make the population evolve. Each iteration process consists of the following steps (Sivanandam and Deepa 2008):

- Selection: Selecting individuals is done randomly with a probability depending on the relative fitness of the individuals so that best ones are often chosen for reproduction.
- Reproduction: New solution (offspring) is bred by the selected individuals. For generating new chromosomes, the algorithm can use both crossover and mutation. The crossover produces an offspring from a randomly selected pair of parent solutions, facilitates the inheritance of basic properties from the parents by the offspring. Mutation results in slight changes to the offspring's structure (position in the chromosome), and maintains a diversity of solutions.

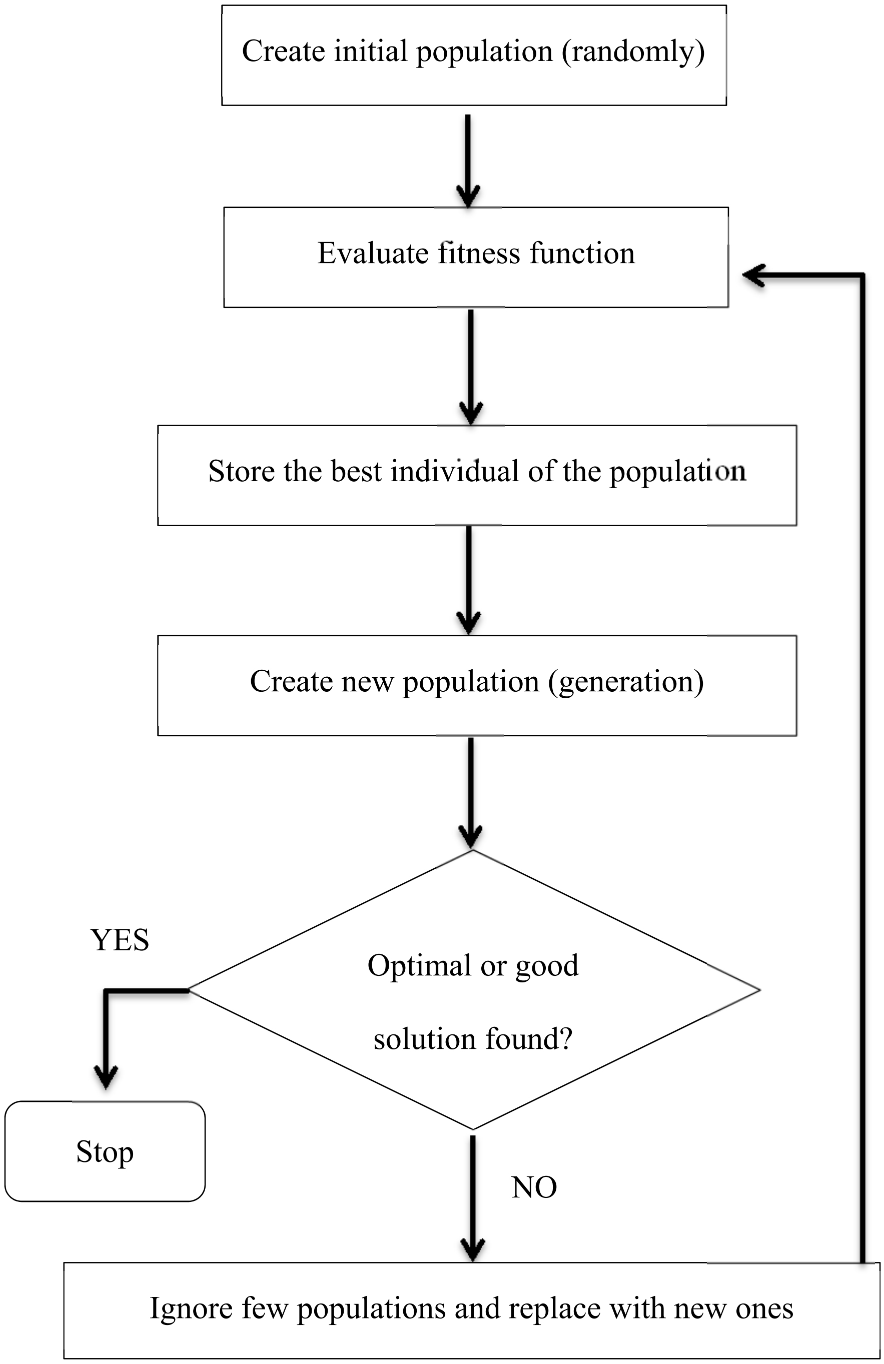

Figure 1-1. Flowchart of genetic algorithm

- Evaluation: The fitness of the new chromosomes is evaluated.
- Replacement: Individuals from the old population are ignored and replaced by the new ones.

The algorithm is stopped when the population converges toward the optimal solution.

1.4. Research scope and organization

The purpose of this thesis is to study human and organizational factors (HOF) in marine transportation and model accident risk, reliability, and design in this field for different kinds of marine transportation systems. The structure of this thesis is illustrated by the flowchart in Figure 1-2.

Chapter 2 provides a brief literature review on different methods and models on HOF investigation, accident risk analysis, availability/reliability assessment, and design of marine transportation systems. In addition, the research gap and contribution of the dissertation is included in this chapter. From chapter 3 to 6 the main works related to accident analysis, risk and availability of marine transportation systems are presented. In chapter 3, a quantitative accident analysis model is presented to assess the contribution of Human and Organizational Factors (HOFs) in marine accidents. The analysis is done by integrating Human Factor Analysis and Classification System (HFACS) and Bayesian Network (BN) with fuzzy AHP. This application model exploits the advantages of existing methods and modifies them. As an approach to compensate the lack of quantitative analysis within HFACS, the integration of BN and fuzzy AHP is selected to estimate quantitatively the contribution of HOFs to accidents. At the same time, the 4-level structure of HFACS provides a systematic guideline for the construction of BN to model how HOFs are related to form a network.

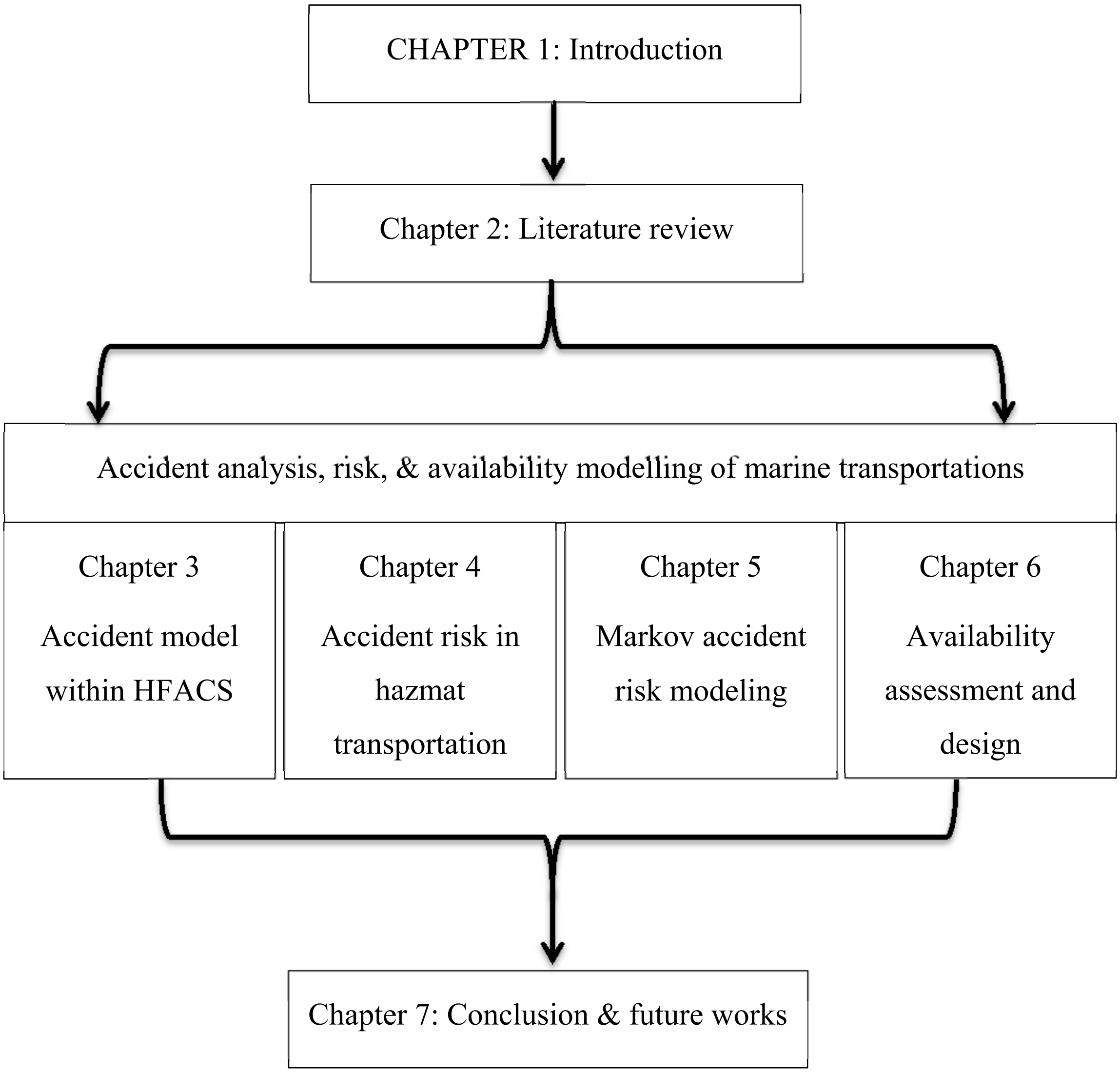

Figure 1-2. The structure of this thesis

The case studies of chapter 3 are related to the accidents which lead to spread toxic vapors as a kind of hazardous materials (hazmat). These case studies encouraged the author to consider the risk of hazmat for optimizing hazmat transportation in different waterways. Thereupon, in chapter 4, a bi-objective optimization model for transportation of hazardous materials is proposed. It is intended to determine the number of container ships for transmitting hazmat or regular freight from origins to destinations in different itineraries. The expected risk evaluated in this problem is based on the water area exposed by hazmat containers during shipment in the routes (waterways).

The optimization model in chapter 4 proposes an accident risk function which depends only on sea pollution factors. Also, the quantitative model proposed in chapter 3 is particular and basically dependent on a specific safety factor, HOF. Therefore, the lack of a general accident risk model which would be applicable for all types of marine accidents is understandable. In this regard, proposing a general quantitative model for accident analysis and risk modeling of marine transportation systems becomes a necessity and purpose in this thesis. With this purpose, in chapter 5, a new analytic approach of accident risk modeling is presented with an application example in marine transportation. The approach is based on Markov modeling and Markov Chain Monte Carlo (MCMC) simulation. In this model, a simple homogeneous continuous time Markov chain is used to record and estimate many marine occurrence rates and probabilities. The MCMC simulation only requires the occurrence data of three-state Markov model to estimate the accident risk and can be used when only a limited amount of information is available.

During accident analysis and risk modeling in previous chapters, the different state-based structure of the systems draws our attention to analyze accident risk and assess availability for multi-state marine transportation systems. Therefore, in chapter 6, a dynamic model is developed for the availability assessment of a most common type of marine transportation systems called multi-state *K*-out-of-*N* systems. Regarding the dynamic property of the system and its components, the problem of optimal design of the components is solved by using Genetic algorithm. In the dynamic model, the probabilities and utilities of components in different states are allowed to be changed over time. For availability assessment, universal generating function and Markov process are adopted. The application of the proposed model is illustrated using a real-world marine transportation system in order to evaluate and compare them in assessing system availability. Finally, chapter 7 makes related conclusions from each of the four but integrated works of this thesis. It also discusses the limitations of the works contained in this dissertation and suggests some directions and potential works for future research.

CHAPTER 2: LITERATURE REVIEW

Marine transportation is subjected to many regulations due to the risk, environmental/ human cost of marine accidents and the importance of safe and efficient operation of ships (Kristiansen 2005). Beside of the regulations which are agreed at the International Maritime Organization (IMO), analyzing the safety factors and accident risk of marine transportation systems are necessary for increasing the safety and prevention of critical accidents. This chapter is the review of marine accident models that covers four aspects:

- Human and Organizational Factor (HOF) as a safety factor in marine accidents
- Hazardous material (hazmat) transportation
- Quantitative accident risk analysis of marine transportation
- Multi-state marine transportation systems and availability/reliability assessment

Various key research gaps are identified and noted in the literature that helps to understand the contribution of this thesis. At the end of this chapter, the research gaps are pinpointed again.

2.1. Models on HOF investigation in marine accidents

Many models have been established that discuss HOF in accidents, e.g. Reason's Swiss Cheese Model, Human Factors Analysis and Classification System (HFACS), Classifications of Socio-Technical Systems involved in safety control, Systems-Theoretic Accident Model and Processes (Rao 2007). An inductive reasoning approach is employed to develop an Aviation System Risk Model (ASRM) to build probabilistic causal models representing the safety risk involved in aviation accidents (Oztekin and Luxhoj 2010). ASRM model is based on revised HFACS and reflects the failure/error levels imposed by HFACS taxonomy (Reason 1995).

A set of principles for organizational safety risk analysis are proposed to integrate the technical risk analysis models with social aspects of safety prediction models (Mohaghegh and Mosleh 2009). Based on these principles, probabilistic risk assessment model is extended to include the effects of organizational factors as the fundamental causes of accidents (Mohaghegh et al. 2009). Mohaghegh and Mosleh (2009) propose organizational safety causal analysis model and present a Bayesian approach to operate the multi-dimensional measurements. An organizational factor framework is developed for the quantification of the impact of organizational factor on risk, which also chooses Bayesian Network (BN) as a quantitative modeling technique based on an element-by-element evaluation of the existing framework (Oien 2001). However, this model is attributed to specific leak events without using extensive resources and does not focus on the risk-reducing measures. The Human Factors Investigation Tool and Curtailing

Accidents by Managing Social Capital are recognized as relatively new tools built based on the HFACS model (Gordon et al. 2005; Rao 2007).

HFACS model can be integrated with BN, which is capable of providing quantitative interrelationships as well as calculating numerical values of occurrence probability (Ren, Jenkinson et al. 2008). The earliest research in the integration of HFACS with BN appeared in Luxhoj and Coit (2006), which construct BBN model utilizing the HFACS taxonomy as a basis. Lu (2010) also establishes the causal relationships of accidents by using BN from the perspective of HOFs and tries to apply the fuzzy semantics and the integral value method to quantify the conditional probability table (CPT) of basic events. However, the expert elicitations of CPT and quantitative inference of BN may not be enough. In order to modify the deficiency of their work, fuzzy analytical hierarchy process (AHP) method and decomposition method are adopted in this work to compensate uncertainty and vagueness in the experts' judgment of BN. With regards to the elicitation of CPT in BN, it is worthwhile to note that reliable HOF data are generally absent (Grabowski et al. 2009). In such situations, CPT can be elicited using judgments from domain experts. However, experts may find it difficult to come up with precise probability values for the relationships between nodes (Chen et al. 2007). Since BN is an effective tool for updating prior probabilities and fuzzy set theory is a useful tool for analyzing subjective information, the two theories can be combined for the updates of prior probabilities and the calculation of posterior probabilities (Blair et al. 2001). Fuzzy AHP can tackle fuzziness and uncertainty of vague decision-making more efficiently using fuzzy sets, membership functions, and fuzzy numbers (Lee et al. 2008).

There are many fuzzy AHP methods and applications in literatures. The earliest work is that a fuzzy logarithmic least squares method (LLSM) is suggested to obtain relative weights from a triangular fuzzy comparison matrix (Van Laarhoven and Pedrycz 1983). A constrained nonlinear optimization model is later proposed to modify the fuzzy LLSM (Wang et al. 2006). An extent analysis method, which has been employed in a number of applications due to its computational simplicity, is introduced by Chang (1996). However, such a method is found unable to derive the true weights from a fuzzy comparison matrix. It is improved by modifying the fuzzy LLSM, which can directly derive normalized triangular fuzzy weights for both complete and incomplete triangular fuzzy comparison matrices (Wang et al. 2008). In another study, fuzzy AHP is combined with HFACS to prioritize the list of HOFs involved in an accident (Celik and Cebi 2009). Fuzzy AHP and Fuzzy Data Envelopment Analysis are applied to calculate the relative fuzzy weight, which is integrated with BN to create the risk evaluation models (Chiang and Che 2010). From above literature reviews, we can see that the fuzzy AHP method is an ideal tool for relative weights elicitation, which can be used to elicit the CPT of BN.

2.2. Models and problems on hazardous material transportation

The risk involved in hazmat transportation has generally been analyzed in the literature from the perspective of potential or future occurrences of release incidents (Diaz-Banez, Gomez et al. 2005; Clark and Besterfield-Sacre 2009). Up to now, most of the studies on risk optimization of hazardous material transportations are related to hazmat transportations in roads or railways. Sometimes the problems are called hazmat network design, sometimes multi objective hazmat routing or scheduling problems. Whatever the titles of the works are, two aspects are considered in the problems: minimum risks and less costs (Zhang et al. 2012).

Many methods are introduced for the selection of best routes in transportation of hazmat based on risk analysis (Leonelli et al. 2000; Kheirkhah et al. 2009; Saat and Barkan 2011). In some papers, constraints related to hazmat transportation are considered for a kind of vehicle routing problem with time windows (Meng et al. 2005; Pradhananga et al. 2010).The determination of hazardous materials distribution routes can be defined as a bi-objective vehicle routing problem since risk minimization accompanies the cost minimization in the objective function. Carotenuto et al. (2007) found the minimum and equitable risk routes for hazmat shipments. Erkut and Gzara (2008); Bianco et al. (2009) considered a bi-level flow model and a heuristic algorithm for hazmat transportation network design problem. In their work, a set of hazmat shipments has to be shipped over a road transportation network in order to transport a given amount of hazardous materials from specific origin points to specific destination points. Verma (2009) developed an optimization model, where cost is determined based on the characteristics of railroad industry and the determination of transport risk incorporates the dynamics of railroad accident. From the review of recent problems, it becomes clear that accident risk definition and determination in hazmat transportation is recently under the interest of many researches and still it can be investigated in different aspects.

2.3. Quantitative marine Accident risk models

Recently, modeling and quantifying risk and reliability is regarded as one of the most important research topics in transportation (Sun et al. 2012). The existing risk analysis literature in maritime systems mainly focuses on probabilistic risk analysis arguments, simulation modeling, and statistical analysis of data (Uluscu et al. 2009). Early works concentrated on assessing the risk of individual vessels or marine structures, but recently, probabilistic risk assessment has been introduced in the assessment of risk in the maritime domain (Merrick and van Dorp 2006).

Li, Meng et al. (2012) had an overview on maritime quantitative risk assessment studies. Many of these studies have been done to investigate the associations between marine accident risks and the effective safety factors. In this area, Wang et al. (2002) reviewed some of the published works on assessing ship damage and oil outflow after collision and grounding. Pedersen (2010) published a literature review on estimating the frequency and consequences of collision and grounding accidents. Wang, Roohi et al. (2011) presented a quantitative accident analysis model to assess the contribution of human organizational factors in accidents. Yip (2008) used regression method for accident risk modeling in Honk Kong waters. Kujala, Hanninen et al. (2009) modeled marine risk using ship traffic data and defined risk for one type of marine accidents, collision. In the model, accident probability equals to collision probability. Commonly, many factors were involved in these studies such as accident count, vessel count, weather conditions, size of the vessels, and season. Attwood, Khan et al. (2006) developed a model to predict the frequency of accidents in the offshore oil and gas industry. Aven, Sklet et al. (2006), similarly, designed a model which included many input factors for risk modeling. Toffoli, Lefevre et al. (2005) analyzed the accident risk based on sea state parameters, such as wave heights and periods. Fowler and Sorgard (2000) developed a quantitative risk model called MARCS (Marine Accident Risk Calculation System) based on fault tree analysis.

2.4. Availability/reliability modeling of marine multi-state systems

A multi-state system may have a basic architecture such as series, parallel, *K*-out-of-*N*, and network. The *K*-out-of-*N* structure is a very popular structure of the multi-state systems with wide application and research works (Yam et al. 2003; Lia et al. 2006; Tian et al. 2009) . Multi-state weighted *K*-out-of-*N* system is a generation of multi-state *K*-out-of-*N* system and it has wide spread applications such as in traffic systems, telecommunication networks, and satellites (Li and Zuo 2008a). As is clear from its name, weighted multi-state systems are composed of multi-state components which have different performance levels and several failure modes. Due to the importance and wide application of multi-state systems, many research works have been devoted to model the availability/reliability of these systems. In General, there are four approaches of modeling:

1) The stochastic process approach

Xue and Yang (1995) analyzed the reliability of the coherent multi-state systems by combining a Markov model and the structure function of the system. Zhang et al.

(2002) formed a replacement policy model for multi-state systems with stochastic deterioration process. Lanus et al. (2003) partitioned complex Markov models into a hierarchy of sub-models and applied for multi-state telecommunication systems. Later, Li et al. (2005) calculate the system reliability again by Markov process, but this time, the state sequences of all components were collected periodically, and this information was used to predict the reliability of the components in several periods.

2) The universal generating function approach

The Universal Generating Function (UGF) was first introduced by Ushakov (1986). Later, it was commonly used for analyzing availability/reliability of different multi-state system structures such as series, parallel, series-parallel and bridge structure rather than multi-state *K*-out-of-*N* systems (Levitin 2003; Agarwal and Gupta 2007; Tian et al. 2009; Yeh 2009; Levitin 2011; Peng et al. 2012).

3) The Monte-Carlo simulation technique

Markov chain Monte Carlo simulation started in earnest by Metropolis et al. (1953). Since then, it has become an indispensable tool with applications in many branches of science (Kendall, Liang et al. 2005). Simulation approach is applicable for availability assessment of most of the multi-state systems. Zio and Podofillini (2003); Zio et al. (2004); Ramirez-Marquez and Coit (2005); Ramirez-Marquez et al. (2006); Zio et al. (2007) have presented a Monte-Carlo simulation approach to modeling multi-state system availability. The simulation approach is flexible to model the availability of the systems consist of parallel components with load-sharing and parallel components with operational dependencies. However, the main issue and problem in using this approach is the long-time taking and the expenses of simulation runs.

4) The recursive algorithm.

Huang et al. (2000) have provided a performance evaluation algorithm for calculating the state distribution of generalized multi-state *K*-out-of-*N* systems. However, their presented algorithm is enumerative in nature, and not efficient enough. Recursive algorithm is an efficient approach that has been introduced into the generalized multi-state *K*-out-of-*N* system availability field in the last few years (Tian et al. 2005; Zuo and Tian 2006). Zuo et al. (2007) studied the availability assessment of two terminal multi-state networks using a recursive algorithm. Tian et al. (2008) also developed a reliability bounding approach based on the recursive algorithm.

Liu and Kapur (2006) developed reliability measures and analyzed reliability for dynamic non-repairable multistate systems. In this dissertation, besides reliability analyses, we investigate the best design of a dynamic multi-state system in a case for each component some weights are assigned in different states. Li and Zuo (2008a) have done a study on reliability optimal design of multi-state weighted *K*-out-of-*N* systems for a non-dynamic model. In their work, the objective was to select the component choices to minimize the system cost subject to requirement on system availability.

2.5. Research gaps

According to the literature review of accident risk models, the following research gaps are identified and studied in this thesis:

- HFACS is a validated and reliable human error model (Wiegmann and Shappell 2001), which is utilized intensively in investigating accidents (Shappell, Detwiler et al. 2007; Olsen and Shorrock 2010). HFACS is selected for HOF analysis after the review of different HOF models. However, the reviewed literatures mainly focus on the construction of complicated conceptual model, whereas quantitative risk assessment is not enough. Adding quantification analysis to the qualitative HFACS model can enhance the accident investigation process. On the other hand, the review of many works indicated that although BN gives a sound and transparent approach to modeling marine operational risk, it cannot incorporate unobserved variables easily, owing to the fact that the size of the conditional probability table (CPT) for a child node can become quite large. Therefore, HFACS model can be integrated with BN, which is capable of providing quantitative interrelationships as well as calculating numerical values of occurrence probability (Ren, Jenkinson et al. 2008). Moreover, experts may find it difficult to come up with precise probability values for the relationships between nodes in BN (Chen, Lee et al. 2007). Since fuzzy set theory is a useful tool for analyzing subjective information, the two theories can be combined for the updates of prior probabilities and the calculation of posterior probabilities in BN.

- Majority of research on hazmat transportation focuses on road shipments (Erkut 2007), and mostly on route selection and scheduling problems for transferring the hazmat (Patel and Horowitz 1994; Dadkar et al. 2008; Verter and Kara 2008; Androutsopoulos and Zografos 2010; Caramia, Giordani et al. 2010). In these problems, the routes selected can be quite sensitive to the risk function defined. Most popular measure of the risk is the expected consequence of the accident (Guo and Verma 2010). But, this risk measure may not be appropriate to be used in route selection problems when hazmat container ship capacities are not considered as variables in the optimization. The reason is that the risk consequence such as pollution depends on the amount of hazmat to be transported and hazmat release rates. It is clearly understandable that the amount of hazmat and the number of hazmat containers may impact on the probability of hazmat accidents. When the number of hazmat vehicles is assumed constant in the routes, there would be no difference with the risk measured for rare hazmat released events and more probable hazmat vehicle accidents. As a result, in this thesis, we are not seeking for the best routes to transport hazmat, but we intend to find the optimal number of containers with different freights (hazmat and regular) to be moved in the preselected routes. A bi-objective optimization model is proposed to formulate the problem. Accident risk analysis models associated with the marine transportation of hazmat are mostly qualitative in nature. Another serious gap in the literature of hazmat transportation optimization problems is the estimation and assignment of accident risk and costs to the transportation links. The way of risk estimation to the links is a very important input for marine hazmat transportation models and problems.

- From the review on maritime quantitative risk assessment studies, there is a gap that many of these studies have been done to investigate the associations between marine accident risks and many specific safety factors. Mullai and Paulsson (2011) reviewed the current accident risk models for marine transportation systems. They concluded that there is no single model which would be capable of serving all types of systems, issues, and needs in marine industry at all times. Among all the recent studied models, only their model is applicable for any type of accident and ship. However, different types of data are required to be collected for each accident type. For example, for the collision frequency model, data on "visibility" is required, while for grounding frequency model, data on "ship drift speed" is needed in advance. Therefore, it is intended to propose a general accident risk model which would be applicable for all types of marine accidents and systems.

- In spite of vast reliability research, less attention was paid to the reliability-based structure of a marine transportation system, while the availability/reliability of marine transportation system is dependent upon the structure of the systems. Multi-state structure is commonly observed for marine transportation systems. Li and Zuo (2008b) reviewed the methods for availability or reliability assessment of multi-state systems, and applied the recursive algorithm for availability assessment of multi-state systems in a non-dynamic model. In light of our knowledge, most reliability/availability studies of multi-state system pre-assumed that the state probability of system/component does not change throughout system lifetime. However, complex systems are often subject to aging process which implies that the system/component state probability may gradually change with time (Kolowrocki and Kwiatuszewska-Sarnecka 2008). Therefore, it is of large practical value to model the state probability as a function of time.

CHAPTER 3: QUANTITATIVE MARINE ACCIDENT MODEL WITHIN HUMAN FACTOR ANALYSIS AND CLASSIFICATION SYSTEM

It has been widely recognized that Human and Organizational Factors (HOF) are leading causes of most accidents. A report of United States Coast Guard also points out that 75-96% of casualties are due to some forms of human errors (Rothblum 2000). In this aspect, it is emphasized that human factor is one of the most important contributory aspects to the causation and avoidance of accident. The prevalence of HOF in accidents warrants the need to incorporate HOF analysis in accident investigations, so that valuable measures to prevent similar accidents from recurring can be derived. Feedbacks and lessons learnt from accident analysis will provide help on improving safety climate and preventing accidents. Effectively preventing accidents requires the use of accident analysis models that include the effect of HOF (Leveson 2004).

In this chapter, a quantitative accident analysis model is proposed by integrating Human Factor Analysis and Classification System (HFACS) and Bayesian Network (BN) with fuzzy AHP to assess the contribution of HOFs in accidents. This application model exploits the advantages of each method and modifies the existing methods. As an approach to compensate the lack of quantitative analysis within HFACS, the integration of BN and fuzzy AHP is selected to estimate quantitatively the contribution of HOFs to accidents. At the same time, the 4-level structure of HFACS provides a systematic guideline for the construction of BN to model how HOFs are related to form a network.

The organization of this chapter is as follows. Section 3.1 presents a two-phase accident analysis model for the systematical assessment of HOFs in both qualitative and quantitative manner. In Section 3.2 and 3.3, two cases are analyzed to demonstrate the application of the model. Section 3.4 concludes the merits and drawbacks of the proposed model.

3.1. Two-phase accident analysis model

As reviewed in the chapter of Literature Review, many qualitative models have been established that discuss HOF in accidents (Reason 1995; Rao 2007; Shappell, Detwiler et al. 2007; Mohaghegh, Kazemi et al. 2009; Oztekin and Luxhoj 2010). But, to assess the contribution of HOFs in both qualitative and quantitative manner, a two-phase accident analysis model is proposed in this chapter.

In the first phase, concerning the qualitative analysis of accident, HFACS is used to investigate various HOFs causing accidents. The second phase of the proposed model is the quantitative analysis of the HOFs identified in the first phase. This quantification process is achieved by using BN. The two-phase accident analysis model is shown in Figure 3-1. The proposed model taps on the joint capabilities of HFACS and BN for the purpose of investigating HOFs in accidents.

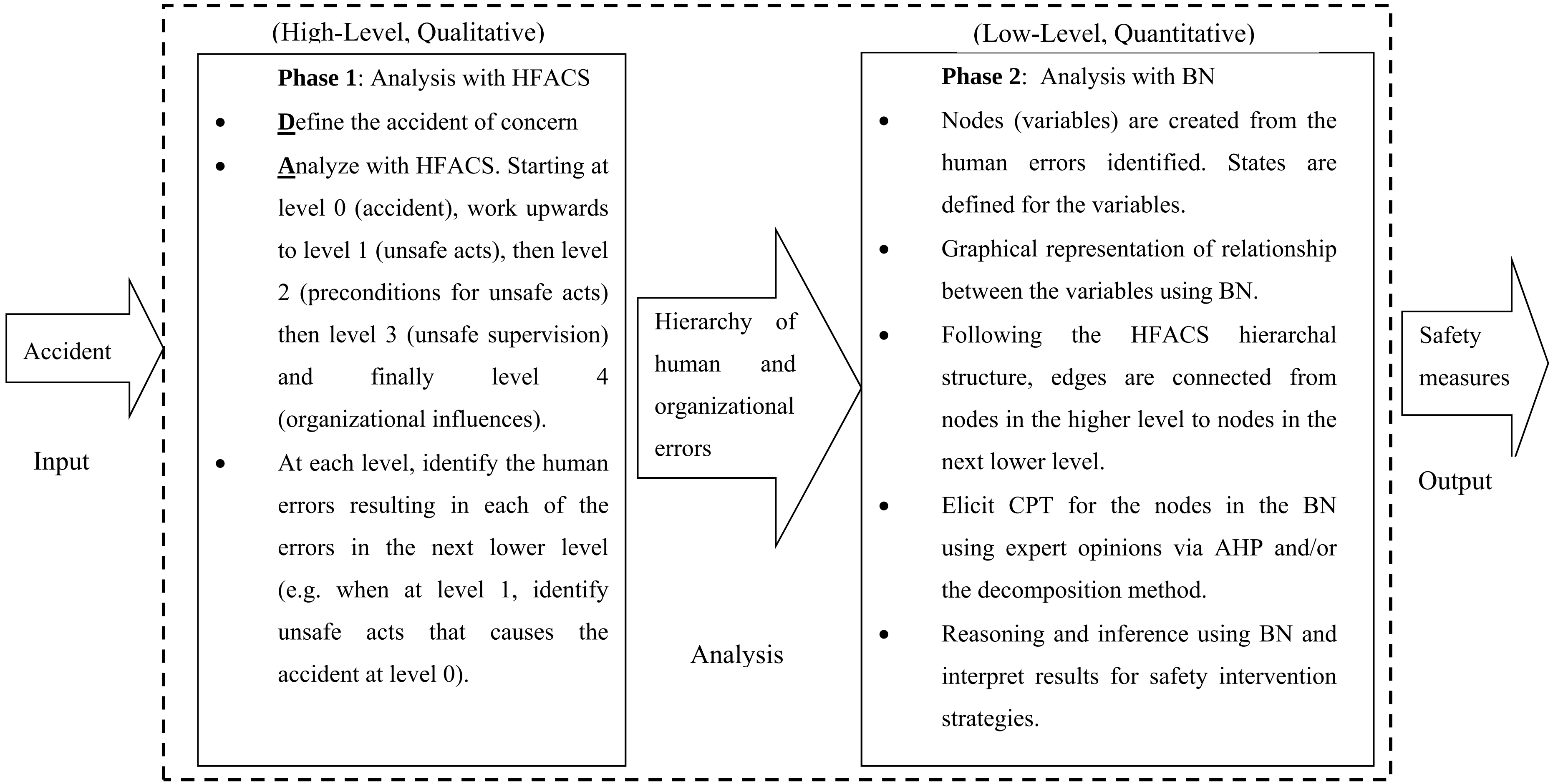

Figure 3-1. The proposed accident analysis framework

- Phase one is a qualitative analysis model of HOFs and their relationships. This phase utilizes HFACS to identify a hierarchy of HOFs causing accidents. The output of this phase provides the input for the second phase of the model.

- Phase two constructs a quantitative analysis model of the HOFs using BN. The CPTs of BN are elicited by integrating fuzzy AHP with a decomposition method to quantify the degree of relationships among HOFs. And then, BN inferences are performed to prioritize the importance of HOFs identified in the first Phase.

3.1.1. 6-Step accident analysis model

The model is made up of 6 steps including: “Define”, “Analyze”, “Node”, “Graphic”, “Elicit” and “Reasoning” that briefly called “DANGER”. Here, each step is explained in details:

- Define. This step is to clearly define accidents. The scope of accidents and conditions under which the accidents occur should be clearly stated. A statement describing the accident should be produced. For instance, “collision between a ship and shuttle tanker at night under poor visibility” states the accident of concern (ship and shuttle tank collision) and the conditions (night time, poor visibility).

- Analyze. This step utilizes HFACS to identify various HOFs, ranging from active errors of operators to latent errors in organization. In general, HFACS has a four-level hierarchical structure. Level 1, which is the "unsafe acts" level, consists of active errors by the operators. Errors in this layer directly lead to the accident, and thus are the most visible to investigators. With the "unsafe acts" errors listed in level 1, experts can proceed to investigate the "preconditions for unsafe acts" errors in level 2 that influences the HOFs of level 1. After level 2 is completed, level 3 "unsafe supervision" can be identified with final leading to level 4 "organizational influence". Therefore, beginning investigations at level 1 allows a progressive probing of the HOFs at higher levels. This process pushes investigators to address latent failures at higher levels of the HFACS model, which tend to be overlooked in accident analysis. The output of this step is a 4-level hierarchy of HOFs. Utilizing HFACS effectively requires understanding the definitions of different type of HOFs at each level.

- Nodes. This step converts the hierarchy of HOFs identified in step 2 into a hierarchy of variables (nodes). Thereafter, states are defined for the nodes to indicate various values the variables can take. For instance, a HOF can be converted to a variable with 2 states ("yes" and "no"). A 3-state variable ("high", "medium" and "low") is also possible depending on the required depth of the accident analysis.

- Graphic. With a hierarchy of nodes and states defined, a BN representing the relationships among HOFs can be constructed. The relationships depicted in HFACS will be mapped onto a BN via its graphical representation with edge-connecting nodes. In this step, the BN is systematically constructed according to the hierarchal structure of HFACS.

- Elicit. With the graphical structure of BN, this step is eliciting CPT for all the nodes. In the elicitation procedure, the relative priority weights are derived using fuzzy AHP. Fuzzy AHP is an extension of the traditional AHP methodology that incorporates fuzzy comparison ratios $\tilde{c}_{ij}$. With such pair-wise comparisons, fuzzy AHP is effectively utilized to convert linguistic variables to probability values. For example, to determine the probability of one node at states $S_1, S_2,$ and S_3 precise values need to be given for the conditional probabilities in AHP, which are more difficult for experts to estimate. Instead, in fuzzy AHP, it is easier to give linguistic evaluation scale of pair-wise comparisons by questions such as "comparing states S_i and S_j, which one is more probable to occur and how much more?" In addition, it is noted that as the number of parent nodes grows, the elicitation process may become complicated. In this work, the decomposition method that allows domain experts to elicit CPT by considering each parent node separately is applied to reduce this complexity. Details about using fuzzy AHP and decomposition method for CPT elicitation are elaborated in Section 3.1.2.

- Reasoning. The last step of the model is BN inference from which safety intervention strategies can be derived. After all the CPTs are elicited, the quantitative analysis can be performed via Bayesian inference. The type of Bayesian inference depends on the specific goals of each accident analysis. For example, the probability of accident can be calculated if the prior probability of HOFs is known. The relative contribution of HOFs to the accident can also be investigated, which is indicated by the posterior conditional probability of each node. Finally, with these quantitative results, safety intervention measures can be suggested to prevent the accident reoccurring.

3.1.2. CPT elicitation by integrating fuzzy AHP with a decomposition method

CPT elicitation has been known to be a complicated issue due to the large number of judgments required to fully quantify the relationships in the BN. For a binary node with n parents, 2^n conditional probabilities are required. The lack of data related with HOFs prompts for CPT elicitation via expert judgments. However, expert's judgments are subjected to biases (Fox and Clemen 2005), especially when encountering a large BN. The integration of AHP and a decomposition method can reduce subjective biases and help domain experts to elicit the CPT in an efficient manner (Chin et al. 2009). However, the conventional AHP may not be able to truly reflect human cognitive processes, especially for the situation when it is difficult for experts to estimate the precise values. In these cases, fuzzy AHP enables domain experts to avoid giving precise probability for the CPTs. Instead they give triangular fuzzy number to perform pair-wise comparisons of the states according to their relative occurrence probability (Haghighi et al. 2010). This section gives an illustration on how to integrate fuzzy AHP with a decomposition method for the elicitation of CPT. Three types of nodes are considered:

- A node without parents:

Suppose a node X has k states $(S_1, S_2, \ldots, S_k)$ without parents. To elicit prior probabilities for each state of X, it is required to determine $w = [w_1, w_2, \ldots, w_s, \ldots, w_k]$, where w_s is the probability of X at state S_s. Traditionally, w_s is specified directly by experts, using their knowledge and experiences. When the number of states is small, such a method may be efficient. With the increase of states, simultaneously estimating probabilities of all the states inevitably involve inaccuracies.

An alternative way is using triangular fuzzy number to perform pair-wise comparisons between states for generating their probabilities. Because there are only two instead of multiple states considered simultaneously in a pair-wise comparison, it should be much easier to provide fuzzy linguistic scale of comparison than the direct estimation of probabilities. Fuzzy AHP is also a useful tool for dealing with uncertainties (Paralikas and Lygeros 2005). The prior probability of each state can be determined by the following pair-wise comparison matrix (Hsieh et al. 2004):

$$A = \begin{pmatrix} 1 & \cdots & \tilde{c}_{1k} \\ \vdots & \ddots & \vdots \\ \tilde{c}_{k1} & \cdots & 1 \end{pmatrix} \tag{3-1}$$

where $\tilde{c}_{ij}$ is a triangular fuzzy number to show the probability comparison of S_i over S_j:

$$\tilde{c}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \tag{3-2}$$

$\tilde{c}_{ij}$ is a fuzzy linguistic scale that is specified by asking domain experts questions like "comparing states S_i and S_j, which one is more likely to occur and how much more?" Domain experts answer these questions using the fuzzy linguistic scale provided in Table 3.1 (Abdel-Kader and Dugdale 2001).

If there is more than one expert, the following equation can be used to aggregate the opinions of the experts:

$$\tilde{c}_{ij} = \frac{1}{n}\left(\tilde{c}_{ij}^{1} + \tilde{c}_{ij}^{2} + \cdots + \tilde{c}_{ij}^{n}\right) \tag{3-3}$$

where n is the number of experts.

Perform the fuzzy addition operation of $\sum_{j=1}^{k} \tilde{c}_i^j \; (i = 1,2,\ldots,k)$ like that:

$$R_i = \sum_{j=1}^{k} \tilde{c}_i^j = \left(\sum_{i=1}^{k} l_i^j, \sum_{i=1}^{k} m_i^j, \sum_{i=1}^{k} u_i^j\right) \tag{3-4}$$

Table 3.1. Fuzzy scale in AHP

Linguistic scales	Triangular fuzzy scale	Triangular fuzzy reciprocal scale
Just equal	(1, 1, 1)	(1, 1, 1)
Equally probable	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly probable	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more probable	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more probable	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more probable	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

The value of fuzzy synthetic extent with respect to ith object is defined as (Celik and Cebi 2009):

$$S_i = \left(\frac{\sum_{j=1}^{n} l_{ij}}{\sum_{j=1}^{n} l_{ij} + \sum_{k=1,k\neq i}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{j=1}^{n} u_{ij} + \sum_{k=1,k\neq 1}^{n} \sum_{j=1}^{n} l_{kj}} \right) \quad (3\text{-}5)$$

If A is a perfectly consistent comparison matrix, fuzzy weight vector can be precisely characterized by $w' = (S_1, S_2, \dots, S_n)^T$. Otherwise, the weight vectors of A can be derived through the solution of the following constrained nonlinear optimization model (Lee, Mogi et al. 2008):

$$\begin{aligned} \min j = \sum_{i=1}^{n} \sum_{j=1}^{n} \Big(& \left(\ln w_i^L - \ln w_j^U - \ln l_{ij} \right)^2 \\ & + \left(\ln w_i^M - \ln w_j^M - \ln m_{ij} \right)^2 \\ & + \left(\ln w_i^U - \ln w_j^L - \ln u_{ij} \right)^2 \Big) \end{aligned} \quad (3\text{-}6)$$

$$s.t. \begin{cases} w_i^L + \sum_{j=1, j\neq 1}^{n} w_j^U \geq 1, \\ w_i^U + \sum_{j=1, j\neq 1}^{n} w_j^L \geq 1, \\ \sum_{i=1}^{n} w_i^M = 1, \\ \sum_{i=1}^{n} \left(w_i^L + w_i^U \right) = 2, \\ 0 < w_i^L \leq w_i^M \leq w_i^U. \end{cases} \quad (3\text{-}7)$$

The model is solved using GAMS program. The optimum solution to the above model forms normalized fuzzy weights:

$$w = \left(w_i^L, w_i^M, w_i^U\right) \quad i = 1,2,\dots,n \tag{3-8}$$

The fuzzy weight vector is a fuzzy number. Therefore, it is necessary to employ a non-fuzzy ranking method for fuzzy numbers to compare the states. In other words, the procedure of de-fuzzification should be done to locate the Best Non-fuzzy Performance (*BNP*) value. Such related common methods include mean of maximal, center of area (*COA*) and α-cut. Among these methods, utilizing *COA* method to find out *BNP* is simpler and more practical. Also, there is no need to bring in the preferences of any evaluators, so it is used in this study. The *BNP* value of the fuzzy number w_i can be found by the following equation:

$$BNP_{wi} = \frac{\left[\left(w_i^U - w_i^L\right) - \left(w_i^M - w_i^L\right)\right]}{3} + w_i^L \qquad \forall i = 1,\dots,n. \tag{3-9}$$

The normalized weight BNP_{wi} is the prior probability of the ith state of node *X*.

- A node with one parent:

Suppose a node *X* has k states $(S_1, S_2, \dots, S_k)$ and one parent T (with m states $t_1, t_2, \dots, t_m$). Let $w_p = \left[w_{p1}, w_{p2}, \dots, w_{pk}\right]$, where w_{ps} is the probability of *X* at state *S* given parent *T* at state $p(p = 1,2,\dots,m \; and \; s = 1,2,\dots,k)$. When node *T* is at state t_p, the corresponding comparison matrix is shown in Table 3.2. After $w_{ps} = (S = 1,2,\dots,k)$ is computed, $P\left(X = S_s | T = t_p\right) = w_{ps}$ can be set.

Table 3.2. Corresponding comparison matrix of $P(X = S_s | T = t_p)$

T is at state p	S_1	S_2	...	S_k	w_p
S_1	$\tilde{c}_{11}$	$\tilde{c}_{21}$	...	$\tilde{c}_{1k}$	w_{p1}
S_2	$\tilde{c}_{21}$	$\tilde{c}_{22}$	...	$\tilde{c}_{2k}$	w_{p2}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
S_k	$\tilde{c}_{k1}$	$\tilde{c}_{k2}$	...	$\tilde{c}_{kk}$	w_{pk}

Since node T has m states, m pair-wise comparison matrices for each state of T should be constructed.

For each matrix, the question "if node T is at state t_p, comparing states S_i and S_j of X, which one is more likely to occur?" will be evaluated to specify $\tilde{c}_{ij}$. And then the m pair-wise comparisons can be solved individually just similar to the computation of prior probabilities for a node with no parents. All the m vectors w_p (as shown in Table 3.3) will be calculated, which are the elements of the CPT for the node X with one parent T.

Table 3.3. Conditional probability table for the node X with one parent T.

		State of node T			
		t_1	t_2	...	t_m
State of node X	S_1	w_{11}	w_{21}	...	w_{m1}
	S_2	w_{12}	w_{22}	...	w_{m2}
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	
	S_k	w_{1k}	w_{2k}	...	w_{mk}

- A node with multiple parents:

Suppose a node X has k states $(S_1, S_2, \dots, S_k)$ and n parents $T^{(1)}, T^{(2)}, \dots, T^{(j)}$, $\dots, T^{(n)}$. The node $T^{(j)}$ has the states of ${T^{(j)}}_1$, ${T^{(j)}}_2, \dots, {T^{(j)}}_{t_j}$ (t_j is the state number of node $T^{(j)}; j = 1, \dots, n$).

It will be difficult for experts to directly estimate the probability of each state of X conditional on the combination of the states of its parents, which is defined by the following equation:

$$P\left(X = S_i | T^{(1)} = T^{(1)}_{p_j}, T^{(2)} = T^{(2)}_{p_j}, \dots, T^{(n)} = T^{(n)}_{p_j}\right)$$
$$(i = 1,2, \dots, k; p_j = 1,2, \dots, t_j; j = 1,2, \dots, n) \tag{3-10}$$

When a node A in a Bayesian Network has two parents B and C, its probability conditional on B and C can be approximated by:

$$P(A|B,C) = \alpha P(A|B)P(A|C) \tag{3-11}$$

where α is a normalizing constant to ensure that $\sum_{a \in A} P(a|B,C) = 1$.

According to Eq. (3-11), Eq. (3-10) can be simplified as:

$$P\left(X = S_i | T^{(1)} = T^{(1)}_{p_j}, T^{(2)} = T^{(2)}_{p_j}, \dots, T^{(n)} = T^{(n)}_{p_j}\right) = \alpha \prod_{j=1}^{n} P\left(X = S_i | T^{(j)} = T^{(j)}_{p_j}\right) \tag{3-12}$$

$$\left(i = 1,2, \dots, k; p_j = 1,2, \dots, t_j; j = 1,2, \dots, n\right)$$

where α is a normalizing constant to ensure that:

$$\sum_{i=1}^{k} P\left(X = S_i | T^{(1)} = T_{p_j}^{(1)}, T^{(2)} = T_{p_j}^{(2)}, \ldots, T^{(n)} = T_{p_j}^{(n)}\right) = 1 \tag{3-13}$$

In cases for nodes with multiple parents as shown in Figure 3-2, the decomposition method greatly simplifies the CPT elicitation by allowing conditioning to be done on each parent separately.

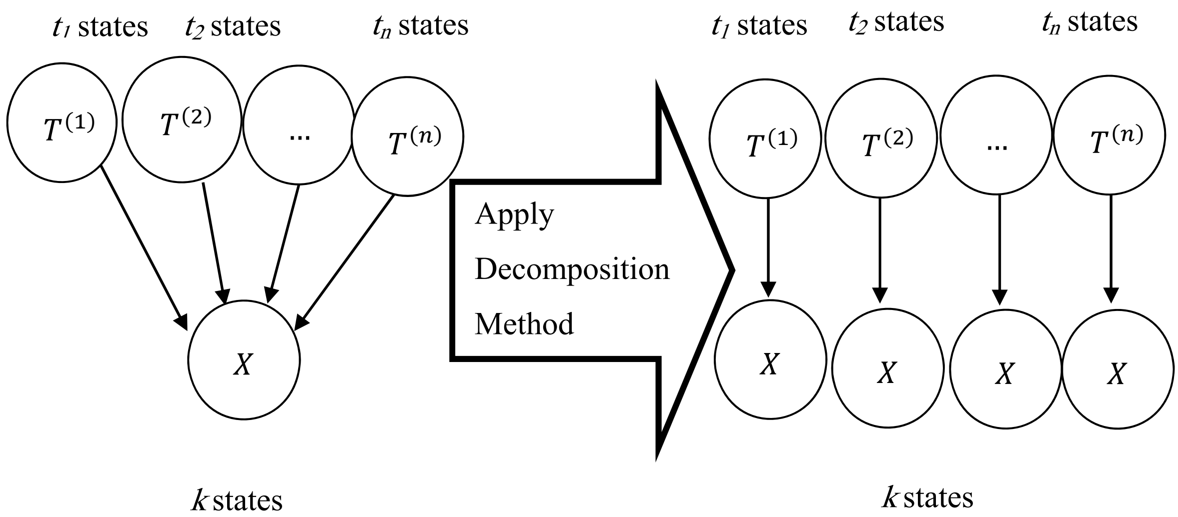

Figure 3-2. Decomposition method of conditional probability calculation

3.1.3. Validation using sensitivity analysis

When a new model is proposed, validation is required to ensure its soundness. This is especially important when subjective estimation is involved in the model (Yang et al. 2008). There are several well-accepted validation methods available. In this thesis, a sensitivity analysis for partial validation of the proposed model is adopted. The following three axioms should be satisfied (Jones et al. 2010).

Axiom1. A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the posterior probabilities of child nodes.

Axiom2. Given the variation of subjective probability distributions of each parent node, its influence magnitude to child node values should keep consistent.

Axiom3. The total influence magnitudes of the combination of the probability variations from x attributes on the values should be always greater than the one from the set of $x–y$ $(y \in x)$ attributes.

3.2. Case study 1: Release of toxic vapors from a chemical tanker

Jo Eik, a chemical tanker completed a ship-to-ship transfer at Vopak Terminal Tessiside on 6 May 2009 (Marine-accident-investigation-branch 2009). Following the end of ship-to-ship transfer, Jo Eik carried out mandatory pre-wash using portable washing equipment because the majority of the fixed washing systems were defective. The water supply hose of washing machine crossed through cargo tank inboard Butterworth hatch (an opening on the deck of a vessel opened when cleaning or ventilating the tanks), which remained open. As the cargo tank was washed, water mist containing cargo vapors escaped through the open hatch as the tank’s atmosphere was agitated. The vapors accumulated around the Butterworth hatch in which was an unidentified enclosed space. After the final pre-wash of the cargo tanks, a deck rating noticed a strong pungent smell before climbing down the ladder to shut off the power to the pump, but he did not wear respiratory protection. The deck rating lost consciousness and slumped due to exposure to the toxic crude sulfate turpentine vapor, containing hydrogen sulfide. The chief officer, who attempted a rescue without wearing respiratory protection, lost his sense of smell and was unable to speak. Another deck rating who accompanied the chief officer suffered effects of vapor inhalation but managed to escape.

3.2.1. Applying the proposed model

1) Define the accident clearly

After reviewing the accident report from marine accident investigation branch (MAIB), the accident is defined as "Inhalation of hazardous vapor by crew due to the discharge of poisonous cargo vapor."

2) Analyze with HFACS

Working on the four-level hierarchy structure discussed earlier, level 1 "unsafe acts" identifies the HOFs which directly lead to the accident. Followed by level 2 "preconditions for unsafe acts", the purpose of level 2 is seeking out the conditions that result in the HOFs at level 1. The analysis process continues to level 3 "unsafe supervision" and ends at level 4 "organizational influences", which identifies the fundamental causes of the accident. The list of HOFs generated from the first accident is shown in Table 3.4.

Table 3.4. Hierarchy of human and organizational errors in the first accident

Nodes / Errors	Descriptions	States
Level 0: Accidents		
Inhale hazardous vapor	Inhalation of hazardous cargo vapor by crew while washing tank	Yes, No
Level 1: Unsafe Acts		
Open butter-worth hatch	Open P10 butter-worth hatch to let washer water hose passed through	Yes, No
No BA /wrong BA	Not wear any breathing apparatus (BA) when go into hazardous atmosphere/ Check wearing an inappropriate BA	
Not locate sources of smell	Not investigate and locate the gas source causing the smell timely	
Not test atmosphere	Not test the atmosphere before going into hazardous atmosphere	
Level 2: Preconditions For Unsafe Acts		
Unaware of cargo's danger	Not be warned of the hazards posed by cargo contents	Yes, No
Using unsuitable equipment	wash tank using portable washing equipment contrary to the vessel's P & A manual instructions	
Complacent attitude	Overly-confident about dangers or one's actions	High, Medium, Low
Wrong risk assessment	Identify wrongly or insufficiently the hazards of cargo and recommending the wrong or insufficient precautions	
Level 3: Unsafe Supervision		
Not check	Failed to check fixed washing system defective	High,

equipment defective		Medium, Low
Deficient training	rescuers acting on instinct rather than knowledge and training	
Not provide specific MSDS	Not provide the cargo specific MSDS /Used Wrong MSDS	Yes, No
Inadequate brief	not brief the crew about the likely risk and necessary precautions	
Not provide instructions	There were no specific instructions on board for handling H_2S cargoes	
Failed to identify unsafe	the dangers posed by the presence of H_2S were not identified	
Level 4: Organizational Influences		
Not enforcing safety standard	Available guidance and procedures discipline are not followed strictly/ various documentation, including checklists were not complied with	High, Medium, Low
Ineffective emergency drill	Locations where similar accidents might occur are not identified when planning drills.	
Insufficient check	Not performing or insufficient checks. E.g. inspection checklists did not specifically target the tank washing equipment	
No guidance standard	Vopak Terminal did not provide guidance or set any limitations on open tank washing/ no specific instructions for handling cargoes	
Ignore mutual aid messages	Terminal's investigation of mutual aid messages was not conducted	Yes, No
No pre-arrival conference	A further pre-arrival conference was not carried out	

3) Nodes and states of the identified HOFs

The HOFs identified in step 2 are converted to the nodes of BN. After that, states are defined for each node according to the real conditions and the required depth of accident analysis. The states of each node are shown in the third column of Table 3.4.

4) Graphical representation with BN

With the nodes defined, the BN of "Inhalation of hazardous vapor by crew due to the discharge of poisonous cargo vapor" is constructed as shown in Figure 3-3.

5) Elicit CPT for the nodes of BN

With the graphical structure of BN, this step requires the elicitation of CPT for the nodes. The experts we invited for elicitation process are a group of four experts. The first one is a full professor of Shanghai Jiaotong University, who is an expert of maritime safety. The second one is an experienced engineer of Great ship Global Offshore Service Company in Singapore. The third one is an associate professor of fuzzy reliability from Goa College of Engineering. The fourth one is an assistant professor of safety engineering from China University of Petroleum. Discussing the real conditions of the case study, they elicit the values for each pair-wise comparison matrix. After all the comparison matrixes are estimated, the CPTs are elicited by integrating fuzzy AHP with decomposition method as shown in Section 3.1.2. After all CPTs are assigned, the quantitative analysis can be performed using Bayesian inference.

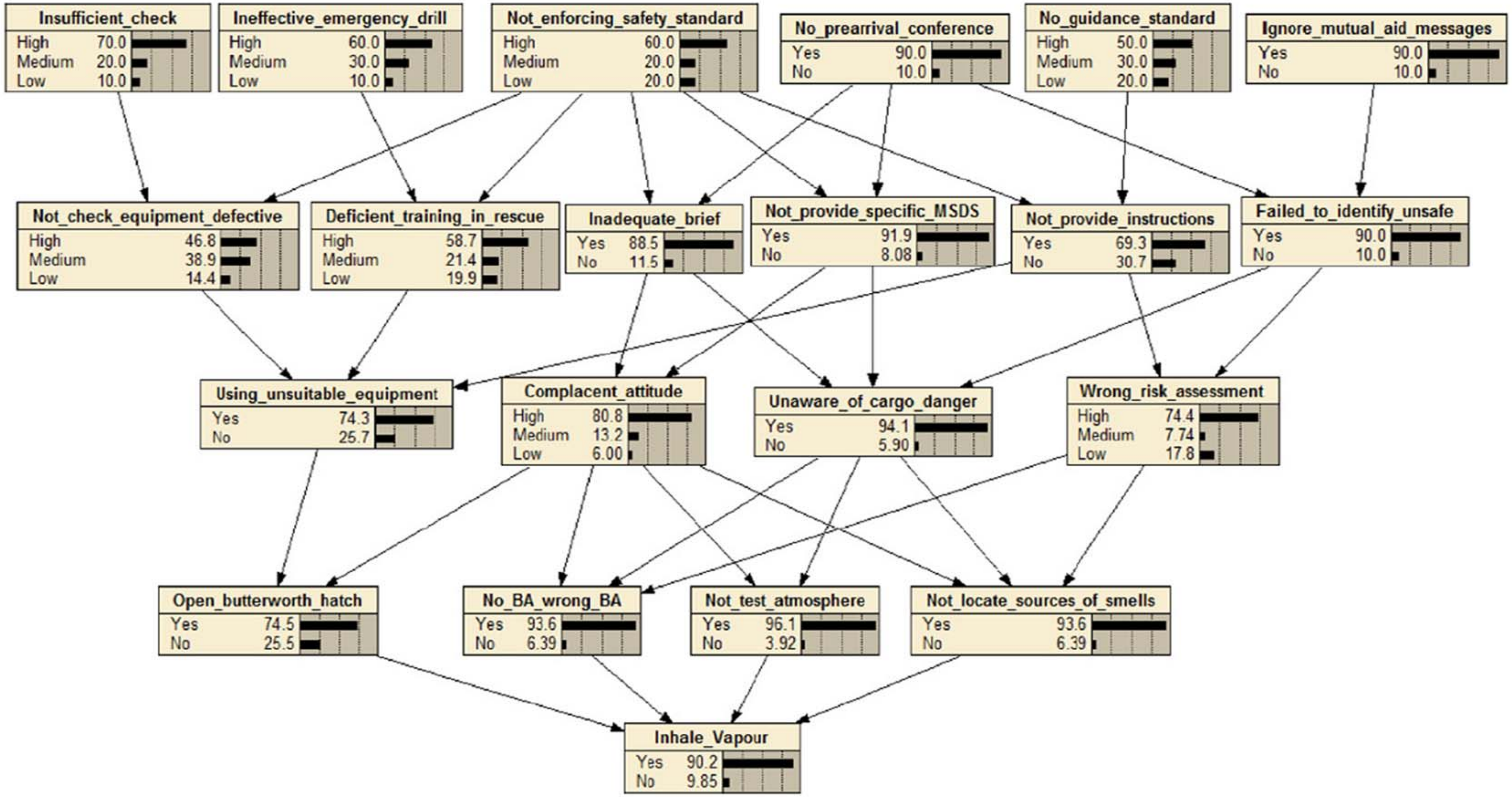

Figure 3-3. Graphical representation of “inhale vapor” accident with prior probabilities

6) Inference with BN

Given the occurrence of "Inhale vapor", a backward inference can be performed to calculate the posterior probabilities of each node to identify the important HOFs. The posterior probabilities of the HOF nodes are shown in Figure 3-4.

These posterior probabilities can be compared with their original prior probabilities to give an indication of the relative contribution of the HOFs. Such as, the HOF with the highest percentage change from prior to posterior probability indicates that it is sensitive to the occurrence of the accident.

As an example, the calculation of CPT for the node "Not check equipment defective" is presented in this section. The conditional probability of node "Not_check_equipment_defective" are shown in Table 3.5, given the different states of node "Insufficient_check".

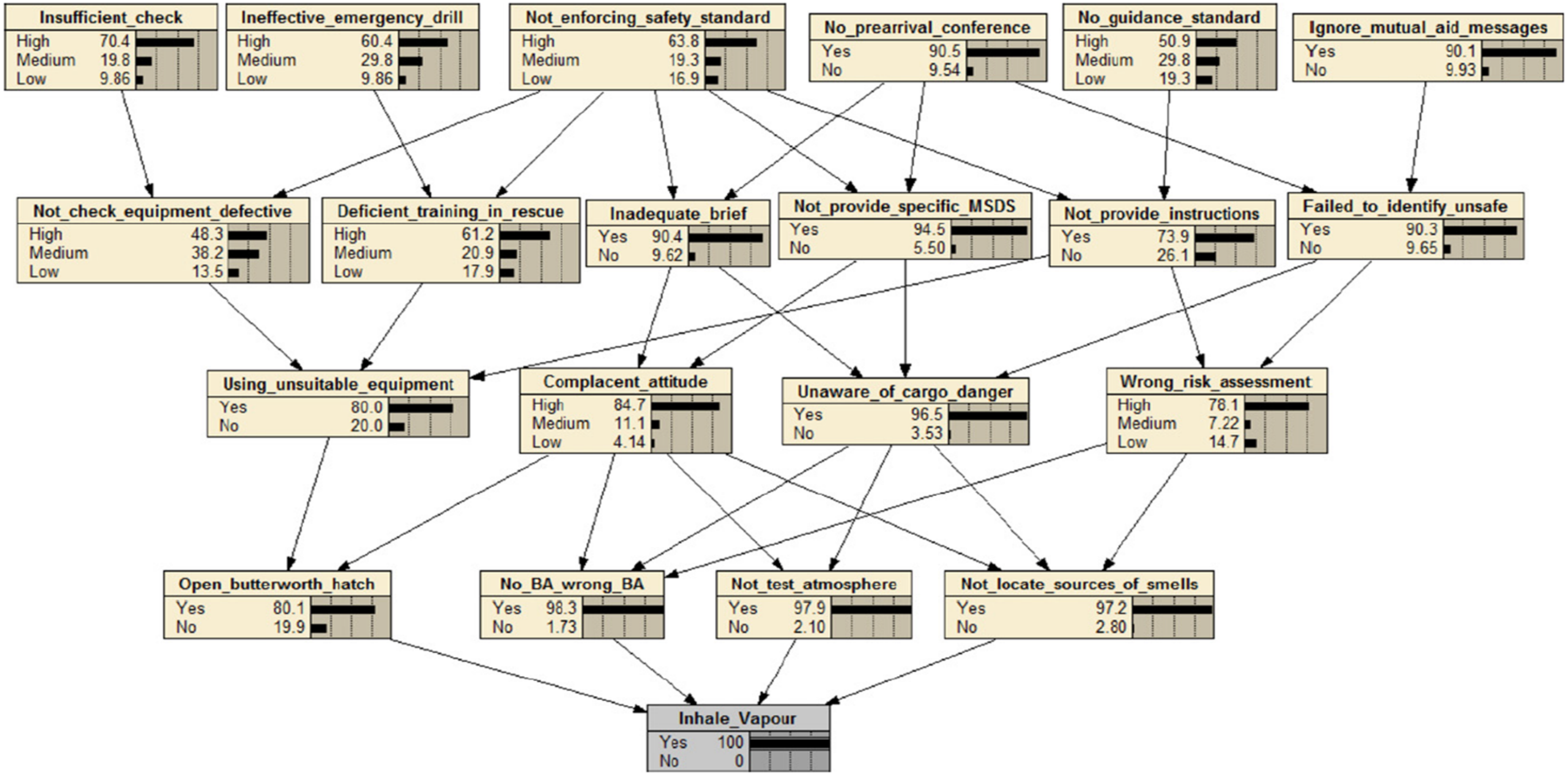

Figure 3-4. Posterior probabilities of the human factor given the first accident happened

Table 3.5. Conditional probability of "Not-check-equipment-defective" given "Insufficient check" (high)

Not-check-equipment-defective				
	S_1	S_2	S_3	$BNPw$
High	(1, 1, 1)	(2/3, 1, 2)	(2/7, 1/3, 2/5)	0.324
	(1/2, 1, 3/2)	(1, 1, 1)	(1/7, 1/3, 3/5)	0.343
	(5/2, 3, 7/2)	(5/3, 3, 7)	(1, 1, 1)	0.106
Medium	(1, 1, 1)	(1, 3/2, 2)	(2, 5/2, 3)	0.200
	(1/2, 2/3, 1)	(1, 1, 1)	(2, 5/2, 3)	0.207
	(1/3, 2/5, 1/2)	(1/3, 3/5, 1)	(1, 1, 1)	0.407
Low	(1, 1, 1)	(1/2, 1, 3/2)	(2, 5/2, 3)	0.233
	(2/3, 1, 2)	(1, 1, 1)	(4/3, 5/2, 6)	0.120
	(1, 1, 1)	(1/2, 1, 3/2)	(2, 5/2, 3)	0.470

When the state of node "Insufficient_check" is high, the conditional probability of "Not_check_equipment_defective" is calculated according to Eq. (3-8).

The optimum solution to the model using GAMS program is:

$$w = \begin{bmatrix} (0.317, 0.43, 0.5) \\ (0.335, 0.43, 0.578) \\ (0.105, 0.143, 0.168) \end{bmatrix}$$

Substitute w into Eq. (3-9), we can get:

$$BNP_{w_i} = (0.324,0.343,0.106)$$

Given the different states of node "Insufficient check", the conditional probability of node "Not check equipment defective" are shown in Table 3.6. Integrating the above calculation method with the decomposition method, the conditional probabilities of node "Not check equipment defective" are shown in Table 3.7.

Table 3.6. Conditional probability of "Not-check-equipment-defective" given different states of "Insufficient-check"

Not-check-equipment-defective				
	S_1	S_2	S_3	w
High	$(1, 1, 1)$	$(1/2, 2/3, 1)$	$(2/7, 1/3, 2/5)$	0.438
	$(1, 3/2,2)$	$(1, 1, 1)$	$(2/7, 1/2, 4/5)$	0.270
	$(5/2, 3, 7/2)$	$(5/4, 2, 7/2)$	$(1, 1, 1)$	0.136
Medium	$(1, 1, 1)$	$(1, 3/2, 2)$	$(1, 1, 1)$	0.263
	$(1/2, 2/3, 1)$	$(1, 1, 1)$	$(1/2, 2/3, 1)$	0.353
	$(1, 1, 1)$	$(1, 3/2, 2)$	$(1, 1, 1)$	0.263
Low	$(1, 1, 1)$	$(2/3, 1, 3)$	$(2/7, 1/3, 2/5)$	0.274
	$(1/3, 1,3/ 2)$	$(1, 1, 1)$	$(2/21, 1/3, 3/5)$	0.351
	$(5/2, 3, 7/2)$	$(5/3, 3, 21/2)$	$(1, 1, 1)$	0.091

Table 3.7. Conditional probability of "Not-check-equipment-defective" given "Insufficient-check" and "Not-enforcing-safety-standard"

Insufficient-check	Not-enforcing-safety-standard	High	Medium	Low
High	High	0.5706	0.3717	0.0577
High	Medium	0.3642	0.5168	0.1190
High	Low	0.4054	0.5504	0.0442
Medium	High	0.4414	0.2807	0.2779
Medium	Medium	0.2263	0.3136	0.4601
Medium	Low	0.3330	0.4414	0.2256
Low	High	0.5152	0.1629	0.3219
Low	Medium	0.2698	0.1859	0.5443
Low	Low	0.4289	0.2827	0.2884

3.2.2. Sensitivity analysis and results

Sensitivity analyses are conducted in this section to validate the proposed model. The importance degree of each HOF regarding to the node "Inhale vapor" can be assessed using entropy reduction (mutual information). Intuitively, mutual information measures the information that X and Y share: it measures how much knowing one of these variables reduces the uncertainty about the other.

Formally, the mutual information of two random variables *X* and *Y* can be defined as:

$$H(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) log_2 \frac{p(x,y)}{p(x)P(y)} \tag{3-14}$$

where *p(x, y)* is the joint probability distribution function of *X* and *Y*, and p(x) and p(y) are the marginal probability distribution functions of *X* and *Y*, respectively.

The prior probability, posterior probability and mutual information of each HOF are compared as shown in Table 3.8.

Table 3.8. Mutual information of prior and posterior probability for each HOF (case 1)

Organizational factor	Prior probability (%)	Posterior probability (%)	Change rate of (%) probability	Mutual information
Node of level 4: organizational influences				
Insufficient_check	70	70.4	0.571	0.000449
Ineffective_emergency_drill	60	60.4	1.667	0.000403
Not_enforcing_safety_standard	60	63.8	6.333	0.04462
No_prearrival_conference	90	90.5	0.556	0.001423
No_guidance_standard	50	50.9	1.800	0.002796
Ignore_mutual_aid_messages	90	90.1	0.111	3.982e-005
Node of level 3: unsafe supervision				
Not_check_equipment_defective	46.8	48.3	3.205	0.00739

Deficient_training	58.7	61.2	4.259	0.01919
Inadequate_brief	88.5	90.4	2.147	0.01851
Not_provide_specific_MSDS	91.9	94.5	2.829	0.0392
Not_provide_instructions	69.3	73.9	6.638	0.0591
Failed_to_identify_unsafe	90	90.3	0.333	0.00087
Node of level 2: preconditions for unsafe acts				
Using_unsuitable_equipment	74.3	80	7.672	0.0933
Complacent_attitude	80.0	84.7	5.875	0.0545
Unaware_of_cargo_danger	94.1	96.5	2.550	0.0412
Wrong_risk_assessment	74.4	78.1	4.973	0.0426
Node of level 1: unsafe acts				
Open_butterworth_hatch	74.5	80.1	7.517	0.0941
No_BA_wrong_BA	93.6	98.3	5.021	0.131
Not_test_atmosphere	96.1	97.9	1.873	0.0339
Not_locate_sources_of_smells	93.6	97.2	3.846	0.0815

The posterior probability of the node “Not enforcing safety standard” has the larger increment than other nodes of level 4 given the accident occurrence. This suggests that the occurrence of the accident is likely due to not enforcing safety standard. In addition, “Not provide instructions”, “Not provide specific MSDS”, “Using unsuitable equipment”, “Complacent attitude”, “Open butter worth hatch”, “No BA wrong BA” and “Not locate sources of smells” also contribute significantly to the occurrence of the accident.

While the 5% step by step reduction of prior probability of each organizational node varies from 5% to 30%, the reduction rates of accident probability are computed, which are shown in Figure 3-5, from which, it can be seen that the probability of accident has the largest reduction when the prior probability of “Not enforcing safety standard” decreases the same as other factors. It highlights that “Not enforcing safety standard” is the most important organizational factor.

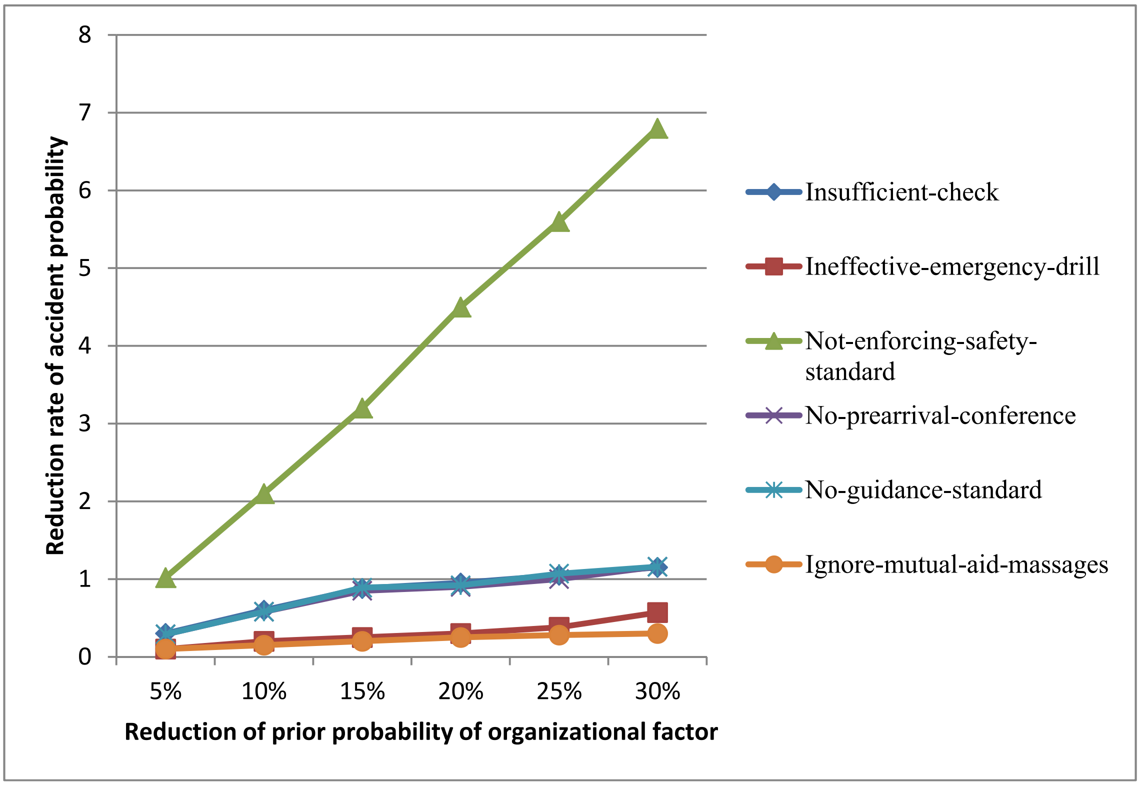

Figure 3-5. Effect of change in prior probabilities of each organizational factor on the probabilities of the second accident

With the BN inference mentioned earlier, the following recommendations of safety measures (corresponding to above major accident contributors) are given to avoid recurrence:

- All crews should be enforced and eligible to strictly following the safety standards and requirements. Some example of the standards could be that safety precaution must be taken when crew is in some enclosed spaces.

- The pre-arrival conference must be held before the loading/unloading operation and adequate brief should be provided. All the relevant information of cargo and related hazards and safety procedures should be covered at the pre-arrival conference.

- A specific MSDS of cargoes should be provided, which need contain the comprehensive information to determine special procedures for ensuring the safety of the crew.

- The defective equipment, such as the defective fixed washing system, should be repaired or renewed as soon as possible.

- Operator must wear appropriate breathing apparatus when dealing with hazardous cargo.

- The mutual aid messages should be immediately investigated to identify the risk avoiding complacent attitude.

- Detailed instruction should be provided for managing of unfamiliar cargoes and cargo operation.

- It should be arranged for crews to carry out additional training in rescue operations to enlighten the crisis consciousness and the right contingency measures.

- Cargo operations should be kept as “closed operations” to prevent vapours spilling and releasing. For this case, leaving the Butterworth hatches open directly causes the release of cargo vapours.

- Comprehensive check covering all phases should be carried out to ensure the cargo operation is conducted safely.

- The full briefing should be given to the chief officer after receiving the cargo stowage plan. Followed by the briefing, all items in the safety checklists in the Cargo Information Book have to be completed.

3.3. Case study 2: Vinyl chloride monomer eruption

The gas carrier Coral Acropora was preparing to start to discharge her cargo into shore cargo tanks when there was an escape of Vinyl Chloride Monomer (VCM) (Yang, Bonsall et al. 2008). On arrival at the berth, a cargo surveyor had boarded the vessel and, after calculating the cargo quantity, he had asked the chief officer to run a cargo pump in each tank as he took cargo samples. The chief officer had not been aware of the need for sampling and he had not made preparations or planned for it. However, he acceded to the request without including the operation in the discharge plan. The chief officer opened the valves on the aft tank, which allowed recirculation of the cargo in that tank. He then started the aft tank cargo pump using local controls sited on the tank top.

The cargo surveyor began filling his sample cylinder from the designated tank sampling point. After a few minutes, the cargo alarm klaxon sounded on deck. The chief officer walked around the tank dome and, using a local control, stopped the klaxon from sounding. He assumed the alarm indicated that the cargo pump had tripped, but he could not be certain without going to the cargo office. A few moments later, the klaxon sounded again. The chief officer then noticed a large cloud of white vapor advancing down the deck towards him. He quickly ran aft, taking hold of the cargo surveyor, hitting the emergency shutdown (ESD) button as he passed by. They managed to reach the shelter provided by the accommodation before the cloud overtook them. A little less than 600 kilograms of liquid and vapor VCM had erupted from the vessel's forward cargo tank mast riser after the forward tank had become over-pressurized.

3.3.1. Applying the proposed model

After reviewing the accident report from MAIB, the accident is defined as "Eruption to form vapor cloud". The 6 "DANGER" steps of the proposed model are carried out to analyze the critical HOFs of the second accident. The list of HOFs is shown in Table 3.9. With the nodes and states defined, the BN of "Eruption to form vapor cloud" is built in Figure 3-6. After all the CPTs are elicited by integrating fuzzy AHP with decomposition method, the quantitative analysis can be performed using Bayesian inference. The posterior probabilities of the HOF nodes are shown in Figure 3-7.

Table 3.9. Hierarchy of HOFs in the second accident case

Nodes / Errors	Descriptions	States
Level 0: Accidents		
Eruption to form vapor cloud	Vinyl Chloride Monomer had erupted to form a large cloud of white vapor cloud.	Yes, No
Level 1: Unsafe Acts		
Override safety feature	It was common to use override switch during operations.	Yes, No
Not wear PPE	Personnel did not wear proper personal protective equipment.	

No closed loop sampling	The cargo survey not used “closed loop sampling”.	
No double valve segregation	The chief officer habitually left manual valves open for expediency.	
Slow response to alarm	Not manning cargo office led to alarms not being positively and immediately identified.	
Not stop pump promptly	The chief officer did not stop the cargo pump when he became aware of the first deck cargo alarm.	
Level 2: Preconditions For Unsafe Acts		
Poor liaison	A poor liaison between vessel’s staff and those on the terminal, both parties carrying out their roles in isolation.	High, Medium, Low
Not uncover deficiencies	Gas carrier inspections and vetting did not uncover the ship or shore deficiencies in the operational procedures.	
Overload	Cargo tanks were loaded in excess of maximum allowable.	Yes, No
No preparation work	Chief officer could not plan ahead and not prepared.	
Insufficient sample point	The aft dome of the vessel’s after tank is not equipped with sufficient sample points.	
No pre-operational check	Checklists were not completed prior to the operation starting.	
Level 3: Unsafe Supervision		
No vetting inspection	Neither EVC, nor Agility, made any other vetting inspections	High, Medium, Low
Lack of information	The shore emergency response was initially hampered by a lack of information from the vessel	Yes, No

Ineffective inspection	The owner's inspection program was not effective in uncovering and halting poor operational practices.	
Not maintain oversight	No-one maintaining an oversight of the cargo operations	
No forewarned cargo sampling	The chief officer did not have prior warning that cargo sampling, necessitating the use of cargo pumps, was required.	
Not manned cargo office	The cargo office was not manned during the critical stages of cargo operations	
Level 4: Organizational Influences		
Not enforcing safety standard	The safe system existed on paper in the vessel's safety management system, but was not put into practice.	High, Medium, Low
Inappropriate safety awareness	The chief officer's decision not to go to the cargo office to determine what had caused the alarm indicated an inappropriate level of safety awareness.	
External muster point	Muster point was outside on deck	Yes, No
No cargo control room	There is not a cargo control room.	
No communication means	The vessel had no means of direct communication with the terminal	
No experienced staff	Neither EVC nor Agility employed experienced permanent staff to call on to undertake such inspections	
Inexperienced chief officer	Newly promoted and relatively inexperienced masters and chief officers sail together.	

Figure 3-6. Graphical representation of the second accident with prior probabilities

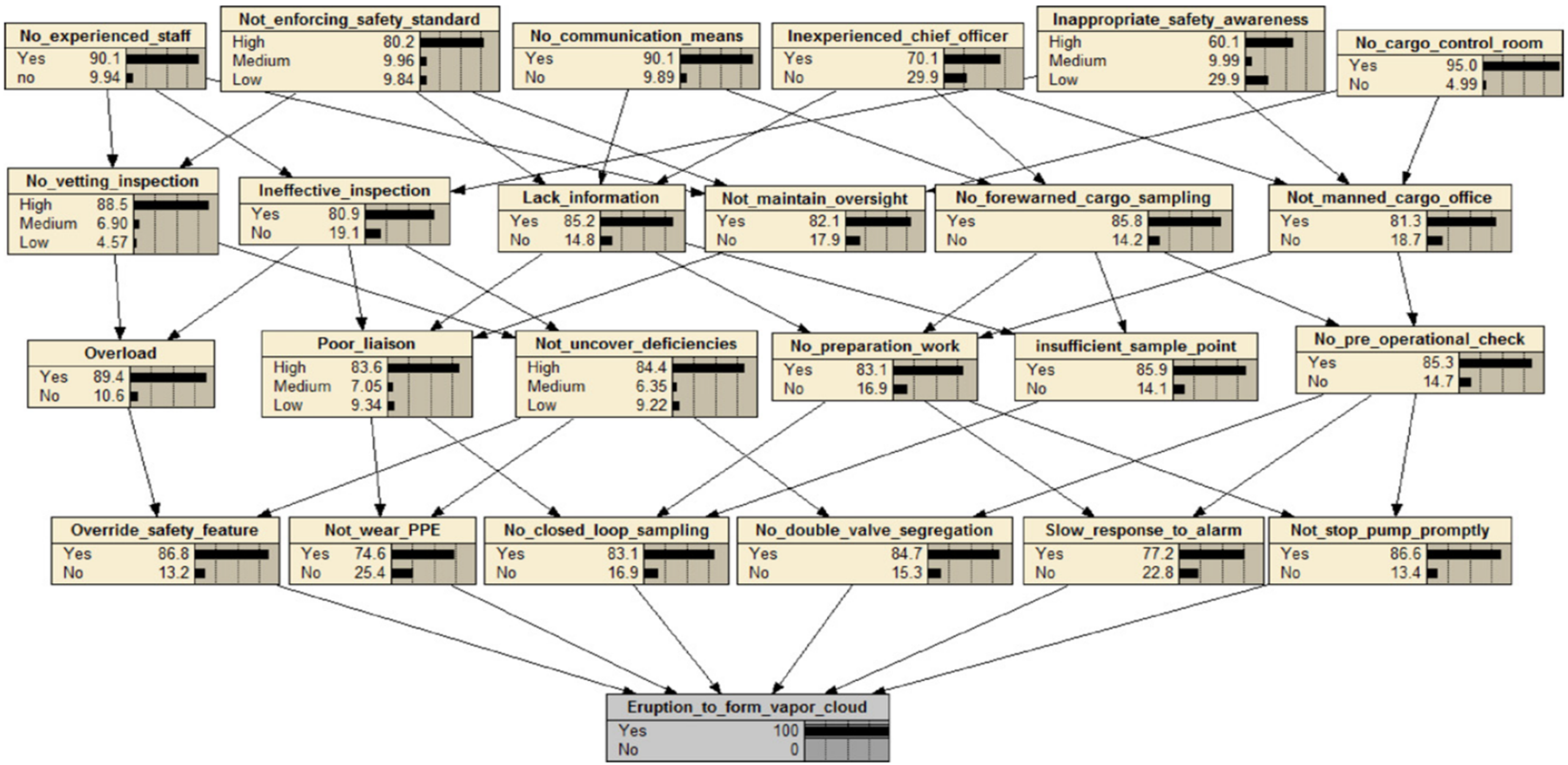

Figure 3-7. Posterior probabilities of the human factor given the second accident happened

3.3.2. Sensitivity analysis and results

Sensitivity analyses are conducted to validate the proposed model. The importance degree of HOFs regarding to the node “Eruption to form vapor cloud” can be assessed using entropy reduction (mutual information). The prior probability, posterior probability and mutual information of each HOF are compared as shown in Table 3.10.

Table 3.10. Mutual information of prior and posterior probability for each HOF (case two)

Organizational factor	Prior probability (%)	Posterior probability (%)	Change rate of (%) probability	Mutual information
Node of level 4: organizational influences				
No_experienced_staff	90	90.3	0.333	2.003e-005
Not_enforcing_safety_standard	80	80.8	1	0.0001506
No_communication_means	90	90.2	0.222	6.779e-005
Inexperienced_chief_officer	70	70.1	0.143	2.206e-005
Inappropriate_safety_awareness	60	60.4	0.667	1.726e-005
No_cargo_control_room	95	95	0	2.878e-007
Node of level 3: unsafe supervision				
No_vetting_inspection	88.3	89.3	1.133	0.000379
Ineffective_inspection	80.6	82	1.737	0.000223

Lack_information	85	85.7	0.824	0.000186
Not_maintain_oversight	83	83.5	0.602	2.376e-005
No_forewarned_cargo_sampling	85.4	85.9	0.586	0.0006016
Not_manned_cargo_office	81.7	82	0.367	7.37e-005
Node of level 2: preconditions for unsafe acts				
Overload	89	90.1	1.236	0.000507
Poor_liaison	83.5	85.4	2.275	9.378e-005
Not_uncover_deficiencies	83.6	87.9	5.144	0.00268
No_preparation_work	82.3	82.8	0.608	0.00218
Insufficient_sample_point	85.6	85.7	0.117	0.000332
No_preoperational_check	84.7	86	1.535	0.00172
Node of level 1: unsafe acts				
Override_safety_feature	85.2	89.5	5.047	0.00864
Not_wear_PPE	74.8	89.4	19.52	7.771e-005
No_closed_loop_sampling	82.2	82.6	0.487	0.00258
No_double_valve_segregation	82.6	90.3	9.322	0.0139
Slow_response_to_alarm	74.9	76.8	2.537	0.013
Not_stop_pump_promptly	84.9	85.2	0.353	0.00901

As can be seen, the posterior probability of “Not enforcing safety standard” among the nodes of level 4 increase most largely given the accident occurrence. It highlights the need of enforcing all crews to strictly follow safety standard.

Among the nodes of level 3, the posterior probability of the node “No forewarned cargo sampling” has the largest increment given the accident occurs. This suggests that the occurrence of the accident is likely due to not providing prior warning of cargo sampling.

Among the nodes of level 2, the posterior probability of the node “Not uncover deficiencies” and “No preparation work” have the largest increment when the accident occurs. It suggests “Not uncover deficiencies” and “No preparation work” contribute significantly to the occurrence of the accident. The posterior probability of the node “No double valve segregation” and “Slow response to alarm” have the larger increase among the nodes of level 1. It highlights the need of maintaining double valve segregation and immediate responding to alarm.

While the 5% step by step reduction of prior probability of each organizational node varies from 5% to 30%, the reduction rates of accident probability are calculated as shown in Figure 3-8. It can be seen that the probability of accident has the largest reduction when the prior probability of “Not enforcing safety standard” decreases the same as other factors. It again highlights that “Not enforcing safety standard” is the most important HOF. Thus, the probability of “Eruption to form vapor cloud” accidents would drastically be reduced by enforcing safety standard.

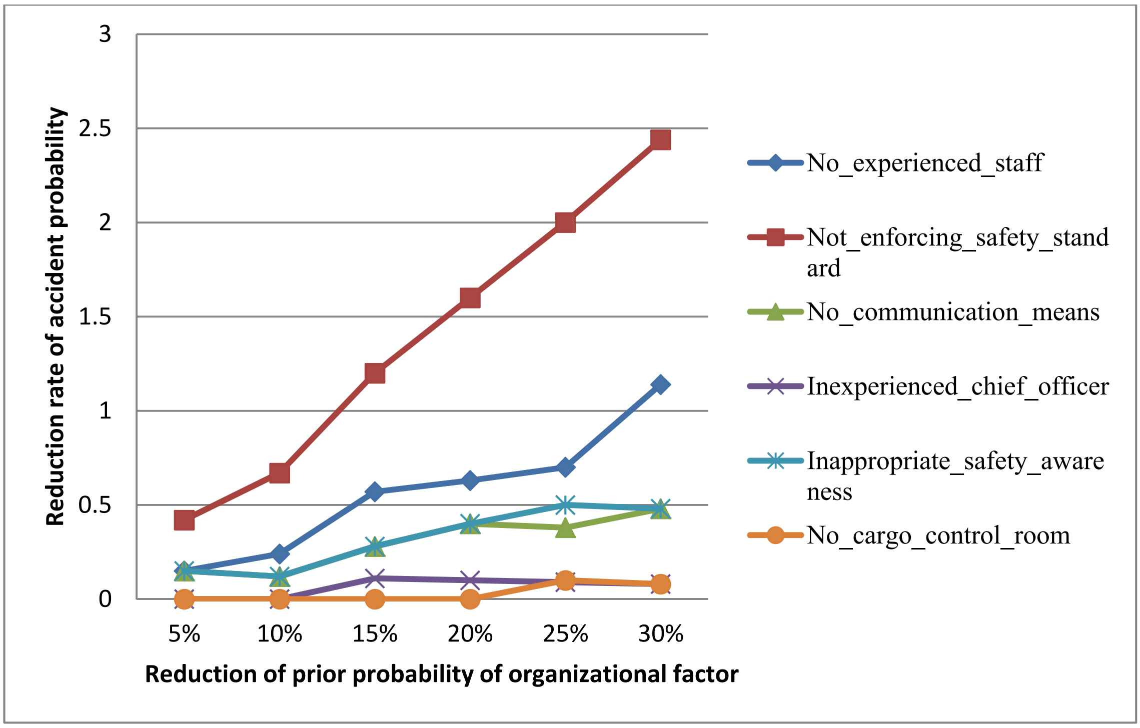

Figure 3-8. Effect of change in prior probabilities of each organizational factor on the probabilities of the second accident

By sensitivity analysis, we can see that the model satisfies the three axioms presented in Section 3.1.3, which allows us to conclude that the inference made earlier is reliable. From above BN inference, important safety measures corresponding to the major accident contributors can be derived to prevent the similar accidents from recurring:

- All crews should strictly follow the safety standards and put the safety management system into practice.

- Have the vessel advised about cargo sampling prior to arrival and the chief office should prepare well.
- The charterer should make vetting inspections and employ permanent staff with marine gas carrier experience to call on to undertake such inspections.
- When a tanker arrives alongside a terminal, she should do a lot of preparation work before loading or discharging cargo. The ship owner's operating instructions must be carefully written to avoid putting undue pressure on crews.
- Maintain double valves segregation system to avoid cargo transfer from one tank to the other as long as one of the 98% alarm and shutdown system is placed in override position.
- The chief officer should take immediate steps to stop the operation when the cargo alarm sound and ascertain the true nature of the alarm.
- Avoid overriding the 98% alarm/shutdown system by limit full cargo allowance.
- The ship shore checklist should be completed by the loading master and the chief officer prior to cargo operations.
- All personnel involved must wear appropriate protective equipment in case there is a risk from toxic gas or a liquid spill is present on deck.
- Evaluate the performance of the chief officer and establish further actions to monitor performance and/training needs.

- Means for (emergency) communication between the vessel and the terminal is established as first priority and emergency contact numbers are available before commencing any cargo operations including cargo sampling.

3.4. Conclusion

From the application of the model to the two case studies, it can be concluded that the model is useful in investigating HOFs for the derivation of safety interventions. And, in general, “Not enforcing safety standard” contribute mostly to the accident occurrence.

The application of HFACS allows a complete identification of HOFs, both active and latent, that are leading causes of accidents. The hierarchal structure of HFACS encourages investigators to seek out latent HOFs, which are often neglected in accident investigations. The model enables a quantitative assessment by using BN. BN enhances the ability of HFACS by allowing investigators or experts to quantify the degree of relationships among the HOFs. Fuzzy AHP is used to reduce the subjective biases by avoiding the need of defining exact probability for the nodes’ states. The decomposition method that is applied in CPT elicitation reduces the complexity by allowing probability calculation conditioning on each of the parent nodes separately.

CHAPTER 4: RISK AND COST OPTIMIZATION IN MARINE HAZARDOUS MATERIAL TRANSPORTATION

Accident risk minimization in transportation of hazardous materials (hazmat) has been an active area of study with remarkable improvements in route selection domains. In this chapter, a bi-objective optimization model (including accident risk and cost) is proposed for transportation of hazardous materials in different routes (waterways). It is intended to determine the number of ships for transmitting hazmat or regular freight from origins to destinations in different itineraries. The expected risk evaluated in this problem is based on the expected area exposed by hazmat containers during transportation in the routes. The optimization model and the solution framework are used to solve a numerical but realistic problem instance.

The chapter is organized as follows. In Section 4.1, a descriptive definition, essential assumptions, and the proposed optimization formulated problem are provided. In Section 4.2, a numerical example with a solution methodology is described in details to show the results. Section 4.3 concludes from the results.

4.1. Problem description

Transportation of hazardous materials is always risky and vulnerable to many types of accidents. It has a potentially negative impact on the marine environment (risk) and economic disadvantages (cost) (Chang et al. 2010). In regard of this risk and cost, a marine hazmat transportation problem is proposed and mathematically formulated in this section. Also, the assumptions of the problem are described. Our problem is to find out the best transportation plan (number of containers to be transported between nodes) for both hazardous and regular freights in a marine port network. There is a pre-specified delivery time that must be satisfied in transportation between the supplier storage nodes and customer storage nodes. In general, the objectives are to minimize the total cost of transportation and the total accident risk associated with hazmat.

There are two assumptions in the modeling:

- Each type of container ship being used in shipment of hazmat or regular freights refers to the specific path between origin and destination terminals. With this assumption, the estimated exposed area of hazmats is related to the number of container ships of different types transporting between origin and destination terminals.

- There is no traffic and waiting time at the terminals by assuming that the delivery system in the network is time-reliable.

The network schematic is shown in Figure 4-1. It includes supplier storage nodes (*a*), origin terminals (*o*), destination terminals (*d*), customer storage nodes (*b*), and the links between nodes.

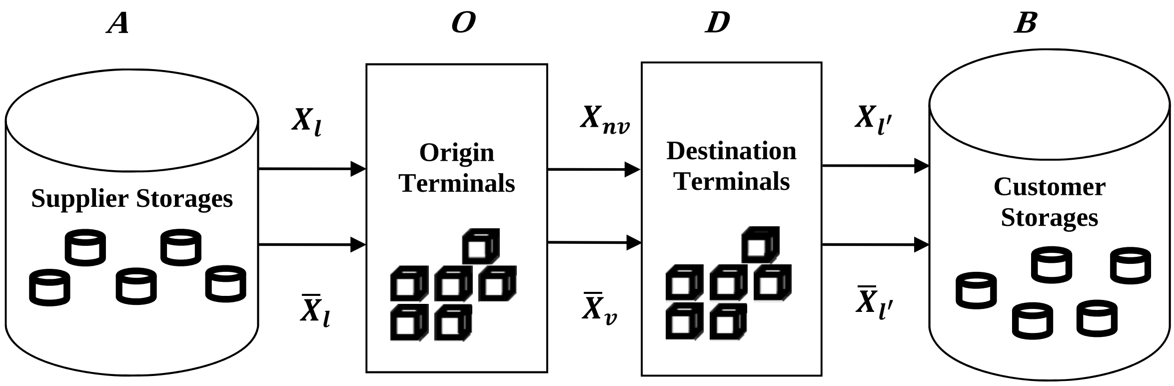

Figure 4-1. Marine hazmat and regular freight transportation network

- **Nomenclatures**

Sets

A	Set of supplier storages, indexed by a.
O	Set of origin terminals, indexed by o.
D	Set of destination terminals, indexed by d.
B	Set of customer storages, indexed by b.
L_{ao}	Set of links between each supplier storage $a \in A$ and each origin

terminals $o \in O$, indexed by l.

L_{db} Set of links between each destination terminal $d \in D$ and each customer storage $b \in B$, indexed by l'.

V_{od} Set of ship types shipped between each terminal pair $o - d$, where $o \in O$ and $d \in D$, indexed by v.

Variables

X_l Number of hazmat containers using link l.

$\bar{X}_l$ Number of regular containers using link l.

X_{nv} Number of hazmat containers in the nth ship of type v.

$\bar{X}_v$ Number of regular containers in ship of type v.

$X_{l'}$ Number of hazmat containers using link l'.

$\bar{X}_{l'}$ Number of regular containers using link l'.

Indicator Variables

$$Y_l = \begin{cases} 1, & if\ X_l > 0\ or\ \bar{X}_l > 0 \\ 0 & o.w. \end{cases}$$

$$Y_v = \begin{cases} 1, & if\ X_{nv} > 0\ or\ \bar{X}_v > 0 \\ 0 & o.w. \end{cases}$$

$$Y_{l'} = \begin{cases} 1, & if\ X_{l'} > 0\ or\ \bar{X}_{l'} > 0 \\ 0 & o.w. \end{cases}$$

Parameters

M A large positive integer

R_l Exposure risk due to moving one hazmat container in link l.

R_v Exposure risk due to moving one hazmat container by ship of type v.

$R_{l'}$ Exposure risk due to moving one hazmat container in link l'.

C_l Cost of moving one hazmat container in link l.

$\bar{C}_l$ Cost of moving one regular container in link l.

C_v Cost of moving one hazmat container using ship of type v.

$\bar{C}_v$ Cost of moving one regular container using ship of type v.

$C_{l'}$ Cost of moving one hazmat container in link l'.

$\bar{C}_{l'}$ Cost of moving one regular container in link l'.

De Number of hazmat containers demanded.

$\overline{De}$ Number of regular containers demanded.

N_v Number of container ships of type v.

U_v Maximum number of containers that can be loaded in the ship of type v.

Dt Delivery time of the network.

t_l Transportation time in link l.

t_v Transportation time using ship of type v.

$t_{l'}$ Transportation time in link l'.

The problem is a bi-objective optimization model as presented in Eq. (4-1) and (4-2). The risk objective represents water area exposure due to hazmat release from an accident. It should be remarked that the risk of exposure depends on the types of ships and the number of hazmat containers. The cost objective function contains the cost of transportation of hazmat and regular containers from origin terminals to destination terminals, the cost of shipment from supplier storages to origin terminals, and from destination terminals to the customer storages. Constraint (4-3) represents the balanced transshipment equation of hazmat and regular containers between different terminals. Constraint (4-4) guarantees that each customer's hazmat and regular freight demands are satisfied. In constraint (4-5), the number of ships of a specific type is determined by the total number of containers to be shipped between two consecutive terminals. Constraint (4-6) ensures the balance in delivery time. Constraint (4-7) expresses the activation of indicator variables relating to the links. At the end, constraint (4-8) represents that all variables should be positive integer numbers and constraint (4-9) shows the sign restriction for indicator variables.

Exposure risk:

$$\sum_{l\in L_{ao}} R_l X_l + \sum_{n\in N_v}\sum_{v\in V_{od}} R_v X_{nv} + \sum_{l'\in L_{db}} R_{l'} X_{l'} \tag{4-1}$$

Transportation cost:

$$\sum_{l\in L_{ao}} (C_l X_l + \bar{C}_l \bar{X}_l) + \sum_{v\in V_{od}} \left[C_v \sum_{n\in N_v} X_{nv} + \bar{C}_v \bar{X}_v \right] + \sum_{l'\in L_{db}} (C_{l'} X_{l'} + \bar{C}_{l'} \bar{X}_{l'}) \tag{4-2}$$

Constraints:

$$\begin{aligned} &\textstyle\sum_{l\in L_{ao}} X_l = \sum_{n\in N_v}\sum_{v\in V_{od}} X_{nv} && \forall o \in O \\ &\textstyle\sum_{l\in L_{ao}} \bar{X}_l = \sum_{v\in V_{od}} \bar{X}_v && \forall o \in O \\ &\textstyle\sum_{n\in N_v}\sum_{v\in V_{od}} X_{nv} = \sum_{l'\in L_{db}} X_{l'} && \forall d \in D \\ &\textstyle\sum_{l'\in L_{db}} \bar{X}_{l'} = \sum_{v\in V_{od}} \bar{X}_v && \forall d \in D \end{aligned} \tag{4-3}$$

$$\begin{aligned} \sum_{l'\in L_{db}} X_{l'} &= De \\ \sum_{l'\in L_{db}} \bar{X}_{l'} &= \overline{De} \end{aligned} \tag{4-4}$$

$$\sum_{n\in N_v} X_{nv} + \bar{X}_v \le U_v N_v \qquad \forall v \in V_{od} \tag{4-5}$$

$$t_l Y_l + t_v Y_v + t_{l'} Y_{l'} \le Dt \qquad \forall l \in L_{ao}, \quad \forall v \in V_{od}, \quad \forall l' \in L_{db} \tag{4-6}$$

$$
\begin{array}{lll}
MY_l \geq X_l \ or \ \bar{X}_l & \forall l \in L_{ao} & \\
MY_v \geq X_{nv} \ or \ \bar{X}_v & \forall n \in N_v, \ \forall v \in V_{od} & \quad (4\text{-}7) \\
MY_{l'} \geq X_{l'} \ or \ \bar{X}_{l'} & \forall l' \in L_{db} &
\end{array}
$$

$$
\begin{array}{lll}
X_l \geq 0, \ \bar{X}_l \geq 0 \quad integer & \forall l \in L_{ao} & \\
X_{l'} \geq 0, \ \bar{X}_{l'} \geq 0 \ \ integer & \forall l' \in L_{db} & \\
\bar{X}_v \geq 0 \ , X_{nv} \ \geq 0 \ integer & \forall n \in N_v, \ \forall v \in V_{od} & \quad (4\text{-}8)
\end{array}
$$

$$
\begin{array}{lll}
Y_l \in \{0,1\} & \forall l \in L_{ao} & \\
Y_v \in \{0,1\} & \forall v \in V_{od} & \quad (4\text{-}9) \\
Y_{l'} \in \{0,1\} & \forall l' \in L_{db} &
\end{array}
$$

For the risk estimation of water exposure by hazmat accidents, the equation presented by Evans et al. (2002) is extended to our case of study regarding to the links of hazmat containers shipments by different types of ships. Moreover, for each of the links between terminals, it is assumed only one type of ship can move. Assuming that the hazmat release makes water pollution, the area exposure risk in different links can be formulated as:

$$R_l = \left(Br \times \rho_l \times Ar_l^{1/2}\right)/(u_l \times H_l) \qquad \forall l \in L_{ao}$$

$$R_v = \left(Br \times \rho_v \times Ar_v^{1/2}\right)/(u_v \times H_v) \qquad \forall v \in V_{od} \qquad (4\text{-}10)$$

$$R_{l'} = \left(Br \times \rho_{l'} \times Ar_{l'}^{1/2}\right)/(u_{l'} \times H_{l'}) \qquad \forall l' \in L_{db}$$

where Br is the nominal breathing (respiration) rate of the marine ecosystems mostly fish, ρ is the population density of the marine ecosystem, u is the average velocity of water waves, and if we consider the waterways' area as a box, Ar is the square base of area and H is the average height of the box (sea depth).

4.2. Numerical example

4.2.1. Case and optimization description

A simple marine hazmat transportation network as in Figure 4-2 is considered. There are two big tankers to keep and storage hazmats in both supplier and customer nodes. Two origin terminal ports and destination terminal ports are existed in between. The waterways between storages and terminals are depicted that four types of container ships may transfer the freights between terminal ports (two for the regular freight and two for the hazmat). Also, for each type of container ship, two ships are available. The customer demands totally 7 hazmat containers and 7 regular containers. Between the terminals, maximum numbers of containers that can be loaded in a ship of type one and two are 5 and 4 units, respectively. The delivery time for the customer is considered as

48 hours. The expected costs and estimated risks for the different routes of the network are given in Table 4.1 and Table 4.2.

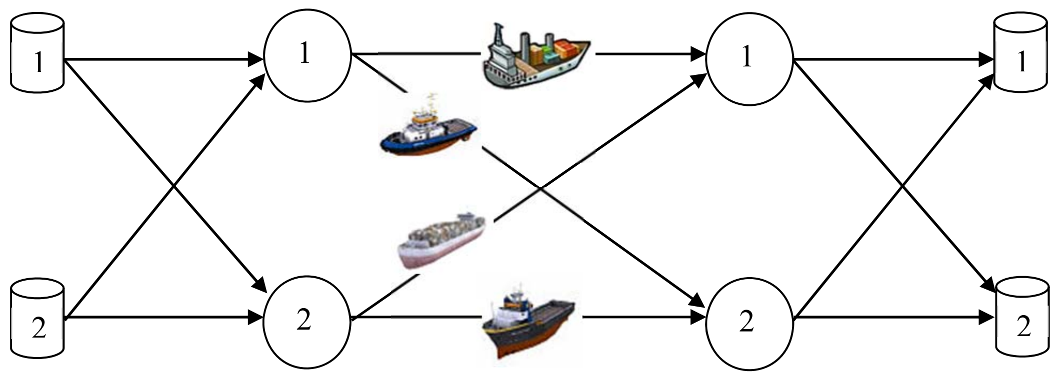

Figure 4-2. A hazmat and regular containers' transportation chain

Table 4.1. Cost, risk and transport times of hazmat containers for the network depicted in Figure 4-2

Hazmat container transportation	Cost	Risk	Time
From supplier storage 1 to origin terminal 1	7.4	1.5	2.8
From supplier storage 1 to origin terminal 2	7.5	1.6	3
From supplier storage 2 to origin terminal 1	6.9	1.7	2.5
From supplier storage 2 to origin terminal 2	8	1.4	3.1
Transportation between terminals by ship type 1	6	1.7	41
Transportation between terminals by ship type 2	5.7	1.9	38
From destination terminal 1 to customer storage 1	8.5	2.8	4.8
From destination terminal 1 to customer storage 2	8.3	2.6	4.2
From destination terminal 2 to customer storage 1	7.9	2.9	4.5
From destination terminal 2 to customer storage 2	8	3	4.9

Table 4.2. Cost, risk and transport times of regular containers for the network depicted in Figure 4-2

Regular container transportation	Cost	Risk	Time
From supplier storage 1 to origin terminal 1	2.8	-	2.8
From supplier storage 1 to origin terminal 2	3	-	3
From supplier storage 2 to origin terminal 1	2.5	-	2.5
From supplier storage 2 to origin terminal 2	2.7	-	3.1
Transportation between terminals by ship type 1	3.3	-	41
Transportation between terminals by ship type 2	3.5	-	38
From destination terminal 1 to customer storage 1	4.3	-	4.8
From destination terminal 1 to customer storage 2	4.1	-	4.2
From destination terminal 2 to customer storage 1	3.9	-	4.5
From destination terminal 2 to customer storage 2	4	-	4.9

A simple solution approach is to reforming the problem as a binary integer program. The converted problem is solved by using “bintprog” algorithm in the optimization toolbox of Matlab R2012a software. “bintprog” uses a linear programming (LP)-based branch-and-bound algorithm to solve binary integer programming problems. The algorithm creates a search tree by repeatedly adding constraints (branches) to the problem. Each constraint leads to a node which can be zero or one. At each node, the algorithm solves an LP-relaxation problem. The binary integer requirement on the variables of the problem is replaced by the weaker constraint $0 \le$ *(variable value)* ≤ 1.

Before applying bintprog solver, we need to define the problem in the form below:

$$\begin{cases} min\, fZ \\ AZ \leq b \\ A_{eq}Z = b_{eq} \\ Z \in \{0,1\} \end{cases} \tag{4-11}$$

where f, b, b_{eq}, and Z are vectors, and A and A_{eq} are matrices.

The algorithm faces to three possibilities for LP-relaxation problem:

- Infeasible at the node: the algorithm removes the node from the tree, and it does not search any branch behind that node.
- A new feasible integer point with lower objective value than previous nodes: the algorithm updates the best integer point and moves to the next node.
- The LP-relaxation problem is optimal at the node but not integer and the optimal objective value of the LP relaxation problem is less than the best integer point: the algorithm branches to new nodes behind this node.

The integer variables of the problem (X) are converted to binary integer variables (Z) by using below equation:

$$X = Z_0 + 2Z_1 + 2^2Z_2 \ldots + 2^kZ_k \tag{4-12}$$

where k is the biggest integer number such that:

$$\begin{cases} 2^k \leq De < 2^{(k+1)} & for\ variables\ X_l, X_{nv},\ and\ X_{l'} \\ 2^k \leq \overline{De} < 2^{(k+1)} & for\ variables\ \bar{X}_l, \bar{X}_v, and\ \bar{X}_{l'} \end{cases} \tag{4-13}$$

4.2.2. Results

In the proposed optimization model, both the two linear objective functions should be minimized. Therefore, these two functions are combined together as one objective function. The combination is by normalizing the coefficients of the variables and making the summation of the normalized coefficients associated with each of the variables. Table 4.3 and Table 4.4 present the optimal results using bintprog solver.

Table 4.3. Optimums for the shipment of hazmat containers in routes of the network depicted in Figure 4-2

Hazmat container transportation	Optimal number of containers
From supplier storage 1 to origin terminal 1	0
From supplier storage 1 to origin terminal 2	0
From supplier storage 2 to origin terminal 1	7
From supplier storage 2 to origin terminal 2	0
Transportation between terminals by the 1st ship of type 1	5
Transportation between terminals by the 2nd ship of type 1	2
Transportation between terminals by the 1st ship of type 2	0
Transportation between terminals by the 2nd ship of type 2	0
From destination terminal 1 to customer storage 1	0
From destination terminal 1 to customer storage 2	7
From destination terminal 2 to customer storage 1	0
From destination terminal 2 to customer storage 2	0

Table 4.4. Optimums for the shipment of regular containers in routes of the network depicted in Figure 4-2

Regular container transportation	Optimal number of containers
From supplier storage 1 to origin terminal 1	0
From supplier storage 1 to origin terminal 2	0
From supplier storage 2 to origin terminal 1	1
From supplier storage 2 to origin terminal 2	6
Transportation between terminals by the 1st ship of type 1	1
Transportation between terminals by the 2nd ship of type 1	0
Transportation between terminals by the 1st ship of type 2	4
Transportation between terminals by the 2nd ship of type 2	2
From destination terminal 1 to customer storage 1	0
From destination terminal 1 to customer storage 2	1
From destination terminal 2 to customer storage 1	6
From destination terminal 2 to customer storage 2	0

From the results, the supplier should transfer all the demanded hazmat containers from supplier storage 2 to origin terminal 1. Then, by the first ship of type 1 which is located at origin terminal 1, 5 containers should be transported to destination terminal 1 and the remained 2 containers should be transported by the second ship of type 1. Later, all the hazmat containers should be shipped to customer storage 2.

For regular containers, the supplier should transfer one of the demanded containers from supplier storage 2 to origin terminal 1 and the rest to terminal 2. Then, by the first ship of type 1 which is located at origin terminal 1, one container should be transported to destination terminal 1, and from there it should be transported to customer storage 2. In the first ship of type 2, 4 containers should be loaded to fill the ship capacity and in the second ship of type 2, the rest 2 containers. Both ships of type 2 transport to the destination terminal 2 and then, they transport to customer storage 1.

The incorporation of multiple port terminals in this example enables us to show that emphasizing one objective over the other determines traffic-throughput at different terminals and number of containers in various intermodal ships in the network.

4.3. Conclusion

In this chapter, a risk-based optimization model was proposed to plan the ship capacities during transportation from supplier storages to customer storages. The optimal number of containers with different freights (hazmat and regular) was found by solving a bi-objective integer programming problem. We took advantage of the "bintprog" algorithm which is designed in Matlab R2012a software. The bi-objective integer programming problem was converted to the single objective binary programming problem to be compatible with "bintprog" algorithm requirements. The optimal numbers of containers in different routes were searched and resulted by the algorithm considering the exposure risk estimation formula.

CHAPTER 5: ACCIDENT RISK MODELING OF MARINE TRANSPORTATION SYSTEM

Accurate analysis of the reliability of maritime transportation systems is critical for decision making, especially when associated with unexpected risk of accidents. In this chapter, a novel approach for reliability and risk analysis of such systems is proposed through homogenous continuous time Markov chain modeling, for which the parameter estimation method is given. It is shown that the transition rates of Markov chains can be estimated from yearly observed data with Markov Chain Monte Carlo (MCMC) simulation. Using risk analysis results, the reliability of the system can be computed as the probability of the event that the system works without any accident occurring.

Many studies in maritime accident risk modelling are rooted in summary statistics such as expected value of accident frequency over time (Roberts and Marlow 2002; Darbra and Casal 2004; Korczewski 2008; Fabiano et al. 2010). Risk has a probabilistic essence which is conditioned on many negative outcomes of the system in different times. Therefore, straightforward statistics, such as a single accident rate value, are not sufficient enough to explain and predict accident risk over time. The add value of our model to the current studied models is in updating estimated accident risks by updating marine occurrence conditional probabilities.

The chapter is organized as follows. A general approach is presented in Section 5.1. The approach includes Markov modeling for three states of marine systems and MCMC simulation for risk assessment. Later, two case studies are shown in this chapter. In Section 5.2, for Australian commercial vessels, the accident risk model is presented with sensitivity analyses on model's time span and initial transition rates. In Section 5.3, for vessels moving within Hong Kong waters, the proposed accident risk model is applied with sensitivity analysis on initial transition value. At the end of this chapter, conclusions are drawn in Section 5.4.

5.1. General modeling approach

Probabilistic risk assessment models should be improved dynamically due to the dynamic changes in safety levels of maritime transportation systems. On the other hand, simplicity and flexibility of the model are important. With this purpose, the general structure of the proposed accident risk model is presented in Figure 5-1.

The depicted structure includes a three-state Markov modeling, MCMC simulation algorithm, and sensitivity analysis, respectively. Following the steps, marine accident risk can be estimated from the mathematical relations between occurrence rates and occurrence probabilities of Markov model. MCMC simulation is Monte Carlo simulation using Markov chain. In Markov chain, the probability of obtaining a value for a sample is dependent only on the previous sample. In this way, it can be paired with Bayesian updating to develop new probability density function for Markov occurrences.

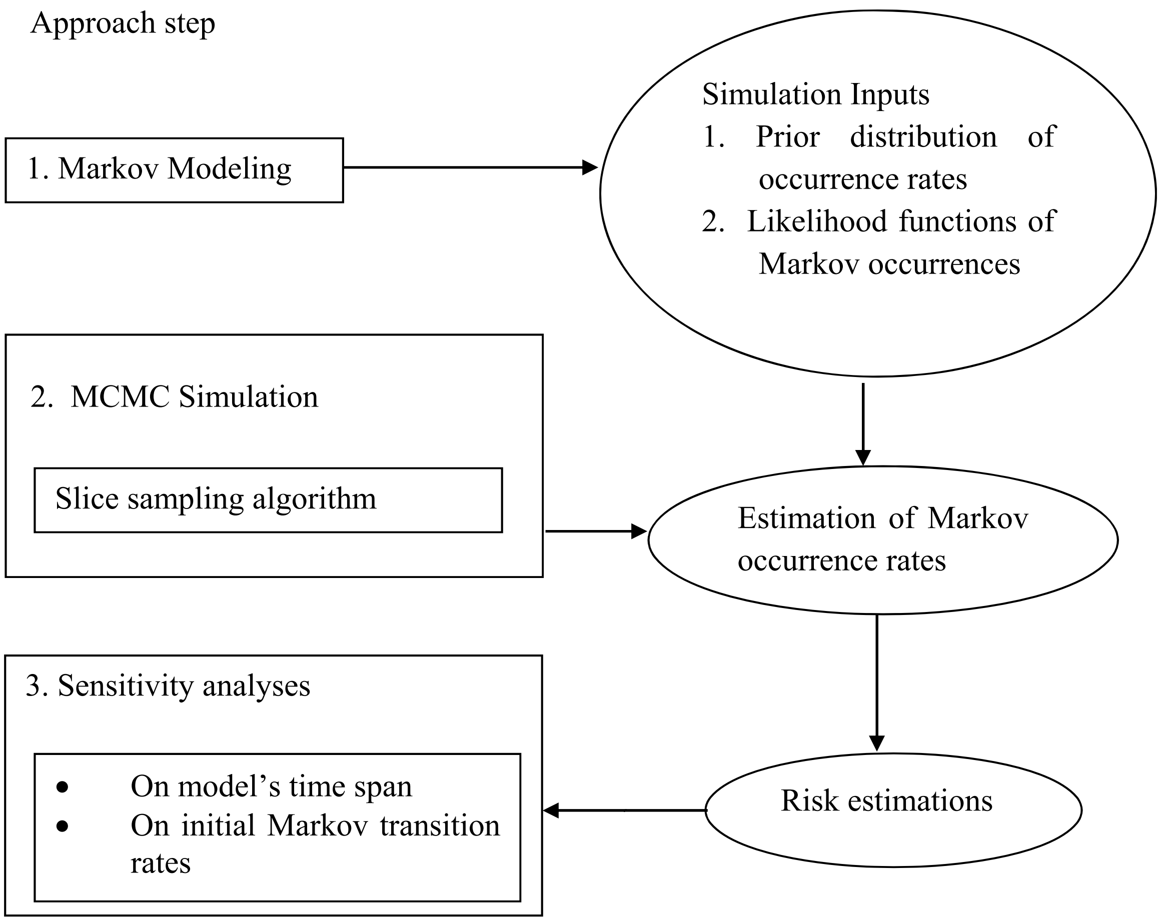

Figure 5-1. Structure of the proposed accident risk model

5.1.1. Markov model

In our Markov model, a three-state graph is drawn which can show accident occurrences for any type of marine transportation systems (see Figure 5-2). It is clear that state 3 (S3) means the full risky situation. Entering to this state is by two types of occurrences:

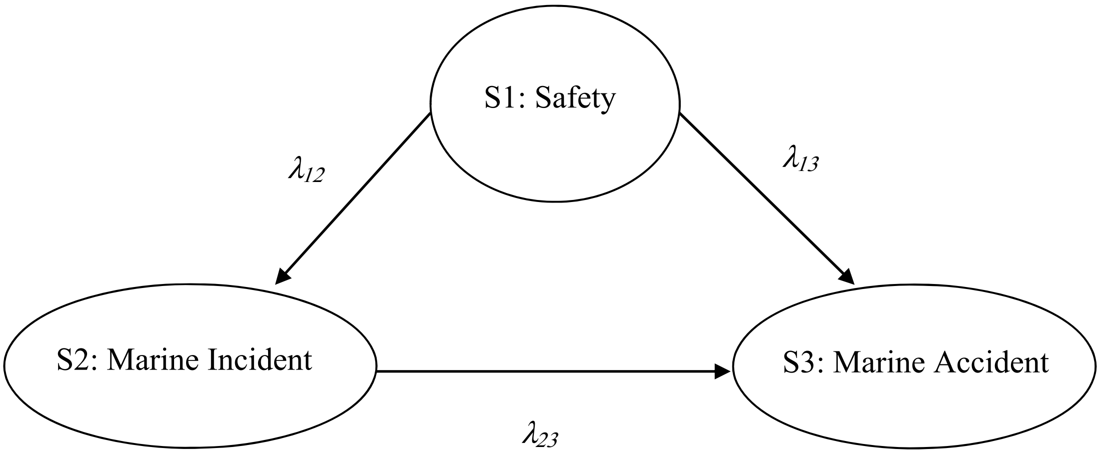

Figure 5-2. Markov accident model (λ_{kl}: occurrence rate from state *k* to state *l*)

1) Some marine incidents such as machinery failures, which were non-significant at first stages, become serious by time and cause the transition from state 2 to 3.
2) Without any history and background, some serious accidents occur including death, serious injuries and damages. They cause the transition from state 1 to 3.

In Markov model, each occurrence between states is characterized by an occurrence rate λ_{kl}. k and l are the indices for the start and end states, respectively (Modarres 2006). It is assumed that the occurrence probability in state *k* at time $t, p_k(t)$, is differentiable. Then, we can write the Kolmogorov's forward equations for Markov model. For the numerical examples of this chapter, the below set of differential equations is solved and the time dependent probabilities of states are calculated.

$$\frac{dp_i(t)}{dt} = -\left(\sum_j \lambda_{ij}(t)\right) \cdot p_i(t) + \sum_j \left(\lambda_{ij}(t) \cdot p_j(t)\right) \tag{5-1}$$

In the Markov diagram, it is shown that serious incidents may occur after and in continue of marine incidents. Sometimes, the exact time of a serious incident is unknown, because the system is not controlled and observed continuously. However, we can distinguish incidents and serious incidents after a period of time. Therefore, we consider a time span that starts from S1 state and ends with S3. We count the occurrences in this time span indifferent that which route is taken from S1 to S3 through the Markov model. We call this partially observation. In this way, partial data are collectable from marine statistical reports.

The first step in the reliability assessment of a system is to know the history of failures and accidents observed for the kind of system of concern. The data collected on the number of failures and accidents of the system is the prior knowledge of the system. From this step, through identifying the most frequent type of accidents, we can know about the main states of the Markov model. If the frequency of one type of accident is high or considerable, then the related data of that accident should be recorded. From the collected data, prior distributions for failure and accident rates of the system are estimated. These distributions are required to initiate the simulation algorithms.

5.1.2. MCMC simulation

To start MCMC simulation, we need to consider two distributions in advance. The first distribution is the prior distribution of unknown occurrence rates. The prior distribution, $\pi_0(\lambda)$, refers to the initial belief of occurrence rate's values (λ) to be true. It is typically an estimate of the distribution for the continuous parameter λ. Although the choice of a prior or determination of prior distribution is often subjective, a rational agreement can be achieved by analyzing historical data from the same or other similar databases (Thodi et al. 2010). The second distribution is the likelihood function of occurrences. The likelihood function, $f(r|\lambda)$, is the prior distribution of observations (r) conditioned by assumed values for occurrence rates (λ).

In MCMC simulation, Bayes' theorem states how to update the prior probability distribution of occurrence rates, $\pi_0(\lambda)$, with a likelihood function, $f(r|\lambda)$, to obtain the posterior distribution of occurrence rates. Commonly written formula for Bayesian updating is:

$$\pi(\lambda|r) = \frac{f(r|\lambda).\pi_0(\lambda)}{f(r)} \propto f(r|\lambda).\pi_0(\lambda) \tag{5-2}$$

In this formula, the samples for posterior distribution of occurrence rates, $\pi(\lambda|r)$, will be generated by combining the prior distribution with observed data. The posterior density, $\pi(\lambda|r)$ summarizes the total information, after viewing the initial data of occurrences, and provides a basis for inference regarding the parameter λ (vector of occurrence rates).

With this background on MCMC simulation, the procedure of slice sampling algorithm is as follows:

1) Assume initial values for occurrences rates λ_0 within the domain of posterior distribution $\pi(\lambda|r)$ which is estimated by the multiplication of likelihood function and prior distribution from Eq. (5-2).

2) Draw a real value for occurrence rates λ^* uniformly between 0 and λ_0 (*i*.e. $[0, \pi(\lambda_0|r)]$). In this way, the horizontal slice defines as $S = \{\lambda|\lambda^* < \pi(\lambda|r)\}$.

3) Find an interval $I = (L, R)$ around λ_0 that contains all or much of the slice S.

4) Draw the new point λ_1 within interval *I*.

5) Repeat steps 2 through 4 starting with new point λ_1 until getting the desired number of samples.

6) Find the mean and variance of occurrence rates from the resulted sample of step (5).

In Markov model, there are relationships between probability of occurrences and occurrence rates (see Eq. (5-1)). In the three-state Markov model, if we assume that the occurrence of marine occurrences are homogeneous Poisson process with mean λ_{kl} in matrix *G*, the state occurrence probabilities can be calculated as the elements of matrix *P(t)*.

$$G = \begin{bmatrix} -(\lambda_{12} + \lambda_{13}) & \lambda_{12} & \lambda_{13} \\ 0 & -\lambda_{23} & \lambda_{23} \\ 0 & 0 & 0 \end{bmatrix} \tag{5-3}$$

$$P(t) = \begin{bmatrix} e^{-(\lambda_{12}+\lambda_{13})t} & \frac{\lambda_{12}e^{-\lambda_{23}t}(1-e^{-(\lambda_{12}+\lambda_{13}-\lambda_{23})t})}{(\lambda_{12}+\lambda_{13}-\lambda_{23})} & 1 - \pi_{11}(t) - \pi_{12}(t) \\ 0 & e^{-\lambda_{23}t} & 1 - e^{-\lambda_{23}t} \\ 0 & 0 & 1 \end{bmatrix} \tag{5-4}$$

where $\pi_{kl}(t)$ equals to the occurrence probability that is from state *k* to *l* at time *t*.

By slice sampling algorithm, we estimated the expected value of occurrence rates (incident rate, serious incident rate, and accident rate). Thereby, we put estimated occurrence rates in Kolmogorov equations and found the probability of occurrences by solving these equations. The solved occurrence probabilities represent the "Marine Risk."

$$Risk(t) = \pi_{13}(t) + \pi_{23}(t) \tag{5-5}$$

$$R(t) = 1 - Risk(t) = 1 - (\pi_{13} + \pi_{23}) \tag{5-6}$$

5.2. Case study 1: Accident risk model for Australian commercial vessels

In this case, marine risk associated with three concepts of marine events: incident, serious incident and accident. There is a distinction between "accident" and "incident" in terms of the magnitude of consequences (Mullai and Paulsson 2011). We provide a definition for each of these events after reviewing different marine statistics and annual reports that are published by various marine organizations (e.g. ATSB[1], TSBC[2], EMSA[3], HELCOM[4], and AIBF[5]).

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[1]Australian Transportation Safety Board
[2]Transportation Safety Board of Canada
[3]European Maritime Safety Agency

- Marine accident:

An occurrence involving a vessel where: a person dies or suffers serious injury as a result of an serious incident occurrence associated with the operation of the vessel; or the vessel is destroyed or seriously damaged as a result of an occurrence associated with the operation of the vessel.

- Marine incident:

An occurrence, other than an accident, associated with the operation of a vessel which affects or could affect the safety of operation. This occurrence involves circumstances indicating that an accident nearly occurred.

- Marine serious incident:

An incident involving circumstances indicating that an accident nearly occurred.

5.2.1. Data and Case Description

In this section, we use the proposed methodology with the purpose of accident risk estimation of Australian commercial vessels. We referred to marine research and analysis report of Australian Transport Safety Bureau (ATSB) in year 2011. In this report, data is provided for occurrences involving Australian flag ships operating as

[4] Helsinky Commission
[5] Accident Investigation Board of Finland

trading ships (cargo and/or passengers) around the world and trading vessels flying foreign flags within Australia's maritime jurisdictions.

Table 5.1 presents the number of occurrences from years 2005 to 2010 related to Australian vessels or vessels within Australian marine jurisdictions. In this table, the observed occurrences from S2 to S3 are given in the category of serious incident. The variations for incident and serious incident are insignificant, but it is sensible for accident rates.

Table 5.1. Australian commercial shipping occurrences over the 5-year period (2005-2010)

Occurrence type	2005	2006	2007	2008	2009	2010
Accident	8	8	8	3	3	3
Serious Incident	4	5	3	3	2	5
Incident	81	98	81	65	94	72

We considered uniform distributions for the prior distribution of occurrence rates, for example Uniform $(65, 98)$ for incident rate distribution. Then, we started slice sampling algorithm by considering and normalizing mean values of Uniform distributions as initial transition rates, λ_0. The multinomial distribution was assumed as the likelihood distribution of occurrence rate vector λ, $f(r|\lambda)$. Therefore, the occurrence numbers for each row k of matrix G are drawn from a multinomial distribution with probabilities:

$$(r_{k1}, r_{k2}, \dots, r_{kl}) \sim Multinomial\ (\pi_{k1}(t), \pi_{k2}(t), \dots, \pi_{kl}(t);\ r_k) \qquad (5\text{-}7)$$

5.2.2. Some numerical results

After running the coded algorithm described in Section 2 in Matlab R2012a software for 1000 times, the resulted estimations of occurrence probability and rates over a 5-year time span were shown in Figure 5-3. From MCMC simulation results for mean probabilities of marine occurrences in Australian waters, the determination of marine risk for next 5 years is possible. Based on simulation results, the mean probabilities for incident, accident, and serious incident were 0.1004, 0.0059, and 0.0069, respectively. The mean values can be interpreted as the "risk of marine occurrences" in 5 years. Commercial vessels moving in Australian waters are about 90% reliable not to face any incident, 99.4% reliable not to face any accident, and 99.3% reliable not to face any serious incident.

As can be seen, the observed accident and serious incident rates gently change during the 5-year time span and their estimated values are nearly stabilized for the same duration. However, the averages of estimated accident and serious incident rates in five years are less than the average values of observed initial rates. Similarly, in comparison of the expected incident rates with the observed initial ones, the decreasing trend is clearly observable. This decrease of occurrence rates is consistent with what we expect to happen in real world. Marine occurrences are slightly decreasing because of IMO standards, industry initiatives and ever improving technology.

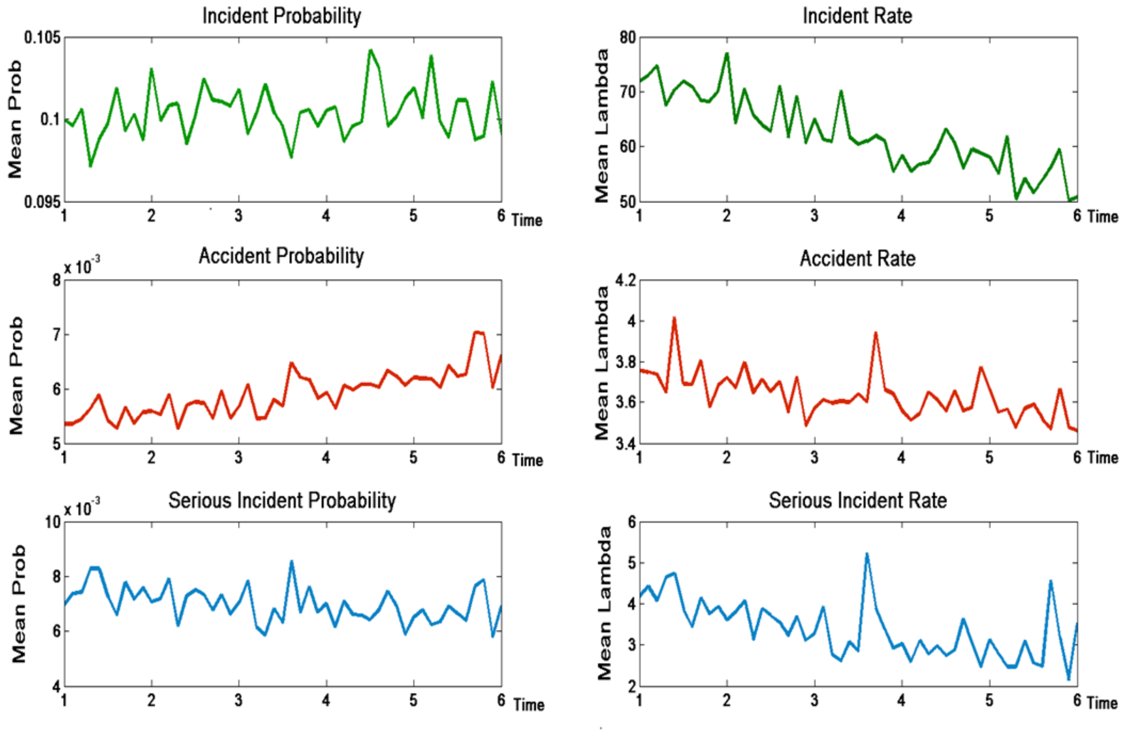

Figure 5-3. Marine occurrence probabilities and occurrence rates for Australian commercial vessels in a 5-year time span resulted from 1000 runs of MCMC simulation

We may observe the variation of probability and rate of the marine occurrences in different times by surface plots. In fact, the surface plotting is the generation of a mathematical surface to pass through, or close to, a set of existing elevation points. In this regard, the surface fitting tool in Matlab R2012a is used with the application of Biharmonic (*v4*) method under the category of interpolation fit. The contour plot, surface plot, and residual plot of simulated occurrence probabilities vs. time and occurrence rates are shown in Figure 5-4 to Figure 5-6.

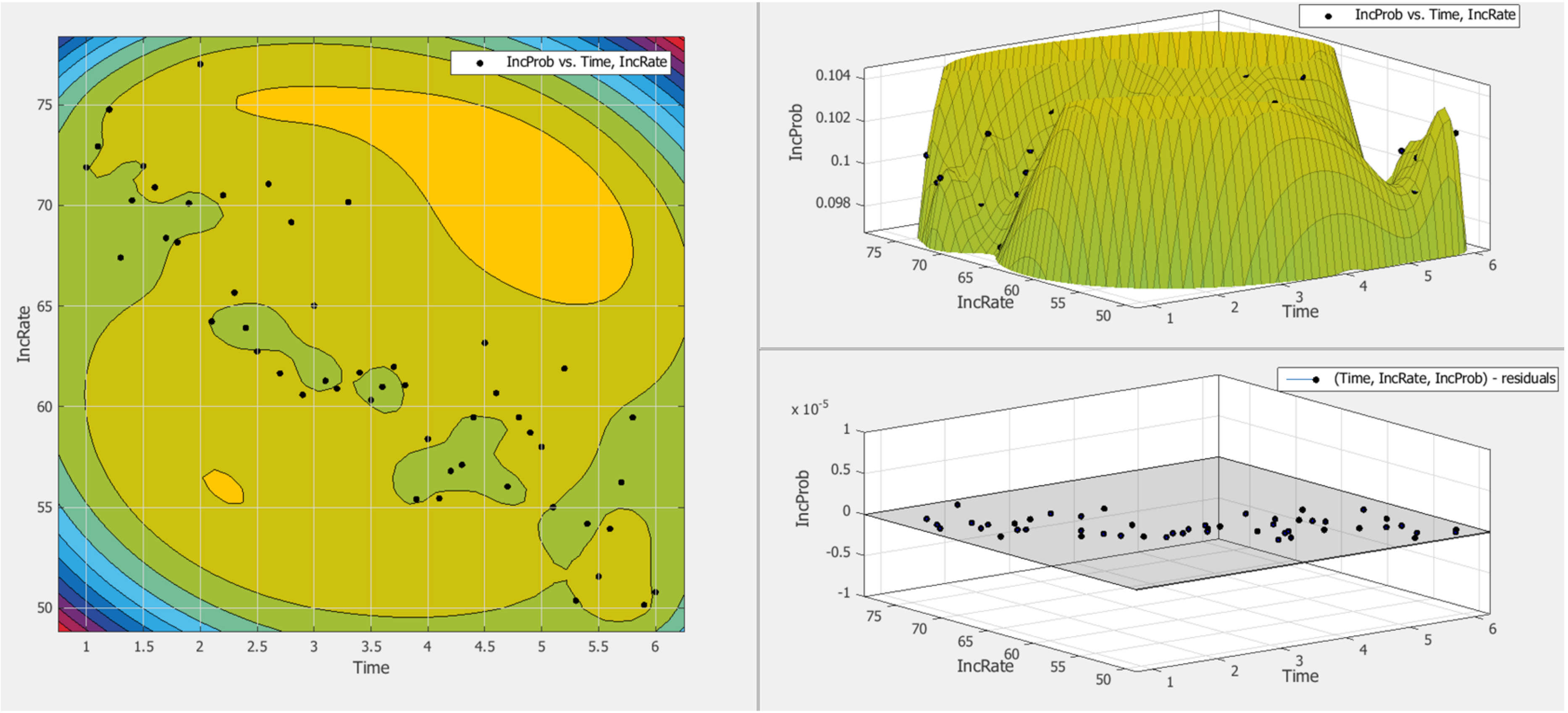

Figure 5-4. The contour plot, surface plot, and residual plot of simulated incident probability vs. time and incident rate

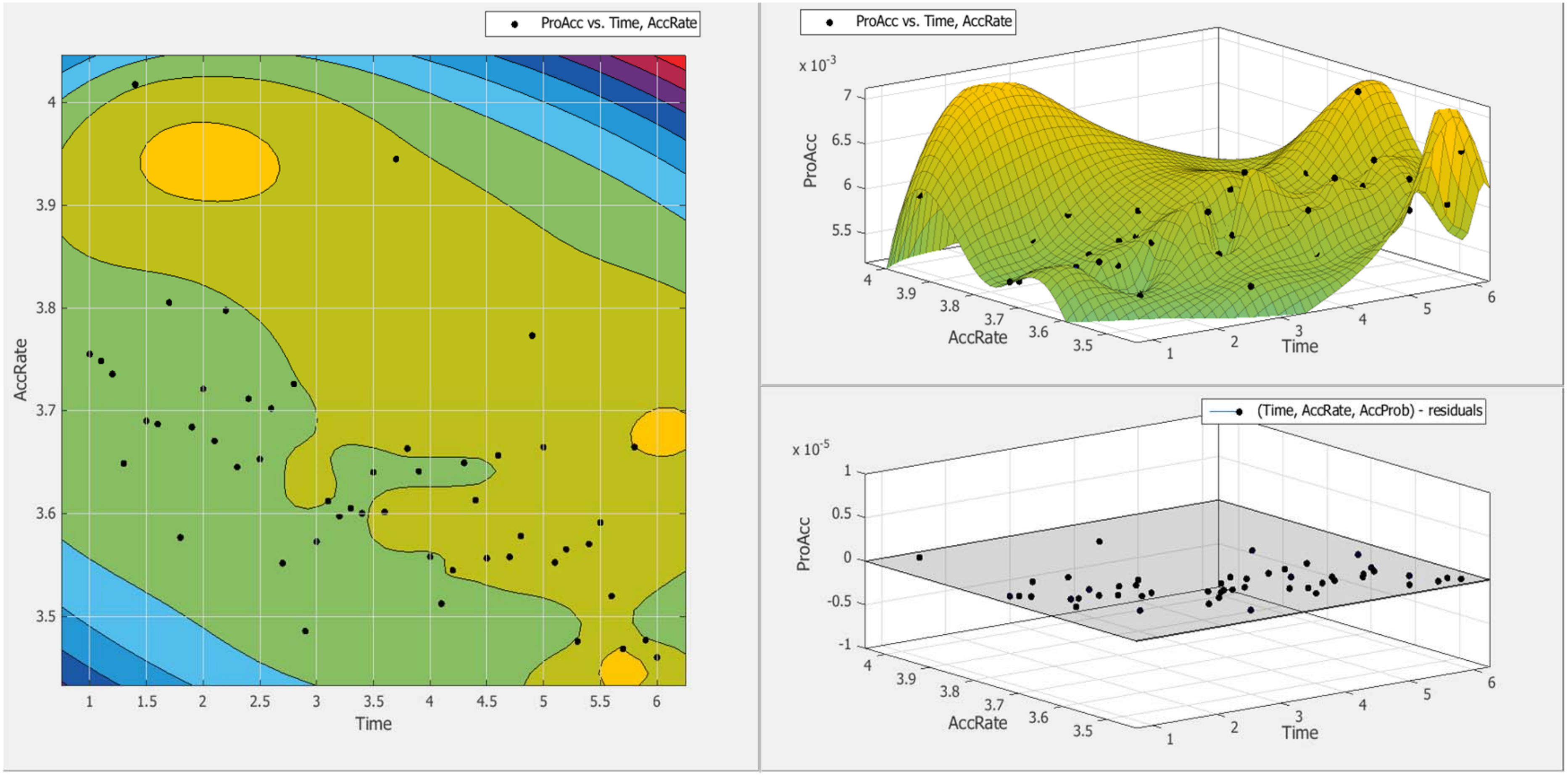

Figure 5-5. The contour plot, surface plot, and residual plot of simulated accident probability vs. time and accident rate

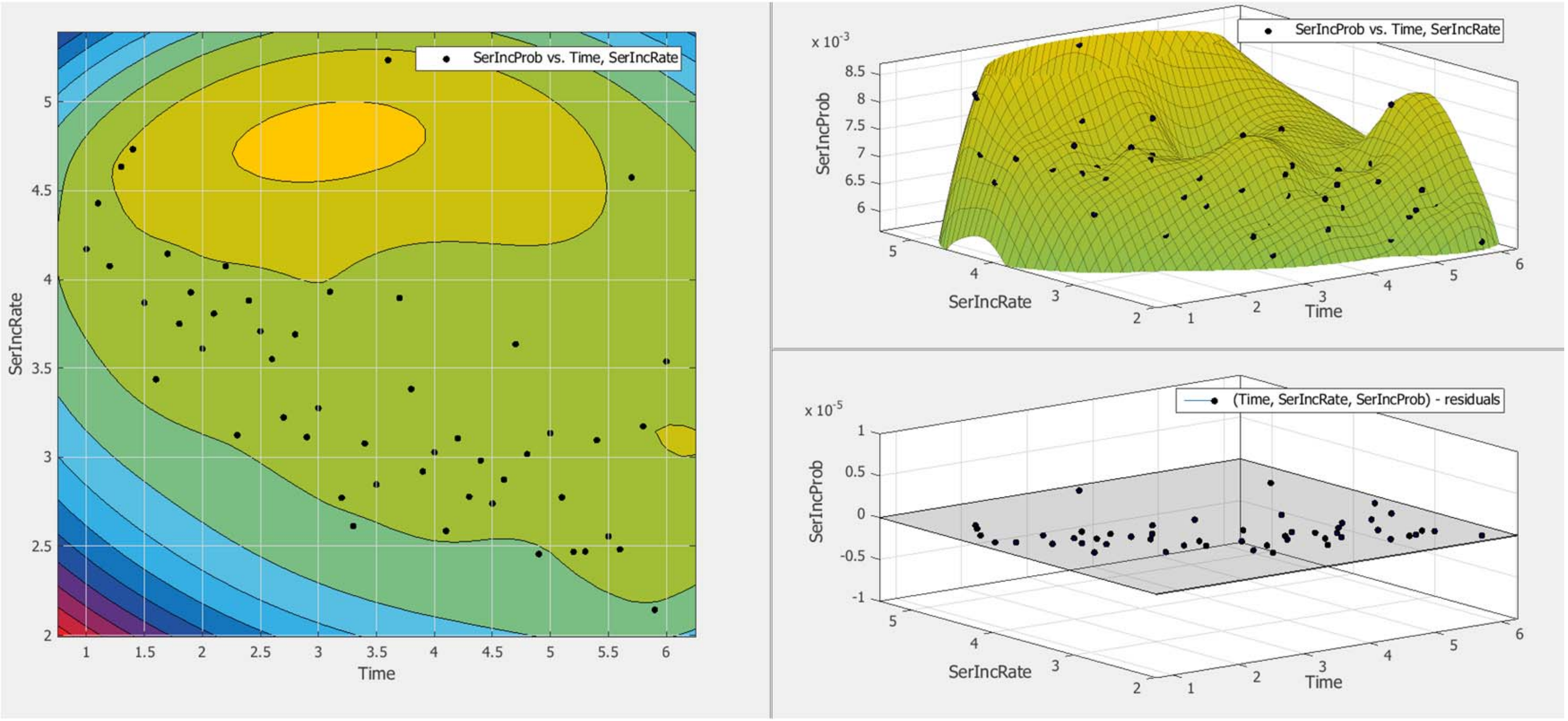

Figure 5-6. The contour plot, surface plot, and residual plot of simulated serious incident probability vs. time and serious incident rate

The results depicted in contour plots reveal that for more than 90% of the occurrence rates, the estimated occurrence probabilities locate in the same color contour regions. In other words, the occurrence probabilities remain stable while occurrence rates vary in time. For example, the contour plot for serious incident probabilities clearly applies to this fact. This means that the risk associated with serious incidents is almost constant during the 6 years. Intuitively, in surface plots, the contour regions with highest occurrence probabilities (surface peaks) are distinguished with higher level colors.

5.2.3. Sensitivity analysis on model's time span

Recent work in the assessment of risk in maritime transportation systems has used simulation-based probabilistic risk assessment techniques (Merrick et al. 2005). In simulation-based models, we combine the characteristics of real marine accidents and make them act out a future event. Therefore, to investigate the applicability of the model and draw conclusions, a sensitivity analysis on main characteristics and assumptions is important. In other words, we should pinpoint which initial assumptions are appropriate candidates for additional data collection to narrow the degree of uncertainty in the results.

In this section, a sensitivity analysis is carried out on time span of the model to see how it may effect on algorithm's results. In numerical example, we considered a 5-year time span for estimation of marine risks by running the slice sampling algorithm in 1000 times. Without changing other initial assumptions, we changed the model's time span from 5 year to 20 year with the step length of half year (i.e. thirty one estimations for occurrence probabilities). It is noted that number of runs was fixed (1000 times) in every variation. At each time span, the model resulted different estimations for occurrence probabilities. We observed and saved the variations of occurrence probabilities in response to the changes of simulation time span. Mean and standard deviation of estimated incident and accident probabilities were calculated (see Table 5.2). Moreover, we set up $\bar{x}$ and (s) control charts for the estimated incident and accident probabilities by SPSS 20.0.0 software. Totally thirty one samples with thirty one observations (thirty one estimations for occurrence probabilities) were considered. The three-sigma control limits for $\bar{x}$ and (s) were calculated and stated in Table 5.2. In this way, there is a 95% confidence that the estimated probabilities and the standard deviation values locate in between the control limits.

Table 5.2. Statistical information of incident and accident probabilities over time

(1-6) years statistical information	Incident	Accident
Mean of probabilities ($\bar{x}$)	0.10030	0.00601
Standard deviation (s) of probabilities	2.037E-03	4.573E-04
Upper control limit for $\bar{x}$	0.10646	0.00731
Lower control limit for $\bar{x}$	0.09414	0.00471
Upper control limit for (s)	2.680E-03	4.971E-04
Lower control limit for (s)	1.394E-03	4.175E-04

The statistical information shows that risks of incidents and accidents do not dramatically change with different time spans. This can be also interpreted as: although marine occurrence rates decrease through time (what we resulted in previous section), the estimated occurrence risk change slightly over time. Practically, this result is significant and observable in real. In spite of current safety improvements, still the risk of accidents and incidents exists. We cannot consider that this probability is going to significantly decrease or lead to zero through time.

5.2.4. Sensitivity analysis on initial transition rates

In most of the marine accident reports, number of accidents is updated by time (e.g. monthly, annually). Therefore, it is necessary to propose a model to be flexible in updating accident rates and probabilities by time. In this section, we investigate the effect of initial transition rate values on simulation results and estimations of probabilities.

Slice sampling algorithm begins with a set of initial transition rates ($\lambda_{12}, \lambda_{13}$, and λ_{23}). For example, mean value of Uniform (a_{12}, b_{12}) was assumed as the initial incident rate where a_{12} and b_{12} are the minimum and maximum of incident rates in Table 5.1. In this section, the initial rates were changed (increased) by the step length of $(\frac{b-a}{20})$ for 10 times. At each step, the time span of the model was considered to change from 5 to 10 years. MCMC simulation runs for 1000 times at each step. Figure 5-7 includes the plots for the mean of occurrence rates ($\lambda_{12},\ \lambda_{13}$, and λ_{23}) versus time.

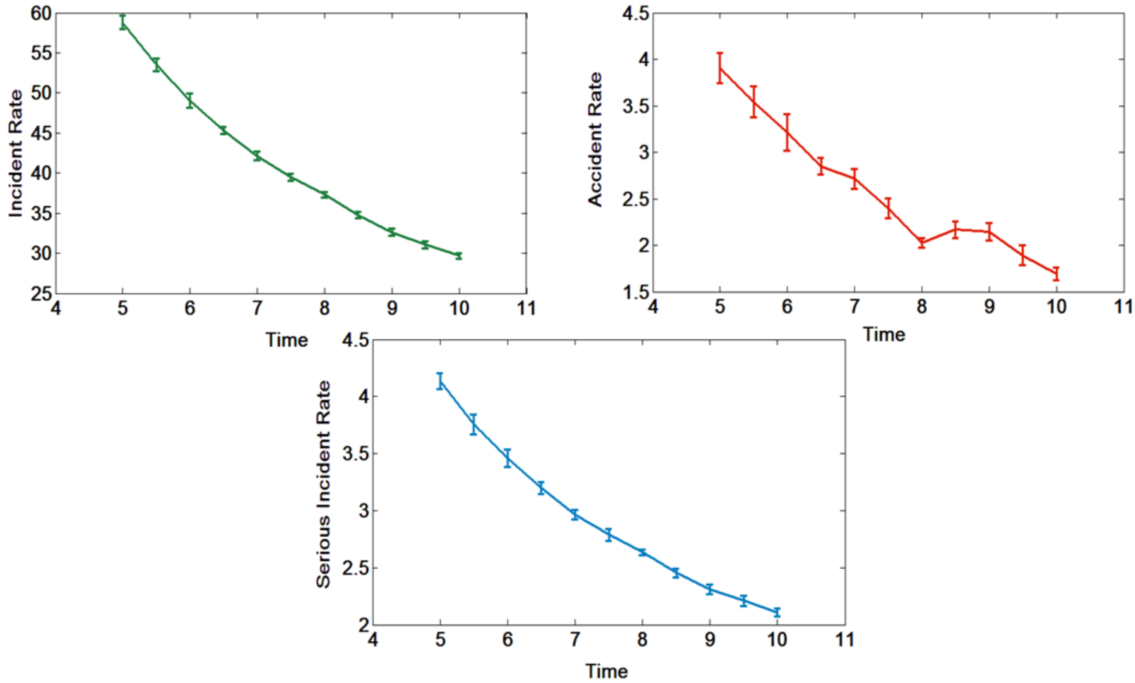

Figure 5-7. Error bar plots of marine occurrence rates after running MCMC simulation with different initial rates

The plots show symmetric error bars which can indicate the confidence intervals of resulted transition rates. As can be seen, mean values of occurrence rates have descending trends over the model's time. For example, mean of accident rates is decreased from 3.7 in 5 years to 1.7 in 10 years. On the other hand, at each time, the error bars are small and the mean variation is not significant. This means that by fixing the model's time span, simulation results do not vary considerably when initial transition rates are selected at any point of uniform distributions. But when different time spans are considered, the rate's reduction is expected and the model follows what happens by time in real world.

5.3. Case study 2: Accident risk model for vessels in Hong Kong waters

5.3.1. Data and case description

In this section, we use the proposed methodology for the accident risk estimation of vessels moving within Honk Kong waters. We referred to the accident reports by marine department, the government of Hong Kong special administrative region.

International Maritime Organization (IMO) defines some of the key technical terms related to marine accidents which are as follows (Li, Meng et al. 2012):

- Risk: combination of frequency and severity of consequences.
- Accident: an unintended event involving fatality, injury, ship loss or damage, other property loss or damage, or environmental damage.
- Consequence: outcome of an accident (In this case, death is considered as a consequence).
- Frequency: number of occurrences per unit time (e.g., per year).
- Hazard: a potential to threaten human life, health, property, or the environment.
- Collision: striking or being struck by another ship, regardless of whether under way, anchored, or moored.
- Contact: striking any fixed or floating objects other than those included under collision or grounding.

- Grounding: being aground or hitting/touching shore or sea bottom or underwater objects (wrecks, etc.).
- Fire: incidents where fire is the initial event.
- Explosion: incidents where explosion is the initial event.

Table 5.3 presents the number of most significant marine occurrences within Hong Kong waters from years 1984 to 2011. In Table 5.3, the most marine occurrences involve as collision or contact, grounding or stranding, fire or explosion, and sinking or foundering. We considered this data as the number of transition from safe state to accident state in Markov model.

Table 5.3. Number of most significant marine occurrences within Hong Kong waters

Year	Collision/Contact	Grounding/Stranding	Fire/Explosion	Sinking/Foundering
1984	136	13	15	15
1985	116	18	17	24
1986	151	15	18	27
1987	145	21	20	27
1988	150	25	11	24
1989	165	13	24	30
1990	126	16	23	25
1991	163	14	19	20
1992	209	29	16	26

1993	286	34	19	35
1994	239	31	23	26
1995	327	27	16	30
1996	283	18	30	31
1997	246	19	23	29
1998	236	32	17	20
1999	246	42	28	54
2000	302	26	24	29
2001	242	38	30	33
2002	237	32	25	14
2003	263	25	20	15
2004	259	20	24	39
2005	239	29	31	32
2006	253	25	30	21
2007	181	27	14	25
2008	206	18	19	27
2009	201	36	29	26
2010	218	34	11	24
2011	252	23	18	21

From this data, the same distribution was assigned for transition from safe to vulnerable state. If a person killed or injured, then a transition from vulnerable state to accident state was considered (serious accident). In Figure 5-8, the transitions between states are clearly shown.

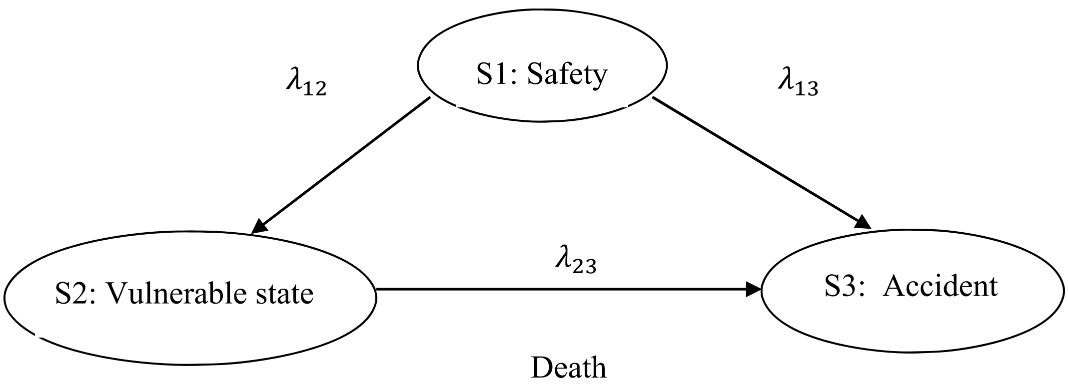

Figure 5-8. Markov accident model (λ_{kl}: occurrence rate from state *k* to state *l*).

Data on number of these transitions is given in Table 5.4. The accident type grounding usually causes no fatality, however it is very common among marine accidents. Therefore, the risk of person injuries instead of death caused by grounding was considered in this study.

Table 5.4. Number of death caused by different types of marine accidents in Hong Kong waters

Year	Death by Collision/Contact	Death/injuries by Grounding/Stranding	Death by Fire/Explosion	Death by Sinking/Foundering
1984	3	0	2	0
1985	1	0	0	1
1986	2	0	0	5
1987	1	0	0	3
1988	2	0	0	0
1989	9	0	1	1
1990	1	0	0	3
1991	3	0	1	0
1992	2	0	0	0
1993	6	0	0	1
1994	2	0	0	0
1995	5	2	0	3
1996	2	0	0	0
1997	5	0	0	1
1998	5	0	0	1
1999	11	0	3	0
2000	0	2	2	0
2001	0	0	1	0
2002	14	2	0	2
2003	0	2	2	0
2004	0	3	1	0

2005	3	2	1	4
2006	1	2	0	0
2007	1	0	0	3
2008	1	1	0	0
2009	1	2	0	0
2010	8	4	0	0
2011	1	0	0	0

5.3.2. Simulation inputs

Slice sampling algorithm was encoded in Matlab R2012a software. The inputs of the algorithm for accident type collision/contact are given in Table 5.5. With the lack of knowledge, continuous uniform distributions were considered as priors. For example, the prior distribution of transition from state 1 (Safety) to state 3 (Collision) is Uniform (116,327). This represents the situation where number of collisions/contacts in the range between the minimum and maximum of observed data are equally likely. Multinomial distributions were assumed as the likelihood distribution of occurrence rates $f(r|\lambda)$ to calculate posterior distributions (see Eq. (5-7)).

Table 5.5. Inputs of the coded slice sampling algorithm for accident type collision/contact in Matlab R2012a.

Description	Code
Prior for Transition Rates	*prior12 = @(G12) unifpdf(G12,116,327);* *prior13 = @(G13) unifpdf(G13,116,327);* *prior23 = @(G23) unifpdf(G23,0.01,14);*
Transition Rate Likelihoods	*P11 = @(G) exp(-(G(1) + G(2)) * t);* *P12 = @(G) G(1)/(G(1) + G(2) - G(3)) * exp(-(G(3) * t)) * (1 - exp(-(G(1) + G(2) - G(3)) * t));* *P13 = @(G) 1 - G(1)/(G(1) + G(2) - G(3)) * exp(-(G(3) * t)) * (1 - exp(-(G(1) + G(2) - G(3)) * t)) - exp(-(G(1) + G(2)) * t);* *P22 = @(G) exp (-(G(3) * t));* *P23 = @(G) 1 - exp (-(G(3) * t));*
Initial Transitions	*r = [200000,136,136;0,1000,3];*
Posterior distribution	*post = @(G) mnpdf(r(1,:),[P11,P12,P13]) * mnpdf(r(2,2:3),[P22,P23])* prior12(G(1)) * prior13(G(2)) * prior23(G(3));*
Initial Lambda (*G*) values	*Initial = [221.5,221.5,7];*
Slice Sampling	*trace = slicesample(Initial,NMC,'pdf',post);* *NMC = 1000;*

Based on the average yearly arrival and departure patterns of ocean-going and river going vessels within Hong Kong waters, the initial transition from safe to safe state was considered as 200,000 transitions. Among these transitions, 136 collisions/contacts were observed in year 1984. In addition, from average number of 1000 crew members and passengers, 3 deaths were observed in year 1984. Therefore, vector (*r*) presented in Table 5.5 was considered as initial transition vector.

In slice sampling algorithm, the mean values of prior distributions were considered as initial transition rate values. After 1000 Monte Carlo runs (*NMC = 1000*), the risk values at different years were estimated based on Eq. (5-5). The reliability of marine systems (e.g. vessels) while moving within Hong Kong water is also obtainable from Eq. (5-6) given in Section 5.1.2.

5.3.3. Some numerical results

After running the coded slice sampling algorithm in Matlab R2012a software for 1000 times, the resulted estimations of occurrence probability for accident type collision/contact are shown in Figure 5-9.

As can be seen, the mean probability of vulnerability and collision increase with the slightly same trend due to the similar prior distributions. With the effect of continuous Poisson process in Markov model, mean probability of death increases in time. As a result of increasing occurrence probabilities, the estimated risk values grow in time.

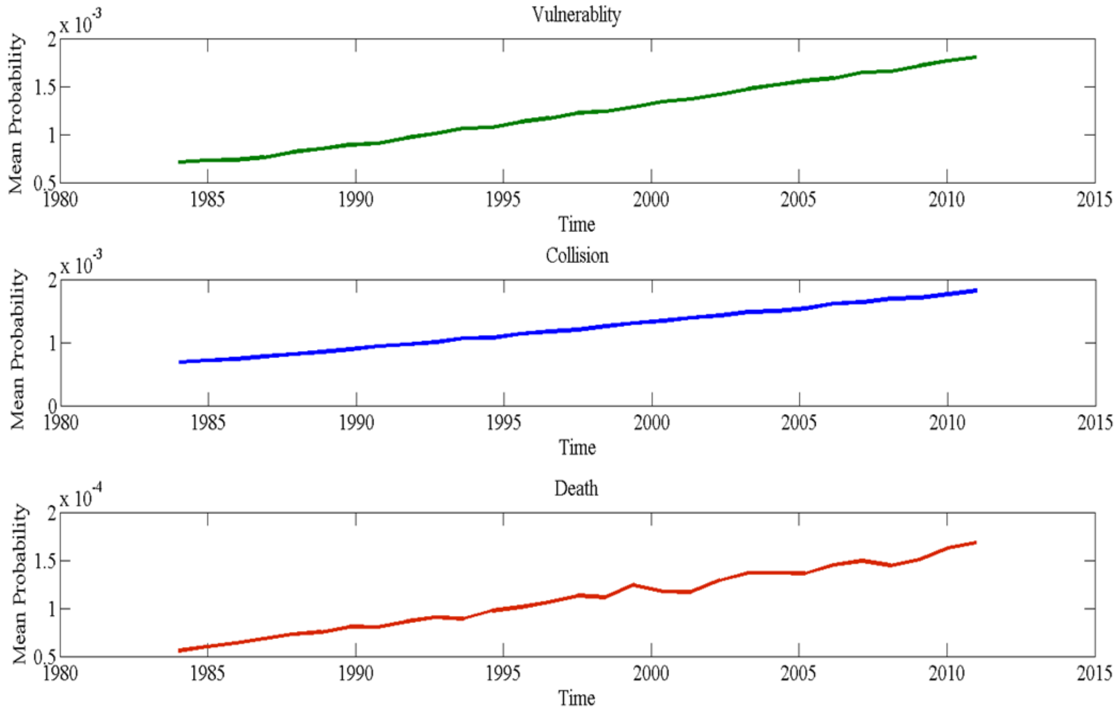

Figure 5-9. Marine occurrence probability trends for vessels moving within Hong Kong waters resulted from 1000 runs of MCMC simulation

The resulted risk estimations of collision/contact, grounding/stranding, fire/explosion, and sinking/foundering for 28 years (1984-2011) are shown in Table 5.6.

The average estimated risks for collision/contact, grounding/stranding, fire/explosion, and sinking/foundering are 0.001311, 0.000165, 0.000142, and 0.000182, respectively. Risk of collision/contacts is much higher that other types of accidents in Hong Kong waters.

Table 5.6. Estimation of marine accident risks resulted from 1000 runs of MCMC simulation.

Year	Collision/Contact Risk	Grounding/Stranding Risk	Fire/Explosion Risk	Sinking/Foundering Risk
1984	0.00074	0.00009	0.00010	0.00011
1985	0.00078	0.00010	0.00009	0.00011
1986	0.00080	0.00010	0.00010	0.00012
1987	0.00084	0.00011	0.00010	0.00012
1988	0.00089	0.00011	0.00010	0.00013
1989	0.00092	0.00012	0.00011	0.00013
1990	0.00097	0.00012	0.00011	0.00014
1991	0.00102	0.00013	0.00011	0.00014
1992	0.00105	0.00014	0.00012	0.00015
1993	0.00110	0.00014	0.00012	0.00015
1994	0.00116	0.00014	0.00012	0.00016
1995	0.00117	0.00015	0.00013	0.00017
1996	0.00124	0.00015	0.00013	0.00017
1997	0.00128	0.00016	0.00014	0.00018
1998	0.00131	0.00017	0.00014	0.00019
1999	0.00137	0.00018	0.00015	0.00019
2000	0.00143	0.00018	0.00015	0.00020
2001	0.00146	0.00018	0.00016	0.00020

2002	0.00151	0.00019	0.00016	0.00021
2003	0.00155	0.00019	0.00016	0.00021
2004	0.00162	0.00020	0.00017	0.00022
2005	0.00163	0.00021	0.00017	0.00023
2006	0.00168	0.00021	0.00018	0.00023
2007	0.00176	0.00022	0.00018	0.00024
2008	0.00179	0.00022	0.00019	0.00024
2009	0.00184	0.00023	0.00019	0.00025
2010	0.00186	0.00024	0.00020	0.00025
2011	0.00193	0.00024	0.00020	0.00026

Table 5.7 shows the ratios between different number of marine occurrences and the ratios between estimated marine occurrence risks. As can be seen, the average estimated value of risk ratios and the average value of marine occurrence ratios are noticeably close. The closeness of these two values to each other, to a large extent, supports the validity and usefulness of risk results. On the one hand, using statistics such as expected value of number of occurrences alone is not enough for risk analysis and risk management discussions. And, on the other, other criteria to be used for risk estimation such as those (based on probabilities) in this thesis should also reflect the changes of statistics and show similar behaviour.

Table 5.7. Comparison matrix of estimated accident risk ratios and marine occurrence ratios

Occurrence	Collision/ Contact		Grounding/ Stranding		Fire/ Explosion		Sinking/ Foundering	
	Risk ratio	Occurrence ratio	Risk ratio	Occurrence ratio	Risk ratio	Occurrence ratio	Risk ratio	Occurrence ratio
Collision/ Contact	1	1	7.94	8.68	9.23	10.23	7.20	8.11
Grounding/ Stranding	1/7.94	1/8.68	1	1	1.16	1.17	0.91	0.93
Fire/ Explosion	1/9.23	1/10.23	1/1.16	1/1.17	1	1	0.78	0.79
Sinking/ Foundering	1/7.2	1/8.11	1/0.91	1/0.93	1/0.78	1/0.79	1	1

5.3.4. Sensitivity analysis on initial transition value

One of the main problems in a Bayesian statistical analysis is the robustness of estimates with respect to data and model errors (Bardossy et al. 1991). It is necessary to propose a Bayesian-based model to be flexible in updating accident rates and probabilities by time. In this section, we investigate the effect of initial transition values on simulation results and estimations of probabilities. Slice sampling algorithm begins with a set of initial transition vector r = [200000, 136, 136; 0, 1000, 3]. Sensitivity analysis is done on the variation of initial number of transitions. Based on the statistical report published by marine department in Hong Kong in 2011, almost 200000 arrival and departure patterns of ocean-going and river going vessels within Hong Kong waters (i.e. safe transitions) were observed. However, this approximation is less for the previous decades. Therefore, the value of safe transitions is increased by steps of 10000 transitions up to 200000 transitions and at each step, different risks are estimated. Figure 5-10 shows the sensitivity analysis results for collision risk estimations. Also, in Figure 5-11, Figure 5-12, and Figure 5-13 the estimations of grounding, fire, and sinking risks for different initial transition numbers are shown, respectively.

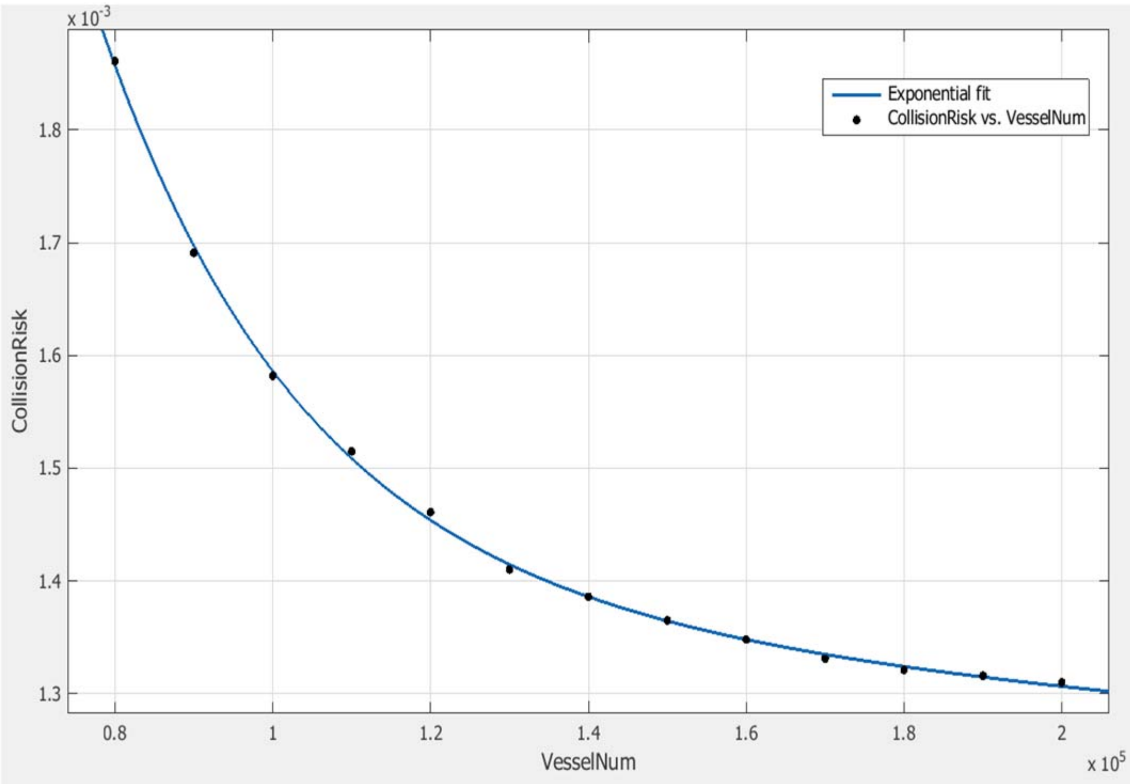

Figure 5-10. Collision risk estimations for different number of vessels moving within Hong Kong waters

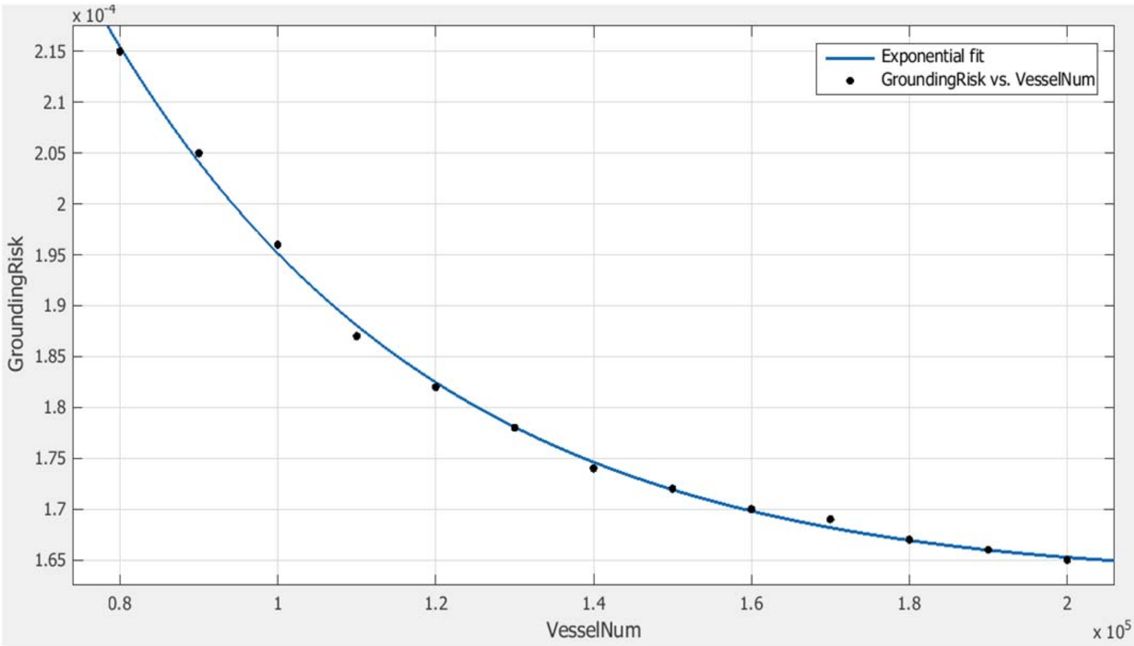

Figure 5-11. Grounding risk estimations for different number of vessels moving within Hong Kong waters

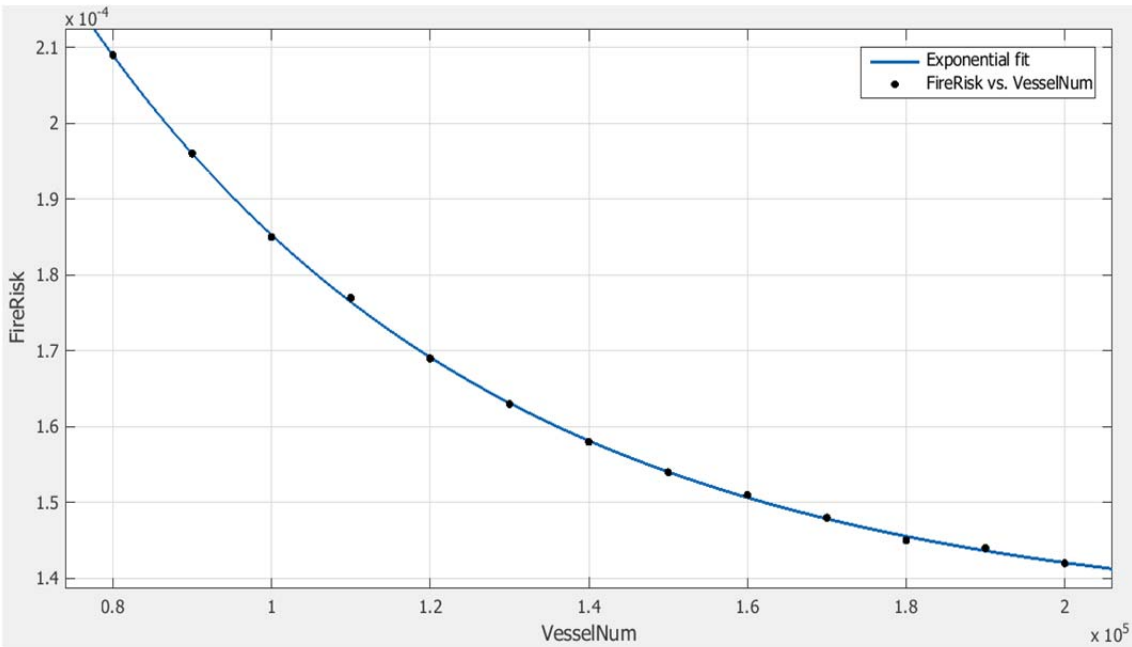

Figure 5-12. Fire risk estimations for different number of vessels moving within Hong Kong waters

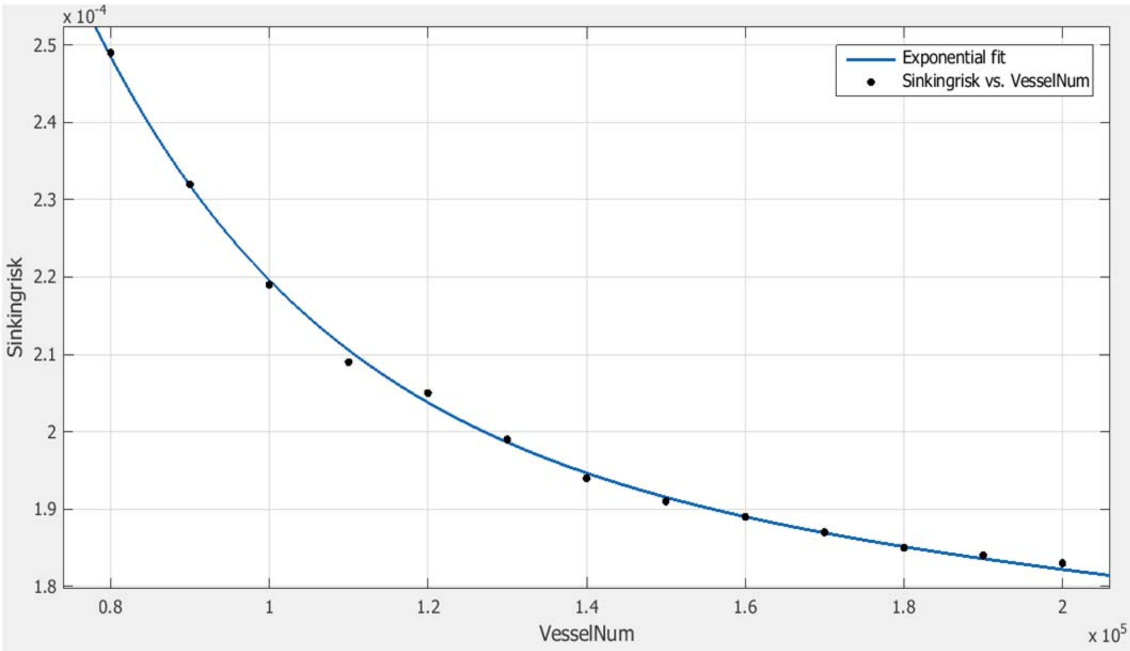

Figure 5-13. Sinking risk estimations for different number of vessels moving within Hong Kong waters

As can be seen, risk would clearly decrease by increasing number of safe transitions. For showing better the risk decline, trend lines were added to the scatter charts in Matlab R2012a. The fitted trend line equations and the goodness of the fits are shown in Table 5.8.

The sensitivity analysis shows that the proposed approach does not require any information on safety factors of the marine system. It is quite simple to find the relations of changed inputs of the model with the accident risk. Most of the recent risk models were proposed for the specific types of accidents or vessels. Our model has this advantage that it can generally consider any accident.

Table 5.8. Estimated fitting curves for different accident risks with the goodness of fit results

Type of risk	General Exponential model *f(x) = a*exp(b*x) + c*exp(d*x)* Coefficients (with 95% confidence bounds)	Goodness of fit
Collision Risk	*a* = 0.01043 (0.006861, 0.014)	SSE: 2.203e-10
	b = -3.842e-05 (-4.376e-05, -3.308e-05)	R-square: 0.9994
	c = 0.001426 (0.001339, 0.001513)	Adjusted R-square: 0.9991
	d = -4.564e-07 (-7.727e-07, -1.402e-07)	RMSE: 4.947e-06
Grounding Risk	*a* = 0.0003541 (0.000244, 0.0004642)	SSE: 4.233e-12
	b = -2.3e-05 (-3.09e-05, -1.51e-05)	R-square: 0.9986
	c = 0.0001576 (0.0001277, 0.0001875)	Adjusted R-square: 0.9982
	d = 1.27e-07 (-7.076e-07, 9.616e-07)	RMSE: 6.858e-07
Fire Risk	*a* = 0.0003444 (0.0003149, 0.000374)	SSE: 1.024e-12
	b = -1.914e-05 (-2.262e-05, -1.566e-05)	R-square: 0.9998
	c = 0.0001344 (0.0001116, 0.0001573)	Adjusted R-square: 0.9998
	d = 5.816e-09 (-6.873e-07, 6.99e-07)	RMSE: 3.373e-07
Sinking Risk	*a* = 0.0007933 (0.0004094, 0.001177)	SSE: 6.264e-12
	b = -3.335e-05 (-4.163e-05, -2.508e-05)	R-square: 0.9988
	c = 0.0002021 (0.0001826, 0.0002217)	Adjusted R-square: 0.9983
	d = -5.464e-07 (-1.026e-06, -6.64e-08)	RMSE: 8.343e-07

5.4. Conclusion

In this chapter, a new approach including Markov model and MCMC simulation is presented to estimate accident risks of marine transportation systems. For the case studies, initial data are collected from ATSB annual reports and from accident reports by marine department, the government of Hong Kong special administrative region. However, this model is applicable for any database in which marine accidents are recorded indifferent of their types and severities. MCMC simulation was applied for estimation of occurrence rates and probabilities.

For the first case study, sensitivity analysis on the time span of MCMC simulation showed accident and incident risks were remained constant in different time spans. Also, sensitivity analysis on initial transition rates showed that marine occurrence rates generally decrease by time. However, the simulated result of occurrence rates at each time does not affected considerably by initial rates. For the second case study, sensitivity analysis on initial input of MCMC simulation showed accident risks decreased exponentially over different number of vessels moving in the region.

There are two main advantages with the approach presented in this chapter. First, in the current risk estimation methods, many safety factors are involved in models that make these methods complicated. In practice, we should look for an easy-usable comprehensive method for risk estimation that it is even applicable without having enough information on effecting factors. The approach of this thesis does not require any information on safety factors of the system. Second, most of the recent risk models were proposed for the specific types of accidents or vessels. Our model has this advantage that it can generally consider any accident or marine system.

Overall, the approach of this thesis intends to fill the gap when there is a lack of information related to the 'safety factors' of the system. The proposed approach has the potentiality to consider any incident/accident in the Marine system. The research in this study could have potential application in other sectors such as oil or gas industry, and other systems such as the railways and road transportation systems.

CHAPTER 6: AVAILABILITY ASSESSMENT AND DESIGN OF MARINE MULTI-STATE SYSTEMS

In this chapter, first, we present a dynamic model to assess the availability of multi-state weighted *K*-out-of-*N* systems as a kind of marine transportation system. Second, regarding to the dynamic property of the systems and its components, we find the optimal design of the components by using Genetic algorithm. In the dynamic model, we change the probabilities and utilities of components in different states over time. For availability assessment, we use universal generating function and Markov process. We apply the proposed models to one real-world marine transportation system in order to evaluate and compare them in assessing systems' availability.

The organization of this chapter is as follows. Section 6.1 presents a dynamic model to assess the availability of multi-state weighted *K*-out-of-*N* systems. In Section 6.2, a dynamic design problem is introduced to be solved by genetic algorithm. In Section 6.3, one real-world numerical example from maritime transportation system is used to apply the dynamic availability model. Conclusions are provided in Section 6.4.

- **Nomenclatures**

N: The number of components of the system.

M: The best operating state for the components of the system, $M + 1$: Total number of states.

i: Index of component number in the system $1 \leq i \leq N$.

j: Index of component state in the system $0 \leq j \leq M$.

c_i: The design and manufacturing cost of component i.

k_j: The minimum total capacity required to ensure that the system is in state j or above.

C_j: Cost of system being in state below j (Cost of failure).

$A(t)$: Availability of a multi-state K-out-of-N system at time t.

$k(t)$: The demand capacity to ensure that the system is working properly at time t.

u_{ij}: Capacity of component i in state j.

$u_{ij}(t)$: Capacity of component i in state j at time t.

p_{ij}: Probability of component i being in state j.

$p_{ij}(t)$: Probability of component i being in state j at time t.

$\lambda_{j,k}^{i}$: Transition (failure) rate of component i from state j to state k $(j > k)$.

μ_{jk}^{i}: Transition (repair) rate of component i from state j to state k $(j < k)$.

Φ: The system's structure function representing the state of the system.

K: Total capacity of all components of the system.

$\hat{A}_{Sys}$: The minimum required probability for the system to attain a state of j or above.

C_{Sys}: Total cost of the system.

6.1. Dynamic availability model

In weighted K-out-of-N systems, each component of the system and the whole system have $(M+1)$ states: *0, 1, 2… M*. In Figure 6-1, a general Markov model for a system with N components and with $(M+1)$ states is presented. Component $i(1 \leq i \leq N)$ in state $j(0 \leq j \leq M)$ has a capacity value of u_{ij}. System is in state j or above if the total capacity of all components is larger than or equal to the value k_j. Then, this definition means:

$$Pr\{\Phi \geq j\} = Pr\{K \geq k_j\} \tag{6-1}$$

In dynamic availability assessment of multi-state weighted K-out-of-N systems, we consider a time function for probability distribution of component i in state j as $p_{ij}(t)$. The probability functions $p_{ij}(t)$ of the components are obtained from Chapman-Kolmogorov equations. Then, the system probability function is obtained from system Universal Generating Function (UGF).

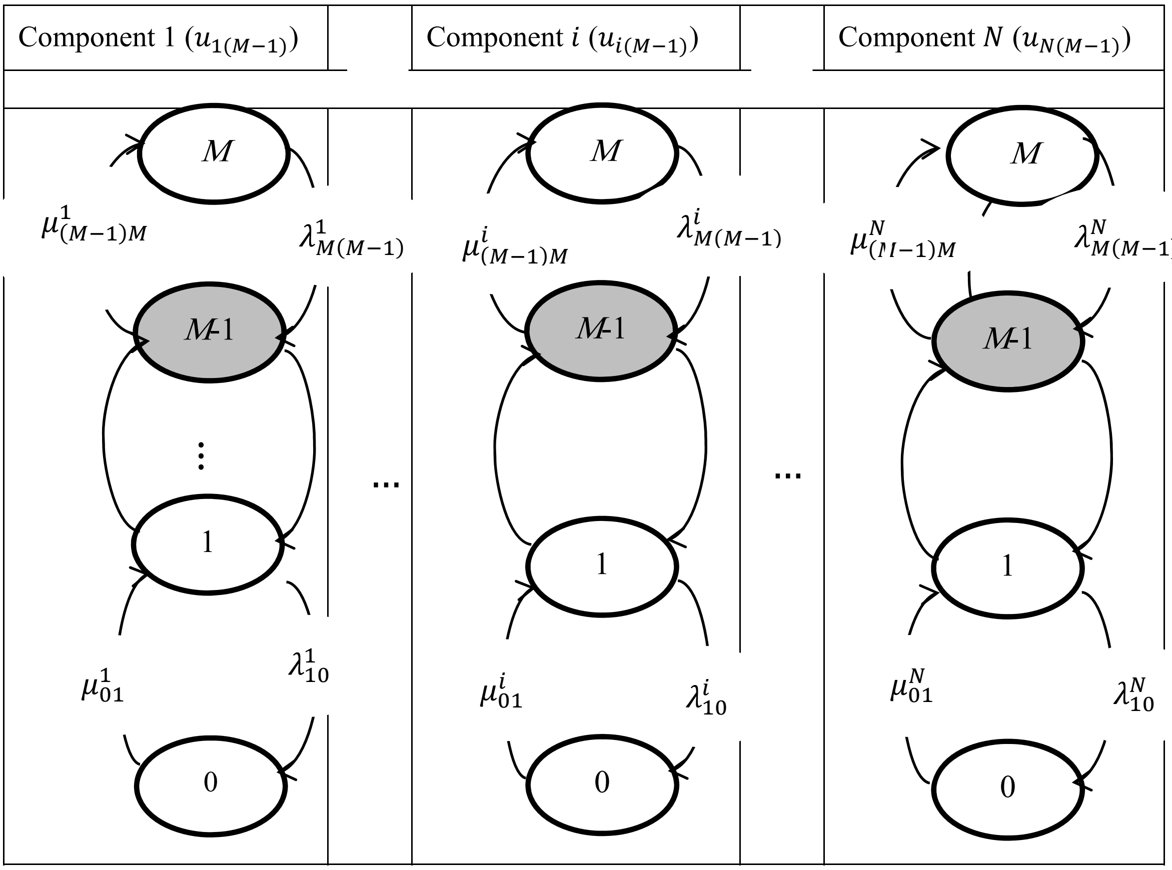

Figure 6-1. A general Markov model for a system with N components, e.g. if all components are in state $(M-1)$, then the system is in state j or above if $k_j = N(M-1)$, $u_{i(M-1)} = M - 1$ for $\forall i \in \{1, \dots, N\}$.

$$\begin{cases} \dfrac{dp_{i0}(t)}{dt} = \sum_{j=1}^{M} \lambda_{j0}^{i} p_{ij}(t) - \sum_{j=1}^{M} p_{ij}(t) \mu_{0j}^{i} \\ \vdots \\ \dfrac{dp_{ik}(t)}{dt} = \sum_{j=k+1}^{M} \lambda_{jk}^{i} p_{ij}(t) + \sum_{j=0}^{k-1} p_{ij}(t) \mu_{jk}^{i} - p_{ik}(t) \left(\sum_{j=0}^{k-1} \lambda_{kj}^{i} + \sum_{j=k+1}^{M} \mu_{kj}^{i} \right) \\ \vdots \\ \dfrac{dp_{iM}(t)}{dt} = \sum_{j=0}^{M-1} \mu_{jM}^{i} p_{ij}(t) - \sum_{j=1}^{M} p_{iM}(t) \lambda_{Mj}^{i} \end{cases} \tag{6-2}$$

According to the definition of the system, the sum of all state probabilities at any time should be equal to 1:

$$\sum_{j=0}^{M} p_{ij}(t) = 1 \tag{6-3}$$

We solve equations (6-2) and (6-3) simultaneously, with the initial conditions:

$$p_{iM}(0) = 1, \dots, p_{ik}(0) = 0, \dots, p_{i0}(0) = 0, \tag{6-4}$$

and get the state probability function $p_{ij}(t)$ for $i = 1, \dots, N$ and $j = 0, \dots, M$.

For the component i in state j, UGF links probability $p_{ij}(t)$ to the capacity (performance) level u_{ij}. The UGF of one component is given below:

$$U_i(z,t) = \sum_{j=0}^{M} p_{ij}(t) z^{u_{ij}} \tag{6-5}$$

We consider a marine transportation system with M + 1 different states $(0, 1, \dots, M)$, where state M is the perfect functioning state and state 0 is the completely failure state. In dynamic case, the system UGF can be re-written as:

$$\begin{aligned} U_{sys}(z,t) &= \Omega\big(U_1(z,t), U_2(z,t), \dots, U_N(z,t)\big) \\ &= \sum_{j_1=0}^{M} \sum_{j_2=0}^{M} \dots \sum_{j_N=0}^{M} \left(\prod_{i=1}^{N} p_{ij_i}(t) z^{\phi\left(u_{1j_1}, \dots, u_{Nj_N}\right)} \right) \end{aligned} \tag{6-6}$$

where $\phi(\cdot)$ is the so called system structure function. For multi-state weighted *K*-out-of-*N* system, the structure function is:

$$\phi\big(u_{1j_1}, \dots, u_{Nj_N}\big) = \sum_{i=1}^{N} u_{ij_i} \tag{6-7}$$

Once the UGF of the multi-state *K*-out-of-*N* system is obtained, the availability of the system is determined as the probability that the system at instant *t* is in one of the acceptable states:

$$A(t) = Pr\{\phi(u_{1j_1}, \dots, u_{Nj_N}) - k(t) \geq 0\} \tag{6-8}$$

where $k(t)$ is the system demand at time *t*.

6.2. Dynamic design problem

In commonly design problems of multi-state systems, goal is to determine and design optimal system based on two evaluation elements: availability/reliability and cost. In this study, we consider these two elements in an optimal design problem for multi-state weighted *K*-out-of-*N* systems which have not yet been studied as a dynamic problem.

Li and Zuo (2008b) presented two optimization problems for design of multi-state weighted *K*-out-of-*N* systems in non-dynamic cases. In this study, we improve the problem and find the optimal distribution of components' probabilities and utilities as functions of time. The dynamic design optimization problems are formulated as:

- **Problem P1**

Minimize:

$$C_{sys} = \sum_{i=1}^{N} c_i(t) + (1 - A(t)).C_j \tag{6-9}$$

Subject to:

$$\begin{cases} A(t) \geq \hat{A}_{sys} \\ \displaystyle\sum_{j=0}^{M} p_{ij}(t) = 1, \ \ 0 \leq p_{ij}(t) \leq 1 \quad (i = 1,2,\ldots,N; j = 0,1,2,\ldots,M) \\ u_{i0}(t) = 0, \qquad u_{ij}(t) \geq 0 \ \ (i = 1,2,\ldots,N; j = 0,1,2,\ldots,M) \end{cases} \tag{6-10}$$

- **Problem P2**

Maximize:

$A(t)$

Subject to:

$$\begin{cases} C_{sys} = \displaystyle\sum_{i=1}^{N} c_i(t) + \big(1 - A(t)\big).C_j \leq \hat{C}_{sys} \\ \displaystyle\sum_{j=0}^{M} p_{ij}(t) = 1, \ \ 0 \leq p_{ij}(t) \leq 1 \quad (i = 1,2,\ldots,N; j = 0,1,2,\ldots,M) \\ u_{i0}(t) = 0, \qquad u_{ij}(t) \geq 0 \ \ (i = 1,2,\ldots,N; j = 0,1,2,\ldots,M) \end{cases} \tag{6-11}$$

In above problems, the availability of the system, $A(t)$, can be obtained from Eq. (6-8). Similar to Li and Zuo (2008b), we refer to Mettas (2000) and define the cost of components in terms of considering the relationship between design variables (component availability and utility) and component cost. The formulation of Mettas (2000) has been extended to equations below to be compatible with dynamic problem:

$$c_i^P(t) = exp\left[(1 - f_i).\frac{\sum_{j=1}^{M} p_{ij}(t) - p_{i_{min}}(t)}{p_{i_{max}}(t) - \sum_{j=1}^{M} p_{ij}(t)}\right] \tag{6-12}$$

$$c_i^U(t) = g_i exp\left[\sum_{j=1}^{M} p_{ij}(t)u_{ij}(t) - u_{i_{min}}(t)\right] \tag{6-13}$$

where $p_{i_{min}}(t)$ and $p_{i_{max}}(t)$ are respectively the minimum and maximum availability of component i in the normal state during the interval $(0, t]$; $u_{i_{min}}(t)$ is the minimum capacity of component i in the normal state during the interval $(0, t]$; f_i and g_i are respectively the feasibility of increasing the availability and capacity of component i; and respectively, $c_i^P(t)$ and $c_i^U(t)$ are cost of component i associated with the availability and capacity at time *t*.

The defined component cost function describes the general behaviour of the component cost over time when actual distribution is not available.

$$c_i(t) = c_i^P(t) + c_i^U(t) \tag{6-14}$$

Meta-heuristic optimization techniques are more powerful than other methods for solving large-scale and complex optimization problems. Among the meta-heuristic optimization techniques, genetic algorithm (GA) is most widely applied due to the flexibility in modelling and global optimization ability. In this thesis, GA is adopted to solve the dynamic problem.

6.3. Numerical case study

Our numerical example is from a real world application case in maritime transportation in naval shipyard Gdynia of Poland. The naval shipyard consists of two transportation systems to move the ships coming for repair to the designated location (Blokus-

Roszkowska and Kolowrocki 2010). The ship-rope elevator is used to dock and undock ships coming to the Naval Shipyard in Gdynia for repairs. The elevator is composed of a steel platform carriage and 10 rope-hosting winches fed by separate motors.

The rope transportation system is composed of three broaching machines working independently. This system is used to transfer ships coming to the shipyard for repairs from platform to the repair post and back from repair post to the platform.

Generally all actions taken to the ships coming to the shipyard for repairs can be divided into 5 tasks:

- Task 1 – ship docking (rope elevator is working)
- Task 2 – ship's transportation to the repair post (rope transportation system is working)
- Task 3 – the repair measures (both systems are not working)
- Task 4 – ship's transportation to the platform (rope transportation system is working),
- Task 5 – ship undocking (rope elevator is working).

During ship docking, the ship settled in special supporting carriages on the platform is raised to the wharf level and then the ship is transferred from the platform with the rope broaching machine on a traverser. After that, the ship with the traverser, on which the ship is settled, is shifted in the repair post direction. Then after stretching the ropes from the ship to the broaching machine through some blocs, the ship is transferred from the traverser to the repair post. After some repair measures, the ship is transferred back to the traverser and then on the platform. Finally, during undocking the ship on the platform is moved down to the water.

There are nine repair posts, denoted by symbols R1-R9. The first repair post R1 can be lengthening to the post R1/B1 for long ships. There are also available two repair depots denoted by symbols B and D. Generally all kind of repairs can be carried out in any repair post. The repair posts R1 and R2 are equipped in crane. The submarines are repaired in the depot. Additionally large vessels are transferred to the repair post R1/B1.

The broaching machines in the transportation system are numbered 1, 2, and 3. At least two broaching machines will be used to transport the ships on the traverse. The three broaching machines are differentiated in terms of capacity. Each of the broaching machines has 4 different states, namely state 3, 2, 1 and 0.

In some systems, the components of the system can still contribute some basic utilities to the system even in the lowest state. However, in this example, the performance or utility of each broaching machine in state 0 was assumed as 0. Different weights are assigned to the machines at different states. Therefore, the system under consideration is a typical weighted 2-out-of-3 system.

In dynamic model, we assumed the state probabilities of broaching machines change exponentially by time. The Markov transition graph of the dynamic model is shown in Figure 6-2.

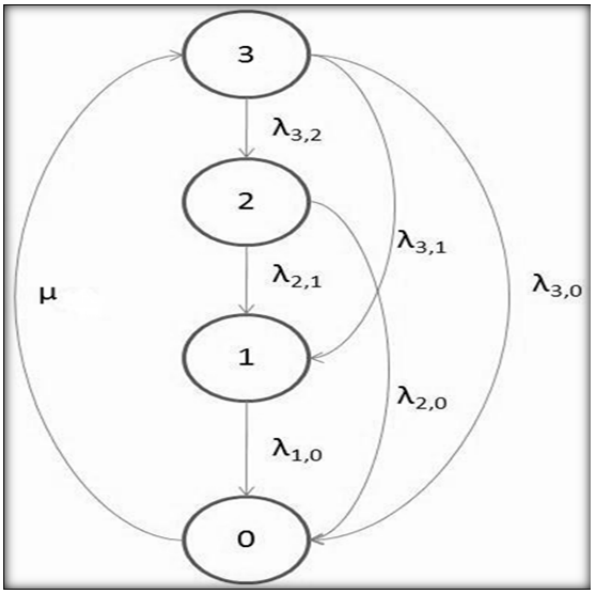

Figure 6-2. Markov model of the state transitions of broaching machines in dynamic system

Sate 0 is called the complete failure state, and state 3 is the perfect functioning state. States 1 and 2 are known as partial failure states. In states 1 and 2, broaching machines still operate but such operations with low performance levels. In constructing such transition graph, we assumed that the broaching machine was repairable only if it completely failed.

6.3.1. Availability assessment of broaching machine system

In this section, we apply the presented dynamic model of section 6.1 for availability assessment of broaching machine system. In this model, probability distributions of the three broaching machines (M1-M2-M3) in each of the four states (S0-S1-S2-S3) are exponential with given transition rates. In Table 6.1, the transition rates in addition of performance rates (utility values) of the three machines are given.

Table 6.1. Transition and performance rates of broaching machines

Broaching Machines		Transition Rates (1/yr)				
Types	States	S3	S2	S1	S0	Performance Rates
M1	S3	0	2	1.3	0.7	2000
	S2	0	0	0.9	0.5	1500
	S1	0	0	0	0.3	1000
	S0	4.2	0	0	0	0
M2	S3	0	1.8	1.1	0.8	2200
	S2	0	0	0.8	0.4	1400
	S1	0	0	0	0.2	1200
	S0	7.2	0	0	0	0
M3	S3	0	2.2	1.6	0.9	2500
	S2	0	0	1.2	0.7	2000
	S1	0	0	0	0.5	1500
	S0	5.4	0	0	0	0

We have the following set of equations:

$$
\begin{aligned}
\frac{dp_{i3}(t)}{dt} &= -\left(\lambda^{i}{}_{3,2} + \lambda^{i}{}_{3,1} + \lambda^{i}{}_{3,0}\right)p_{i3}(t) + \mu^{i}p_{i0}(t) \\
\frac{dp_{i2}(t)}{dt} &= \lambda^{i}{}_{3,2}p_{i3}(t) - \left(\lambda^{i}{}_{2,1} + \lambda^{i}{}_{2,0}\right)p_{i2}(t) \\
\frac{dp_{i1}(t)}{dt} &= \lambda^{i}{}_{3,1}p_{i3}(t) + \lambda^{i}{}_{2,1}p_{i2}(t) - \lambda^{i}{}_{1,0}p_{i1}(t) \\
\frac{dp_{i0}(t)}{dt} &= -\mu^{i}p_{i0}(t) + \lambda^{i}{}_{3,0}p_{i3}(t) + \lambda^{i}{}_{2,0}p_{i2}(t) + \lambda^{i}{}_{1,0}p_{i1}(t)
\end{aligned}
\tag{6-15}
$$

$$p_{i3}(t) + p_{i2}(t) + p_{i1}(t) + p_{i0}(t) = 1 \tag{6-16}$$

The initial state probabilities of the machines are:

$$p_{i3}(0) = 1,\ p_{i2}(0) = 0, p_{i1}(0) = 0, \text{and } p_{i0}(0) = 0 \tag{6-17}$$

Then, we solved the set of above equations by using Eigen-value method in Matlab R2012a and obtained the state probability results of the three broaching machines as depicted in Figure 6-3.

The performance UGF of each broaching machine is:

- Machine 1:

$$U_1(z,t) = p_{13}(t)z^{2000} + p_{12}(t)z^{1500} + p_{11}(t)z^{1000} + p_{10}(t) \tag{6-18}$$

- Machine 2:

$$U_2(z,t) = p_{23}(t)z^{2200} + p_{22}(t)z^{1400} + p_{21}(t)z^{1200} + p_{20}(t) \tag{6-19}$$

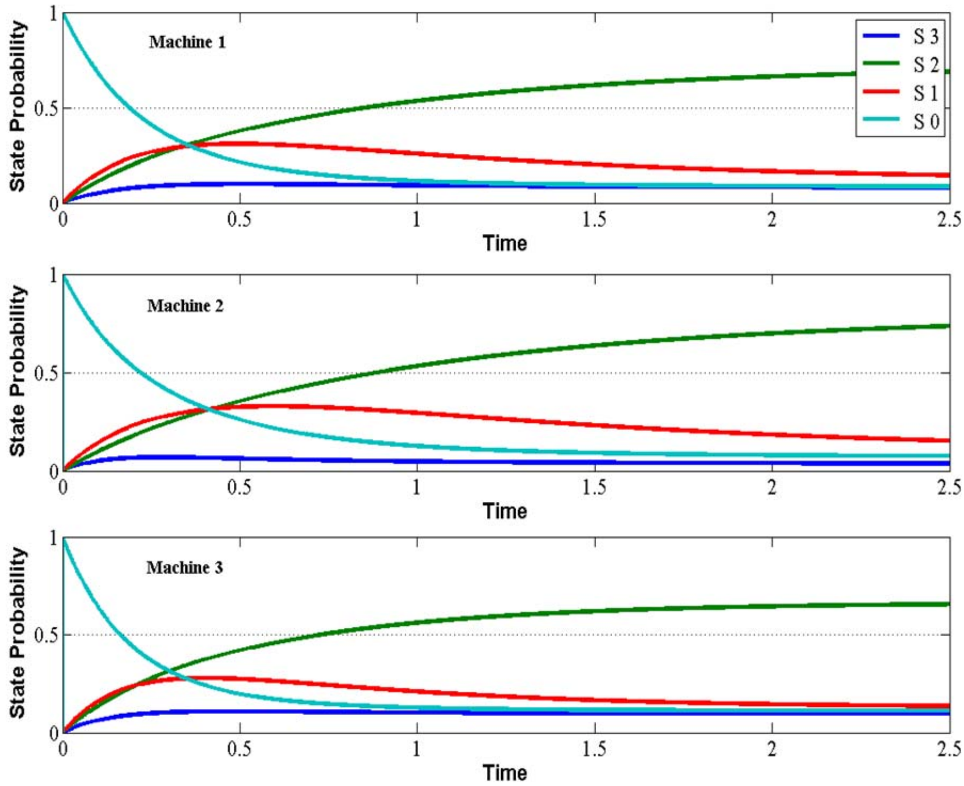

Figure 6-3. State probability distributions of broaching machines for the dynamic system

- Machine 3:

$$U_3(z,t) = p_{33}(t)z^{2500} + p_{32}(t)z^{2000} + p_{31}(t)z^{1500} + p_{30}(t) \qquad (6\text{-}20)$$

The UGF of the system as the product of the UGF for three broaching machines is:

$$U_{sys}(z,t) = \Omega\big(U_1(z,t), U_2(z,t), U_3(z,t)\big) \qquad (6\text{-}21)$$

Incorporating UGF equations, we have:

$$U_{sys}(z,t) = \Omega\Big(\big(p_{13}(t)z^{2000} + p_{12}(t)z^{1500} + p_{11}(t)z^{1000} + p_{10}(t)\big), \big(p_{23}(t)z^{2200} + p_{22}(t)z^{1400} + p_{21}(t)z^{1200} + p_{20}(t)\big), \big(p_{33}(t)z^{2500} + p_{32}(t)z^{2000} + p_{31}(t)z^{1500} + p_{30}(t)\big)\Big) \quad (6\text{-}22)$$

Finally, the availability of the system can be determined from the system UGF depending on the minimum system's performance or utility ($k_j(t)$). To show the availability as a function of time and minimum performance level, we used a three-dimensional plot, shown in Figure 6-4.

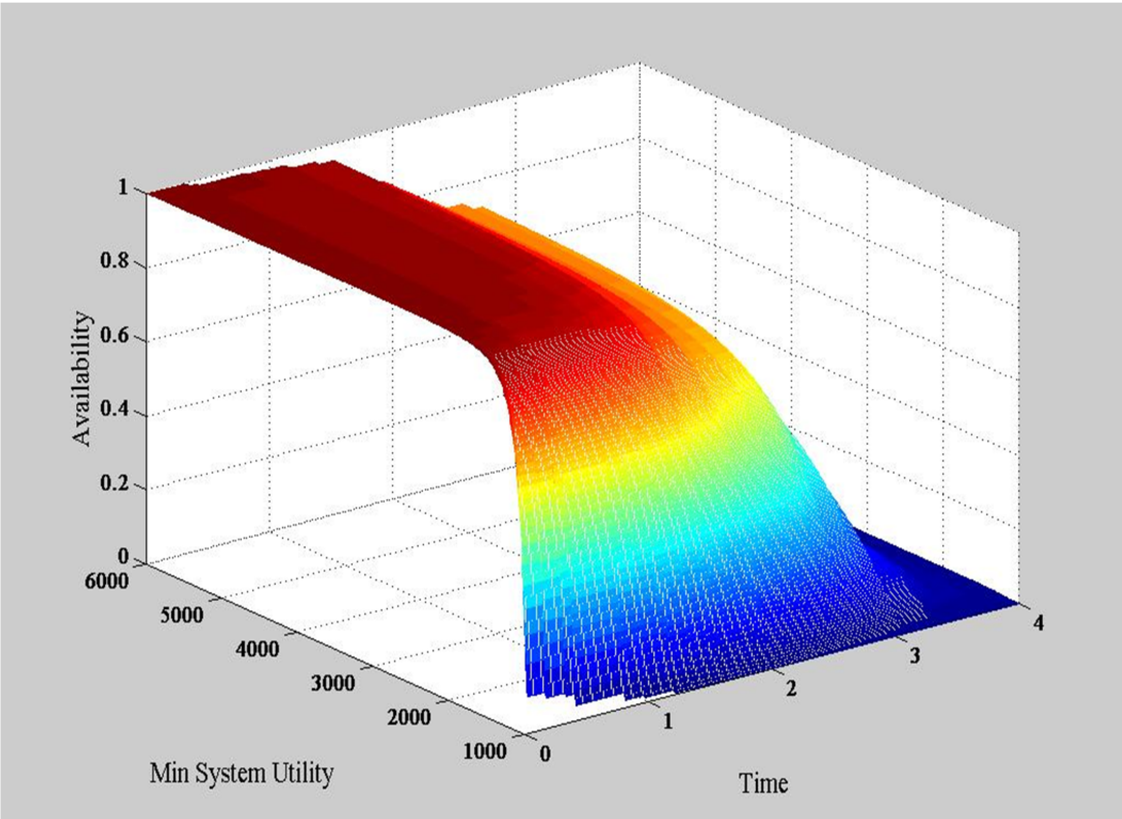

Figure 6-4. Availability of the dynamic broaching machine system under different utilities and times

We moved through the axis "Time" from 0 to 4 years. At the same time, we changed the minimum required utility values from 1000kg to 6000kg. As can be seen, the availability of the broaching machine system is almost less than 0.6 for all values of minimum utility after year 3. There is a same story for availability of the broaching machine system when minimum system utility gets values less than 2000 at any time between 0 and 4 year.

6.3.2. Optimal design of broaching machine system

In this section, the marine company decided to install a new system of broaching machines. The new installation would be a four-state weighted 2-out-of-3 system. However, in design problem, the availability and utility distribution of the broaching machines in different states are unknown. In this case, we evaluated different systems in time (dynamically) and find the optimal design (availability and utility distributions) of the broaching machines.

As described in Section (6-20), we used GA approach from the GA toolbox in Matlab R2012a to solve the dynamic design problems. Before, the problems were written into the penalty function forms to make calculations easier.

- **Problem P1**

Minimize:

$$C_{sys} = \sum_{i=1}^{N} c_i(t) + \big(1 - A(t)\big).\, C_j + max(\hat{A}_{sys} - A(t), 0) * \eta \qquad (6\text{-}23)$$

Subject to:

$$\begin{cases} \sum_{j=0}^{M} p_{ij}(t) = 1, \;\; 0 \le p_{ij}(t) \le 1 \quad (i = 1,2,\dots,N; j = 0,1,2,\dots,M) \\ u_{i0}(t) = 0, \;\; u_{ij}(t) \ge 0 \;\; (i = 1,2,\dots,N; j = 0,1,2,\dots,M) \end{cases} \tag{6-24}$$

- **Problem P2**

Minimize:

$$-A(t) + max\left(\sum_{i=1}^{N} c_i(t) + \big(1 - A(t)\big).C_j - \hat{C}_{sys}, 0\right) * \eta \tag{6-25}$$

Subject to:

$$\begin{cases} \sum_{j=0}^{M} p_{ij}(t) = 1, \;\; 0 \le p_{ij}(t) \le 1 \quad (i = 1,2,\dots,N; j = 0,1,2,\dots,M) \\ u_{i0}(t) = 0, \qquad u_{ij}(t) \ge 0 \;\; (i = 1,2,\dots,N; j = 0,1,2,\dots,M) \end{cases} \tag{6-26}$$

In penalty functions, η is a very large number (e.g. $\eta = 99999$). Other parameters of the problems are given in Table 6.2. In dynamic design, the optimal solutions are highly dependent on the demand of the system at each time ($k(t)$) especially when other parameters of the problem such as $u_{i_{min}}(t), P_{i_{min}}(t)$, and $p_{i_{max}}(t)$ are considered constant. System demand is a changing factor to system availability (see Eq. (6-8)). We assume that the demand distribution is uniformly distributed between 500 and 2500 ton i.e. the cumulative distribution function of the demand is:

Table 6.2. Parameters in the optimization design problem of broaching machine system

f_i	g_i	$u_{i_{min}}(t)$	$P_{i_{min}}(t)$	$p_{i_{max}}(t)$	$\hat{A}_{sys}$	C_j	$\hat{C}_{sys}$
0.99	1	1000	0.93	0.9999	0.9	10	9.5

$$CDF\big(k(t)\big) = \begin{cases} 0 & for\ k(t) < 500 \\ \dfrac{k(t) - 500}{2000} & for\ 500 \le k(t) < 2500 \\ 1 & for\ k(t) \ge 2500 \end{cases} \tag{6-27}$$

After developing the objective functions and their constraints, we used the GA toolbox in Matlab R2012a to solve the problems. We ran these programs using a computer with 3.30GHZ CPU and 8.00GB RAM under the Windows 7 Enterprise operating system. We set the population data type at double and population size at 100. Elite count and crossover fraction were all set at the default values in Matlab R2012a GA toolbox. The uniform function was used as the population creation function. The adaptive feasible function was used as the mutation function. The rank function was used as the scaling function. The scattered function was used as the crossover function. The stochastic uniform function was used as the selection function. The stopping criteria were 5000 generations, and 5000 stall generations.

The optimization results of problems 1 and 2 for a selected time (t = 2) are presented in Table 6.3 and Table 6.4, respectively.

Table 6.3. Optimization results of the design problem 1 (broaching machines' utility and availability)

Reliability = 0.9677		$k(t = 2) = 3000$			
Cost = 7.354		$j = 0$	$j = 1$	$j = 2$	$j = 3$
Utility	$N = 1$	0	0	1834	1834
	$N = 2$	0	1165	1166	1173
	$N = 3$	0	1834	1834	2999
Availability	$N = 1$	0.0033	0.0007	0.4632	0.5338
	$N = 2$	0.0139	0.2081	0.3598	0.4192
	$N = 3$	0.0201	0.3562	0.4814	0.1433

Table 6.4. Optimization results of the design problem 2 (broaching machines' utility and availability)

Reliability = 0.9597		$k(t = 2) = 3000$			
Cost = 7.298		$j = 0$	$j = 1$	$j = 2$	$j = 3$
Utility	$N = 1$	0	0	2121	2234
	$N = 2$	0	261	2312	2720
	$N = 3$	0	1878	1919	1922
Availability	$N = 1$	0	0	0.4672	0.5338
	$N = 2$	0.0008	0.4263	0.1814	0.3915
	$N = 3$	0.0991	0.2069	0.3781	0.3159

In dynamic model, there are 21 decision variables in each time that all are in non-linear non-integer optimization problems. It is difficult to use traditional optimization approaches for solution, but by using GA, they were all solved in about 4min. In this example, number of broaching machines is set to 3. When 2 more machines are considered and other parameters remain the same, there are 35 variables in each optimization model, and completing the computation takes about 7 min. When number of variables increases to 70 and all the other parameters remain the same, completing the computation takes about 16 min. This shows that in spite of the large system, the GA approach can still solve these optimization problems.

From the result tables, it can be seen that the optimization problems that minimize the total cost have a lower total cost than optimization problems that maximize the system’s availability. On the other hand, the optimization problems that maximize the availability are better able to attain that goal than optimization problems that minimize the total cost. This is reasonable, because obviously when the only objective is to minimize the total cost, the requirements for the system’s availability are sacrificed by just giving a constraint for that availability. That constraint is usually selected not to be too high in order to avoid infeasibility. In similar, when the objective function is to maximize the availability of the system, some requirements for limiting the total cost will be sacrificed, resulting in a larger total cost allowance.

6.4. Conclusion

In this chapter, dynamic modeling is considered for availability assessment of marine multi-state *K*-out-of-*N* systems. As in real world most of the components' characteristics change by time, we may consider most systems as dynamics. However, up to now, the modeling in availability assessment of multi-state *K*-out-of-*N* systems has been non-dynamic. Therefore, first we present an approach for availability modeling of dynamic systems by Markov modeling of the system and using UGF. The results given in the numerical example illustrate the flexibility of dynamic modeling in assessing availability. Then, by using the dynamic availability assessment model, we look for an optimal design of the multi-state weighted *K*-out-of-*N* systems in dynamic case.

The optimization problem presented in this chapter is to minimize the expected total system cost subject to system reliability requirements. The objective is to find the optimal design of the systems when state probabilities and costs of components vary in time. For problem solution, GA is used due to the flexibility in modelling and global optimization ability. The results showed that optimal design for dynamic systems depends on cost of design at different times. This means that against the non-dynamic optimal design that the best solution of the problem is only one design, dynamic optimal design is not necessarily only one best solution of the problem during the time. The results validate that looking at the systems dynamically, gives us the real optimal system designs.

CHAPTER 7: CONCLUSIONS AND FUTURE WORKS

7.1. Conclusions

In this thesis, human and organizational factors in marine accidents are analyzed quantitatively; the accident risk for the marine transportation systems is modeled; and the availability of marine transportation systems is assessed in a dynamic model for further availability and cost based design of the components of these systems.

Chapter 3 presents a model to assess the contribution of Human and Organizational Factor (HOF) to accidents. The proposed model is made up of two phases. The first phase is the qualitative analysis of HOF responsible for accidents, which utilizes Human Factors Analysis and Classification System (HFACS) to seek out latent HOFs. The hierarchy of HOFs identified in the first phase provides inputs for the analysis in the second phase, which is a quantitative analysis using Bayesian Network (BN). BN enhances the ability of HFACS by allowing investigators or domain experts to measure the degree of relationships among the HOFs. In order to estimate the conditional probabilities of BN, fuzzy analytical hierarchy process and decomposition method are applied in the model. Case studies show that the model is capable of seeking out critical latent human and organizational errors and carrying out quantitative analysis of accidents. From the application of the model to the two case studies, it can be concluded that the model is useful in investigating HOFs for the derivation of safety interventions. Thereafter, corresponding safety prevention measures are derived.

Chapter 4 proposes a bi-objective optimization problem to plan the container ship capacities during transportation of hazardous materials from supplier storages to customer storages. The expected risk as an objective function of this problem is proposed based on the water area exposed by hazmat containers accidents and it depends on sea pollution factors. In between of the storages, port terminals are considered to show that how objective functions may effect on the optimum number of containers. The optimal number of containers with different freights (hazmat and regular) is found by solving a bi-objective integer programming problem.

Chapter 5 studies accident risk of marine transportation systems and presents a new model to estimate accident probabilities. The model includes a three-state homogeneous Markov model and slice sampling algorithm as a MCMC simulation method. For two case studies, the proposed model is applied and sensitivity analyses are done. Sensitivity analyses on the inputs and assumptions of the model shows how the model behaves in various conditions and for different collected data. In addition, the proposed model is applicable even having no data on safety factors such as type of human errors. The proposed approach has the potentiality to consider any incident/accident of marine transportation systems.

Chapter 6 studies a dynamic model for availability assessment of multi-state weighted K-out-of-N systems with a case study in marine transportation. To the present time, the availability assessment of this kind of systems was in non-dynamic ways. In this chapter, a dynamic availability assessment model is presented by Markov modeling of the system and using Universal Generating Function (UGF). The results given in the numerical example illustrate the flexibility of dynamic modeling in assessing availability. Moreover, the problem of optimal design of the components is solved by using Genetic algorithm, regarding the dynamic property of the marine multi-state weighted K-out-of-N system and its components. The optimization problem is to minimize the expected total system cost subject to system availability requirements. The results showed that optimal design for dynamic systems depends on cost of design at different times. This means that against the non-dynamic optimal design that the best solution of the problem is only one design, dynamic optimal design is not necessarily only one best solution of the problem during the time. The results validate that looking at the systems dynamically, gives us the real optimal system designs.

7.2. Future works

This section discusses the limitations of the works contained in this thesis and suggests some directions for future research.

In Chapter 3, a model is presented to quantify human errors which contributed to the accidents in marine transportation industry. All calculations and model's steps are done by using different software packages. The lack of unique software for the implementation and evaluation is quite apparent. Future work is suggested to be done on developing specific software which facilitates the application of the proposed model. In addition, the elicitation of conditional probability table is still subjective and time consuming. Other methods of reducing subjective biasness and improving efficiency in CPT elicitation deserved to be further explored. It would be interesting to build a standardized accident reporting system and collect enough HOF data of accidents.

In Chapter 4, the algorithm adapted for solving this problem is good enough in case of small and medium size networks. It is suggested by the authors to evaluate the efficiency of this algorithm for the large size networks or to improve and validate the solution approach by application of heuristic algorithms.

In Chapter 5, it is assumed a three-state Markov model for accident risk modeling of marine transportation systems. The states are safe, vulnerable, and serious accident. These three states are general and observable in the lifetime of many systems. That is why the proposed approach in this chapter has potential application in other sectors such as oil or gas industry, and other systems such as the railways and road transportation systems. In spite of vast applicability of current Markov model, extension of this model to Markov models with more states of failure or accidents can be suggested. A challenging issue regarding to this extension is the computational complexity of the approach while incorporating Markov model with MCMC simulation.

In Chapter 6, a dynamic model is presented for the availability assessment and design of multi-state weighted K-out-of-N systems in marine transportation. There are situations where these systems are connected together and make a network system in marine transportation. For example, a multi-state system of generators is operating in connection with a multi-state system of electric engines in a ship. Evaluating network availability can be an interesting topic in these situations regarding to the planning, designing, and control of network systems. Further study can be done to extend the dynamic model of this thesis to the availability assessment and component design of network systems based on the dynamic multi-state weighted models.

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