QUALITATIVE AND QUANTITATIVE ANALYSIS OF MARINE ACCIDENTS USING A HUMAN FACTOR FRAMEWORK

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Abstract

Human factors are becoming the predominate contributors to accidents in the maritime transportation sector. Therefore, a methodology based on Reason's Swiss Cheese Model to qualitatively and quantitatively analyse an accident is proposed. During the analysis, a proposed Human and Organisational Factors (HOFs) framework that is suitable for investigating and analysis maritime accidents can also be integrated with the analysis results for obtaining a more comprehensive insight into the causation of the accident.

The proposed methodology comprises several well-defined Formal Safety Assessment techniques forming a systematic procedure in a series of processes. The methodology mainly applies Why-Because Analysis and Fault Tree Analysis for qualitative analysis, and Bayesian Network and Influence Diagrams for quantitative studies. In addition, Sensitivity Analysis is utilised for validating the analysis results and finding the critical factors of the accident. In the end of the analysis, a Bayesian Network representing the accident can be acquired revealing both the quantitative and qualitative results in a graphic presentation. Furthermore, an Influence Diagram which is extended from the established Bayesian Network of the accident is also achievable, for the decision makers, to evaluate the expected utilities based on the cost-benefit of the potential Risk Control Options against the (or similar) type of accident. Both the Bayesian Networks and Influence Diagrams of the accident are capable of proceeding a "*what if*" examination via the propagation function of the models to carry out a diagnosis and prediction process. This provides the analyst with a simulation functionality to examine the accident under all the possible conditions given.

In summary, the proposed methodology implements the notion of Window of Opportunities of Reason's model for accident analysis with the following contributions to academic knowledge: (1) implementing Reason's Swiss Cheese Model with Venn diagram; (2) proposing a dedicated HOFs framework (HFACS-MA) for maritime accidents; (3) innovating a Backtracking process and its validation mechanism; (4) presenting a Conditional Probability Table of Bayesian Network in Karnaugh-map style (K-CPT); and (5) recommending a notation for List Statements to organise the information and evidence of an accident.

The combined methodology is demonstrated with a case study based on the 1987 Herald of Free Enterprise accident which capsized off Zeebrugge with large loss of life. Human factors were considered to be the main causes of accident with failings at senior ship and shore management level as well as at operational level. The resultant analysis shows how the relevant importance of different causal factors can be evaluated.

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Table of Contents

List of Figures

List of Tables

Abbreviations

AHP	Analytical Hierarchy Process
ATM	Air Traffic Management
BE	Basic Event
BN	Bayesian Network
CF	Causal Factor
CPT	Conditional Probability Table
CS	Cut Set
CSC	Causal Sufficiency Criterion
DAG	Directed Acyclic Graph
EU	Expected Utility
FPSO	Floating Production, Storage and Offloading
FSA	Formal Safety Assessment
FSI	Free Surface Instability
FTA	Fault Tree Analysis
F-VIM	Fussell-Vesely Importance Measure
GEMS	Generic Error Modelling System
GISIS	Global Integrated Shipping Information System
HFACS	Human Factors Analysis and Classification System
HFACS-MA	Human Factors Analysis and Classification System – for Maritime Accidents
HFIT	Human Factors Investigation Tool
HOFs	Human and Organisational Factors
HoFE	Herald of Free Enterprise
HRA	Human Reliability Assessment
IACF	Implied Cost of Averting Fatality
ID	Influence Diagrams
IE	Intermediate Event
IMO	International Maritime Organization
K-CPT	K-style Conditional Probability Tables
K-map	Karnaugh map
LoF	List of Factors
MCDM	Multi-Criteria Decision Making
MCS	Minimal Cut Set
MEU	Maximal Expected Utility
MSC	Maritime Safety Committee
PRA	Probabilistic Risk Assessment

PTFN	Positive Trapezoidal Fuzzy Number
RCO	Risk Control Option
SA	Sensitivity Analysis
SAM	Similarity Aggregation Method
SCM	Swiss Cheese Model
SHEL	Software, Hardware, Environment and Liveware
SOAM	Systemic Occurrence Analysis Methodology
TE	Top Event
TRACEr	Technique for Retrospective Analysis of Cognitive Errors
WBA	Why Because Analysis
WBG	Why Because Graph
WoO	Window of Opportunity

Chapter One – Introduction

Summary

In this chapter, the overview of the present study is given, including the hypothesis of the study, the structure of the thesis and the general description of the proposed methodology.

1.1 Introduction

The ultimate purpose of analysing accidents is to understand the full range of conditions and factors that contributed to an occurrence, so that similar events can be prevented. Licu, Cioran, Hayward and Lowe (2005) have stated that every occurrence provides an opportunity to study how the deviation occurred and to identify ways of preventing it from happening again. Since humans only have a finite set of cognitive and physical resources and are not good at handling complex environments composed of multiple competing stimuli, humans can and will commit errors (Krokos and Baker, 2007). According to a great number of studies devoted to this issue, it has been pointed out that around 20% to 90% of accidents in the maritime transportation sector are mainly caused by human errors (Trucco *et al.*, 2008; Harati-Mokhtari *et al.*, 2007; Wang and Trbojevic 2007; Hetherington *et al.*, 2006; Darbra and Casal, 2004, to name but a few). The International Maritime Organization (IMO) has taken the conscious decision to concentrate its efforts much more strongly on the human element (O'Neil, 2003). That is, despite the difference of the perspectives, human errors are gradually being recognised as the primary causal contributors to accidents.

Nowadays the major aviation accident analysis methods, e.g. *Systemic Occurrence Analysis Methodology* (SOAM) (EUROCONTROL, 2005) and *Human Factors Analysis and Classification System* (HFACS) (Shappell and Wiegmann, 2003b), are the applications of Reason's *Swiss Cheese Model* (Reason, 1997), which have a significant influence on the ways that investigators conduct their investigations to find the overt and underlying causes of aviation accidents. In this sense, the Swiss Cheese Model is assumed to be beneficial to the maritime industry whilst applying it as the core concept of the proposed methodology incorporating with several risk assessment techniques. These techniques include Why-Because Analysis (WBA) (Ladkin, 2001; Paul-Stüve, 2005), Fault Tree Analysis (FTA), Bayesian Network and Influence Diagrams, etc. However, none of these techniques is able to accomplish the analysis alone. This is because, for instance Why-Because Analysis can only produce qualitative analysis results; Fault Tree Analysis cannot solve the quantitative problems when the Basic Events are not mutually independent. Also the basic Bayesian Network lacks mechanisms to ensure that all the nodes in the model are actually necessary and sufficient.

Before covering the scope of the present study, it is worthy to revisit the definition of the Swiss Cheese Model since it is the core concept of the methodology. The definition given by Reason is that "an accident can happen only when the holes in many layers momentarily line up to permit a trajectory of accident opportunity – bringing hazards into damaging contact with victims" (Reason, 2000). Reason further introduces this accident trajectory as a *Window of Opportunity* (WoO) giving the necessary condition of an organisational accident to be triggered. It is "the rare conjunction of a set of holes, which consist of a series of *latent conditions* and *active failures*, in successive defences, allowing hazards to come into damaging contact with people and assets". In the notion, "*active failures* are errors and violations committed by the personal at the sharp end of system, but they are now being seen more as consequence than as principal causes". Such unsafe acts are likely to have a "direct impact on the safety of a system and immediacy of their adverse effects" (Reason, 1997). In contrast, *latent conditions* are the inevitable "resident pathogens" within the system. They arise from decisions made by designers, builders, procedure writer and top level management (Reason, 2000). These *latent conditions*, such as poor design, undetected manufacturing defects, maintenance failures or unworkable procedures, etc., may have been present for many years before they are combined with *local circumstances* and *active failures* to penetrate the multi-layer of defence of any system (see Figure 1-1 for illustration).

Figure 1-1 Reason's Swiss Cheese Model
(from Reason, 2000)

Therefore, in order to prevent the similar accidents from happening again, one has to find a way to shut the WoOs which can penetrate the defences of the system prior to the future accidents. Before shutting the WoO, the holes and the factors which cause the holes to exist have to be identified. Furthermore, not only the causal factors have to be identified, but also the significance, frequency and impact of the factors have to be clarified. Ultimately, the best countermeasure against the reoccurrence of the accident should as well be examined when the investigators carry out the analysis after the investigations and before compiling the accident report and recommendations for public enquiry and lesson learning. The tools which can assist the investigators to perform their work are of vital importance. Thus, the objective of the present study is to propose a methodology which can fulfil the need of analysing human factors involved in maritime accidents qualitatively and quantitatively.

1.2 Research objectives and the hypothesis

The main goal of the present study is to propose a methodology which can qualitatively and quantitatively analyse the Human and Organisational Factors (HOFs) involved in a maritime accident in order to assist the decision makers to choose the best countermeasures for preventing similar accidents from happening again. There is no intention to point out who should be blamed for causing the accidents, but to highlight which parts of the system are vulnerable, according to the accident analysed via the proposed methodology.

Since the IMO has followed the aviation industry in the adoption of Swiss Cheese and SHEL models and proposed guidelines for the investigation of human factors in marine casualties and incidents (IMO A.884, 1999; IMO, 2008), a HOFs framework which based on the guidelines to clarify and classify the human factors involved should be considered and integrated into the analytical methodology as a whole. In addition, probabilistic figures which highlight the significance, frequency and impact of the factor involved are the key issues of the methodology. Furthermore, a systematic procedure of the methodology is also important for improving the objectivity of the analysis outcomes.

The objectives of the present study are formed by considering the following three requirements:

1. applying the Swiss Cheese Model as the core concept of the methodology;
2. being capable of carrying out the accident analysis qualitatively and quantitatively; and
3. a systematic procedure for avoiding unnecessary subjective speculations.

In short, the hypothesis of the study is that the *Swiss Cheese Model* can be implemented by employing well-defined probabilistic assessment techniques to achieve the three requirements mentioned above for analysing maritime accidents. In the proposed methodology, the Swiss Cheese Model is adopted as the fundamental concept of the method and the HFACS is the basis of the HOFs framework applied. In addition, WBA, FTA, Bayesian Network and Influence Diagrams are the main techniques to be employed to deal with the qualitative and quantitative analyses. When required, an application of fuzzy set theory is applied to handle the problem of expert judgements.

1.3 The features of the methodology

The methodology is set up to surround the core concept of the hypothesis which is implementing the Swiss Cheese Model to compose an accident analysis tool by adopting Formal Safety Assessment techniques with HOFs framework to identify, clarify and classify the human factors involved in an accident. In this section, only the brief introduction regarding the features of the methodology and the techniques adopted are included, rather than an in-depth theoretical and mathematical explanation. The details of the techniques adopted are elucidated in the relevant chapters where they are applied. For example, WBA, FTA, Bayesian Networks and Influence Diagrams are covered in Chapters 4 and 5, and HFACS is described in Chapter 6.

Mainly, the qualitative analysis is achieved by WBA and FTA whilst the Bayesian Network and Influence Diagram perform the quantitative part. The Bayesian Network and/or Influence Diagrams also provide the final presentations of the accidents analysis. A modified version of HFACS which can fulfil the needs of the maritime industry in investigating and analysing HOFs involved in an organisational accident is also proposed in the present study in order to fit the requirements of the IMO guidelines and can be utilised as a HOFs framework to integrate with the analysis results. This framework can not only assist the investigators to identified, clarify and classify the factors involved, but also have the advantage to provide a comprehensive illustration associated with the causation of the accident amongst those factors in each level of the system. That is acquired by integrating the qualitative and quantitative analysis results with the framework.

In terms of subjective probability, when historical statistic data is insufficient or unavailable for the quantitative analysis, experts' judgements are the alternative, and an aggregation method based on fuzzy set theory is a solution to obtain the group consensus of the estimations. Both the randomness and fuzziness of the uncertainty are the key issues of the estimates that the methodology has to deal with. The present study therefore proposes a method, in Chapter 7, to address this issue making the proposed methodology more resilient.

Having a systematic procedure is another advantage of the methodology. At each step of the analysis procedure, the analyst only has to concentrate on the inferring or reasoning of the present stage. At each stage, the questions are in a comparatively uncomplicated format, in which the scopes are limited and the questions are easy to answer. By following a systematic procedure, there is no need for the analyst to foresee the orientation of the analysis results in the middle of the analysis if they can carry out the analysis properly at each stage and step. The entire outcome of the analysis is hence obtained by accumulating and integrating the answers given by the analyst at each step and stage.

1.4 The structure of the thesis

The thesis is compiled in eight chapters. Following the introduction of the present study in ***Chapter 1***, ***Chapter 2*** reviews the important literatures influencing this study.

The emphasis and kernel of the methodology start with Chapter 3 and end with Chapter 7. They are presented as follows in an interrelated manner (see Figure 1-2).

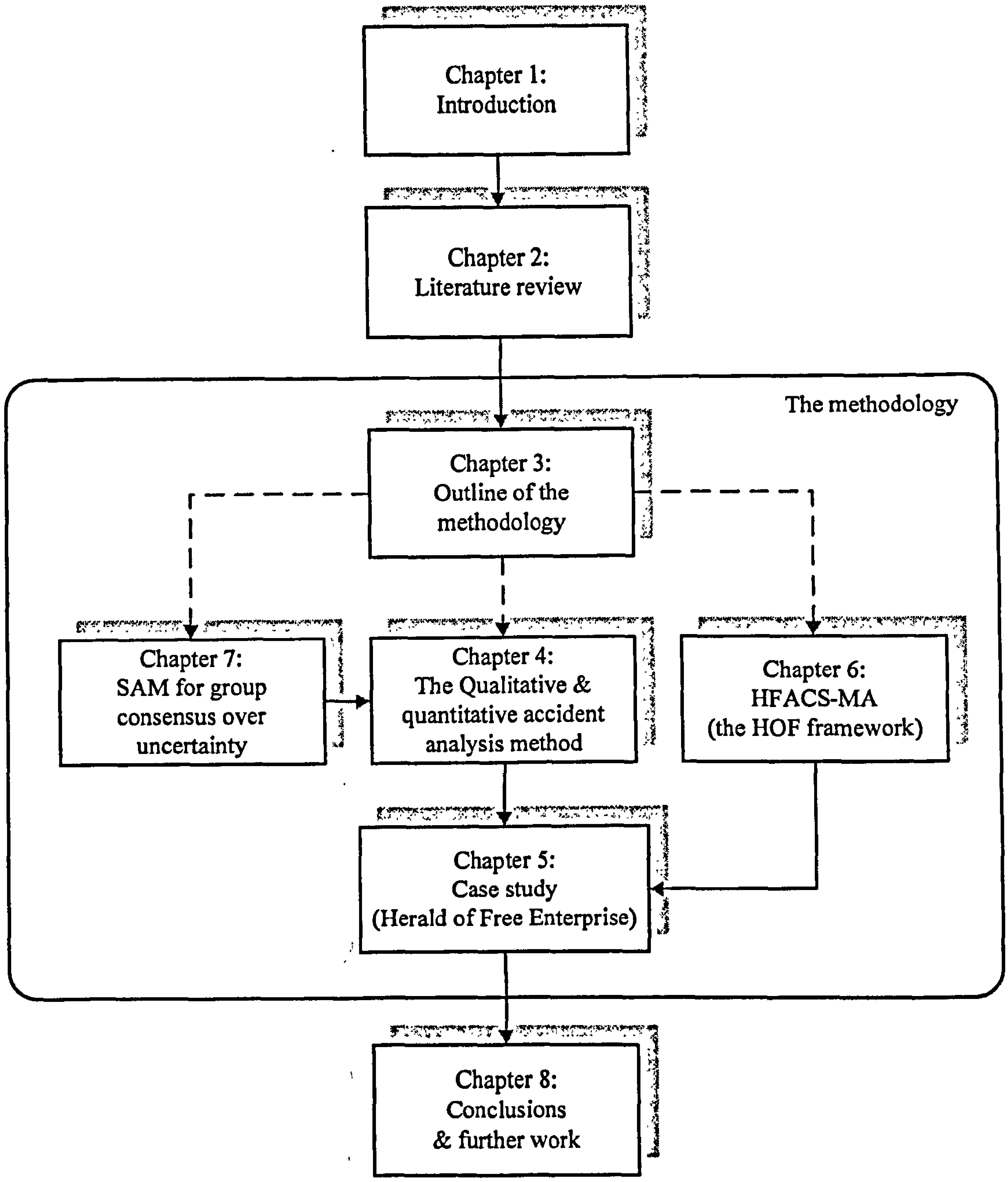


Figure 1-2 The structure of the thesis

In ***Chapter 3***, the outline of the methodology is given, where the background information of the analysis method is shown. The notions of the methods in respect to the hypothesis, implementing the Swiss Cheese Model as a qualitative and quantitative analysis tool, are specified to provide an overview of the proposed methodology. The various techniques are briefly covered prior to the more detailed analysis in Chapters 4 to 7.

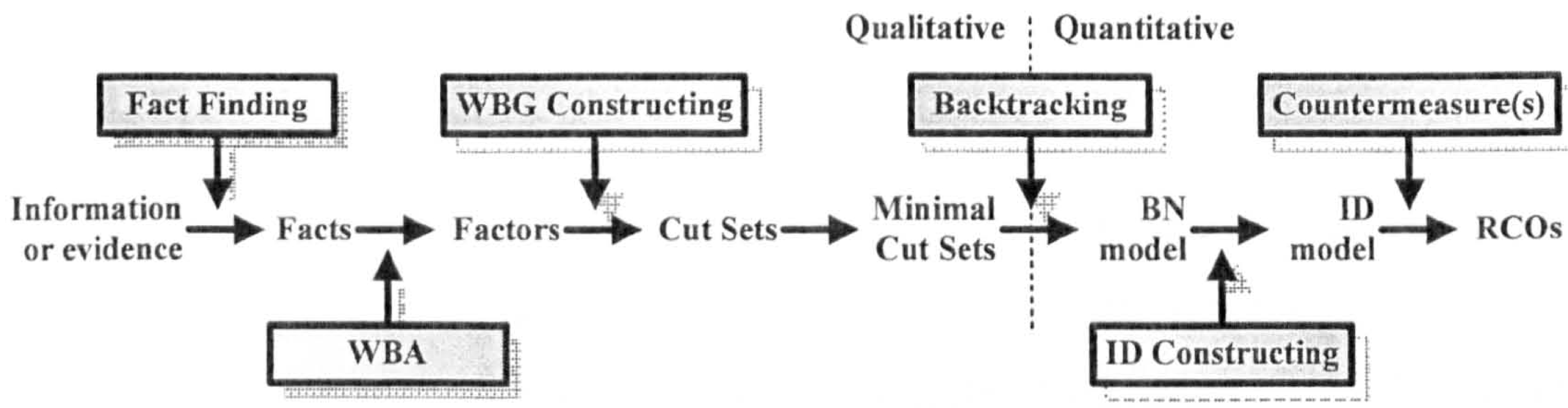


Figure 1-3 The data processing of the method

The data progression of the qualitative and quantitative analysis method shown in Figure 1-3 is depicted in ***Chapter 4***. The method starts with the qualitative analysis to elicit the events and factors involved in an accident and to clarify the causation amongst them. Subsequently, the quantified figures of the factors are added into the qualitative outcomes to form the quantitative results, in which the proposed aggregation method (in Chapter 7) may be utilised for subjective probability and/or group consensus. Finally, the qualitative and quantitative analysis results can be integrated with the proposed HOFs framework to present a more comprehensive insight into the causation of the factors distributed in different levels of the system.

By following the methods depicted, a case study applying these methods to the Herald of Free Enterprise tragedy to carry out the analysis is demonstrated in ***Chapter 5***. Furthermore, the qualitative and quantitative analysis results of the case are incorporated with the proposed HOFs framework, which is elucidated in ***Chapter 6***, to illustrate the causation of the casual factors as well as the associations amongst each level of the system. This framework is important to the methodology to be used in maritime area since it follows the IMO regulations. It implies that this methodology can also be applied onto other realm provided that the dedicated field HOFs framework is in place.

Chapter 7 is the aggregation method, based on fuzzy set theory, to solve the group consensus problem when applying expert judgements due to lack of historical statistic data to perform the quantitative analysis. Finally, ***Chapter 8***, the conclusion chapter of the thesis, summaries the arguments presented in the prior chapters as well as the further considerations and work.

1.5 Discussion

In the proposed methodology, Reason's Swiss Cheese Model is the basis complied by all the methods employed. The qualitative outcomes represent the instances of the WoOs identified in an accident, and the quantitative results reveal the width or extent of the WoOs. From the analysis results shown in the form of Bayesian Networks, not only the causation of the factors involved is displayed, but also the significance, frequency and impact of the factors can be explored.

The HFACS is another application of the Swiss Cheese Model in which the factors are classified into different levels and categories associated with a HOFs framework. A comprehensive insight into the causation of the accident analysed can be obtained by integrating the qualitative and quantitative analysis results with the HOFs framework.

A systematic procedure of the methodology is another important feature to make it feasible and practical. During the procedure, the analysts can only concentrate on every limited scope of questions and infer their rational answers to the questions in each stage and step, without concerning the whole picture of the accident. This feature can reduce the unnecessary speculations and diminish the influences of individual bias. All analysis outcomes are therefore accumulated and integrated together to obtain the final results.

The aggregation method based on fuzzy set theory dealing with the group consensus problem arisen when applying expert judgements due to lack of historical statistic data is one of the key features to make the methodology more resilient. Both the randomness and fuzziness of the uncertainty are considered in the aggregation method to handle the issue of subjective probability.

In addition, this study has made the following contributions to academic knowledge:

1. Implement Reason's Swiss Cheese Model with a Venn diagram (section 3.2). This implementation uses set theory and probability theory to qualitatively and quantitatively analyse the factors within the model.

2. Proposes HFACS-MA for maritime industry (Chapter 6). This HOFs framework in this research is dedicated for investigating and analysing human factors involved in maritime organisational accidents. The framework is based

on the IMO guidelines (IMO A.884, 1999) and Casualty Investigation Code (IMO, 2008).

3. The innovative Backtracking process and its validation mechanism (section 4.5.2 ~ 4.5.4). This process can transform a fault tree into a Bayesian Network in a form of Minimal Cut Set, in which the Top Event is no longer represented by a single object, but several nodes as Minimal Cut Sets. This formulation can benefit the diagnosis and prediction of the network to be performed, offering more valuable information than the traditional Top Event format can provide.

4. The K-CPT (section 4.3.3). This is a combination of Karnaugh-map and Conditional Probability Table of Bayesian Network. The K-CPT can help analysts to find the minimum *sum-of-product* Boolean expression depicting the deterministic correlation between a node and its parent nodes in a Bayesian Network.

5. The notion of *List Statement* utilised in Fact Finding process (section 4.2.2). This data format and index mechanism can facilitate the logical organisation of the information and evidence of an accident as part of the proposed analysis procedure.

In summary, the present study assumes that the proposed methodology should be beneficial to the maritime industry to find the real causes of accidents. In the following chapters the details of the methodology and the ways to apply it are specified one by one according to the topics shown in Figure 1-2.

Chapter Two –
Literature Review

Summary

A proper investigation and analysis to an accident is the key to the understanding of the occurrence and the prevention of reoccurrence. Accident analysis methods are therefore developed to sustain the successfulness of the accident investigation. In this chapter, the literature on this topic is reviewed and has been organised into several sections. These sections are: the development of accident analysis methods, the role human factors play in accidents, the method to identify human factors involved in an accident, the techniques which can be applied in accident analyses, and the fuzzy approach with which experts' judgements can be used to obtain rational information overcoming the problem of insufficient data. The chapter concludes with a proposed methodology, to be developed in this thesis, to provide a sufficiently thorough and comprehensive solution to the problem.

2.1 Introduction

Whatever the types of accidents, the outcomes are always individual suffering, lost properties and/or damaged environment. In order to prevent the similar accidents from happening again, lessons must be learned and preventative measures must be made. It is of vital importance to know what the real causes are in order to formulate proper countermeasures that can effectively and efficiently keep the similar accidents from happening again. Therefore, a comprehensive and thorough accident analysis method to attain this requirement is a vital requirement. A broad introduction to this topic is covered in section 2.2.

Since human factors (or elements) are now being recognised as the primary causes to cause the complex socio-technical system to fail, the method applied for accident analysis must be able to elicit the human factors involved to present a clearer picture in relation to the causation of the accident. The background information with respect to those studies that have been done for this issue are described in section 2.3.

Furthermore, not only qualitative analysis results are necessarily to be provided by the analytical methods, but quantitative information is also ideally needed. This is because the significance, frequency and impact of every contributing factor involved in an accident are different and can be crucial for determining the relative importance of the factors. Indeed, the quantitative information would therefore be preferred, if it can be reliably obtained. Previous methods proposed by other researches are described in section 2.4.

Uncertainty and subjective probability are critical issues when expert judgements are the alternative due to lack of historical statistic data whilst carrying out the quantitative analysis of an accident. Solutions to this issue are varied as to which type of quantitative techniques the analysis applies. The overview and the proposed solution are discussed in section 2.5.

2.2 The development of human factor analysis of accidents

Gordon, Flin and Mearns (2005) have reviewed and summarise the development of Human Factors Incident Investigation Tool (HFIT) between 1980 and 2002 listing a total of 18 major HFITs developed, in addition to their proposed HFIT. These HFITs are categorised into three categories: *Reactive Incident Reporting Systems*, *Combined pro-active and reactive investigation systems* and *Confidential incident reporting systems*. In the *Reactive Incident Reporting Systems* category, several renowned programs, e.g. the *Human Factors Analysis and Classification System* (HFACS) (Shappell and Wiegmann, 2000; Shappell and Wiegmann 2003b) and *Technique for Retrospective Analysis of Cognitive Errors* (TRACEr) (Shorrock and Kirwan, 2002), acknowledge that organisational and social factors should be included in the analyses. This has led to the development of different HFITs in order to cope with this complexity. In addition to these HFITs, other examples found in the literature are as follows.

⇨ The *AcciMap* (Svedung and Rasmussen, 2002): a graphic presentation represents a particular accident scenario. It is based on the classic cause-consequence chart representing the causal flow of events supplemented by representation of planning, management and regulating bodies contributed to creation of the scenario.

⇨ The *Systemic Occurrence Analysis Methodology* (SOAM) (EUROCONTROL, 2005): guidelines to the investigation of Air Traffic Management (ATM) safety occurrences. The SOAM developed for EUROCONTROL is one of the accident investigation methodologies based on Reason's Swiss Cheese Model for organisational accidents.

⇨ The *Wheel of Misfortune* (O'Hare, 2000): an attempt to overcome the difficulties of Reason's Swiss Cheese Model which consists of a linear sequence of `planes'. That can obscure a better thought that, in terms of intersecting influences, accident causation is spreading outward from various points.

⇨ The *Why-Because Analysis* (WBA) (Paul- Stüve, 2005; RVS WBA homepage): a technique for causally analysing the behaviour of complex technical and socio-technical systems. Its primary application is in the analysis of accidents, mainly to transportation systems (air, rail and sea).

Common elements of all these HFITs are that the techniques are all based on the notion of a structured socio-technical system which indicates the preconditions, the functions on the different system levels involved and an analysis of how they have contributed to the developments of an accident causation in order to elicit the 'real' human factors. A shortcoming is that they all lack quantified indicators to distinguish the magnitude (i.e. the quantification) of the identified human factors involved in an accident.

Another field with a growing concern for human performance in a complex technical control system is Human Reliability Assessment (HRA) which focuses on the reliability of human operators (Wang and Trbojevic, 2007). A great number of HRA techniques for quantifying human factors have been developed. Wu and the co-authors (2009) have categorised these techniques into two generations. The first generation is developed for probabilistic safety assessment of plant risk; the representatives are:

- Technique for Human Error Rate Prediction (THERP).
- Human Error and Reduction Technique (HEART)

- Success Likelihood Index Method (SLIM) using Multi-Attribute Utility Decomposition (MAUD)
- Technica Empirica Stime Errori Operati (TESEO)

The second generation of the HRA techniques applied cognition analysis. The typical one is:

- A Technique for human Error Analysis (ATHEANA)

By following a standard procedure in risk assessment and risk criteria that the techniques provide, the identification of human factors in a failure case provides the links between operations, critical failures and consequences of these failures and may be formulated in terms of overall system risk. However a current weakness of these techniques is in validation of the proposed models (Wang and Trbojevic 2007).

In terms of Probabilistic Risk Assessment (PRA), the Fault Tree Analysis (FTA) and Bayesian Network are the techniques have been widely applied in variant professional fields, such as aviation and nuclear power industries. They are even utilised as the tool to analysis the human factors involved in an accident. For example, Johnson (1999) has applied FTA to analysis the relationship between human error and organisational failure that occurred in a railway accident. Lee and Cha (2005) have proposed a technique based on FTA to qualitatively evaluate casual relationship between software faults and physical hazards. Celik, Lavasani and Wang (2010) have illustrated a Fuzzy extended Fault Tree Analysis (FFTA) methodology to clarify the probability of technical failures, operational misapplications and legislative shortages leading to shipping accidents. Martin and the co-authors (2009) have used a Bayesian Network model to analyse the human factors regarding workplace accidents caused by falls from a height. Another example using a Bayesian Network to identify human safety behaviour in construction industry in China by considering safety climate factors and personal experience factors has been shown by Zhou, Fang and Wang (2008). Meanwhile, Eleye-Datubo, Wall, Saajedi and Wang (2006) have adopted Bayesian Network and Influence Diagrams to formalise a methodology that makes a risk assessments model easier to be built for a marine and offshore evacuation scenario.

A case study analysing organisational factors in maritime transportation has been carried out by combining FTA and Bayesian Network to form a model for risk assessment (Trucco *et al.*, 2008). This study is derived from previous research which mapped a Fault Tree model into a Bayesian Network model in order to improve the analysis amongst components dependence of a computer system (Bobbio *et al.*, 2001). Anderson and Felici (2003) have made a study that reviewed the techniques in the analysis of safety, reliability and security of industrial computer systems. They found that using a Bayesian Network model can extend the Fault Tree model by capturing the probabilistic logical operators, multi-state variables and sequentially dependent failures. However, the Bayesian Network failed to model actions that happen to the system in a previous state, over time. In summary, translating a Fault Tree model into a Bayesian Network model may further enrich the safety analysis, but not having adopted a well-defined human error model or framework with FTA and/or Bayesian Network analysis techniques makes them somewhat deficient in practice.

In the conjunction of human error and Formal Safety Assessment (FSA) methodologies, a groundbreaking Fuzzy Bayesian Network (FBN) method which integrates the human element into a probabilistic risk-based model in maritime safety assessment is proposed by Eleye-Datubo, Wall and Wang (2008) to demonstrate the human performance in maritime industry. Moreover, Celik and Cebi (2009) have proposed a methodology which is based on HFACS and Fuzzy Analytical Hierarchy Process (FAHP) to generate an analytical HFACS as the quantitative assessment tool in order to clearly identify the roles of human errors in shipping accidents. Despite the growing number and sophistication of the techniques, the challenges associated with understanding and organising human error and its causes are continuing. This is because in different fields each organisation tends to develop its own error classification system, which makes it difficult to compare the analysed data across techniques within an industry or across industries (Krokos and Baker, 2007).

2.3 Human and Organisational Factors (HOFs) framework for accident analysis

Before the end of the 1970s, the study of human error contributing to the occurrence of accidents never managed to achieve high priority in psychology realm until the occurrence of the first major modern industrial disasters caused by human error (ground collision between two large aircraft in Tenerife, 1977, 587 casualties; and the well-know nuclear accident of Three Miles Island, 1979). Then, research was quickly driven towards life science, psychology (i.e. enhancing psychological and psycho-sociological), typology and mechanism of human errors (Amalberti, 2001). These studies made their first emphasis on individual human failures, in which Rasmussen's (1982) *Skill-Rule-Knowledge* based error taxonomy and Reason's (1990) *Generic Error Modelling System* (GEMS) are representative. Subsequently, at the end of 1990s, the concept of the organisational accident linking individual, systemic and organisational failures came to the forefront of industrial research. *Swiss Cheese Model* (Reason, 1997) and SHEL model (i.e. the acronym of Software, Hardware, Environment and Liveware) (Hawkins, 1987) are renowned examples. In terms of human factors involved in aviation accidents, these two models are now widely applied as the fundamental of the analysis methodology (e.g. the SOAM and the HFACS) across North America and Europe

The International Maritime Organization (IMO) has followed the aviation industry in the adoption of Swiss Cheese and SHEL models and proposed guidelines for the investigation of human factors in marine casualties and incidents (IMO A.884, 1999; IMO, 2008). Both of the methodologies and guidelines have realised that, when investigating an accident, the investigators should not only focus on the actions of the sharp end personnel at the time of the occurrence, but also have to consider the following two aspects in order to align with and support "Just Culture" principle (Licu *et al.*, 2005).

- Seeking explanation for the conditions that shapes the actions of sharp end personnel.
- Identifying latent organisational factors that allowed the unsafe conditions to exist, under which an occurrence can be triggered.

In addition to Swiss Cheese and SHEL models, there are several other research studies which posture different viewpoints with respect to HOFs. Gordon *et al.* (2005) have proposed a HFIT model, which divides the human factor into four categories: 'Threats', 'Situation Awareness', 'Action Errors' and 'Error Recovery'. Another example is the '*Wheel of Misfortune*' model (see Figure 2-1), which consists of three concentric spheres: the actions of the front line (innermost), local precipitating (middle) and the global conditions generated by organisation (outermost) (O'Hare, 2000).

Figure 2-1 The Wheel of Misfortune (from O'Hare, 2000)

Amongst those HOFs models that have been proposed, the Swiss Cheese Model and SHEL model have their unique merits and continue to influence the realms of organisational accident investigation and analysis. For example, the SOAM and the HFACS are derived from Reason's Swiss Cheese Model; the IMO guidelines and the SOAM are both influenced by the SHEL model forming the core concept of the methodology. Reason himself also keeps evolving the Swiss Cheese Model both on the applicability and functionality of the model. For instance, a practical guide on managing maintenance error (Reason and Hobbs, 2003) addresses the features of human performance, risks, error-provoking factors, principle of error management and safety culture, etc., for the application of aircraft maintenance. Aside from this, a latest extended Swiss Cheese Model is proposed from the perspective of safety, in which a slice of Cheddar is considered, as the system defences or barriers for safety, in order to increase the resilience of the system (Reason, 2008).

Besides, some transformations of SHEL models are as well developed by different organisations or industries for their particular requirements. For example, a modified SHEL model which adds an additional *Organisation* (O) factor, as the fifth category, to form a SHELO model in order to denote the interaction between aircraft maintenance technician and the organisation (Chang and Wang, 2010). Another example is m-SHEL model, which introduces an additional *Management* (m) factor to specify the factors in association with corporate organisation, administration and system that influence the atmosphere at job site and safety culture (Kawano, 1997). In the same way, HFACS-RR (a modified HFACS to the railroad industry) is introduced to conduct investigations associated with train accident/incident in order to understand and manage the contributing factors in all levels of the railroad industry (Reinach and Viale, 2006). Generally speaking, although some modifications of the category descriptions are required for different professions, the HFACS framework has been proven that it is effective in categorising errors from investigations reports and is useful in capturing the full range of relevant human factors (Baysari *et al.*, 2008).

Yet, these models and methodologies are continuing concentrating on qualitative side without considering a quantitative analysing mechanism in conjunction with the applied HOFs model or framework.

2.4 Qualitative and quantitative analysis on human factors involved in an accident

Since human error continues to be the predominant factor in maritime accidents, in which organisational factors are known playing a significant part in accident causation, a sufficiently thorough and comprehensive accident/incident investigation procedure to establish the significance, frequency and impact of the factors involved is needed (Barnett, 2005). From the viewpoint of engineering, analyses can be roughly divided into two categories: qualitative and quantitative. In the perspective of qualitative analysis of an accident, the answers to the questions of analysing outcomes are normally the factors involved in the occurrence and the causation amongst them. The main purpose of the quantitative analysis of the accident is to look for the significance and/or frequency of the causal factors identified. Therefore, it is of vital importance while performing the analysing task – not to only concentrate on the qualitative outcomes, but also to seek the quantitative results of the analysed factors.

2.4.1 Qualitative analysis on human factors

It is suggested that, when performing an analysis task, one thing should be kept in mind all the time is that – "not to become satisfied and stop questioning but to always try to establish whether the last answer might give rise to a new follow-up question" (Schager, 2008). Moreover, "it is critical to understand why people did what they did, rather than judging them for not doing what we now know they should have done" (Dekker, 2002). Dekker also urges investigators should keep mindsets on the "new view of human error", avoiding the perspective of hindsight and outside, when reconstructing the human contributions to an accident. Despite the new view and notions, lacking of a systematic procedure to construct the human contribution to accidents is the shortcoming of the method that Dekker proposes. Svedung and Rasmussen (2002) have pointed out that graphic representation of the causal flow of accidents is very effective in creating an overview of complex occurrences, and hence they develop a tool named as AcciMap for the purpose. Other similar graphic methodologies, such as SOAM (EUROCONTROL, 2005), WBA (Paul-Stüve, 2005) and HFIT (Gordon *et al.*, 2005), are also developed by following this principle.

However, another trend also arises that analysis is carried out by applying or modifying well-defined Formal Safety Assessment techniques as the tools, instead of developing a dedicated method, for clarifying both the factors and causation of an accident. For example, Johnson (1999) has applied the FTA as the tool to visualise the relationship between human errors and organisational failures that occurred in a railway accident; Lee and Cha (2005) have proposed a technique – Causal Requirements Safety Analysis (CRSA) – by extending the FTA to qualitatively evaluate causal relationship between software faults and physical hazards; Celik *et al.* (2010) have integrated fuzzy feature into FTA in order to clarify the probability of technical failures, operational misapplications and legislative shortages leading to a shipping accident; and Trucco, Cagno, Ruggeri and Grande (2008) have combined FTA and Bayesian Network to model a Maritime Transport System (MTS), at the preliminary design stage of High Speed Craft (HSC), for analysing the HOFs in a collision scenario in open sea.

In terms of qualitative analysis, FTA can really provide an effective graphic presentation to illustrate the causation of an accident. Nevertheless, it is insufficient in analysing accidents quantitatively. This is because it lacks probabilistic information for the intermediate events and the rigid restriction of dependencies between basic and intermediate events although FTA has the mechanism to perform the probabilistic inferring for the Top Event. In contrast, Bayesian Networks are models with clear advantage over fault tree because they allow the representation of network instead of trees. This is particularly useful for common cause analyses (Castillo *et al.*, 1999).

2.4.2 Quantitative analysis on human factors

Bobbio, Portinal, Minichino and Ciancamerla (2001) have shown that Bayesian Networks provide a robust probabilistic method of reasoning with uncertainty and are becoming widely used for dependability analysis of safety critical system such as the Programmable Electronic Systems. They state that Bayesian Networks are more suitable to represent complex dependencies amongst components and to include uncertainty in modelling. Mohaghegh, Kazemi and Mosleh (2009) have supported this argument and also claim that Bayesian Networks are a network-based framework for representing and analyzing models involving uncertainty. Yang, Bonsall and Wang (2009) have concluded that Bayesian Networks enable risk diagnosis and prediction to be made using uncertainty inference foundation.

As well as modelling uncertainty, probabilistic inference is another advantage provided by Bayesian Networks technique, under which interventions (i.e. believe updating or evidence propagation) can be conducted with other network variables resulting in predictions and diagnoses (Anderson and Vastag, 2004). They recommend that if objectives included prediction and diagnosis of observed variables, then Bayesian Network approach should be selected. Zhou, Fang and Wang (2008) have demonstrated that human safety behaviour can be improved more efficiently and effectively by controlling 'safety climate factors', rather than 'personal experience factors' by using a Bayesian Network model to represent the construction industry in China. That is achieved by including local conditional dependencies into the model, by directly specifying the causes that influence a given effect (Bobbio *et al.*, 2001). Martin et al (2009) have stated that the identification of the dependency relationships between different variables, and expressing these relationships in probabilistic terms, enables Bayesian Networks to offer a broad-based perspective on the circumstances surrounding work. Bayesian Networks thus represent a statistical tool of huge potential in investigating the causes of accidents falling from a high above two metres at workplaces in Spain.

However, the Bayesian Network approach cannot solve all the problems, and there is a need for a systematic procedure to establish the model. Thus, a hybrid approach integrating deterministic and probabilistic perspectives may need to be considered. In the research by Mohaghegh *et al.* (2009), a Bayesian Network was integrated with System Dynamics, Event Sequence Diagrams and a Fault Tree in order to demonstrate the effects of organisational factors as the deeper (or more fundamental) causes of accidents and incidents. This provided a flexible risk management tool for complex socio-technical system in the aviation safety domain, focusing on airline maintenance systems.

2.5 Expert judgements and uncertainty

Yang and Liu (1998) have stated that there are two different meanings of uncertainty; one is randomness, and the other is fuzziness. The randomness looks at the occurrence probability, which is normally described by a probability distribution function. In contrast, the fuzziness is the uncertainty of belongingness, which is normally described by a membership function. This is relevant to this research, because, in practice, the lack of historical statistic data is often a conundrum in applying PRA techniques to carry out accident analyses. Expert judgements are often the alternative to mitigate this difficulty in order to get rational data for the occurrence probability of the events. The data given according to experts' subjective opinions can be seen as subjective probability information. However, this alternative raises another two issues: (1) how to express the uncertainty (both randomness and fuzziness) of the data, and (2) how to attain the group consensus under a common ground.

Celik *et al.* (2010) have suggested that fuzzy probability has the merits to flexibly express the vagueness of data and insufficient information associated with the occurrence of the Top Event regarding an accident, or a system in a safety case. Wang, Yang and Sen (1996; 1995) have shown an approach that provides a rational way of articulating and processing subjective safety and cost information to achieve a hierarchical system safety analysis by using fuzzy sets to express the subjective opinions and to synthesise the estimates. Furthermore, Yang, Wang, Xu, and Chin (2006) have proven that by using a fuzzy belief structure to accommodate numerical data and subjective judgements with probability and fuzzy uncertainties can provide a systematic yet strict procedure for aggregating both probabilistic and fuzzy information in an analytical fashion. That allows the incorporation of incomplete assessment information with fuzziness.

When fuzzy belief structures are applied to deal with the uncertainties of subjective estimations with group of experts, an aggregation (or synthesis) method regarding the type of the structures has to be introduced. This is because a group consensus of the estimates is always preferred, sometimes is even mandatory. Therefore, variant aggregation methods have been developed for different types of fuzzy PRA techniques. For example, Celik and Cebi (2009) have applied the Buckley solution algorithm to aggregate the experts' opinions in a form of triangular fuzzy numbers depicting linguistic terms, based on a FAHP, in order to identify the role of human error in shipping accidents. Other instances, such as Wang *et al.* (1996; 1995), have applied an Evidential Reasoning approach to synthesise the safety expressions which are described by linguistic variables characterised by fuzzy membership functions to evaluate the safety of a system. However, linguistic variables and fuzzy number cannot be directly applied as the conditional probability data in the used Bayesian Network software (i.e. Netica), only a numerical crisp value can be accepted. Thus, in Chapter 7, the Similarity Aggregation Method (SAM) (Hsu and Chen, 1996) aggregating individual fuzzy opinions in Positive Trapezoidal Fuzzy Number (PTFN) format to obtain a group consensus is applied and specified. Furthermore, the *f-weighted* valuation function, developed by Detyniecki and Yager (2000), to defuzzify fuzzy number is utilised in order to obtain the crisp value of the PTFN.

2.6 Discussion

In this chapter, the literature regarding the accident analysis methodologies has been reviewed. Several issues on this topic have been discussed. These issues include: the development of the analysis methods, the human factors involved, the qualitative and quantitative analysis techniques, and fuzzy approach solving uncertainty and subjective probability for group consensus. The deficiencies and insufficiencies of the methods reviewed are also discussed in each section.

The overall summary is that a thorough and comprehensive accident analysis methodology is desperately needed. This should include a systematic procedure to sort out the causation of the factors involved, a HOFs framework to clarify and classify the identified factors, a mechanism to perform the analysis qualitatively as well quantitatively and a solution to obtain the estimates from a group of experts. The proposed methodology for accident analysis (derived from the work described in this chapter) is therefore developed in Chapter 3 with the detailed description of the individual components of the methodology in the subsequent chapters.

Chapter Three – Outlines of the Methodology

Summary

The overview of the developed methodology which can assist investigators in analysing an accident qualitatively and quantitatively is given in this chapter. The methodology is based on the concept of Reason's Swiss Cheese Model. The accident is analysed in the form of Bayesian Network by implementing the Window of Opportunities (WoO) of the Swiss Cheese Model associated with the accident. This implementation is also combined with a Human and Organisational Factor (HOFs) framework which can be utilised to provide a comprehensive insight into the causation of the accident with a human and organisational factors hierarchy. This framework has the merit of assisting investigators to both classify the identified human factors and ascertain the more remote organisational factors.

The ideal data for calibrating such models is historical statistic data. When this is not available, expert judgements should be used. An aggregation method based on fuzzy set theory is applied for handling the group consensus issue during the analysing procedure when experts do not agree with each other at first. The chapter concludes with a summary of the broad features of the methodology provided and the consideration of further research needed.

3.1 Introduction

Reason's (1997) Swiss Cheese Model (see Figure 1-1) provides a valuable abstract explanation regarding how an accident can happen, but the way to implement the model in analysing the accident qualitatively as well as quantitatively still remains uncertain.

According to the latest elucidation made by Reason (2008), the notion of the Swiss Cheese Model is as follows.

> The current model (1997) involves a succession of defensive layers separating potential losses from the local hazards. ... Each 'slice' has holes in it like Emmenthale cheese; but unlike cheese the gaps are in continuous motion, moving from place to place, opening and shutting. Only when a series of holes 'line up' can an accident trajectory pass through the defences to cause harm to people, asset and the environment. The holes arise from unsafe acts (usually short-lived windows of opportunity) and latent conditions. The latter occur because the designers, builders, managers and operators cannot foresee all possible accident scenarios. They are much more long-lasting than the gaps due to active failure and are present before an adverse event occurs. ...There were two important changes. First, the defensive layers were not specified. They included a variety of barriers and safeguards – physical protection, engineered safety features, administrative controls (regulations, rule and procedures), personal protective equipment and the frontline operators themselves: pilots, drivers, watchkeepers and the like. They often constituted the last line of defence. The second change was the use of the term 'latent conditions'. Conditions are not causes, as such, but they are necessary for the causal agent to have their effect.

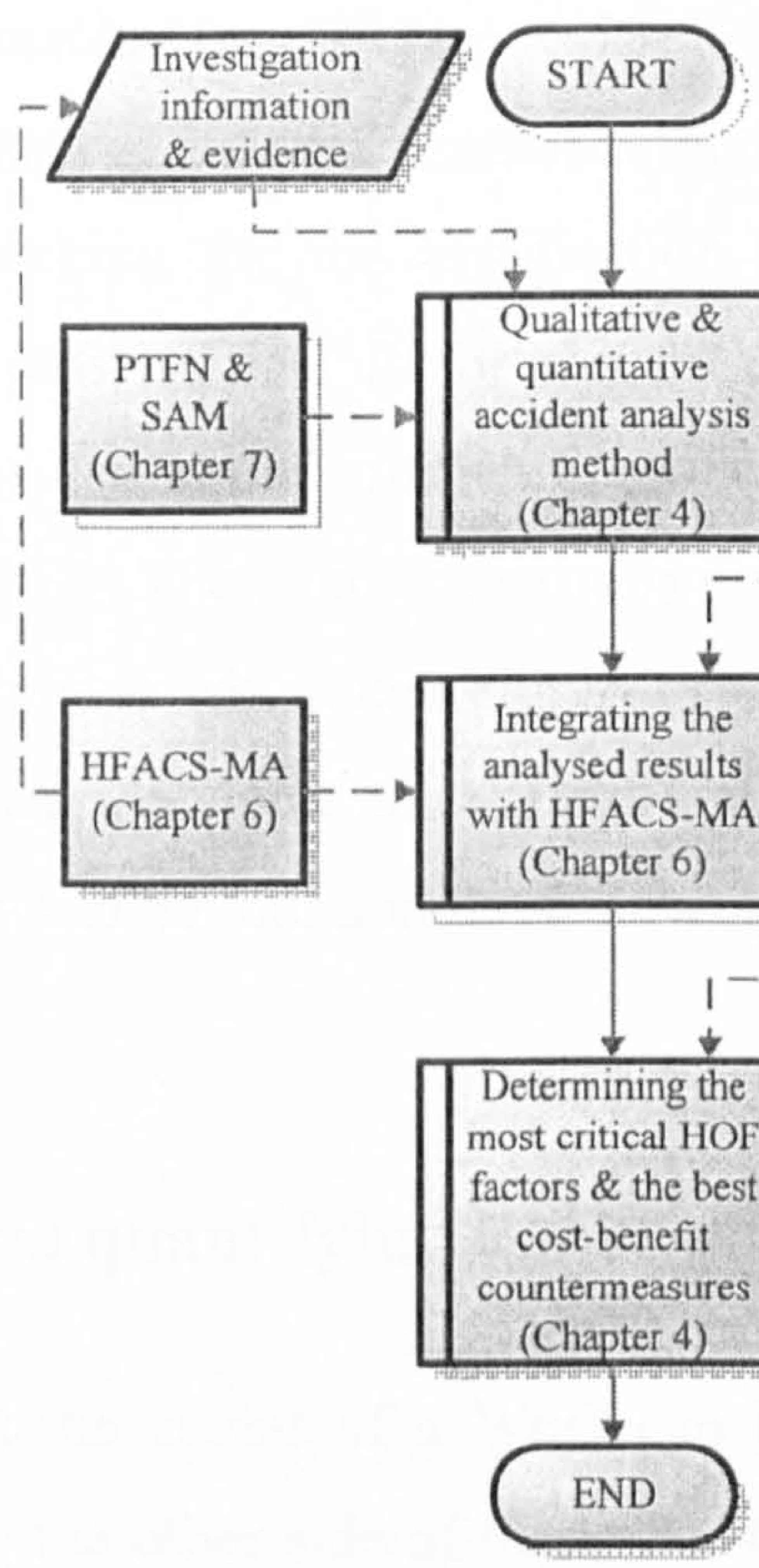


Figure 3-1 The overview of the proposed methodology for accident analysis

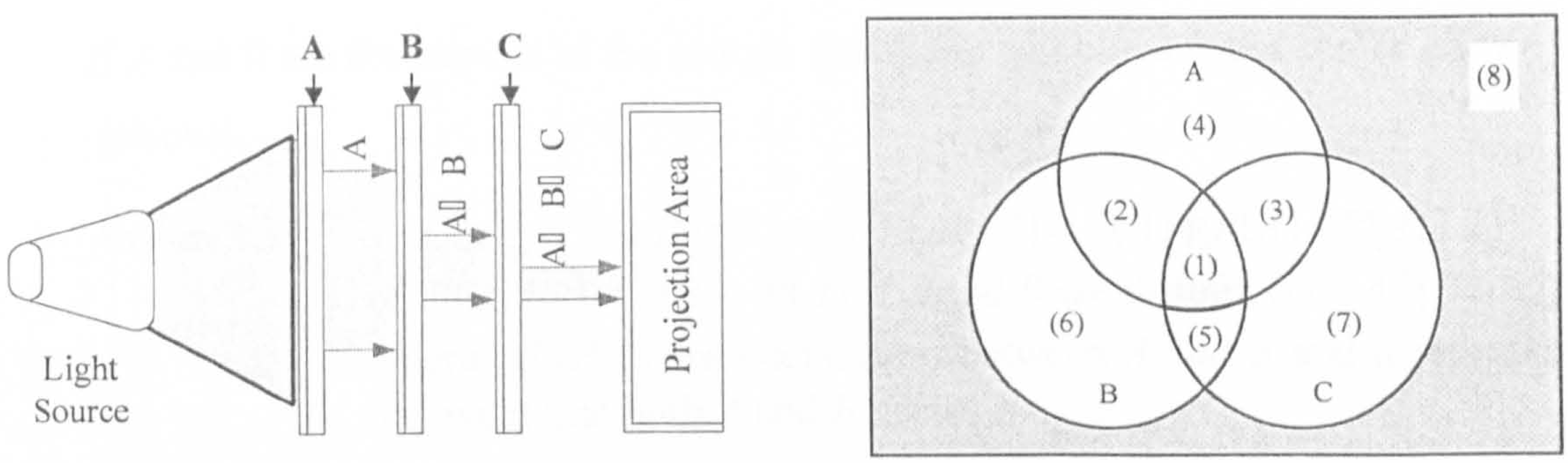
Therefore the present study presumes that the WoO of Swiss Cheese Model may be able to be instantiated by the *set theory* and the *probability theory*, which is introduced in section 3.2 and specified in Chapter 4. Meanwhile, a Human and

Organisational Factor framework, which follows the notion of defensive layers in the Swiss Cheese Model, to categorise the factors identified in an accident has also been investigated (see section 3.3 and Chapter 6). Finally, a method associated with aggregating a group of experts' estimates and resulting in a group consensus is proposed in Chapter 7 and briefed in section 3.4. Figure 3-1 illustrates the overview of the procedure when it is applied for accident analysis.

At the beginning, the information and evidence collected during the investigation period are handled qualitatively in order to find out the factors involved as well as the causation amongst them. By following a quantitative analysing procedure with a fuzzy set theory application, the qualitative analysis results are value-added with quantitative figures producing the Fault Tree – Bayesian Network (FT-BN) analysis results. Then a proposed HOFs framework is used, as a mask, to integrate the qualitative and quantitative analysis results (see Figure 6-10 as an example) for classifying the categories of the identified factors, demonstrating the association between them in different layers and seeking for the justification and insufficiency of the accident causation. Finally the most critical factor can be obtained, as well as the best cost-benefit countermeasures can be inferred, through the finalised analysis results over the proposed HOFs framework. The countermeasures referred in the proposed methodology are the Risk Control Options which can eliminate hazards from the system or mitigate the risks if accidents happen. More theoretical and applicative details regarding each part of the methodology can be found in the following sections and relevant chapters.

3.2 Qualifying and quantifying the Window of Opportunity (WoO)

It is assumed that the extent of a WoO can be determined by the illumination which is projected onto the other side of the Swiss Cheese Model through the lined up holes. The light source (e.g. lamp or torch) on the one end of the Swiss Cheese Model is deemed as the pathogens (or local circumstances) which may attack the system and cause an accident to happen. The other side of the Swiss Cheese Model may see the projected illumination if and only if the light source is on and there is at least one WoO existing in the Swiss Cheese Model at the time (see Figure 3-2(a)). Therefore, the intensity of the light is considered as the severity of the damage, and the coverage area of the illumination is as the probability of the events occurrence. In addition, the coverage of the illumination on the projection area directly relates to the width, the number and the position of the WoOs in the model. Meanwhile, each WoO is decided by the factors that cause the holes existing in each layers of the model and lining up the WoO to penetrate the defences of the system. Hence the aims of the proposed qualitative and quantitative accident analysis method are to find: (1) the factors that cause these holes of the WoOs existing; and (2) the coverage of the illumination as the probability of the events occurrence. Therefore, the *set theory* is mainly applied to clarify the causation of the causal factors – the qualitative issue – according to the association of the holes regarding the WoOs, and the *probability theory* provides a tool to solve the probability of events occurrence – the quantitative issue.



(a) an example of Swiss Cheese Model (b) Venn Diagrams

Figure 3-2 Illustrating the model with Venn Diagrams using illumination

In the example of Figure 3-2, there are three layers comprising the Swiss Cheese Model and each layer has a hole. The name of the hole is the same as the label of the layer (e.g. the hole A is in layer A). It is evident that the illumination coverage projected on the projection area due to this WoO is the area labelled as "(1)" shown on the Venn Diagrams in Figure 3-2 (b). That is, the WoO is caused by $A \cap B \cap C$ and the occurrence probability of the WoO is $P(A \cap B \cap C)$. Meanwhile, in this example, the sample space S can be seen as made up of eight pieces of areas which are denoted as areas (1) ~ (8). Additionally, since a subset of a sample space is called *event*, there are three events in this example; they are events A, B and C. That is,

$S = \{(1),(2),(3),(4),(5),(6),(7),(8)\}$
$A = \{(1),(2),(3),(4)\}$
$B = \{(1),(2),(5),(6)\}$
$C = \{(1),(3),(5),(7)\}$

Since the probability of aggregating areas in the sample space *S* is exactly one (i.e. $P(S)=1$) and an event *A* is *true* for an experiment if the outcome of the experiment is an element of the event, a probability $P(A)$ is therefore assigned to each event $A \subseteq S$. Those probabilities must obey the following three axioms (Jensen and Nielsen, 2007) (Russell and Norvig, 2003):

Axiom 1 $\quad P(S)=1 \qquad P(\neg S)=0$

Any subset *A* must have a nonnegative probability.

Axiom 2 $\quad$ for all $A \subseteq S$ it holds that $1 \geq P(A) \geq 0$

If *A* and *B* are the subsets of the sample space, the combined event can be shown as follows.

Axiom 3 $\quad$ If $A \subseteq S$ and $B \subseteq S$ then $P(A \cup B) = P(A) + P(B) - P(A \cap B)$, or $P(A \cup B) = P(A) + P(B)$ if *A* and *B* are disjoint (i.e. $A \cap B = \varnothing$) where $A \cap B$ is the intersection between *A* and *B* and it represents the event that both *A* and *B* occur.

The brief introduction regarding the probability above is called *joint probability* (see Table 3-1(a) as an example). In contrast, *conditional probability* (see Table 3-1(b) as an example) depicts the probability from another viewpoint which is given condition on other known factors (see the Venn Diagrams example shown in Figure 3-2(b)). This type of probability is generally stated as the following kind:

⇨ "Given the event *B*, the probability of the event *A* is p", denoted as $P(A \mid B) = p$.

Table 3-1 The comparison between joint and conditional probability

(a) joint probability *P(A,B,C)*

	A=1		A=0	
	B=1	B=0	B=1	B=0
C=1	(1)	(3)	(5)	(7)
C=0	(2)	(4)	(6)	(8)

Note that the probability in the joint distribution sums to 1 (i.e. $P\left(\bigcup_{i=1}^{8}(i)\right)=P((1))+...+P((8))=1$).

(b) conditional probability *P(C|A,B)*

	A=1		A=0	
	B=1	B=0	B=1	B=0
C=1	$\frac{(1)}{(1)+(2)}$	$\frac{(3)}{(3)+(4)}$	$\frac{(5)}{(5)+(6)}$	$\frac{(7)}{(7)+(8)}$
C=0	$\frac{(2)}{(1)+(2)}$	$\frac{(4)}{(3)+(4)}$	$\frac{(6)}{(5)+(6)}$	$\frac{(8)}{(7)+(8)}$

Note that conditional probability of C sums up to 1 for each column of the table.

Moreover, since $P(A\mid B)$ specifies a probability distribution for each event $B=b_j$, the conditional probabilities over A should sum to 1 for each state of B, according to Axiom 1. That is $\sum_{i=1}^{n}P(A=a_i\mid B=b_j)=1$ for each b_j (see Table 3-1(b)). Therefore, the probability of each area shown in Figure 3-2(b) (i.e. the Venn Diagrams) can be expressed as a joint probability (i.e. $P(A,B,C)$) or as a conditional probability (i.e. $P(C\mid A,B)$), and the equality between them is:

$$P(A,B,C)=P(C\mid A,B)P(A,B)$$

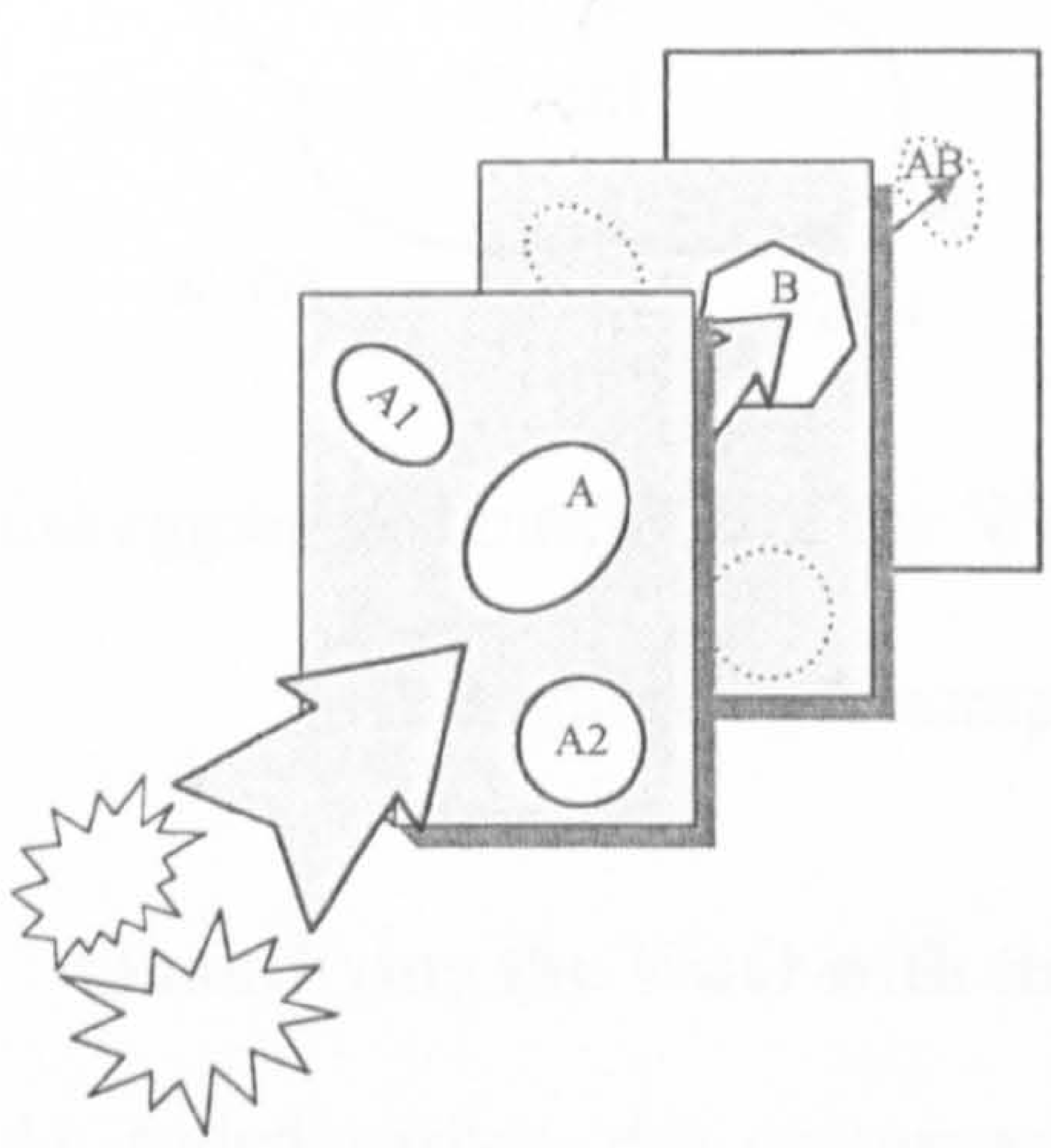
For example, the probability of $A\cap B\cap C$ (i.e. the area (1) in the Venn Diagrams) should read:

$$P(A\cap B\cap C)=P(C\mid A\cap B)P(A\cap B)$$

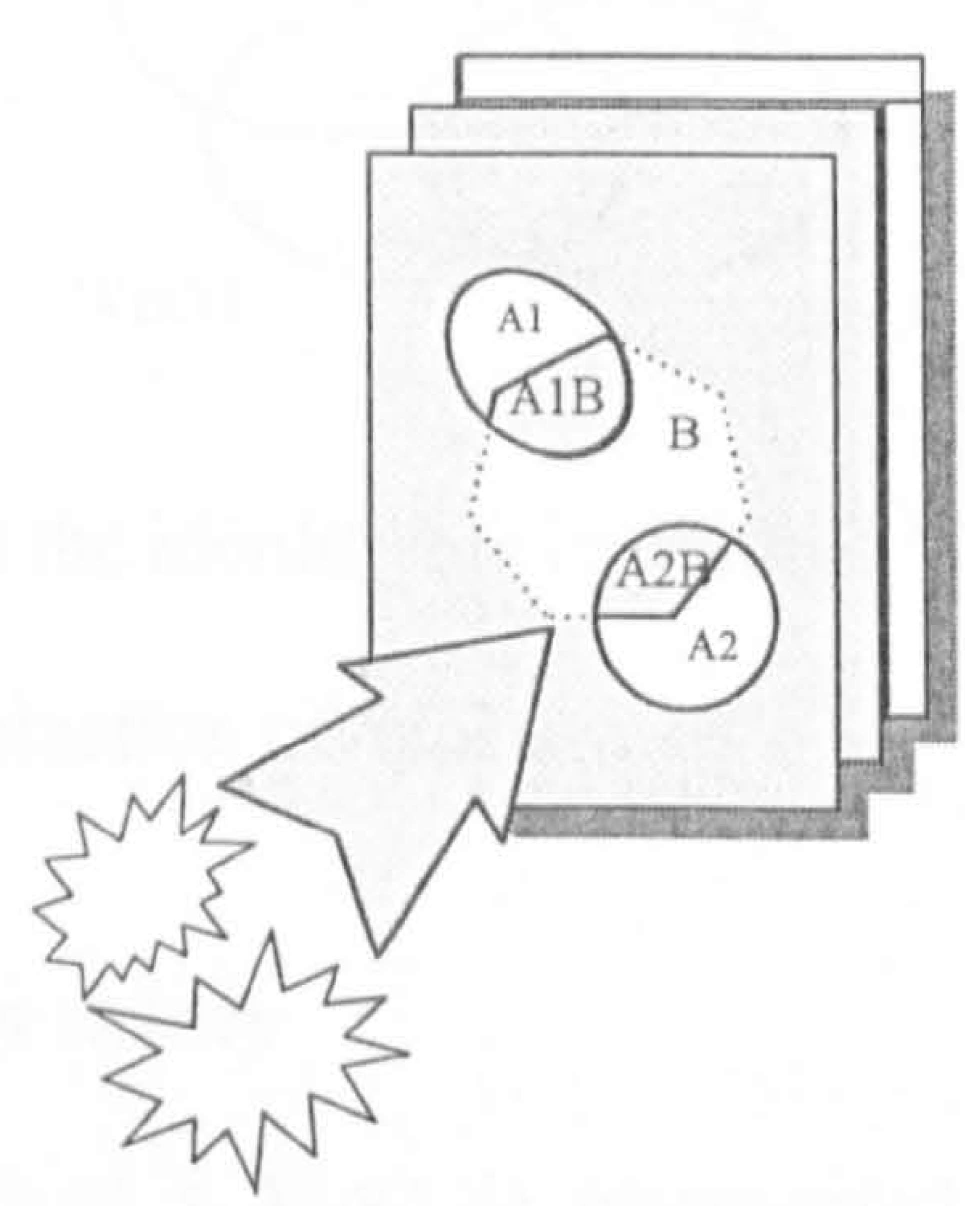
The answer to the equation above is "$P((1))$" which can be directly derived from the joint probability in Table 3-1(a) or computed from the conditional probability shown in Table 3-1(b). For the latter, $P\left(\frac{(1)}{(1)+(2)}\right)P((1)+(2))=P((1))$ is the answer, according to the data shown in the table. The example stated above shows that the *set theory* and the *probability theory* can be utilised to implement the WoO with qualitative and quantitative figures. In the next two sections, the basic qualitative and quantitative patterns of WoOs are discussed respectively. For more details and explanations of these two issues, Chapter 4 covers the essential theoretical information, and Chapter 5 provides a case study.

3.2.1 Qualifying the WoO with the set theory

In the preceding section, the example WoO consists of three holes, one in each layer, resulting in the AND relationship amongst these holes. Each hole represents one of the direct causal events of an accident. The factors identified in the accident are associated with each hole, and cause them to happen at the same time, but only one WoO is formed in this case. The holes and the factors are connected to one another in terms of why-because or cause-consequence relationship. This relationship is similar to the type of family tree; because of the existence of the grandparents, there is the possibility of having the parents, and then the child. For the purpose of contrast, Figure 3-3(a) is a single WoO example showing holes A and B in a two layers model. The projected area labelled as AB in the third layer (i.e. the projection area) is the only WoO of the model. Thus, the association of $A \cap B$ is the qualification of the WoO and the coverage of the projected area AB represents the accident occurrence probability. Once the holes (or events) are certain, factors behind these holes have to be found out in the next step. It is highly likely that one factor may associate with more than one event, as well as a particular event may associate with more than one factor.



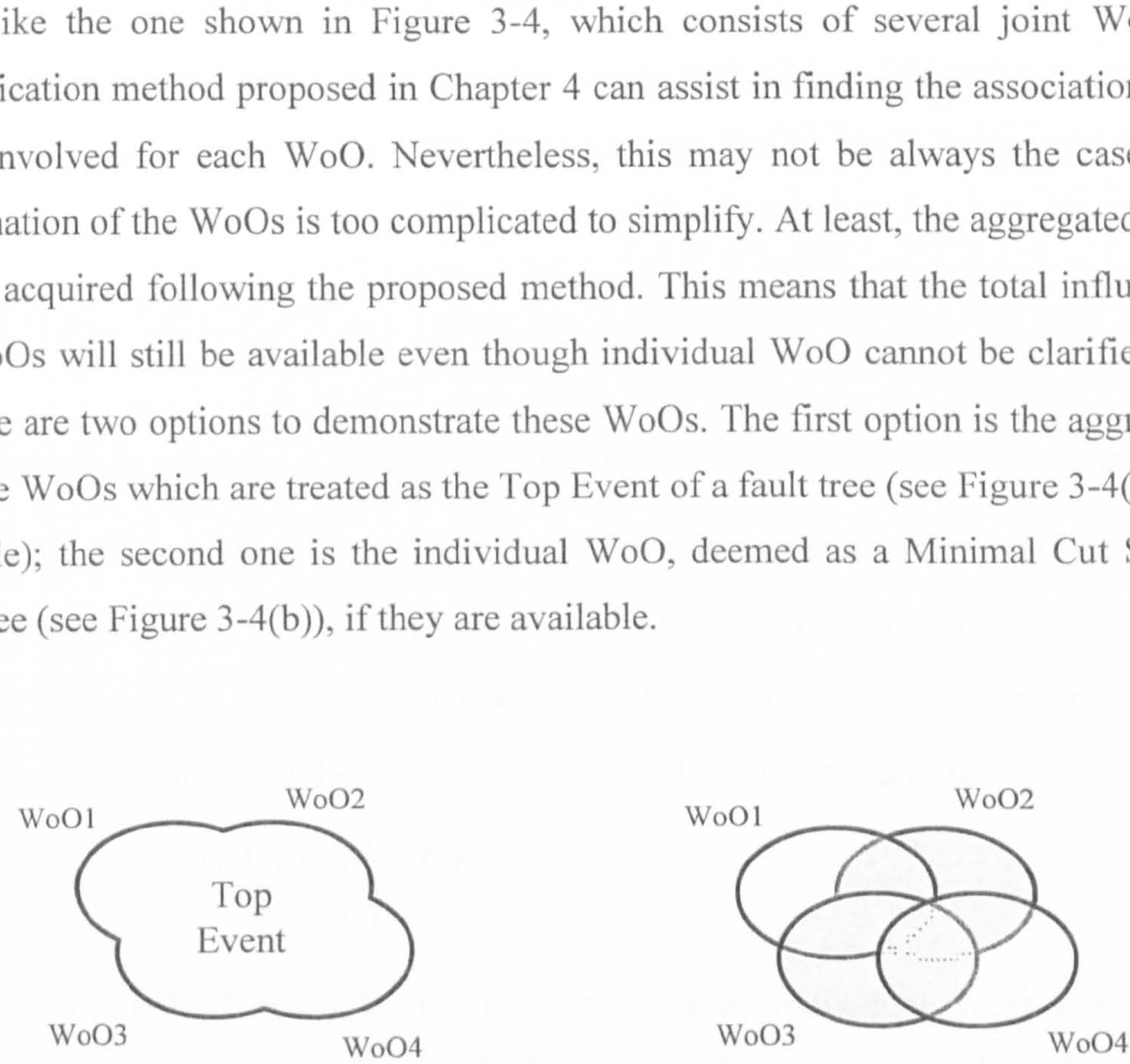
(a) a single WoO through two layers



(b) two disjointed WoOs through two layers

Figure 3-3 Two basic types of WoO qualification

In a multi-WoO instance, each WoO should be considered individually. For example, in Figure 3-3(b) there are two WoOs which consist of holes *A1*, *A2* and *B* where holes *A1* and *A2* are in the same layer whilst hole *B* is in another layer. This combination results in two projected areas *A1B* and *A2B* representing two disjointed WoOs. In this example, they can be qualified as $A1 \cap B$ and $A2 \cap B$ individually. However, if the context of the WoOs is further complicated, for instance, the example looks like the one shown in Figure 3-4, which consists of several joint WoOs. A simplification method proposed in Chapter 4 can assist in finding the association of the holes involved for each WoO. Nevertheless, this may not be always the case if the combination of the WoOs is too complicated to simplify. At least, the aggregated WoOs can be acquired following the proposed method. This means that the total influence of the WoOs will still be available even though individual WoO cannot be clarified. That is, there are two options to demonstrate these WoOs. The first option is the aggregation of these WoOs which are treated as the Top Event of a fault tree (see Figure 3-4(a) as an example); the second one is the individual WoO, deemed as a Minimal Cut Set of a fault tree (see Figure 3-4(b)), if they are available.



(a) the aggregated outcome of the WoOs (b) the identifiable individual WoO

Figure 3-4 A complicated combination of WoOs

3.2.2 Quantifying the WoO with the probability theory

As stated earlier, the occurrence probability of a WoO is represented by the illumination coverage reflected on the projection area resulting from the holes lining up together in the model. For a single WoO example, the intersection area of the associated holes located in each layer is the answer to the probability of the WoO. Thus, the probability of the WoO shown in Figure 3-3(a) can be acquired by Equation (3.1) since A is independent of B in the model.

$$P(A \cap B) = P(A)P(B) \tag{3.1}$$

It can also be expressed in terms of conditional probability, which is the major format to be applied in the proposed method. Thus, the expression is rewritten as follows.

$$P(A \cap B) = P(A \mid B)P(B) = P(B \mid A)P(A) \tag{3.2}$$

When one of the terms in the equation moves to the other side of the equal sign, it becomes the well-known Bayes' rule (Bernardo and Smith, 2002; Jensen and Nielson, 2007).

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

"Bayes'rule provides a method for updating the beliefs about an event A given that information about another event B is known. For this reason $P(A)$ is usually called the *prior probability* of A, whereas $P(A \mid B)$ is called the *posterior probability* of A given B; the probability $P(B \mid A)$ is called the *likelihood* of A given B" (Jensen and Nielsen, 2007). For an extension of the rule in a context C, it can be stated as follows:

$$P(A \mid B, C) = \frac{P(B \mid A, C)P(A \mid C)}{P(B \mid C)}$$

In a multi-WoO example, the quantification of individual WoO can only be obtained if the qualification of each WoO is achievable in the first place. If this is not the case, only the entire aggregated influence outcome of these WoOs (i.e. Top Event case shown in Figure 3-4(a)) is available for the subsequent quantitative analysis in the methodology without respective WoO details. This is because, in the proposed method, the corresponding Top Event model of an accident can be constructed without detailed WoOs involved being figured out in advance. In other words, each WoO is extracted from the Top Event outcome through an approximate simplified process resulting in an approximate outcome associated with these WoOs. It is preferred to have the Minimal Cut Set than the Top Event outcome representing the WoOs of the accident. An analogy is that a compound object without knowing the constitution of the materials can only be utilised in a limited way. For example, knowing nothing about the constitution of iron can only shape the iron, but not be able to produce steel or stainless. Thus, having clarified an individual WoO, there are advantages to analyse each WoO respectively, and then to find the best countermeasure for each of them. The reason why it is better for the WoOs to be handled individually is that each WoO can damage the system alone, only the probabilities of them are different. If an individual WoO is not able to be obtained, at least the aggregated lighted projection area (i.e. Top Event) can be alternatively found. The influence of the Top Event can be computed by following Equation (3.3) with the conditional probabilities data of these factors. For more details, see the relative sections in Chapters 4 and 5.

$$\sum P(PA = light \mid A,B,C)P(A,B,C) \tag{3.3}$$

where "$PA = light$" is the lighted coverage of the Projection Area

If a respective WoO is acquirable, Axiom 3 can be applied to deal with the total probability computation. Hence the aggregated probability of the projected areas $A1B$ and $A2B$ in Figure 3-3(b) can be computed via Equation (3.4).

$$\begin{aligned} P(A1B \cup A2B) &= P(A1 \cap B) + P(A2 \cap B) - P(A1 \cap B \cap A2) \\ &= P(A1 \mid B) + P(A2 \mid B) - P(A1 \cap A2 \mid B) \end{aligned} \tag{3.4}$$

In addition to the identification of individual WoOs, dependency is also an important issue between events. If information changing on event B does not change the belief about the occurrence on event A, A and B are independent. In other words, the events A and B are independent if

$$P(A \mid B) = P(A)$$

Given that the notion of independence is symmetric, if A is independent of B, then B is independent of A. It can be proven by applying Bayes' rule.

$$P(B \mid A) = \frac{P(A \cap B)}{P(A)} = \frac{P(A \mid B)P(B)}{P(A)} = \frac{P(A)P(B)}{P(A)} = P(B)$$

Therefore, since two events are independent, Equation (3.2) (i.e. the fundamental rule) can be rewritten as Equation (3.5). That is also the case shown in Figure 3-3(a).

$$P(A \cap B) = P(A \mid B)P(B) = P(A)P(B) \tag{3.5}$$

3.3 Implementing Reason's Swiss Cheese Model with a Human and Organisational Factors (HOFs) Framework

Although Reason's Swiss Cheese Model (see Figure 3-5) has articulated four layers (i.e. *unsafe acts*, *precursors for unsafe acts*, *line management deficiencies* and *fallible decisions*) as the levels of the model and the contextual association between them (Reason, 1990), no exact nature of the 'holes' which comprise WoOs has been identified, which is a limitation of the model (Shappell and Wiegmann 2003b). Therefore a HOFs framework, based on the Swiss Cheese Model, named *Human Factors Analysis and Classification System* (HFACS) (see Figure 3-6) for the U.S. aviation industry is proposed by Shappell and Wiegmann (2003b) and has been used in analysing the U.S. civil and military airborne accidents since year 2000 (Wiegmann and Rantanen 2003; Wiegmann *et al.*, 2005; Scarborough *et al.* 2005; Shappell and Wiegmann 2003a; Shappell *et al.*, 2007). In addition, it has been shown that a transformation of the framework can also be utilised in the railway industry (Baysari *et al.*, 2008; Reinach and Viale, 2006).

Figure 3-5 The Swiss Cheese Model of accident causation
Source: adapted from Reason (1990) modified by Shappell and Wiegmann (2003b)

Figure 3-6 The Human Factors Analysis and Classification System (HFACS) (from Shappell and Wiegmann (2003b))

The present study assumes that it would be beneficial for the maritime industry to investigate and analyse maritime accidents if a dedicated human factors classification is in place. For that reason, a HOFs framework is proposed and named as *Human Factors Analysis and Classification System – for Maritime Accidents* (HFACS-MA), which is analogous to the HFACS and is the implementation of the notion. The distinction which is different from the original HFACS is that the proposed framework considers and adheres to the requirements of the International Maritime Organization (IMO) guidelines for the investigation of human factors in marine casualties and incidents (IMO A.884, 1999). In Chapter 6, the details regarding the framework and the applications are specified. The proposed HOFs framework (i.e. the HFACS-MA) comprises four levels (see Figure 6-1); they are:

- ⇨ *Unsafe Acts* (i.e. the bottom level);
- ⇨ *Preconditions;*
- ⇨ *Unsafe Supervision;*
- ⇨ *Organisational Influences* (i.e. the top level).

Each level consists of several categories, in which numerous items such as the human factors of the type are defined. It is intended that the specific items of each level can be varied according to the requirements of the applied fields or realm. Having established a framework of the kind, it will be beneficial for the maritime industry from two aspects.

1. It can provide a clear classification and definition of HOFs that helps the investigators to identify the human factors involved in an accident as well as to classify the categories of the factors.
2. It can also offer a clearer causality hierarchy associated with HOFs for the investigators to track the causal sequence among the identified factors as well as to avoid overlooking the organisational predisposing factors.

Barnett (2005) has pointed out that how to establish the significance, frequency and impact of organisational factors is still a research conundrum. The present study proposes one solution to the problem by establishing the dedicated HOFs framework (i.e. HFACS-MA) and combining with the qualitative and quantitative analysis method mentioned in section 3.2. It is the combination of the framework and the method which can provide a comprehensive insight into:

1. The causation and the probability of WoOs which are identified in an accident. The combination of the proposed framework and the method can illustrate the causation of the identified factors, located in different levels of the HOFs framework, making up of the WoOs as well as the probability information regarding the WoOs and the factors as a whole.

2. The influences of the factors from the top level to the lower level of the framework. This portrays the principle of Reason's Swiss Cheese Model that the causal sequence moves from fallible decisions, through the intervening planes, to an accident.

3. The deficiency of information or evidence. The framework can prompt the investigators to pay attention on the factors that are identified in the lower levels without further explanation or underlying factors connected from the higher levels. It will facilitate the investigators to ensure if any factor in the higher level is overlooked and warrants further investigation.

4. The vulnerable parts of the maritime industry. The numerical or statistical data associated with the analysed accidents can easily be exchanged if they are all performed under the same HOFs framework. That is, the framework becomes a platform to bear a broadened analysis by overlapping the data collected from the entire maritime industry in order to highlight the significant defects of the system.

3.4 Solving uncertainty and consensus problem with fuzzy set theory

When historical statistic data is not available, it is a common practise to use experts' judgements evaluating the probabilities of the factors identified in an accident in order to carry on the analysis procedure. It is highly likely that a group of experts will be invited to perform this functionality. However, a question is frequently encountered as to how to obtain a group consensus when their estimates do not coincide with one another in the beginning. From the viewpoint of decision makers, it is preferred that a group consensus, rather than several individual figures, is provided depicting the analysis results. The proposed accident analysis methodology has also recognised this conundrum. Hence, an aggregation method in considering the systematisation, objectivity and the contentment of the experts is proposed.

The proposed method (covered in Chapter 7) applies the form of Positive Trapezoidal Fuzzy Number (PTFN) to handle the uncertainty of estimation and the Similarity Aggregation Method (SAM), which is proposed by Hsu and Chen (1996), to deal with the estimates aggregation. In addition, the *f-weighted* valuation function is the measure to obtain the crisp value of the PTFN. Occasionally, the Delphi method, which is a communication tool developed by Dalkey (1969), is used as a last resort to reach a common ground associated with those PTFNs given by the experts when their estimates are apparently apart. Eventually, the group consensus can be reached, through the proposed aggregation method, and the outcome of the consensus can be accepted by most of the experts involved.

It will be shown in Chapter 7 that the proposed aggregation method can assist the proposed methodology in fulfilling the requirements of obtaining a group consensus with the following features:

- ⇨ The form of PTFN has the advantages to intuitively express an expert's estimate as well as the uncertainty of the estimate. Moreover, this form can not only fulfil the aggregation of the estimates in the SAM process, but also facilitate the common intersection of the estimates to be reached within the Delphi process.
- ⇨ The consensus PTFN can only be attained provided that the common intersection amongst the estimates exists. Since the common intersection is always under the coverage of the consensus PTFN, it can be deemed as that the consensus PTFN is constructed based on the common ground of the group opinion.
- ⇨ The SAM aggregation function considers the "importance of the experts" when deciding the "degree of influence (or contribution)" of each estimate for the group consensus. Moreover, this method can also regulate the overall consensus outcomes bias to the "degree of importance of the experts" or the "agreement degree (or similarity) of the estimates".
- ⇨ The outcome of the *f-weighted* valuation function can be regulated as to bias to the average of the core, or the average of the support, of the PTFN when defuzzifying it into a crisp value.
- ⇨ The Delphi method can ensure a common intersection of the estimates to be reached and the crisp value of the consensus PTFN to be accepted by all the experts involved.

⇨ The form of PTFN and *f-weighted* valuation function can still be utilised even though only one expert's estimate is applied. This is because the form of PTFN has the advantage to deal with the uncertainty.

3.5 Discussion

Reason's Swiss Cheese Model has been widely utilised as the core concept to develop a number of guidelines, frameworks or methods, e.g. IMO guidelines and HFACS, in analysing accidents causation regarding human and organisational factors. It recognises both the *active failures*, at the sharp end of the system, and the *latent conditions*, in design, procedures and management that may lain dormant within the system for years, have the same significant contributions to the safety of a system, or organisation (Barnett, 2005). However, those applications mainly concentrate on a subjective interpretation regarding the occurrence of the identified factors to carry out accidents analysis qualitatively, without a quantitative probability figures to distinguish the significance of the factors objectively.

Hence, by implementing the WoO of Reason's Swiss Cheese Model, this study presumes that a qualitative as well as quantitative accident analysis method based on the notion of the model can be achieved, in which the set theory and the probability theory are applied as the theoretical fundamentals. The method ends with a Bayesian Network to illustrate the analysed accident to deal with not only the causation of the factors identified qualitatively, but also the probability (or significance) of each factor quantitatively. By combining with the proposed HFACS-MA, which is a HOFs framework analogising to the HFACS, a comprehensive insight into the causation of the factors involved, from the sharp end personnel level to the organisational management level, is demonstrated.

The proposed methodology has also considered the group consensus issue. Expert judgements can be applied when there is a lack of historical statistical data. Fuzzy set theory is the means to mitigate the dispute which may arise during the analysis procedure when consensus estimation is required from a group of experts.

Predictably, the proposed methodology has the merit to be utilised in analysing the real causes of accidents. It can also be used in a "safety case" scenario to assess the safety of a system before a real accident happens.

In summary, the significant features of the proposed methodology are briefly listed as follows.

- A systematic procedure to find out the causation of the factors involved in an accident, as the qualitative analysis results, is in line with the notion of WoOs of Reason's Swiss Cheese Model. Meanwhile, the probabilities of the WoO and the factors are the quantitative figures to depict their significance in the occurrences.
- The Bayesian Network model established according to the qualitative and quantitative analysis results can be seen as a dedicated simulator of the accident to perform a series of *what if* examinations in order to identify the significance of the critical factors and to clarify the effectiveness of the countermeasures.
- An Influence Diagrams model based on the established Bayesian Network model of the accident is a useful tool for decision makers to evaluate the best Risk Control Option, whilst considering the cost-benefit issue, among variant available countermeasures.
- Both the qualitative and quantitative analysis results of the accident can simultaneously be shown in a Bayesian Network model to provide a comprehensive insight into the causation of the accident by integrating the HFACS-MA framework, as well as in an Influence Diagrams model to evaluate the cost-benefit outcome of the countermeasures.

Chapter Four –
The method for qualitative and quantitative analysis

Summary

In this chapter, a method of obtaining the qualitative as well as the quantitative analysis results of a maritime accident in conjunction with experts' judgements is proposed. The method mainly applies Why Because Analysis (WBA) and Fault Tree Analysis (FTA) techniques for qualitative analysis, and Bayesian Network techniques for quantitative analysis. In addition, Sensitivity Analysis (SA) and Influence Diagrams are also applied as parts of the method. Every technique applied in the method follows the concept of Reason's *Swiss Cheese Model* to implement a relay-like procedure. The analysed results are presented in a form of Bayesian Network, in which the qualitative and quantitative analytic outcomes of the accident are shown in a graph with probability figures. An Influence Diagram which is derived from the Bayesian Network model of an accident can also be established for decision maker as a tool to select the best Risk Control Option (RCO) based on cost-benefit consideration through the Maximal Expected Utility (MEU) functionality. The proposed method also has merit in that an objective analysis results are still achievable even though the historical statistic data may not be available and experts' judgements have to be employed. This is because the systematic procedure and the validation process of the proposed method can effectively reduce the subjective speculations during the analysis.

4.1 Introduction

From the view of Fault Tree Analysis, the *Window of Opportunity* (WoO) of Reason's (1997) *Swiss Cheese Model* is similar to the *Minimal Cut Sets* (MCS) of Fault Tree Analysis. This is because a *Minimal Cut Set* is a *Cut Set* that if any *Basic Event* is removed from the set, the *Top Event* will not occur; where *Cut Set* is a collection of *Basic Events* such that if they all occur the *Top Event* must also occur (Andrews and

Moss, 2002). In Fault Tree Analysis, the *Basic Events* indicate the limit of resolution of the fault tree and are mutually independent. For a quantitative analysis, it is those events for which data are required in FTA. Thus, the similarity of the definitions between *WoO* and *Minimal Cut Set* inspires the proposed method due to their concept are almost the same. In other words, the *WoO* should be able to be implemented by the *Minimal Cut Set* of FTA if the holes in each layer of the *Swiss Cheese Model* are treated as the events in the fault tree. In this sense, it seems that Reason's *Swiss Cheese Model* can be materialised by the *Minimal Cut Sest* under which the Top Event (i.e. the accident) is triggered by the combination of those events (i.e. the holes). Hence, this study assumes that if the *Minimal Cut Sets* of FTA can implement the *WoOs* of an accident, it would be possible to analyse an accident qualitatively as well as quantitatively. Then the Causal Factors and the countermeasures of the analysed accident may be identified objectively through a systematic procedure in order to prevent the similar occurrences from happening again.

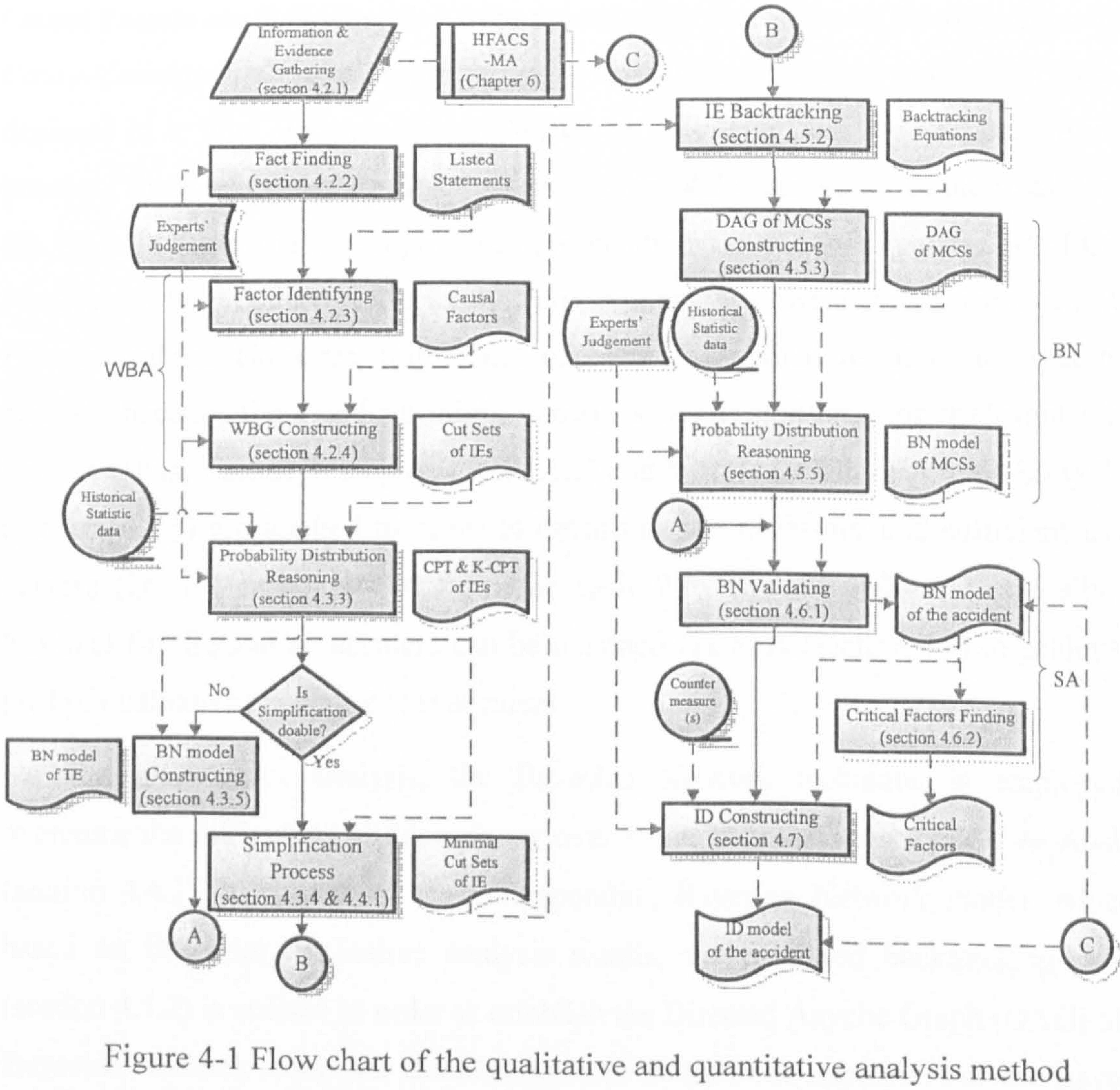


Figure 4-1 Flow chart of the qualitative and quantitative analysis method

In order to obtain the Minimal Cut Sets (or WoOs) of the accident, the Cut Sets involved in the accident have to be identified first. The difference between *Minimal Cut Set* and *Cut Set* is that a Minimal Cut Set consists of "necessary and sufficient" Causal Factors whilst a Cut Set merely consists of "sufficient" Causal Factors. These Causal Factors are the factors that cause the consequence event (i.e. the holes) to happen. In Fault Tree Analysis, this consequence event is represented by the Intermediate Event of a Cut Set (or Minimal Cut Set). For identifying these Cut Sets, the Causal Factors derived from the information or evidence gathered during the investigation stage have to be clarified in advance. The proposed Human and Organisational Factors (HOFs) framework – HFACS-MA – which is specified in Chapter 6 can benefit investigators to identify the factors during the investigation.

Therefore, during the analysis procedure of the proposed method (see Figure 4-1), the first process is to extract the relevant facts from the information or evidence gathered during the investigation (section 4.2.2). Further, as stated in section 4.2.3, the Causal Factors are then identified from the extracted facts. Hence, the *Why-Because* (or *Cause-Consequence*) relationship amongst these Causal Factors can be clarified and depicted in a Why Because Graph (WBG) by following the Why-Because Analysis process. These processes are described in sections 4.2.4 and 4.2.5. In the final stage of the Why-Because Analysis, a graphical presentation (i.e. the WBG) and a list of Causal Factors can be produced to depict the causation amongst these factors for every Why-Because subset. However, this is not necessarily the final result of the qualitative analysis because the Cut Sets might contain some insignificant or irrelevant Causal Factors. Thus, Karnaugh map (section 4.3.2) and K-style Conditional Probability Table (section 4.3.3) are applied in order to determine the necessary and sufficient Causal Factors (i.e. the Minimal Cut Sets) for each Why-Because subset. Eventually, the Minimal Cut Sets of an accident can be obtained via FTA (section 4.4) to achieve the goal of qualitative analysis of the accident.

For quantitative analysis, the Bayesian Network technique is employed to overcome the difficulties of dependency over Basic Events within Fault Tree Analysis (section 4.4.1). To construct the corresponding Bayesian Network model, which is based on the prior qualitative analysis results, the proposed backtracking process (section 4.5.2) is utilised in order to establish the Directed Acyclic Graph (DAG) of the Bayesian Network model for the Minimal Cut Set(s) of an accident. For the Bayesian

Network model of Top Event (TE), the corresponding WBG and K-style Conditional Probability Tables (K-CPT) are the blueprint (section 4.3.5). Having coded the appropriate data to the Conditional Probability Tables (sections 4.3.4 and 4.5.5) for each node in the Directed Acyclic Graph, the preliminary Bayesian Network model of an accident is established. However this is not yet the outcome of the quantitative analysis. It has to pass the Sensitivity Analysis as the validation process (section 4.6.1) before the final quantitative analysis results of the accident can be acquired. By employing sensitivity finding process, the critical Causal Factors of the accident can also be found (section 4.6.2). Furthermore, the selection of the possible countermeasures, as Risk Control Options (RCOs), against the accidents can be fulfilled by expanding the Bayesian Network model to become an Influence Diagrams model (section 4.7) for the decision makers. The entire procedure of the proposed method is briefly illustrated in Figure 4-1 and the details for each process are described in the associated sections of the chapter.

4.2 Why-Because Analysis (WBA) for Causal Factors

In general, at least two questions arise when an accident has occurred; they are "what happened?" and "how did it happen?" In most cases the first question is easier to specify, for example the Estonian-flagged RO–RO passenger ferry 'Estonia', carrying 989 people, departed from Tallinn, the capital of Estonia, at 19:15 hours on 27 September 1994 for a voyage to Stockholm, Sweden. She sank in the northern Baltic Sea in the early hours of 28 September 1994. But it would be difficult to point out which Causal Factors (or causes) are involved immediately. In order to clarify which Causal Factors were really present at the time of the occurrence and the causalities between them, WBA is applied as the first part of the method to ensure the queries can be solved objectively, thoroughly and systematically. However, only parts of the WBA are utilised in the proposed analysis procedure due to the requirements of the method. The main work handled by WBA is merely finding out the sufficient Causal Factors involved in the accident and the causation amongst them. These results will then be passed to another process which is the probability distribution reasoning for further Bayesian Network model construction.

WBA is a method for accident analysis and has been used to analyse many aviation, railway, marine and computer related accidents and incidents (RVS WBA homepage). It is primarily used as a reactive analysis method. The major result developed in WBA is a Why-Because Graph which depicts the cause-consequence relationships (or causations) between Causal Factors and the Top Event (i.e. the accident). The Why-Because Graph consists of nodes and directed edges as a non-cyclic graph. The nodes represent the identified Causal Factors whilst the directed edges denote the causations between the Top Event and the Causal Factors. There are two reasons to apply WBA as the technique for identifying these Causal Factors within the analysis procedure. Firstly, the concept of the Why-Because Graph is in line with the implication of Cut Sets of FTA. This means that each event involved in the fault tree can be illustrated as the consequence of a set of Causal Factors in the Why-Because Graph to implement the idea of Cut Set. This is crucial to the analysis method because these Cut Sets are the foundation for acquiring the Minimal Cut Sets of FTA, which are the instances for implementing the Window of Opportunities of the accident. Secondly, the non-cyclic feature of the Why-Because Graph coincides with the characteristic of the Directed Acyclic Graph of Bayesian Network. The Bayesian Network model of the accident is the cornerstone to deal with the quantitative analysis of the accident and the subsequent selection of countermeasures for the decision makers within the proposed method.

Before specifying the proposed method further, it is worth clarifying some terminologies used in the analysis procedure. These clarifications are not intended to override their original definitions which have been well-defined in the derived techniques, e.g. FTA or WBA. Rather, they seek to provide readers with a clearer aspect about the roles they play and how they will be dealt with within the proposed method. In other words, they are still consistent in their original definitions but just with different interpretations.

- CF (Causal Factor): the factor causes its direct consequence event (i.e. Intermediate Event or Top Event) to occur. It can be deemed as a Basic Event or an Intermediate Event but is definitely not the Top Event.
- BE (Basic Event): it is the primary form of Causal Factor and the analysis boundary of the procedure. That is, the leaf of a causation branch without any factor connected as its Causal Factor.
- IE (Intermediate Event): it is the other form of Causal Factor which locates between the Top Event and the Basic Event of the Fault Tree, the Why-Because

Graph of WBA and/or the Directed Acyclic Graph of Bayesian Network. It can not only be the Causal Factor of an event, but can also be the consequence of its Causal Factors.

- CS (Cut Set): it consists of a set of sufficient Causal Factors to cause its direct consequence event (i.e Intermediate Event or Top Event) to occur. However, it may contain some insignificant or irrelevant factors.
- MCS (Minimal Cut Set): it is a Cut Set that contains only necessary and sufficient Causal Factors to cause its direct consequence event to occur. This means no Causal Factor existed in the MCS is insignificant or irrelevant.

As noted previously, the aim of these processes is to ascertain the Cut Set (or Causal Factors) for the Top Event and each Intermediate Event involved in the accident. This is achieved by inspecting the information and evidence collected during the investigation stage with the help of WBA technique. Therefore the WBA starts at organising the investigation information and ends in forming a Why-Because Graph and the Cut Sets of the accident. It can be divided into five steps; they are (1) information and evidence gathering, (2) facts finding, (3) Causal Factors identifying for each Intermediate/Top Event, (4) Why-Because Graph forming and (5) Causal Factors listing. A variation of WBA used in the present study is that although the WBA consists of eights subroutines to obtain the analysis results (i.e. the Why-Because Graph), neither the execution order nor the subroutines applied in the proposed procedure are the same as the original WBA. Only two of the subroutines are employed. They are the Causal Sufficiency Criterion (CSC) at the causal factors identification stage and Why-Because Graph in the process results forming stage. The details of each process and application are described in the following sections.

4.2.1 Information gathering according to the IMO guidelines

Once an accident occurs, normally the administrative authorities will immediately launch an investigation into the occurrence so that lessons can be learned. There are several field guides (IMO, 2008; EUROCONTROL, 2005; Shappell and Wiegmann, 2000; Dekker, 2002b; Stoop, 2003) specifies how to carry out the investigation objectively, thoroughly and effectively. Since this study considers the human factors involved in the maritime accidents, the resolutions, codes and circulars adopted by the International Maritime Organization (IMO) are the primary guidelines to be followed. In May 2008, the Maritime Safety Committee (MSC) of IMO adopted a dedicated casualty investigation code (IMO, 2008) when the committee met in London for its 84th session. The following announcement, which is introduced on the IMO website (http://www.imo.org), briefly describes the latest innovation of the code.

> **New casualty investigation Code adopted**
> The MSC adopted a new *Code of International Standards and Recommended Practices for a Safety Investigation into a Marine Casualty or Marine Incident (Casualty Investigation Code)*. Relevant amendments to SOLAS Chapter XI 1 were also adopted, to make parts I and II of the Code mandatory. Part III of the Code contains related guidance and explanatory material.
>
> The Code will require a marine safety investigation to be conducted into every "very serious marine casualty", defined as a marine casualty involving the total loss of the ship or a death or severe damage to the environment.
>
> The Code will also recommend an investigation into other marine casualties and incidents, by the flag State of a ship involved, if it is considered likely that it would provide information that could be used to prevent future accidents.
>
> The new regulations expand on SOLAS Regulation I/21, which requires Administrations to undertake to conduct an investigation of any casualty occurring to any of its ships "when it judges that such an investigation may assist in determining what changes in the present regulations might be desirable".

Table 4-1 shown below are the Resolutions adopted by the organization with regard to the casualty investigation code. According to Resolution A.849(20), there are two types of information that should be gathered during the investigation; they are "information generally required in all cases" and "additional information required in specific cases". It further subdivides the information generally required in all cases into ten categories; they are:

1. Particulars of the ship
2. Document to be produced
3. Particulars of voyage
4. Particulars of personnel involved in incident
5. Particulars of sea state, weather and tide
6. Particulars of the incident
7. Assistance after the incident
8. Authentication of documents
9. Engine-room orders
10. External sources of information

In the same way, the additional information required in specific cases is also subdivided into five categories listed as follows.

1. Fire/Explosion
2. Collision
3. Grounding
4. Foundering
5. Pollution resulting from an incident

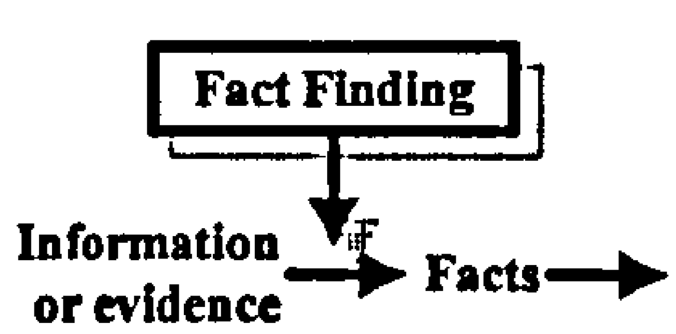
In each category, the guidelines enumerate a series of recommendations about which type of data should be collected as well as which kind of information is referred to.

Table 4-1 The IMO resolutions/circulars regarding the Casualty Investigation Code

Resolution A.173(ES.IV)	Participation in official inquiries into marine casualties.
Resolution A.203(VII)	Recommendation on the conclusion of agreements and arrangements between States on the question of access and employment of foreign seaborne salvage equipment in territorial waters.
Resolution A.322(IX)	The conduct of investigations into casualties.
Resolution A.440(XI)	Exchange of information for investigations into marine casualties.
Resolution A.442(XI)	Personnel and material resource needs of Administrations for the investigation of casualties and contraventions of conventions.
Resolution A.637(16)	Co-operation in maritime casualty investigations.
Resolution A.849(20)	**Code for the investigation of marine casualties and incidents,** as amended by resolution A.884(21).
Resolution A.884(21)	**Amendment to A.849(20)** **(Appendix 2 Guidelines for the investigation of human factors in marine casualties and incidents)**
MSC/Circ.539/ Add.2	Reports on casualty statistics concerning fishing vessels and fishermen at sea.
MSC/Circ.827	(updated by MSC/Circ.953/MEPC/Circ.372): Reports on marine casualties and incidents. Harmonized reporting procedures - Reports required under SOLAS regulation I/21 and MARPOL 73/78 articles 8 and 12.
MSC-MEPC.3/Circ.1	Revised harmonized reporting procedures - Reports required under SOLAS regulation I/21 and MARPOL 73/78, articles 8 and 12

Furthermore, the Code also remarks on the signification of the human factors involved and suggests twenty-five areas of inquiry, from which a series of example questions have been designed. These inquires are roughly subdivided into two categories as "Shipboard Issues" and "Shore-Side Management Issues". This can assist the investigator in searching for human factors involved in an accident. The public can now access a dedicated database (i.e. Global Integrated Shipping Information System (GISIS) http://gisis.imo.org) which has been set up by IMO secretariat with regard to ship casualties and other shipping information. The Casualty Module of GISIS contains two kinds of information collected on ship casualties. The first category of the information comprises factual data collected from various sources. The second category of data is made up of more elaborated information based on the reports of investigations into casualties received at the IMO. This may consist of the analysis of full investigation reports by the organization or reporting forms annexed to MSC-MEPC.3/Circ.1. It is recommended to gather the information by following the domain guidelines since they can help the investigations to ensure that the data collected is comprehensive and sufficient. For maritime accidents and casualty investigation, the IMO guidelines should be the fundamental basis to be followed.

4.2.2 Fact finding with a proper format



The main purpose of this *fact finding* process is to organise the information obtained during the investigation into a proper format. This format has to consider three essential requirements for carrying out the rest of the analysis within the procedure. They are:

1. The facts specified should only focus on a single action, condition, event, etc., at the same time it has to be clear and explicit for the analyst to understand.
2. It should contain a means of index to link up the source information as well as the subsequent analysis outcomes.
3. The maintainability of the data pool which collects and organises the sieved facts should be easy to add in or take out any factual data.

Therefore, the formation of *listed statements* is proposed as the solution to fulfil the requirements. Each listed statement consists of three parts; they are "(#): sequential identifier with a hierarchy feature (e.g. 1.1 or 1.2.1)", "the statement body for one single fact" and "(source index)". The proposed format is shown below and some examples are illustrated in section 5.2.1:

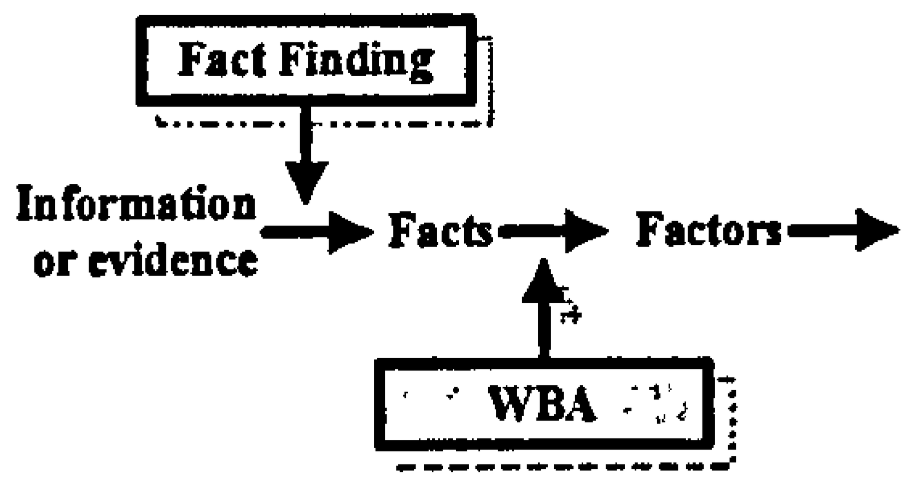
(#) [the statement body for one single fact] (source index)

e.g. (3) [The master ordered a ship speed of 18 knots] (DoT 9.2; pp.7).

The first part of the format, the sequential identifier "(#)", can have various types of notation. The only constraint on the format is that it has to be short and a pure numerical style is preferred. This is because the letter-number (e.g. A-1) notation style will be intensively applied within the following processes. In order not to mix up the notation of listed statements with the others, it is recommended to use a different type of notation style in different analysis processes. The second part of the format is the statement body that contains sentence(s) to depict one particular fact which is extracted from the gathered information. Each statement should only focus on one single fact and describe it as briefly as possible without compromising the clarity. For convenience, for the next process to handle the described fact, it is preferred that the statement matches with an event or a Causal Factor. If this is not the case, 'disorder' may be introduced whilst transferring the statements from facts to Causal Factors in the next process. Although this 'disorder' will not halt the process, it will produce some undesired outcomes such as several statements leading to one Causal Factor or, vice versa, several Causal Factors referring to one statement. The last part of the format is the "(source index)" located at the end of the statement. This is a short notation which links the statement and the source information from which the fact is derived. No particular style of the index needs to be followed but it should be as simple as possible. These indices will be very useful for locating the origin of the information if any doubt arises when reviewing the statements.

Once all the facts have been elicited and organised, according to the proposed format, to create a data pool of listed statements, the next process of identifying the Causal Factors can be proceeded.

4.2.3 Identifying the Cut Sets using Causal Sufficiency Criterion (CSC)



The identification of the direct Causal Factors for each Intermediate/Top Event through the listed statements organised within the previous process is now considered.

The CSC is proposed in the WBA guideline (Paul-Stüve, 2005). It is specified such as "between a set of causal factors $A_1 \cdots A_N$ and a consequence event B, it is impossible for B not to have happened if all of $A_k; k \in [1, N]$ have happened". In contrast, the definition of Cut Set of FTA is that "a Cut Set is a collection of Basic Events such that if they all occur the Top Event must also occur" (Andrews and Moss, 2002). Since the similarity of these two definitions, the study assumes that the CSC of WBA can be utilised to sort out a set of direct Causal Factors for each Intermediate/Top Event of an accident from the listed statements to represent the Cut Set of the Event in FTA. In other words, the CSC is treated as a filter to sieve out the Causal Factors from the data pool of listed statements in order to constitute a Cut Set that is sufficient to trigger a particular event. It is fitting to treat every Causal Factor in WBA as an Intermediate Event in FTA, but it might sometimes be improper to treat it as a Basic Event in FTA. This is because it is very unlikely that the Causal Factors involved in an accident are mutually independent. This feature will result in a problem if the Causal Factors are treated as Basic Events to carry out the quantitative analysis in FTA without clarifying the dependencies amongst them. Fortunately, FTA is only applied to handle the qualitative analysis within the proposed method so that this issue does not halt the process, and the only differentiation between Intermediate Event and Basic Event is whether they are "the limit of resolution of the fault tree" (Andrews and Moss, 2002), i.e. the boundary of the analysis. It implies that, in the proposed application, an event becomes a Basic Event if it is on the boundary of the fault tree, otherwise it is an Intermediate Event. In addition, each Intermediate Event and the set of its direct Causal Factors (i.e. Cut Set) can also be seen as a Why-Because subset. The entire Why-

Because Graph of the accident can then be acquired by assembling every Why-Because subsets into one union, with other subsets subsequently included.

As described in section 4.1, the aim of this process is to clarify which direct Causal Factors triggered an Intermediate Event to occur. Thus, two considerations must be made when transforming the listed statements into the direct Causal Factors of Intermediate/Top Events for further analysis.

Firstly, each listed statement should be depicted as a single fact as possible, but this is not always the case. In other words, there will not always be a one-to-one relation between the listed statements and those Causal Factors. It might be a relationship of many listed statements regarding one Causal Factor, or vice versa, one listed statement refers to many Causal Factors. However, if the index system of the listed statements is well defined, this phenomenon does not cause a serious problem but introduces some 'disorder' only. Secondly, in a practical application, if a dedicated domain/field causal taxonomy is available, it would be helpful for analysts to identify the Causal Factors from the listed statements. This means that, as long as an action, condition or event conforms to one particular definition of the taxonomy, it can easily be identified as a Causal Factor. For example, in section 5.2.1, the listed statement (2) of the case study – "The assistant bosun failed to carry out his duty to close the bow doors at the time" is identified as a Causal Factor because it conforms to one of the definitions of the proposed HFACS-MA framework, which is "Violations: factors in a mishap when the actions of the operator represent wilful disregard for rules and instructions, and lead to an unsafe situation" described in section 6.2.1.2.

As soon as all the gathered information and evidence with respect to the accident are listed and organised as listed statements in the previous process, the causality amongst them becomes the top priority issue of the analysis procedure in order to ascertain the answers of how and why the accident happened. The purpose of this process is similar to piecing together a jigsaw puzzle; all the pieces of the puzzle (i.e. listed statements) are now in place, but the whole picture of the puzzle (i.e. the Why-Because Graph or the Cut Set of each Intermediate Event) is as yet unknown. Therefore, a systematic procedure to transform the listed statements into the Causal Factors and specify the causalities amongst them is proposed as follows.

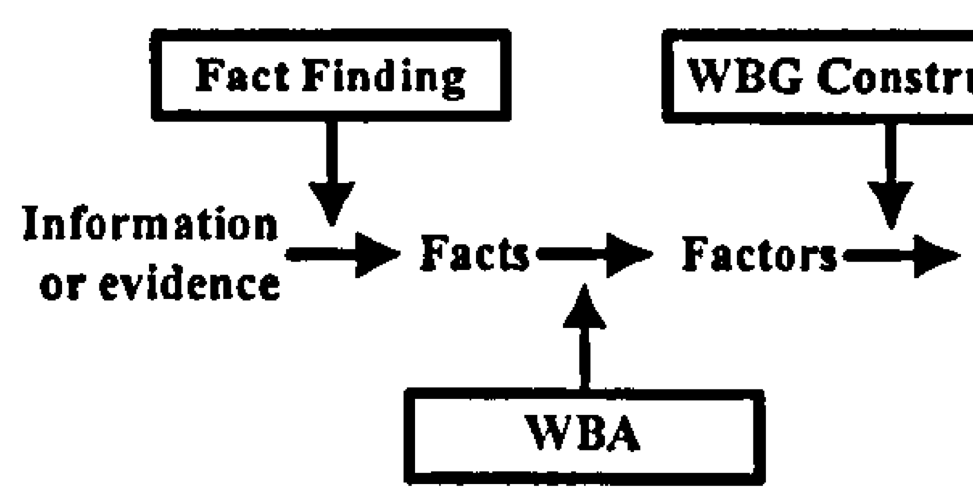
(1) The Causal Factor identifying process starts from the Top Event of the accident. It is similar to starting piecing together a jigsaw puzzle from the first identified piece, and then the adjacent pieces to the first identified piece one after another. That is, the analyst scans all the listed statements searching for the possible direct Causal Factors which could result in the Top Event, one by one, from the top to the bottom of the statements in turn, using Causal Sufficient Criterion as the sufficiency examiner. The purpose of the criterion is to ensure the Cut Set (i.e. set of identified direct Causal Factors) of a particular Intermediate/Top Event is both sufficient and valid to the event. This means that a factor will become one of the identified Causal Factors of a particular Intermediate/Top Event if it is rationally believed that it is responsible for the occurrence of the event.

(2) The factor is subsequently added into the Cut Set of the Intermediate/Top Event. If the direct Causal Factors in the Cut Set are still not enough to support the Intermediate/Top Event to occur, then the Causal Factor identifying process has to iterate for that particular Intermediate/Top Event until the Cut Set satisfies the CSC. An example of transforming those listed statements into the Causal Factors is demonstrated in the case study in section 5.2.2. Once the Cut Set of a particular Intermediate/Top Event passes the CSC, the Causal Factor identifying process for that Event is accomplished.

(3) The Intermediate/Top Event and its Causal Factors are hence grouped as one of the Why-Because subset, which is going to be used to construct the Why-Because Graph in the next stage. This is, the Intermediate/Top Event is deemed as the "why (or consequence)" and its Cut Set as the "because (or causes)" in the graph, in which the direct Causal Factors of a particular Intermediate/Top Event comprise the Cut Set of that event in FTA.

Soon after the Cut Set of Top Event is finalised, each Causal Factor in that Cut Set becomes an Intermediate Event and launches another Causal Factor identifying process for each new Intermediate Event. This process operates iteratively on all new identified Causal Factors until reaching the boundary of the analysis (e.g. beyond the investigation scope) from the information collected. If every Cut Set for each Intermediate/Top Event is satisfied with CSC, it would be confident to say that the entire Why-Because Graph, which consists of these Intermediate/Top Events with their Cut Set, is also satisfied with CSC. After accomplishing this process, there are two groups of intermediate analysis data eventually created; they are the identified Causal Factors and the Cut Set for each Intermediate/Top Event. They are not only the essential material to construct the Why-Because Graph and to make a List of Factors, but also the foundation for the rest of analysis processes. It is important to note that the Causal Factors contained in the Cut Set only represent the sufficient Causal Factors of the Intermediate/Top Event and not the necessary and sufficient Causal Factors. The difference between them will be explained in section 4.3.

4.2.4 Constructing the Why-Because Graph (WBG)



The goal of constructing the Why-Because Graph is to assemble those Why-Because subsets (i.e. the Intermediate/Top Event and its Cut Sets identified in the preceding process) into a singular graph (see Figure 4-2 for the illustration). Each Intermediate/Top Event and its Cut Set have been seen as a subset of the Why-Because Graph, in which Intermediate/Top Event is the "*why* (or *consequence*)" and its Cut Set is the "*because* (or *causes*)". The complete Why-Because Graph should be able to construct via assembling these Why-Because subsets together providing none of the Intermediate Events has been overlooked.

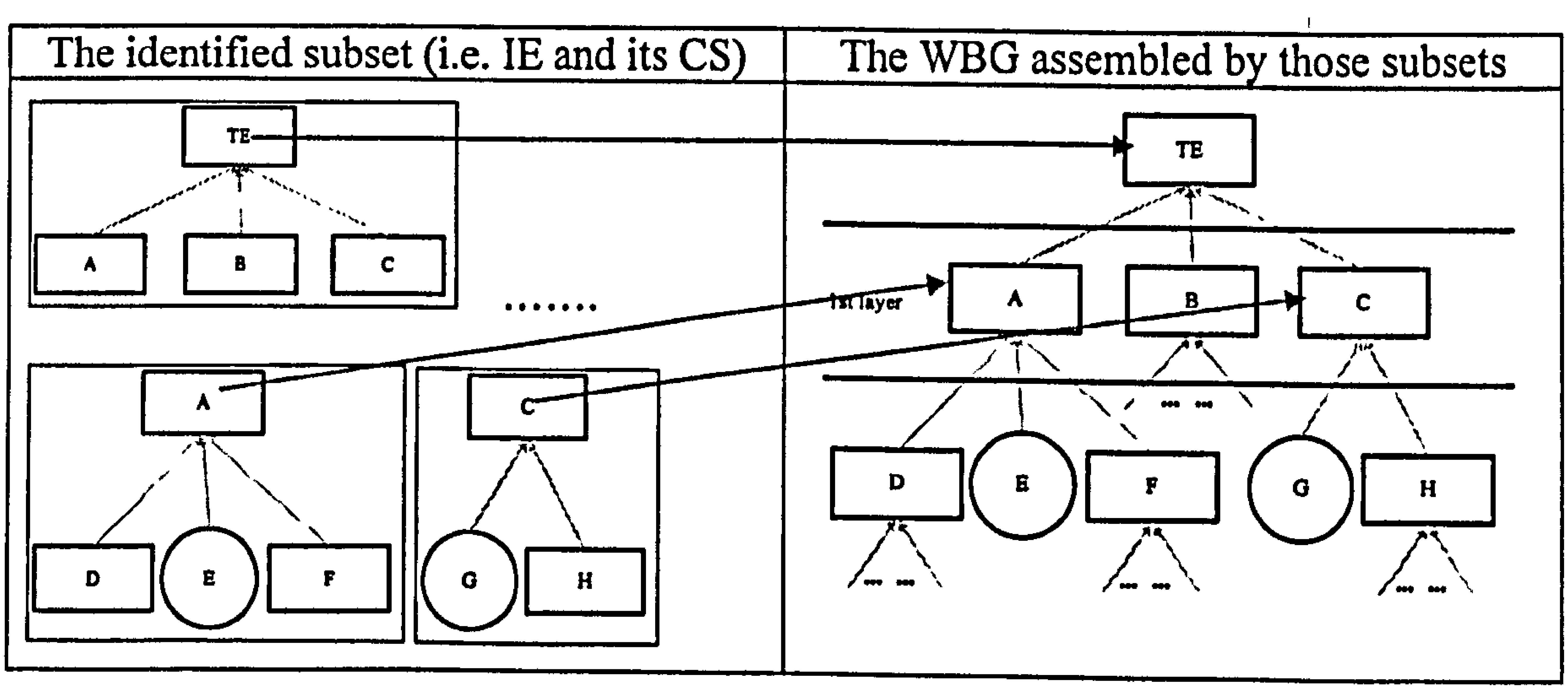
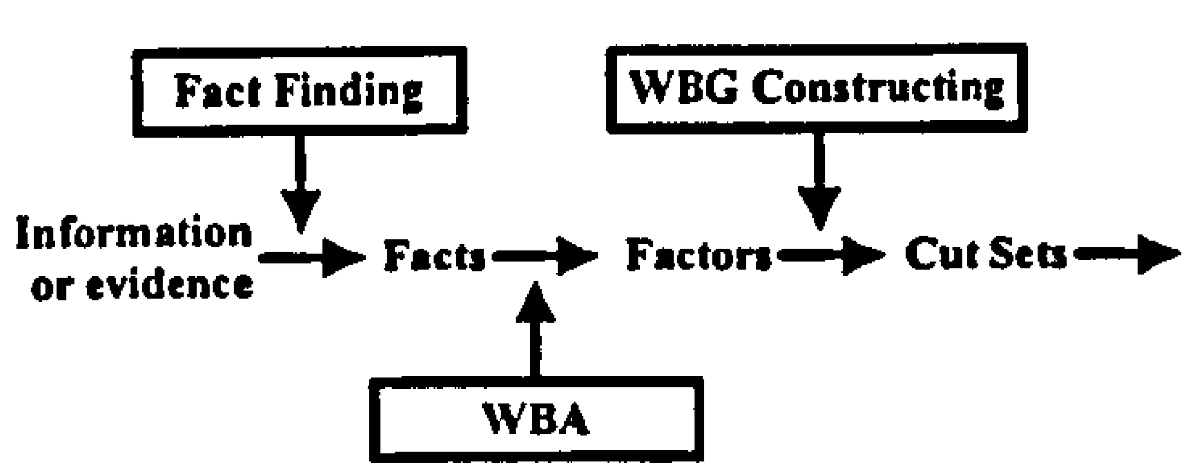


Figure 4-2 The identified subsets and the Why-Because Graph

The construction of the Why-Because Graph is fairly straight forward. As each Intermediate/Top Event and its Cut Set are a subset of Why-Because Graph, the main purpose of the process is to collect and assemble these Why-Because subsets form the top (i.e. Top Event) to the bottom in turn. Therefore, the process starts with the first identified event – Top Event to assemble the Why-Because Graph. Each Causal Factors of the Top Event will becomes one of the first layer's Intermediate Events, if any one of them has a Cut Set (CS) identified in the preceding process. The Cut Set belongs to that Intermediate Event will be concatenated to the tail of the Intermediate Event in the Why-Because Graph, and hence the graph grows. The entire Why-Because Graph is completed when all the Why-Because subsets of each Intermediate Event have been placed in the right location of the graph. It is also possible to construct the Why-Because Graph and identify the Causal Factors of the Intermediate/Top Event simultaneously provided that this is not detrimental to the analyst work. Figure 4-2 illustrates the notion of assembling the Why-Because Graph with the identified subsets and the notion of layers with the horizontal lines.

4.2.5 Create the List of Factors (LoF)



The goal of this process is to organise the identified Causal Factors, which are contained in the Why-Because Graph, with an index mechanism referring to the derived listed statements. The LoF is the key for the Causal Factors and/or the Why-Because Graph to refer to the origin of the listed statements. It also provides a useful auxiliary reference to perform the Boolean algebra operation for clarifying the Minimal Cut Sets of the accident in the following processes. After accomplishing the construction of the Why-Because Graph of the accident, a comprehensive overview is given with regard to "how did the accident occur" and "which Causal Factors were involved in the accident". However, this overview is not yet able to answer the question of "why did the accident happen". This is similar to the whole jigsaw puzzle having now been pieced together, but the story behind the picture is as yet unknown. Before carrying out the analysis further for the answer to "why did it happen", those identified Causal Factors, which are shown in the Why-Because Graph, have to be organised and labelled as a data pool for the following analysis. The principle of the labelling system of the Causal Factors is to assign a symbol or label to each Causal Factor as short and clear as possible. This is because these symbols or labels will be utilised in the Boolean algebra operation for clarifying the Minimal Cut Sets of the accident. The assigned symbol or label has to be simple as well as ordered. Meanwhile it also has to differentiate from the enumerating system of the listed statements. Therefore, this study proposes a letter-number (e.g. "A1" or "A" only) format to deal with the notation of the Causal Factors. It is recommended to initiate the label assigning process after the Why-Because Graph has been accomplished rather than during the Causal Factor identifying process. Without the entire overview of the Why-Because Graph, it is highly likely that the label assigned to a Causal Factor will be changed due to another new Causal Factor being identified. Therefore, it is recommended to assign the symbols or labels to each Causal Factor after accomplishing the Why-Because Graph of the accident to gain the benefit of a coherent symbol outcome.

Having assigned the symbol or label to each Causal Factor in the Why-Because Graph, it is worth making a list of Causal Factor as a quick reference. Since these Causal Factors are derived from the listed statements, it is also worth setting up an index for each Causal Factor to rapidly refer to the related statements. The proposed format of the LoF is shown as follows.

Label: [factor description] (index)

e.g. A: [a large quantity of water entered G deck] (4)

From the example shown above, "A" is the symbol or label of the Causal Factor, and "(4)" in the tail of the sentence is the index which links the Causal Factor "A" to the listed statements No.4. The "[factor description]" depicts the identified Causal Factor in a short sentence emphasising on one single factor. A domain or field error taxonomy will be helpful to identify the factor and to clarify the category of it. As noted previously, a Causal Factor might be derived from more than one listed statement as well as one statement may be referred by more than one Causal Factors. An example of the LoF for the case study is illustrated in section 5.2.3. The index notion between the LoF and listed statements together with the listed statements and source information is demonstrated in Figure 4-3 below.

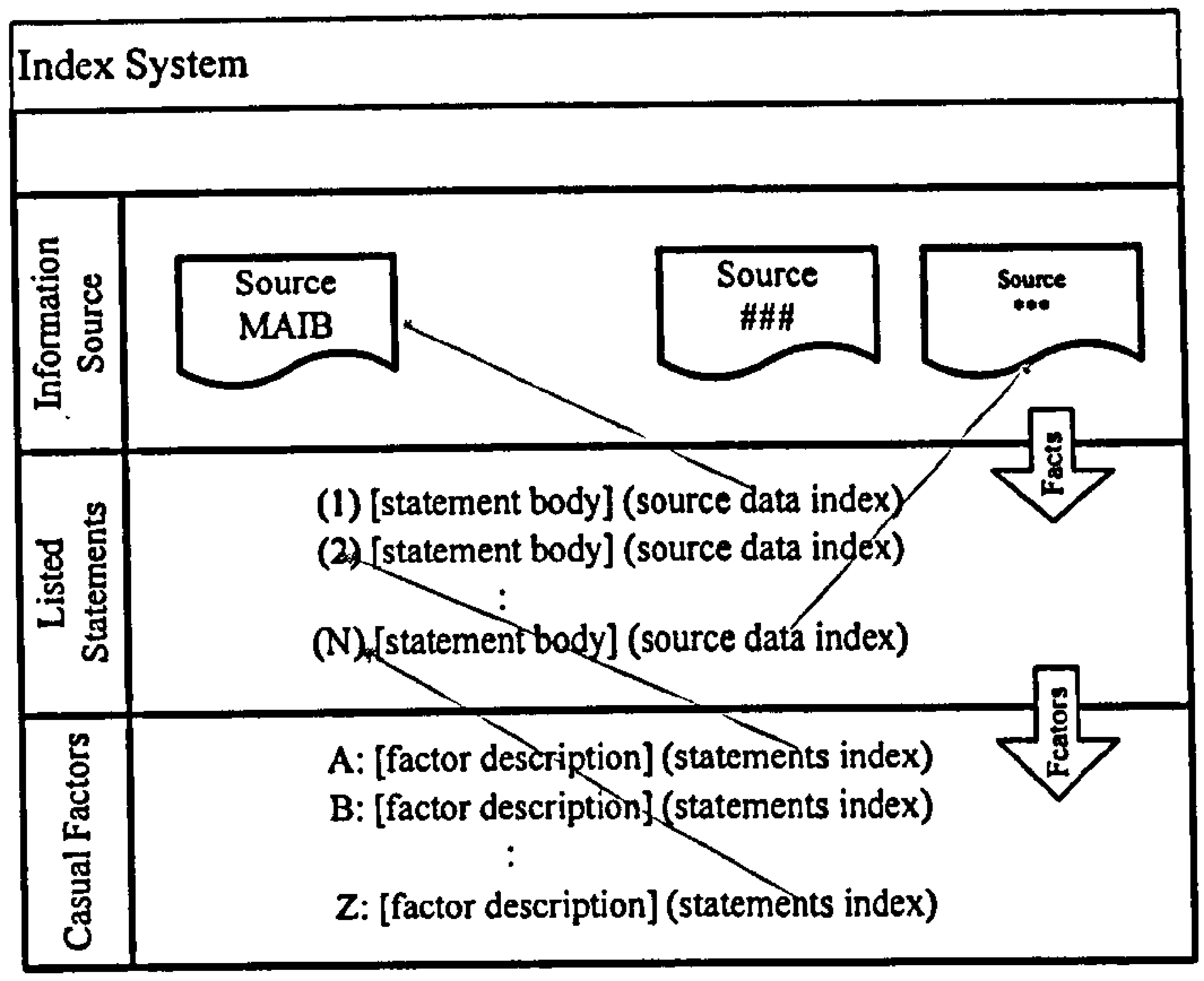


Figure 4-3 The index mechanism amongst LoF, listed statements and source information

4.3 Determining the approximate Minimal Cut Set(s) (MCS) for Intermediate/Top Event and constructing the Bayesian Network model of Top Event

Up to this stage, the analysis results acquired are the Why-Because Graph, Cut Set for each Intermediate/Top Event and the List of Factors. However, in order to perform the best qualitative analysis, Minimal Cut Sets, rather than the Cut Sets, for each Intermediate/Top Event are preferred. Hence, the main purposes of this process are to form a Bayesian Network model of Top Event and to clarify the approximate Minimal Cut Set(s) for each Intermediate/Top Event by ruling out the trivial Causal Factors from the Cut Set. As noted previously, the difference between Minimal Cut Set and Cut Set is that a Minimal Cut Set consists of "necessary and sufficient" Causal Factors whilst a Cut Set merely consists of "sufficient" Causal Factors. That is, a Cut Set might still contain some insignificant or irrelevant Causal Factors. However, the notion of Minimal Cut Sets applied in the proposed methodology is not the same as the type used in FTA; they are in an approximate style. This is because an approximate simplification law is applied to obtain the Minimal Cut Sets in situations where all the traditional "AND", "OR" and "Equal" are defined as "noisy-AND", "noisy-OR" and "noisy-Equal". They are defined as follows:

$C = A \cdot B$ means C occurs if A and B happen simultaneously.

$C \approx A \cdot B$ means C occurs with a high probability (not necessarily equal to 1) if A and B happen simultaneously.

$C = A + B$ means C occurs if A or B happens.

$C \approx A + B$ means C occurs with a high probability (not necessarily equal to 1) if A or B happens.

$C = A$ means C occurs if A happens.

$C \approx A$ means C occurs with a high probability (not necessarily equal to 1) if A happens

Therefore the Minimal Cut Sets applied, hereafter, in the following processes are used in an approximate style without further specification. In order to rule out these trivial Causal Factors from the Cut Set, two instruments are applied as the filter to achieve this goal; they are *Karnaugh map* (or *K-map* in short) and *K-style Conditional Probability Table* (or *K-CPT* in short). Before specifying the details of the transforming process, it is necessary to understand how these two techniques handle the intermediate analysis results obtained so far.

4.3.1 The properties of Boolean algebra

Before specifying the Minimal Cut Set(s) transforming process, it is worth reviewing the properties of Boolean algebra. Table 4 -2 summa rises some of these properties which will be utilised in the proposed process. The symbols for the two primary binary operations are defined as "$\bullet / \cap$"(logical *AND*/set intersection) and "$+ / \cup$" (logical *OR*/set union), and for the single unary operation is as "$\overline{A}/\neg$" (logical *NOT*/set complement). The value of "0" represents logical *FALSE*, and "1" for logical *TRUE*. The frequently applied algebraic manipulation of Boolean expressions or the axiom laws of Boolean algebra are tabulated in Table 4-2, and the engineering style (e.g. $\mathrm{A} \cdot \mathrm{B}$ for "AND" and $\mathrm{A} + \mathrm{B}$ for "OR") is the notation to be followed hereafter.

Table 4-2 Summary of Boolean algebra properties

$A+(B+C)=(A+B)+C$	$A\cdot(B\cdot C)=(A\cdot B)\cdot C$	associativity
$A+B=B+A$	$A\cdot B=B\cdot A$	commutativity
$A+(A\cdot B)=A$	$A\cdot(A+B)=A$	absorption
$A+(B\cdot C)=(A+B)\cdot(A+C)$	$A\cdot(B+C)=(A\cdot B)+(A\cdot C)$	distributivity
$A+\overline{A}=1$	$A\cdot\overline{A}=0$	complement
$A+A=A$	$A\cdot A=A$	idempotency
$A+0=A$	$A\cdot 1=A$	boundedness
$A+1=1$	$A\cdot 0=0$	
$\overline{(A+B)}=\overline{A}\cdot\overline{B}$	$\overline{(A\cdot B)}=\overline{A}+\overline{B}$	De Morgan's laws
$\overline{\overline{A}}=A$		involution

4.3.2 The Karnaugh map (K-map)

The K-map is a pictorial form of a truth table and provides a simple straightforward procedure for minimising Boolean algebra expressions (Mano, 2002). It can reduce the need of Boolean algebra calculations by taking the advantage of humans' pattern-recognition capability. The capability facilitates the rapid identification and elimination of redundant items in the expression. A K-map is a table which consists of numbers of cell. The dimension of a map is decided by the number of Boolean variables shown in the expression and is power of two; i.e. $2^n, n \in N$ (n: the number of variable). Each cell of the map has a unique binary value representing the corresponding combination of the variables, called *terms or minterm.* With reference to the forms and definitions of Boolean expressions, it is obvious that each binary value can be converted to an equivalent decimal value. Besides, the cells of the *terms* in the map are arranged in the way of "Gray code" in which only one variable changes its value between two adjacent cells. For illustration, a four variable K-map which contains Boolean variables A, B, C and D having sixteen cells in the map is shown in Figure 4-4 as an example. In the map, at the top side of the grid, the value of the variables is expressed in binary form. Therefore, "AB=00" means that neither A nor B appear in the expression, "AB=11" represents A and B appear in the *terms* of the expression, and so forth.

	AB=00	AB=01	AB=11	AB=10
CD=00	$\overline{A}\overline{B}\overline{C}\overline{D}$ (0)	$\overline{A}B\overline{C}\overline{D}$ (4)	$AB\overline{C}\overline{D}$ (12)	$A\overline{B}\overline{C}\overline{D}$ (8)
CD=01	$\overline{A}\overline{B}\overline{C}D$ (1)	$\overline{A}B\overline{C}D$ (5)	$AB\overline{C}D$ (13)	$A\overline{B}\overline{C}D$ (9)
CD=11	$\overline{A}\overline{B}CD$ (3)	$\overline{A}BCD$ (7)	$ABCD$ (15)	$A\overline{B}CD$ (11)
CD=10	$\overline{A}\overline{B}C\overline{D}$ (2)	$\overline{A}BC\overline{D}$ (6)	$ABC\overline{D}$ (14)	$A\overline{B}C\overline{D}$ (10)

Figure 4-4 A K-map of four Boolean variables

Once the variables have been defined, the values of the cells are transcribed according to the location of the cells and the Boolean expression. Thus, for every possible combination of Boolean variables, the one-to-one relationship between cell and the combination of variables is defined. For example, if $\overline{A}\overline{B}\overline{C}\overline{D}$ appears in the expression, the value of cell "(0)" must be "True" or "1", otherwise "False" or "0". The K-map may theoretically be applied for the simplification of any Boolean expression regardless of the number of variables contained, but it is normally used when there are fewer than six variables. This is because a K-map comprising more than six variables is complex and tedious to simplify (Mano, 2002).

Having completed a K-map with value assigned to each cell, a minimised Boolean expression can be acquired by grouping together adjacent cells containing "True" or "1". Each group provides a "product" to create a *sum-of-products* in the Boolean expression, e.g. $\overline{A} \cdot B + \overline{C} \cdot D$. A minimum *sum-of-products* expression is defined as "a sum of product terms which (a) has a minimum number of *terms*, and (b) of all those expressions which have the same minimum number of *terms*, has a minimum number of literals" (Roth, 1992). A K-map can use the following rules for simplifying the expressions (Belton, 1998).

1. Groups do not include any cell containing "False" or "0"
2. Groups may be horizontal or vertical, but not diagonal.
3. Groups must be the cell number of 1, 2, 4, 8, or in general $2^n, n \in N$.
4. Each group should be as large as possible.
5. Each cell containing "True" or "1" must be in at least one group.

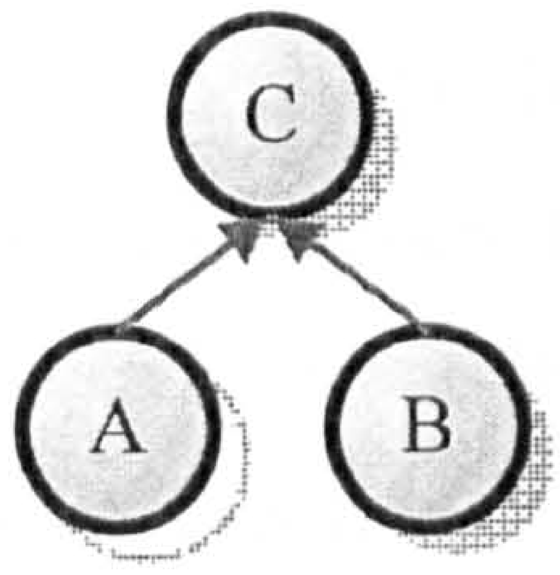
6. Groups may overlap.
7. Groups may wrap around the table. The leftmost cell in a row may be grouped with the rightmost cell and the top cell in a column may be grouped with the bottom cell.
8. There should be as few groups as possible, as long as this does not contradict any of the previous rules.

Eventually, a corresponding minimised *sum-of-products* Boolean expression can be obtained through the K-map if the simplification procedure is carried out correctly. The K-map is mainly applied to clarify the Minimal Cut Set(s) (i.e. the minimised Boolean expressions) for each Intermediate/Top Event, and the result should be the same as the outcome acquired by the algebraic manipulation of Boolean expressions or the axiom laws of Boolean algebra.

4.3.3 The K-style Conditional Probability Table (K-CPT)

The K-CPT is an integration of Karnaugh map and Conditional Probability Table of Bayesian Network. The new K-style Conditional Probability Table is only introduced and used in the next stage for finalising the Minimal Cut Set(s) of Intermediate/Top Events. The layout or arrangement of the K-CPT is similar to a K-map. However, the value assigned into each cell of the table is the probability distribution of the condition that the corresponding combination of Boolean variables represents, instead of "1" or "0" in a K-map. In addition, the K-CPT only displays the probability value that the influenced node occurred, since the occurrence of an influenced node is the only concern and there is always a complementary relationship between each half part of the tables. For instance, in Figure 4-5, an example shows the difference between the original Conditional Probability Table of a Bayesian Network and the K-CPT where only the data under the condition that event *C* occurred is shown in the corresponding K-CPT. It provides the same advantage that K-map has in order to perform the simplification of the Minimal Cut Set(s) from the Cut Set regarding an Intermediate/Top Event in the next stage.

DAG of BN



Original CPT of BN

		C=0	C=1
A=0	B=0	0.9	0.1
	B=1	0.1	0.9
A=1	B=0	0.8	0.2
	B=1	0.7	0.3

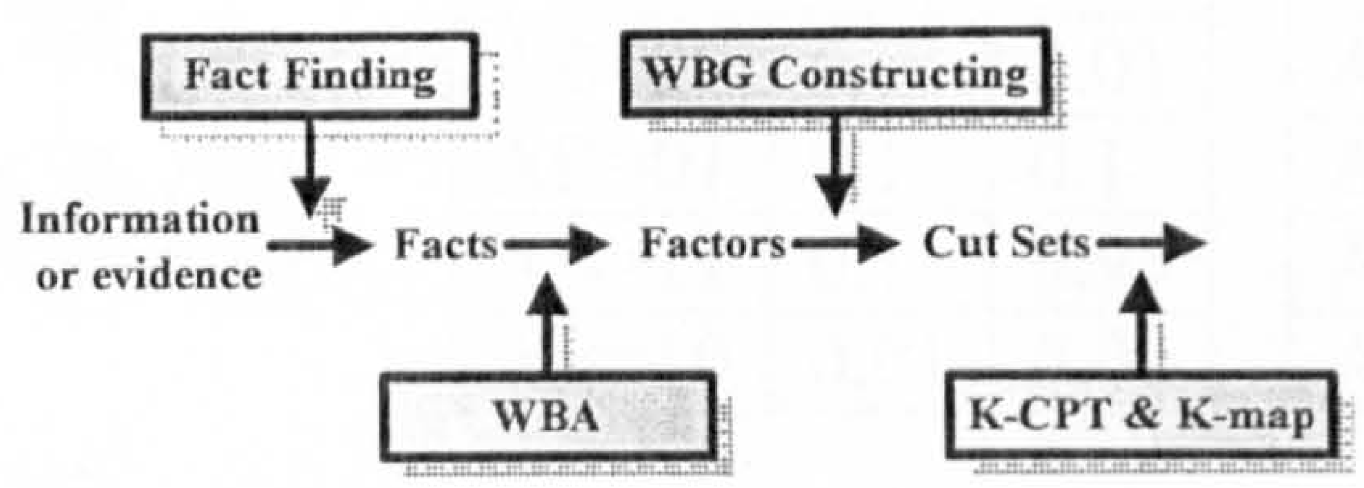
K-CPT

	A=0	A=1
B=0	0.1	0.2
B=1	0.9	0.3

(P.S. only the data for "C=1" is shown)

Figure 4-5 An example of DAG, CPT and corresponding K-CPT

4.3.4 Determining the approximate Minimal Cut Set(s) (MCS) for each Intermediate/Top Event with the K-CPT and the K-map instruments

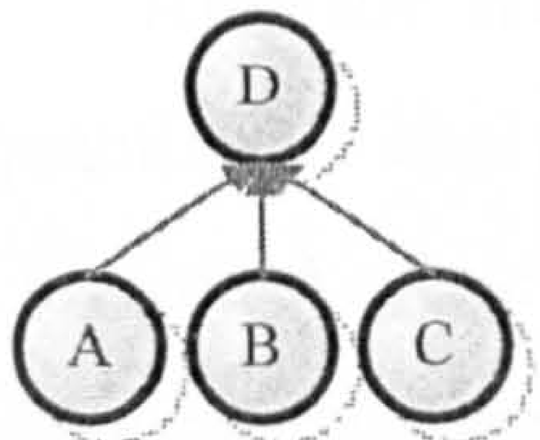


Having specified the functionalities of K-CPT and K-map, this section describes how to carry out the transforming process which sorts out the Minimal Cut Set(s) for each Intermediate/Top Event via these two instruments working together. The K-CPT and the K-map are applied to every *Why-Because* (or *cause-consequence*) subset, one at a time. Each subset consists of an Intermediate/Top Event and its Cut Set (i.e. the set of direct Causal Factors). The K-CPT illustrates the conditional probability distribution relationship between an Intermediate/Top Event and its Casual Factors whilst the K-map can transform the Cut Set of the event into Minimal Cut Set(s). Having finalised the process, the Cut Set of the event is replaced by at least one Minimal Cut Set of the direct Causal Factors to represent the cause-consequence relationship between the event and the factors. All the factors left in the Minimal Cut Set can therefore be ensured as the *Necessary Causal Factors*. After this process, it might be found that the Intermediate/Top Event consists of more than one Minimal Cut Set instead of only one Cut Set as before. This is because the proposed methodology has considered the possibility of different combinations of these Necessary Causal Factors could also lead to the same consequence (i.e. the Intermediate/Top Event).

Later in section 5.3, an example detailing the K-CPT establishing and K-map simplification regarding a tragic case are demonstrated in the case study. Finally a list of

Boolean algebra equations depicting the Minimal Cut Set(s) for each Intermediate/Top Event is provided as the outcome of this simplification process. These equations are essential to clarify the Bayesian Network of Minimal Cut Sets of an accident in the following processes. Figure 4-6 shows three basic types of approximate simplification outcomes as examples. They are similar to the notion of "noisy-AND with leak" and "noisy-OR with leak" relationships which is proposed by Bobbio *et al.* (2001), and as well as the "noisy-Equal".

WBG (or DAG) | K-CPT | K-map | Approximate MCS

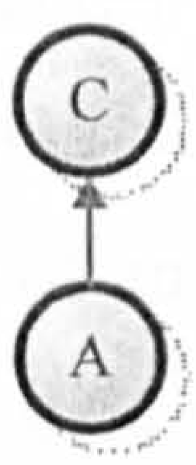


(for D=1)

	C=0	C=1
AB=00	0.01	0.01
AB=01	0.1	0.1
AB=11	0.1	0.95
AB=10	0.01	0.01

	C=0	C=1
AB=00	≈0	≈0
AB=01	≈0	≈0
AB=11	≈0	≈1
AB=10	≈0	≈0

$D \approx A \cdot B \cdot C$
(noisy-AND)

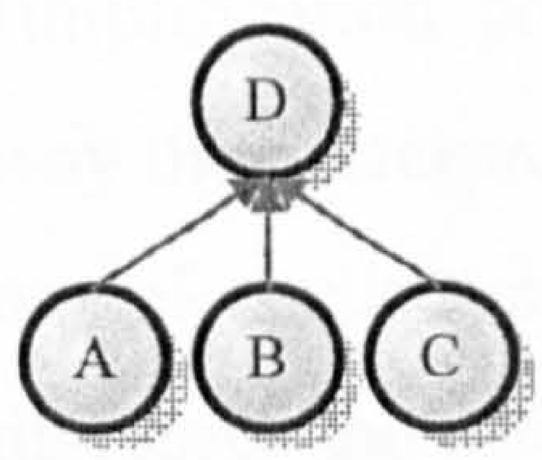


(for C=1)

A=0	0.01
A=1	0.8

A=0	≈0
A=1	≈1

$C \approx A$
(noisy-Equal)



(for D=1)

	C=0	C=1
AB=00	0.05	0.9
AB=01	0.85	0.95
AB=11	0.8	0.85
AB=10	0.95	0.9

	C=0	C=1
AB=00	≈0	≈1
AB=01	≈1	≈1
AB=11	≈1	≈1
AB=10	≈1	≈1

$D \approx A + B + C$
(noisy-OR)

(*P.S. the data shown in K-CPT is examples for demonstration only*)

Figure 4-6 The three basic forms of approximate Minimal Cut Set

In the beginning of the transformation process, an empty K-CPT and K-map, whose size and layout are set according to the number of Causal Factors in the Cut Set, are in place for each Why-Because subset. Subsequently, a probability distribution value is assigned into each cell of the K-CPT (i.e. tables shown in the second column of Figure 4-6) according to historical statistic data or experts' judgement. Once the K-CPT has been completed, the corresponding K-map is also obtained by determining the data in each cell of the K-CPT either becoming to "1" or "0", and then transcribing it into the corresponding cells of the K-map (i.e. tables shown in the third column of Figure 4-6). Having completed the K-map, a Boolean expression representing the approximate Minimal Cut Set(s) of an Intermediate/Top Event can be obtained via a simplification process. By sorting out all of the Why-Because subsets concluded in the preceding processes with the simplification process, both the approximate Minimal Cut Sets of Intermediate/Top Events and the Bayesian Network of Top Event of an accident can be acquired by one further step.

4.3.5 Forming the Bayesian Network of Top Event

After the Why Because Graph (WBG) and K-CPT of an accident are set up, one of quantitative analysis results can be obtained. By applying WBG as the blueprint of the Directed Acyclic Graph of Bayesian Network and K-CPT as the data sources of CPT of Bayesian Network, the Bayesian Network model of Top Event of an accident can be constructed accordingly. There will be two Bayesian Network models as the quantitative analysis results yielded in the proposed methodology. One depicts the Top Event of an accident, and the other specifies the approximate Minimal Cut Set(s) (for short, it is only named Minimal Cut Set hereafter) of the accident if the preceding simplification process is achievable. The difference between these two models is the way they interpret the Window of Opportunities (WoOs) of an accident. The Top Event model concentrates the entire influence of WoOs whilst the Minimal Cut Set model discusses the effect of each WoO individually. In section 5.3, more details in regard to the distinctions between these two models will be shown with a real case applied.

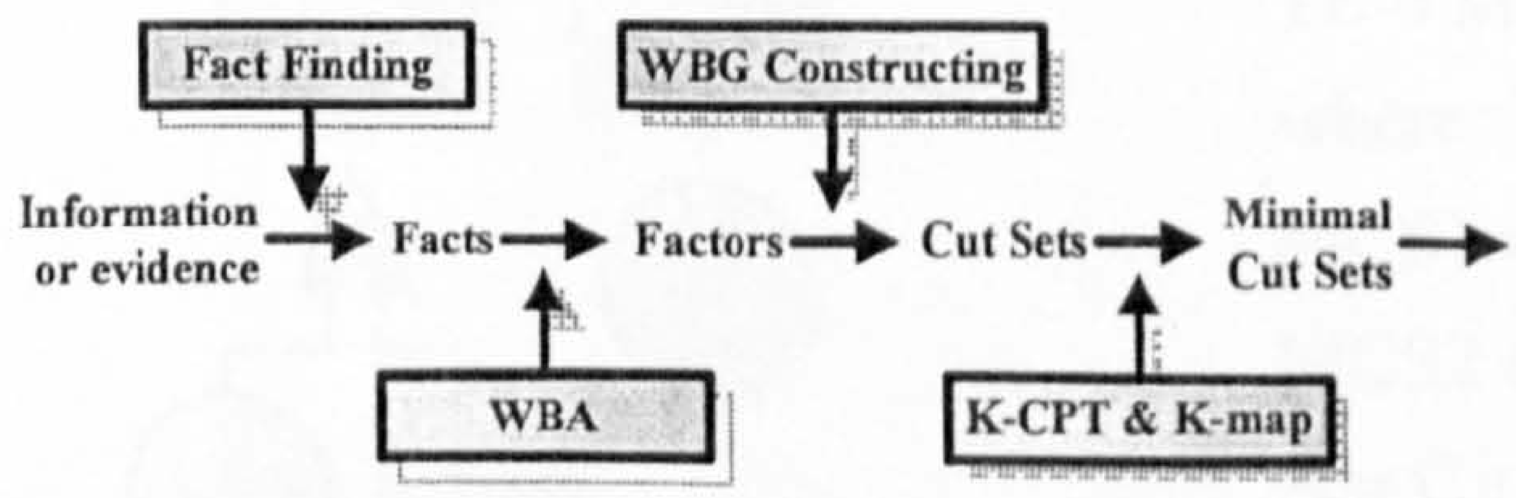
Nonetheless, the Minimal Cut set model of an accident may not be available all the time, or the outcome of the model may not be acceptable. This is because the Minimal Cut Set model has to compromise the precision of the analysis results in order to gain the possibility of simplification. The Minimal Cut Set model is based on the assumption that an Intermediate/Top Event is highly likely to happen if its Minimal Cut set(s) occur (i.e. the approximate simplification law). However, this is not always the case in reality. For example, if the value assigned in K-CPT is less than 0.6 (i.e. an event has 60% of probability to happen if its Minimal Cut set(s) stand), it would be difficult to determine it as "1" in the corresponding K-map (i.e. the event is 100% to happen). The larger the difference in K-CPT, the more the distortion of the Minimal Cut Set(s). Therefore, the outcomes of the Minimal Cut Set model may not be acceptable if the simplification result has been over-distorted. The degree of the distortion can be checked by comparing the quantitative analysis results of FTA and the Bayesian Network model with respect to there Minimal Cut Sets as a validation mechanism. It can be expressed as follows.

$$Distortion = \frac{|FTA(MCS) - BN(MCS)|}{BN(MCS)}$$

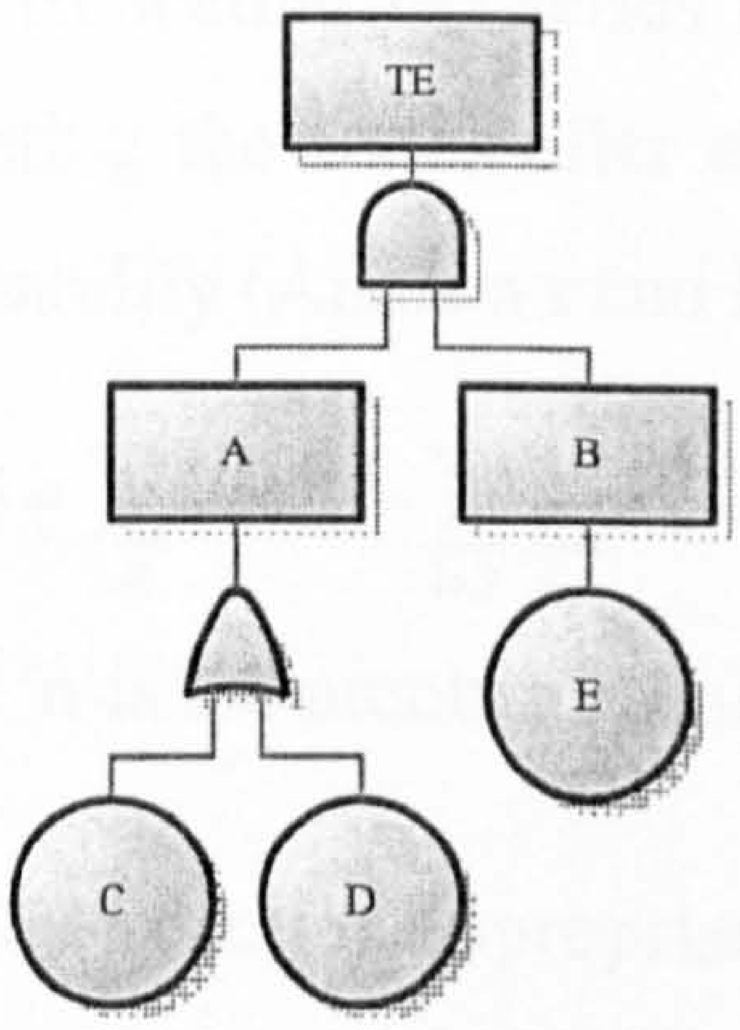
4.4 Fault Tree Analysis (FTA) to finalise the qualitative analysis results

Eventually, having clarified all the Minimal Cut Set(s) (i.e. the set contains Necessary Causal Factors) for each Intermediate/Top Event (i.e. the consequence event of the Why-Because subset), the Minimal Cut Sets of the accident can now be obtained. Again, Boolean algebra manipulation is utilised to determine the Minimal Cut Sets of an accident. At the end of this process, all the possible Minimal Cut Sets of the accident will be revealed as the qualitative analysis results of the accident. Each Minimal Cut Set depicts the possible combinations of these Basic Events that caused the accident to happen. However these Basic Events are not the only factors to cause the accident to happen but the representative only. In other words, they are not necessarily the entire Causal Factors but the deepest latent conditions that reside in every causation branch. These Basic Events are the latent conditions of those Intermediate Events whilst the same Intermediate Events are the latent conditions of the Top Event (i.e. the accident). Those Intermediate Events are located in the middle of the causation branch and should not be overlooked even though they are not present in the Minimal Cut Set(s) of Top Event.

4.4.1 Determining the Minimal Cut Set(s) of a Fault Tree



This process is similar to the mathematic factorisation operation, but the equation of the operation is associated with a list of Boolean algebra expression regarding the Intermediate/Top Events acquired in section 4.3.4. It starts from the Top Event again. The Top Event is substituted by its Minimal Cut Sets, which are represented by sets of its Necessary Causal Factors and are displayed on the right hand side of the equal sign in the equation. Then, each Necessary Causal Factors in the Minimal Cut Sets of the Top Event becomes an Intermediate Event and is replaced by their Minimal Cut Sets, which are shown in column "approximate MCS", for example in Figure 4-6, until reaching the end of the tree (see Figure 4-7 as an example). This also means that the factorisation operation is stopped at the bottom of the Why-Because Graph or the boundary of the analysis (i.e. the Basic Events). The axiom laws of Boolean algebra are applied, from time to time, during the operation in order to obtain the most simplified form of the equation. After reaching the final stage of the factorisation operation, several groups of Necessary Causal Factors (i.e. the Basic Events) in the form of *sum-of-products* are revealed as the results. Each group of Basic Events represents one of the Minimal Cut Sets of the Top Event. For example, in Figure 4-7, a fault tree is shown such that the Top Event is caused by two Intermediate Events (i.e. events A and B) whilst event A is caused by event C or D (as the Basic Events) and event B is triggered by event E respectively. Subsequently, after the factorisation process, the simplified outcome of the equation turns out to be "$(C \cdot E)+(D \cdot E)$". Hence two groups of Necessary Causal Factors emerge as the Minimal Cut Sets of the Top Event; they are "$(C \cdot E)$" and "$(D \cdot E)$". Later, in section 5.4.1, Equation (5.2) which demonstrates the factorisation process for the case of Herald of Free Enterprise (HoFE) will provide a more comprehensive picture about how it works.



$$
\begin{aligned}
&TE = A \cdot B \\
&TE = (C+D) \cdot E \\
&TE = (C \cdot E)+(D \cdot E) \\
&TE = MCS1 + MCS2 \\
&\text{where:} \\
&MCS1 = (C \cdot E) \\
&MCS2 = (D \cdot E) \\
&A = C + D \\
&B = E
\end{aligned}
$$

Figure 4-7 An example of finalising the Minimal Cut Sets of a Fault Tree

However, in the Minimal Cut set(s) of Top Event, there is no any symbol representing events *A* and *B* (i.e. the Intermediate Events). From the example above, it has been shown that these Basic Events contained in the Minimal Cut Sets are not the only Causal Factors to trigger the Top Event to happen. Instead, every Intermediate Event with regard to these Basic Events is also the factors to make those holes existing in the WoOs of the accident and should not be overlooked as well. Those Intermediate Events lying on the middle of the causation breaches are the *consequences* of these Basic Event as well as the *causes* of the Top Event.

The qualitative analysis results of the accident are now finalised. They can not only be presented in the form of Top Event, but also the form of Minimal Cut Sets to materialise the WoOs of an accident reflecting the Reason's Swiss Cheese Model. This means that the half way of the hypothesis is achieved but the nature of FTA obstructs the second half of the hypothesis (i.e. the quantitative analysis of an accident) to fulfil. In the following sections, the difficulties and the solutions for the quantitative analysis of an accident will be discussed.

4.4.2 The difficulties for FTA to perform the quantitative analysis of the accident

It has been demonstrated that FTA is a well-defined technique for qualitative analysis of accidents (Johnson, 1999). Theoretically, the quantitative analysis of the accident (i.e. the Top Event) can be achieved by treating the identified Necessary Causal Factors of the accident as Basic Events and assigning each of them a probability figure. Then, the overall probability of the occurrence of the accident can be calculated via Equation (4.1). In the equation, the first term is numerically more significant than the second term and the second term is more significant than the third term, and so on. Therefore truncating the series at an odd-numbered term will provide an upper bound and truncating the series after an even-numbered term provides a lower bound for the exact probability (Andrews and Moss, 2002).

$$P(TE)=\sum_{i=1}^{n}P(K_i)-\sum_{i=2}^{n}\sum_{j=1}^{i-1}P(K_i\cap K_j)+\ldots+(-1)^{n-1}P(K_1\cap K_2\cap\ldots\cap K_n) \tag{4.1}$$

$$\text{where 'n' is the number of minimal cut set and 'Ki' is minimal cut set } i,\ i=1,\ldots,n$$

This approach is appropriate in all circumstances whether or not Basic Events are repeated providing the assumption that the Basic Events are independent is true

(Andrews and Moss, 2002). However, this assumption (or condition) is almost impossible to apply on the quantitative analysis of an accident. This is because all the events or factors identified in the accident are normally interrelated to each other. In other words, there are at least two difficulties in applying Equation (4.1) to achieve the quantitative analysis of the accident. Firstly, it would be difficult to identify all the Necessary Causal Factors of an accident reaching the condition that they are all mutually independent, such as the Basic Events. Secondly, if these Necessary Causal Factors are not mutually independent, it would be more difficult to find the intersection part (i.e. the common factors) amongst those Minimal Cut Sets in order to apply Equation (4.1).

4.4.3 Acquiring the likelihood of the accident via Minimal Cut Set Upper Bound approach

Having considered the two difficulties mentioned above, it is clear that it would be almost impossible to apply FTA to achieve the quantitative analysis of the accident if the identified Necessary Causal Factors are not mutually independent. Hence, an approach combining the techniques of Fault Tree Analysis and Bayesian Network (FTA-BN) is proposed to overcome the difficulties. In other words, the FTA applied will not deal with the quantification issue at the Basic Event level, but at the Minimal Cut Set level instead. For the remaining part of quantitative analysis (i.e. the likelihood for each Minimal Cut Set), a Bayesian Network technique is applied as the means to acquire the quantified data for each Minimal Cut Set as well as the Top Event. This means, in this approach, that the quantified data for each Minimal Cut Set and Top Event are derived from a Bayesian Network. The FTA technique will only be applied to deal with the qualitative analysis. The Minimal Cut Set upper bound approach (Andrews and Moss, 2002) shown in Equation (4.2) can only be applied to calculate the likelihood of the Intermediate Events with their Minimal Cut Sets results acquired from a Bayesian Network. This is because this approach will introduce a certain amount of overestimate if there are common factors amongst these Minimal Cut Sets. Thus, the more the common factors, the larger the overestimate. The details of the processes regarding Bayesian Network are described in section 4.5.

$$P(TE) \le 1 - \prod_{i=1}^{n}[1 - P(K_i)] \tag{4.2}$$

where 'n' is the number of minimal cut set and 'K_i' is minimal cut set i, i = 1, ..., n (equality exists when no event appears in more than one minimal cut set)

As soon as the likelihood for each Minimal Cut Set has been acquired via the Bayesian Network model of the accident, the Fussell-Vesely Importance Measure (F-VIM) (see Equation (4.3)) can be used to rank the criticality for each Minimal Cut Set. The importance of Minimal Cut Set signifies the role that it plays in either causing or contributing to the occurrence of the Top Event. The importance measure is defined simply as the probability of occurrence of cut set ***i*** given that the system has failed (Andrews and Moss, 2002).

$$I_i = \frac{P(K_i)}{P(T)} \tag{4.3}$$

where 'K_i' is minimal cut set i, i = 1, ..., n

4.4.4 The overestimate issue of Minimal Cut Set upper bound approach

The following example illustrates the overestimate problem of the Minimal Cut Set upper bound approach with real figure. For demonstrating the differentiation between the answers acquired via Equations (4.1) and (4.2), the fault tree shown in Figure 4-7 is utilised in this example, in which three basic events *C*, *D* and *E* are independent to each other with probability 0.1 for each. Therefore the probability of Top Event is 0.019 according to Equation (4.1). The calculation details are shown in Equation (4.4), where the accurate probability of the Top Event is obtained.

$$\begin{aligned} \mathrm{P(TE)} &= \mathrm{P(CE + DE)} \\ &= \mathrm{P(CE) + P(DE) - P(CDE)} \\ &= 0.01 + 0.01 - 0.001 \\ &= 0.019 \end{aligned} \tag{4.4}$$

When Equation (4.2) is applied to deal with the calculation of overall probability of the Top Event, the answer turns out to be 0.0199. The details are shown in Equation (4.5). Both Equation (4.4) and Equation (4.5) are under the same condition that both the likelihoods of *MCS1* and *MCS2* are equal to 0.01. However, in Equation (4.5), a certain amount of overestimate (i.e. 0.0009) is encountered, which is caused by the common factor *E* that has been taken into account more than once, whilst Equation (4.2) is applied. This is also the reason why Equation (4.2) is the style of "not larger than" instead of "equal to".

$$\begin{aligned} P(TE)_{MCSUB} &\leq 1-(1-\mathrm{MCS1})(1-\mathrm{MCS2}) \\ &\leq 1-(1-0.01)(1-0.01) \\ &\leq 0.0199 \end{aligned} \tag{4.5}$$

4.5 Bayesian Network (BN) for quantitative analysis

The main purpose of this process is to construct a corresponding Bayesian Network model of an accident according to the qualitative analysis results described in the preceding sections. The model, which consists of a Directed Acyclic Graph and Conditional Probability Tables, is the major utility to perform the quantitative analysis of the accident. After constructing the model, not only the likelihood of each Minimal Cut Set (and/or Top Event) can be presented, but also the "*what if*" examinations can be carried out. The "*what if*" examination, which resorts to the functionality of propagation of Bayesian Network, can easily reveal the change of factors in the model due to the change of one or few particular factors given. The propagation function is also a very useful tool to infer the critical factors and the effectiveness of countermeasures of an accident, from an objective viewpoint. In the following sections, the following topics are discussed in turn: a brief introduction of Bayesian Network techniques, the systematic procedure to construct the corresponding Bayesian Network model, the way to perform the "what if" examinations and finally the absorption problems that may be encountered whilst constructing the model. As a result of these discussions, an overview of the quantitative analysis of the proposed method emerges.

4.5.1 A brief introduction of Bayesian Network technique

In real world, the events involved in an accident are hardly mutually independent. Therefore, when the dependency amongst events has to be considered (i.e. the first difficulty mentioned in section 4.4.2 above), Bayes' *Rule/Theorem* (Bernardo and Smith, 2002), which is shown in Equation (4.6), seems to be one of the best solutions to handle this issue. However, the conditional probability cannot be computed using a simple application of Bayes' *Rule/Theorem.* Therefore, a Bayesian Network technique is developed to address this difficulty. By exploiting conditional independencies entailed by influence chains, Bayesian Network is able to deal with the probabilistic inference amongst the events in an acceptable amount of time and space (Neapolitan, 2004).

$$P(A \cap B) = P(B \mid A)P(A) = P(A \mid B)P(B) \tag{4.6}$$

where "|" means "given" or "on the condition of"

Since the dependencies amongst those Necessary Causal Factors are the major difficulty that has to be solved, the present study assumes that the Bayesian Network model of the accident, which is modelled and illustrated by the Directed Acyclic Graph to instantiate the WoO, is a feasible way to perform the quantitative analysis of the accident. This is because Bayesian Network technique is designed to deal with dependency with probability distribution, in which a Direct Acyclic Graph that encodes conditional probability distribution at its nodes is the core of Bayesian Network (Wang and Trbojevic, 2007). In short, that is:

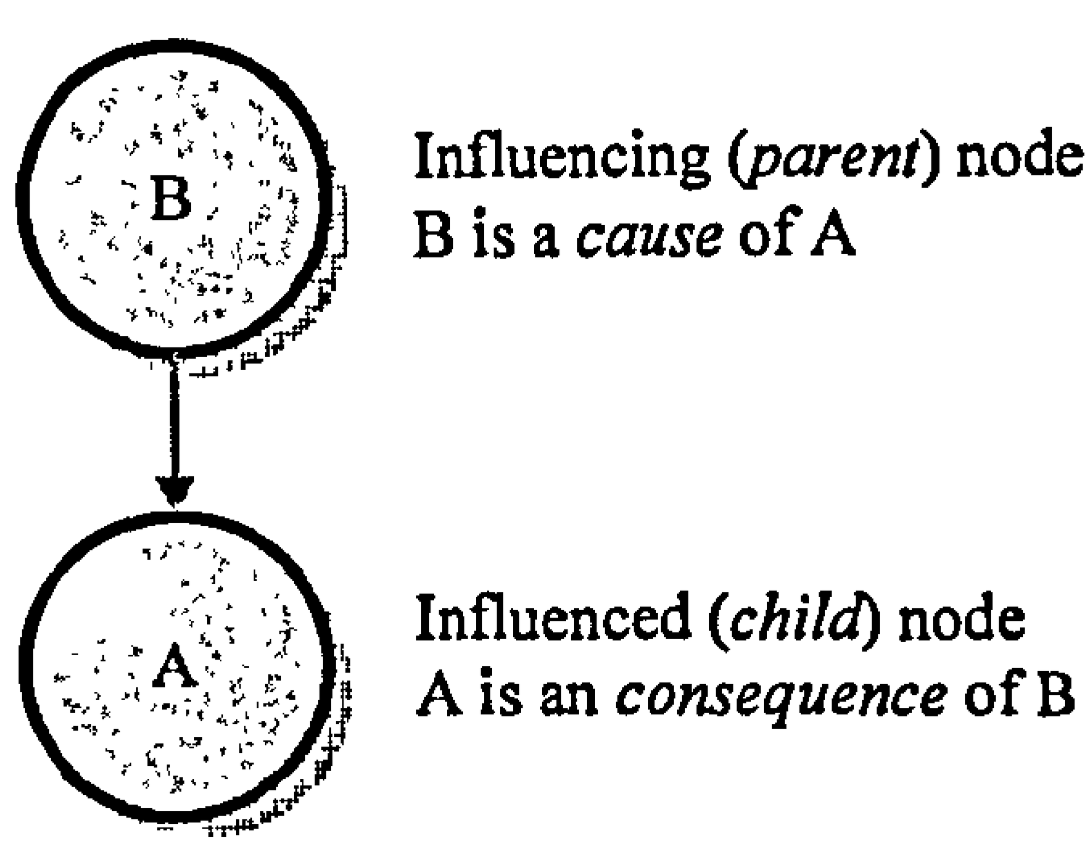
"BN" = "DAG" encoded with "conditional probability distribution"

Wang and Trbojevic (2007) further specify the definition of Bayesian Network as follows.

> In a Directed Acyclic Graph, an *edge* (or *arc*) goes from one node (i.e. the *source*) to another (i.e. the *target*) and hence makes connection in only one direction. *Acyclic* implies that such a graph contains no cycle. In a Bayesian Network structure, *nodes* (usually drawn as circle) represent random (i.e. *chance*) variables such as events, that take values from the given domains. *Arcs* (normally drawn as either curved or straight lines having a terminating *arrowhead*) are used to represent the direct probabilistic dependence relations among the variables. Each influence relationship is described by an arc connecting an influencing (or *parent*) node to an influenced (or *child*) node and has its terminating arrowhead pointing to the child node. If a node has no parents, then its probability distribution is said to be *marginal* (or *unconditional*), otherwise it is *conditional.*

As stated in section 4.3.4, in a Bayesian Network, the quantitative association amongst the modelled nodes is represented via a Conditional Probability Table (CPT). Each node encodes the value of conditional probability distribution into a Conditional

Probability Table associated with it. The encoded nodes with no predecessor are described by *prior* probability distributions. Those nodes with predecessors are described by *posterior* probability distributions. The conditional probability of a parameter, a, given a condition, b, would be written as $P(a|b)$, where the "|" vertical bar is read as "*given that*" or "*given*" (the indication of *conditionality*). Figure 4-8 illustrates a Bayesian Network example with two nodes and its associated Conditional Probability Tables. To obtain the quantified value with respect to these states, Node B is described by prior probabilities $P(b_1)$ and $P(b_2)$. Since Node B has an effect on Node A, then A is conditionally described by its posterior probabilities $P(a_1|b_1)$, $P(a_1|b_2)$, $P(a_2|b_1)$, and $P(a_2|b_2)$. The subscript "1" or "2" is used to denote which state of the two states of the specified variable is addressed.



b_1	$P(b_1)$
b_2	$P(b_2)$

	b_1	b_2
a_1	$P(a_1\|b_1)$	$P(a_1\|b_2)$
a_2	$P(a_2\|b_1)$	$P(a_2\|b_2)$

"|" means "*given*" or "*on the condition of*"

Figure 4-8 The illustration of Directed Acyclic Graph & Conditional Probability Table

From a table $P(A,B)$ of probabilities $P(a_i, b_j)$, the probability distribution $P(A)$ can be calculated via Equation (4.7). Let a_i be a state of A. There are exactly m different states of event B for which A is in state a_i. Therefore:

$$P(a_i) = \sum_{j=1}^{m} P(a_i, b_j) = \sum_{j=1}^{m} P(a_i | b_j) P(b_j) \tag{4.7}$$

This calculation expresses the fact that the variable B is marginalised out of the joint probability distribution, $P(A,B)$ (resulting in $P(A)$) (Eleye-Datubo, 2005). This process is called *marginalisation* (or *summing out*) – because the variables other than a_i are summed out (Russell and Norvig, 2003). In general, for any sets of variables A and B, the marginalisation rule can be written as follows:

$$P(A) = \sum_{B} P(A,B)$$

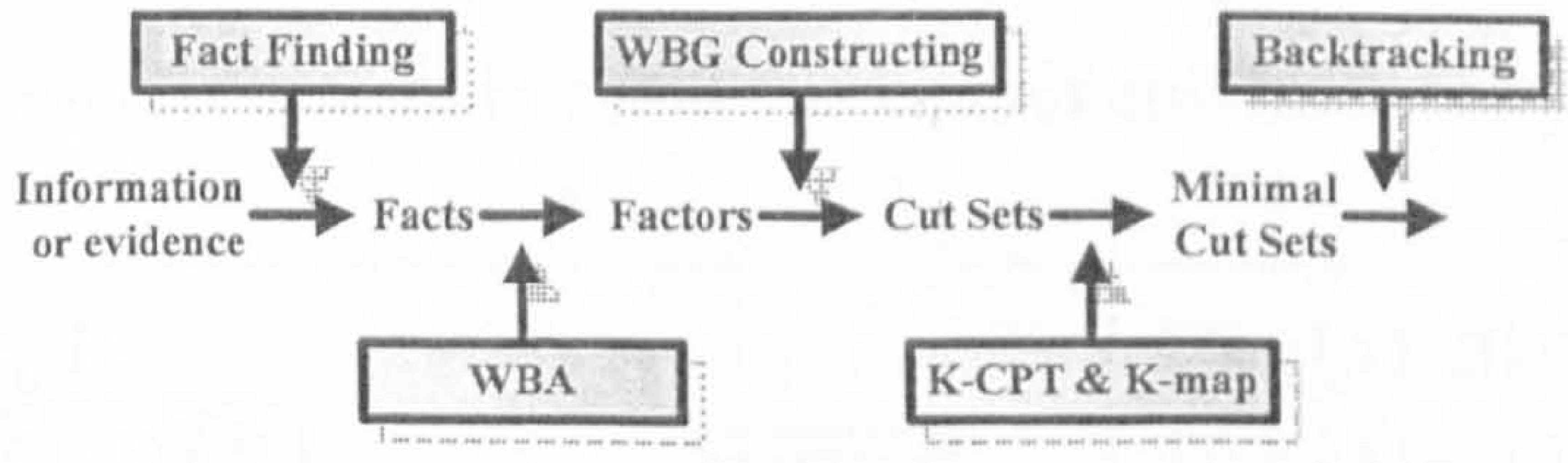
In addition, for conditional probabilities instead of joint probabilities, a variant of this rule uses the product rule as follows:

$$P(A) = \sum_{B} P(A \mid B) P(B)$$

In other words, in Bayesian Network, the *unconditional* (or *marginal*) probability distribution of each node can be acquired via Equation (4.7) where the Directed Acyclic Graph encodes conditional probability distribution for each node (Eleye-Datubo, 2005; Neapolitan, 2004; Jensen, 2001). Therefore, the unconditional probability distribution (or marginalisation of probability) of *P(a)* (i.e. $P(a_1)$ and $P(a_2)$) of the example in Figure 4-8 can be obtained via Equation (4.7), and the details are shown in Equation (4.8).

$$\begin{aligned} P(a_1) &= \sum_{j=1}^{2} P(a_1 \mid b_j)P(b_j) = P(a_1 \mid b_1)P(b_1) + P(a_1 \mid b_2)P(b_2) \\ P(a_2) &= \sum_{j=1}^{2} P(a_2 \mid b_j)P(b_j) = P(a_2 \mid b_1)P(b_1) + P(a_2 \mid b_2)P(b_2) \end{aligned} \qquad (4.8)$$

4.5.2 Backtracking the Intermediate Events via the factorisation equations of Minimal Cut Sets



In the proposed method, the Minimal Cut Sets of an accident are depicted by sets of Basic Events without specifying the Intermediate Events involved. It is very important that those Intermediate Events should not be overlooked when constructing the corresponding Bayesian Network model. This is because both Basic Events and Intermediate Events are all the identified Necessary Causal Factors of the accident, in which the Intermediate Events are both the consequences of the Basic Events and the causes of Top Event. Therefore, in order to discover those Intermediate Events, a backtracking process has to be carried out before constructing the model. This process mainly explores the associated Intermediate Events according to the Basic Events contained in the Minimal Cut Sets of the accident. Through the backtracking process, clues reveal which Intermediate Events have been influenced by the associated Basic Events following a step by step approach, from the Basic Events to the Top event. In this section, only the notion of the process is described. The application of the backtracking regarding a real case is shown in section 5.5 as an example.

When processing, it is helpful to highlight the backtracking paths by using circles and arrows in the equations (see Figure 4-9). For the purpose of quick reference, all the Intermediate Events involved in the Bayesian Network model are summarised in the second half part of the equations (i.e. the "*where*" part) with their influencing events (i.e. their Necessary Causal Factors). These backtracking equations are the blueprints for constructing the Bayesian Network model of Minimal Cut Sets in the next stage. For correctness, it is very important to maintain the equivalency in the equations between both sides of the equal sign from time to time. This is also the means to ensure that the backtracking outcomes are correct otherwise some Intermediate Events will easily be overlooked. Later, an incorrect example, in section 4.5.4, will be utilised to illustrate that the backtracking can be misdirected due to the Boolean absorption property in the factorisation equations and resulting in a wrong answer of backtracking. Since these backtracking equations are the blueprints to construct the Directed Acyclic Graph of Bayesian Network of an accident, the correctness of the backtracking equations is crucial to the subsequent outcome of the quantitative analysis of the accident. A validation mechanism to avoid this kind of error is hence proposed in section 4.5.4.

$$
\begin{aligned}
TE &= A \cdot B \\
TE &= (C + D) \cdot E \\
TE &= (C \cdot E) + (D \cdot E) \\
TE &= MCS1 + MCS2
\end{aligned}
$$

where:

$$
\begin{aligned}
MCS1 &= (C \cdot E) \\
MCS2 &= (D \cdot E) \\
A &= C + D \\
B &= E
\end{aligned}
$$

Factorisation
(Why-Because)

$$
\begin{aligned}
TE &= (A1 \cdot B) + (A2 \cdot B) \\
TE &= (A1 + A2) \cdot E \\
TE &= (C \cdot E) + (D \cdot E) \\
TE &= MCS1 + MCS2
\end{aligned}
$$

where:

$$
\begin{aligned}
MCS1 &= (C \cdot E) = (A1 \cdot B) \\
MCS2 &= (D \cdot E) = (A2 \cdot B) \\
A1 &= C \\
A2 &= D \\
B &= E
\end{aligned}
$$

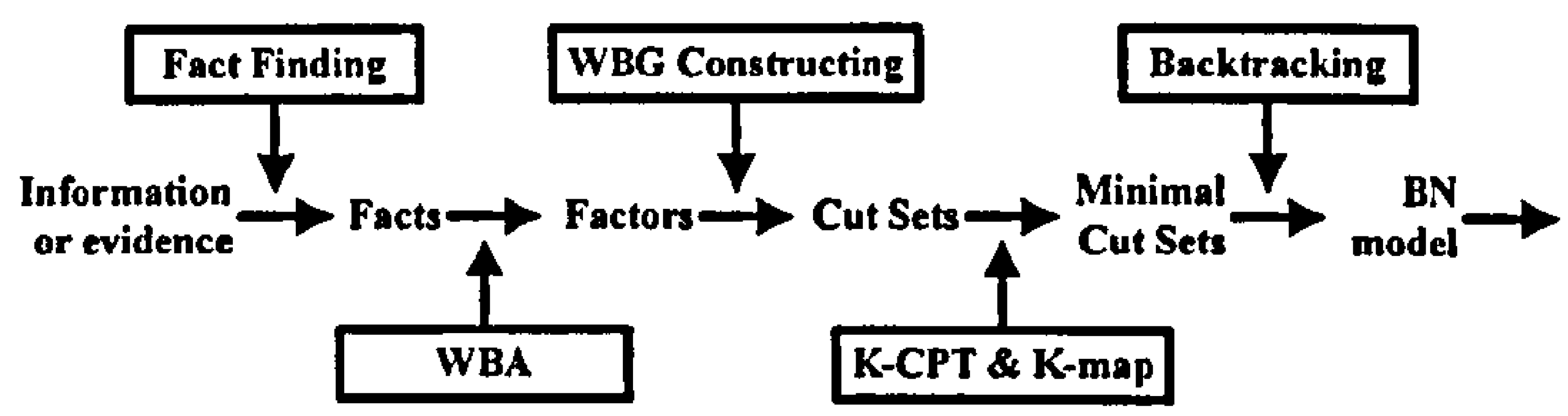
Backtracking
(Cause-Consequence)

Figure 4-9 The illustration of backtracking process and equations for the analysis

For specifying how to perform the process, an example is used to illustrate the procedure as follows. In Figure 4-9, it shows the factorisation equations on the left and the backtracking outcomes on the right with regard to the example utilised in section 4.4.1. Through a systematic procedure in the preceding section, it has shown that the Top Event was triggered by two Minimal Cut Sets; they are $(C \cdot E)$ and $(D \cdot E)$. Meanwhile, it also depicts that there are two Minimal Cut Sets to provoke the event *A* to occur; they are (*C*) and (*D*) respectively. Now, in order to construct the Bayesian Network model of the example for the quantitative analysis, it is needed to clarify the *Cause-Consequence* path by tracking back to the Top Event from its Minimal Cut Sets through all the Intermediate Events involved. This has to resort to the factorisation equations with Boolean algebra again. In the factorisation (or downward) equations, it reveals the *Why-Because* relationship, but it also implies the *Cause-Consequence* information between each row, and the row above/below. This process starts from the last row of the equations. In the row, the Minimal Cut Sets depict all the possible combinations of Basic Events which trigger the Top Event to occur. In addition, the Intermediate Events influenced by these Basic Events can also be revealed by searching for where these Basic Events derived from. For example, the difference between the first and second rows on the left hand side of Figure 4-9 shows that event *A* can either be triggered by event *C* or event *D*. This means either event *C* or event *D* alone can provoke event *A* to occur. Therefore a new symbol *A1* is utilised on the right hand side of the figure to denote the situation that event *A* is triggered by event *C*, and another symbol *A2* denotes another situation that event *A* is triggered by event *D*. Meanwhile, the reason why event *B* happens is because of the existing of event *E*, and so on. In the end, the backtracking results for these Intermediate Events are summarised in the "*where*" part of the equations. They denote the influencing nodes (or Necessary Causal Factors) for each Intermediate Event in the Bayesian Network model. That is, the factors on the right hand side of the equal sign are the predecessor (or influencing) nodes to the Intermediate Events on the left hand side.

On the left hand side of Figure 4-9 (i.e. the *factorisation/downward* part), some of the equations in the first half part have a *backtracking/upward* counterpart on the right hand side. The equations on the right hand side of the figure can be seen as the backward *Why-Because* paths. Although they look slightly different from their counterpart on the left hand side, they are still equivalent except using different symbols to denote the same thing. This means that their results are equivalent despite the expressions on both sides being not the same (i.e. they should be equal). Therefore, it is very important to check the equivalency between both sides of the equations, from time to time, to ensure that the backtracking outcome is correct. If the equivalency between both sides of the equations cannot be maintained in any row of the equations, it indicates that, somewhere in the process, the backtracking results are incorrect. Especially, the absorption property of Boolean operation in the factorisation stage has the tendency to cause this kind of problem to happen. Therefore, extra caution has to be paid to this issue whilst carrying out this process.

4.5.3 Constructing the Directed Acyclic Graph (DAG) of the accident



Having accomplished the backtracking process, a list of backtracking equations is in place. Thus, all the Intermediate Events involved in the accident are listed, one by one, with their direct Necessary Causal Factors on the right hand side of the equal sign. As noted previously, these backtracking equations are the blueprints to construct the Bayesian Network model of Minimal Cut set in the process. The Top Event is no longer represented by a single object. Instead, it is substituted by several Minimal Cut Sets as the proxies in the rest of the analysis procedure. Each Minimal Cut Set represents one of the WoOs in terms of the Reason's Swiss Cheese Model. That means that each combination of the Basic Events is the representative of the factors that cause the accident to occur. However, the Intermediate Events should not be overlooked even though they do not appear in the Minimal Cut Sets. The procedure to construct the Directed Acyclic Graph is described as follows.

At the beginning of the process, the construction of the Directed Acyclic Graph starts from the Top Event, which is now represented by several Minimal Cut Sets. Each time, the process handles and focuses on one Minimal Cut Set only. These equations are interpreted in the way that, in each row of the backtracking equations, the

Intermediate/Top Events, on the left hand side of the equal sign, are the *child* nodes of their Necessary Causal Factors, which are on the right hand side as their *parent* nodes. Meanwhile, in the Directed Acyclic Graph, each influence relationship is described by an arc connecting from an influencing (i.e. *parent* or *predecessor*) node to an influenced (i.e. *child* or *successor*) node and has the arrowhead toward to the child node (Wang and Trbojevic, 2007). If a node does not exist in the Directed Acyclic Graph whilst interpreting one of the equations, the process will place the node into the corresponding location of the Directed Acyclic Graph according to the backtracking results. This process will look at each Minimal Cut Set in turn, from the top to the bottom of the backtracking equations iteratively. Having handled all the Minimal Cut Sets of the Top Event (i.e. the accident) in this process, the Directed Acyclic Graph of the accident should be established accordingly.

In Figure 4-10, a Bayesian Network example which is the case that has been utilised in sections 4.5.2 to demonstrate the backtracking process is constructed. First of all, Node *MCS1* is placed into the corresponding location in the Directed Acyclic Graph with label "*MCS1*". According to the equation "$\mathrm{MCS1} = (\mathrm{A1} \cdot \mathrm{B})$", two extra nodes are added into the Directed Acyclic Graph as the parents nodes of Node *MCS1*, and they are named as "*A1*" and "*B*" respectively. The arcs are drawn from Node *A1* to Node *MCS1* as well as the one from Node *B* to Node *MCS1*. Since there is an equation depicting the causation for factor *A1* (i.e. A1=C), the process continues interpreting the equation and constructing the Directed Acyclic Graph with a new added node as the parent node of Node *A1*. "*C*" is the label of the new added node and it has an arc with arrowhead towards Node *A1*. In the same way, a new parent node for Node *B* is placed, which is labelled as "*E*" with an arc from Node *E* to Node *B*. Up to this stage, it is the end of the construction for *MCS1* since there is no further backtracking equation for either factor *C* or *E*. Therefore, the process turns to *MCS2* for the interpretation and construction.

The corresponding equation for *MCS2* is "$\mathrm{MCS2} = (\mathrm{A2} \cdot \mathrm{B})$". This results in two new nodes being introduced in the Directed Acyclic Graph; they are *MCS2* and *A2* respectively. Since Node *A2* is the influencing node, the arc with an arrowhead is hence connected from Node *A2* to Node *MCS2*. For Node *B*, due to it is already existed, only a new arc form Node *B* to Node *MCS2* is added. This means that a node can influence more than one nodes as well as a node can be influenced by multiple nodes in the Bayesian Network. This feature is also in line with the reality; multiple causes result in one particular consequence or multi consequences result from one particular cause. In addition, a new parent node for Node *A2* is introduced and labelled as "*D*" due to the equation "A2=D". Finally, the entire process is accomplished, because all the Minimal Cut Sets have been handled accordingly. The outcome of the established Directed Acyclic Graph is shown on the right hand side of Figure 4-10 with the corresponding backtracking equations on the left hand side.

$$
\begin{aligned}
&\mathrm{TE}=(\mathrm{A1}\cdot\mathrm{B})+(\mathrm{A2}\cdot\mathrm{B})\\
&\mathrm{TE}=(\mathrm{A1}+\mathrm{A2})\cdot\mathrm{E}\\
&\mathrm{TE}=(\mathrm{C}\cdot\mathrm{E})+(\mathrm{D}\cdot\mathrm{E})\\
&\mathrm{TE}=\mathrm{MCS1}+\mathrm{MCS2}\\
&\text{where:}\\
&\mathrm{MCS1}=(\mathrm{C}\cdot\mathrm{E})=(\mathrm{A1}\cdot\mathrm{B})\\
&\mathrm{MCS2}=(\mathrm{D}\cdot\mathrm{E})=(\mathrm{A2}\cdot\mathrm{B})\\
&\mathrm{A1}=\mathrm{C}\\
&\mathrm{A2}=\mathrm{D}\\
&\mathrm{B}=\mathrm{E}
\end{aligned}
$$

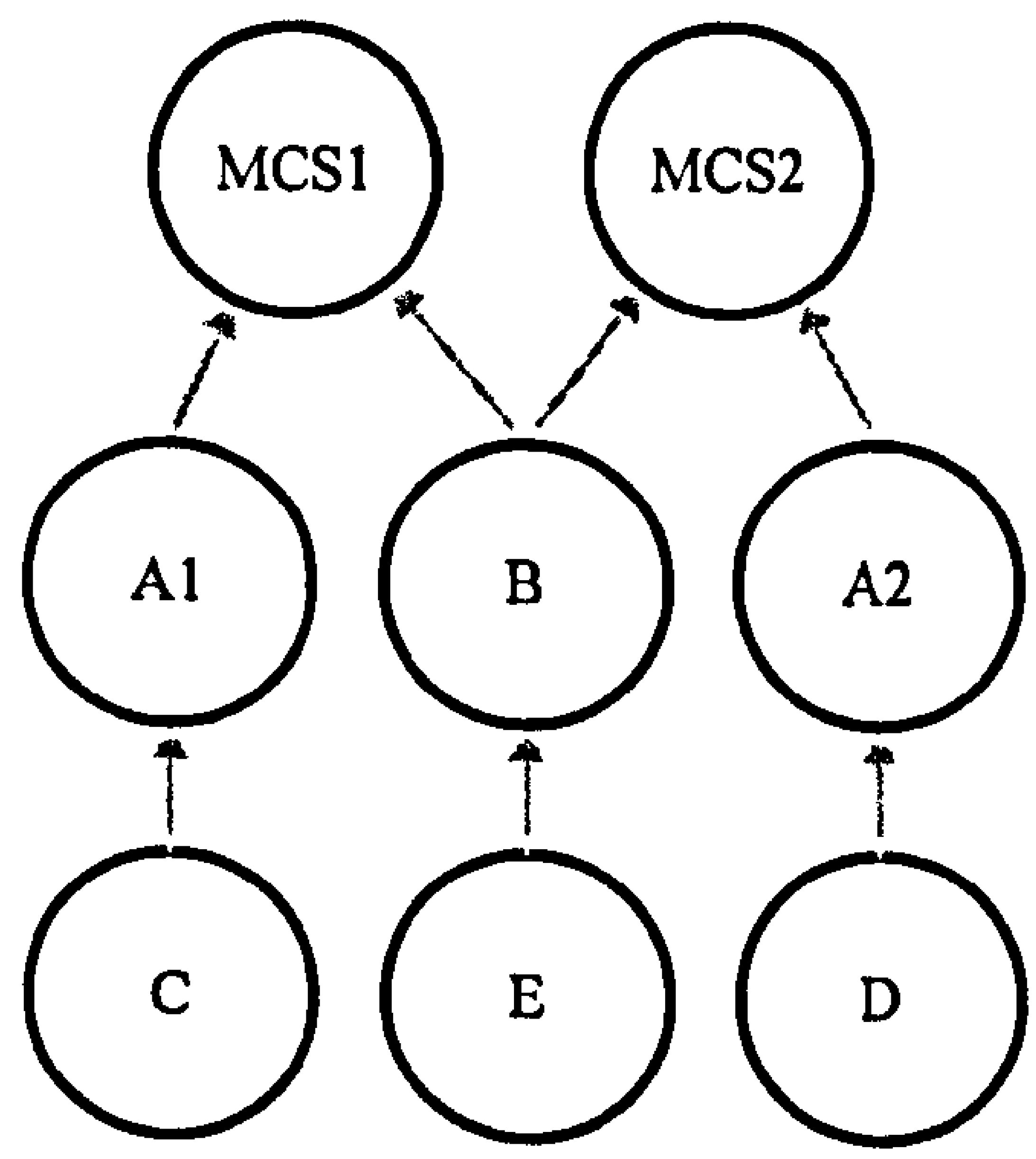
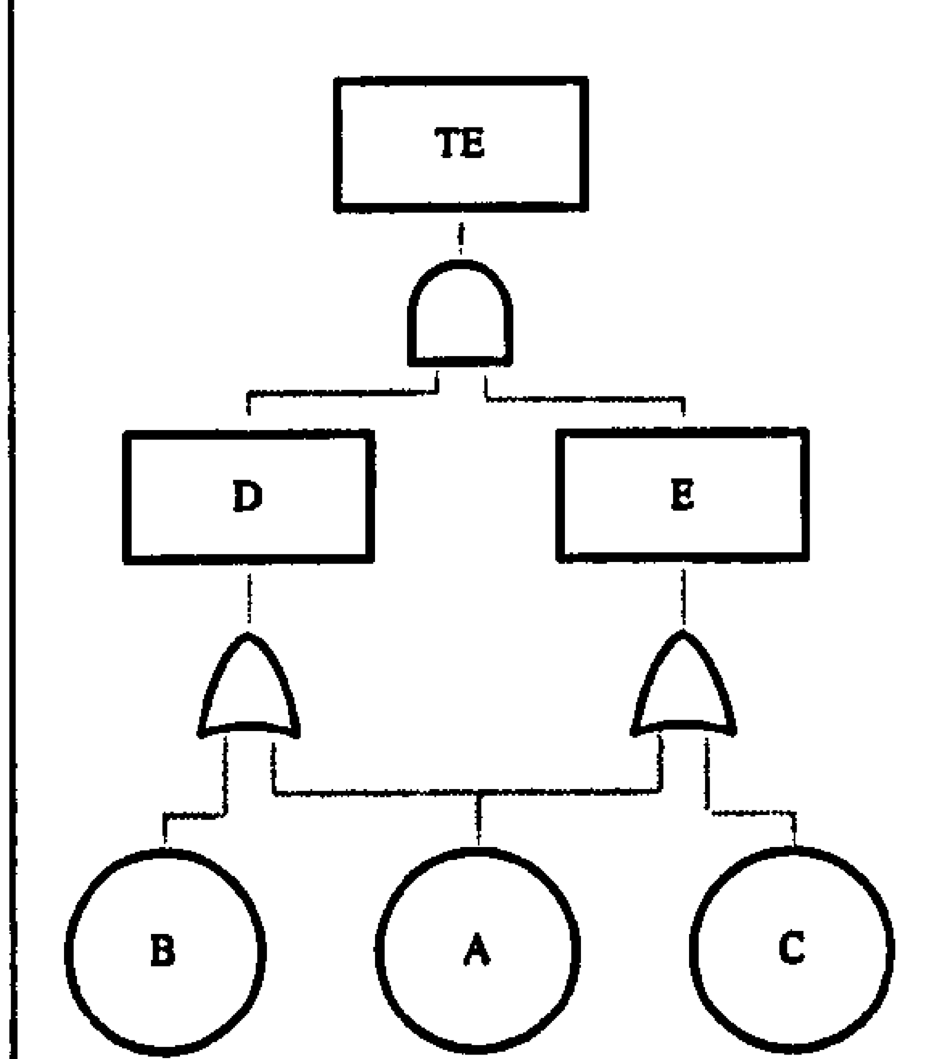


Figure 4-10 The backtracking equations and the corresponding DAG

4.5.4 The absorption problem whilst backtracking

In this section, the problem of overlooking the Intermediate Events, the reason why it happens and the method to avoid it are addressed. The problem may happen when there is more than one backtracking path available, from a Basic Event to the Top Event, and the backtracking process is performed incorrectly due to the absorption in factorisation equations. Consequently, some of the Intermediate Events involved in the accident could be overlooked if the backtracking process does not consider all the possible paths. When this type of error occurs, it results in the established Directed Acyclic Graph being incomplete and the nodes in the Bayesian Network model to represent the associated Minimal Cut Sets being insufficient as a result. It would be helpful to appreciate this issue by using an example to explain how it happens, and how to avoid it through a proposed validation mechanism. Hence, in the rest of this section, an example is utilised and shown in Figure 4-11, in which the fault tree of the example is shown on the left and its corresponding Directed Acyclic Graph of Bayesian Network is on the right of the figure.

In this example, three Basic Events (i.e. event A, B and C) and two Intermediate Events (i.e. events D and E) are the Causal Factors of the Top Event. They result in "$A+BC$" as the outcome of the Minimal Cut Sets where *MCS1* is represented by "A", and *MCS2* is "BC". Since event A is a repeated Basic Event in this example, it will trigger more than one Intermediate Event (i.e. events D and E) to happen simultaneously if it occurs. This also means that there are two backtracking paths from event A to *MCS1*. Due to the fact that AC and AB have been absorbed by A in the factorisation equations, it could easily overlook either event D or event E when the backtracking initiates from the event A and only concentrate on one of the backtracking paths, instead of considering all the possible paths. This is also the reason why the absorption property of Boolean algebra can cause the problem that some Intermediate Events are overlooked during the backtracking process. Since the absorption property is frequently applied in the Boolean algebra operation, this kind of error is highly likely to occur. The correct factorisation and backtracking equations of the example are shown in the middle of Figure 4-11.



$$
\begin{aligned}
TE &= D \cdot E \\
&= (A+B)(A+C) \\
&= A + AC + AB + BC \\
&= A + BC \\
&= MCS1 + MCS2
\end{aligned}
$$

where:

$$
\begin{aligned}
MCS1 &= A = D1 + E1 \\
MCS2 &= BC = D2 \cdot E2 \\
D1 &= A \\
D2 &= B \\
E1 &= A \\
E2 &= C
\end{aligned}
$$

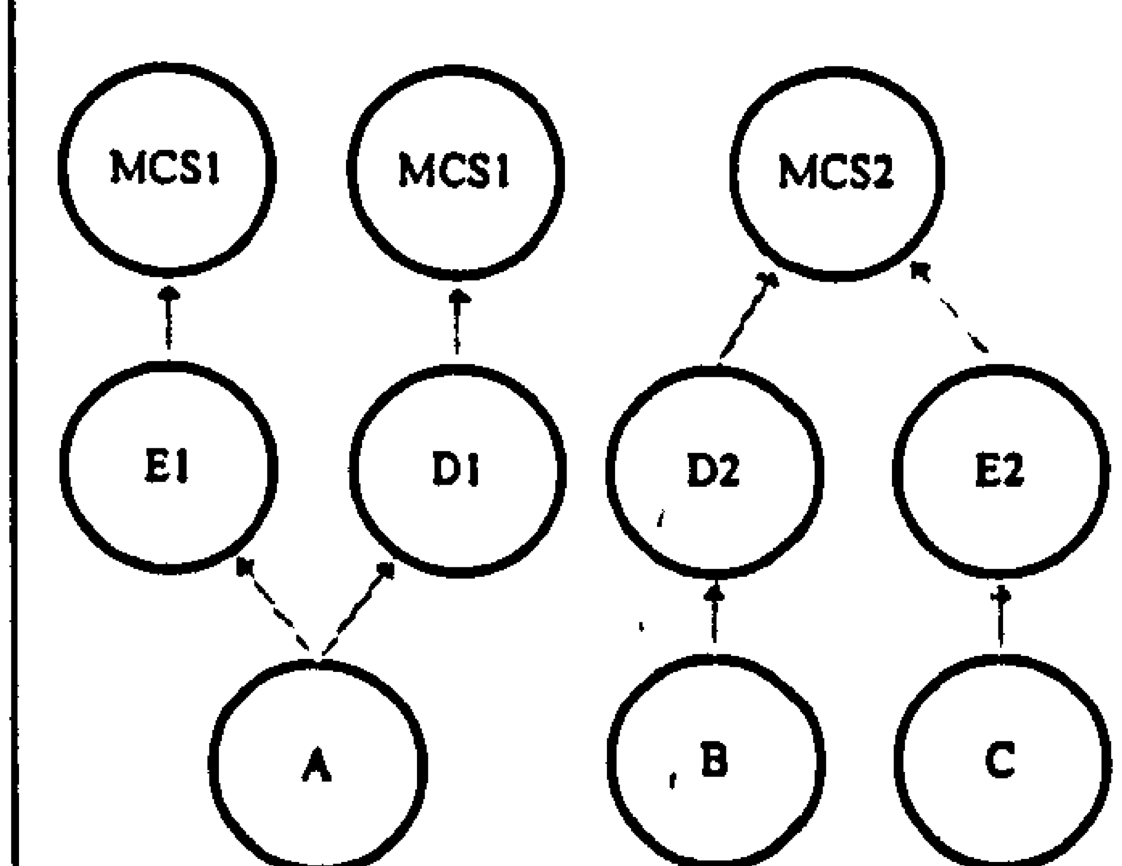


Figure 4-11 The fault tree, equations and Bayesian Network model of the example with repeated Basic Event

In contrast, in Figure 4-12, it is supposed that the incorrect example only reveals one of backtracking path for event A. It results in that event D (i.e. factor $D1$) is the only Intermediate Event which is connected with event A in the Directed Acyclic Graph for

MCS1. As a result, the backtracking path via event *E* has been overlooked and the Directed Acyclic Graph is incomplete.

Fortunately, this kind of error can be easily highlighted by checking the equivalency between the backtracking equations and the factorisation equations (see the equation highlighted by the circle in Figure 4-12). This implies that the equivalency between two equations has to be retained despite different symbols have been applied. In this incorrect example, factor *E1* (i.e. one of the proxies of event *E*) was substituted by factor *D1* in the backtracking equations resulting in that event *E* was overlooked. Since factor *D1* is neither event *E* nor the proxy of event *E*, this contradiction immediately indicates that something has been done wrong with the backtracking process. Thus, in order to ensure that the Directed Acyclic Graph is constructed correctly, a good practice in the backtracking process has to be followed. That is, all the possible backtracking paths for the absorbed items has to be considered as well as the equivalency between the backtracking and factorisation equations has to be checked all the time.

$$
\begin{aligned}
\mathrm{TE} &= \mathrm{D}\cdot\mathrm{E} \neq (\mathrm{D1}+\mathrm{D2})(\mathrm{D1}+\mathrm{E2})\\
&= (\mathrm{A}+\mathrm{B})(\mathrm{A}+\mathrm{C}) = (\mathrm{D1}+\mathrm{D2})(\mathrm{D1}+\mathrm{E2})\\
&= \mathrm{A}+\mathrm{AC}+\mathrm{AB}+\mathrm{BC}\\
&= \mathrm{A}+\mathrm{BC}\\
&= \mathrm{MCS1}+\mathrm{MCS2}
\end{aligned}
$$

where:

$$
\begin{aligned}
&\mathrm{MCS1} = \mathrm{A} = \mathrm{D1}\\
&\mathrm{MCS2} = \mathrm{BC} = \mathrm{D2}\cdot\mathrm{E2}\\
&\mathrm{D1} = \mathrm{A}\\
&\mathrm{D2} = \mathrm{B}\\
&\mathrm{E2} = \mathrm{C}
\end{aligned}
$$

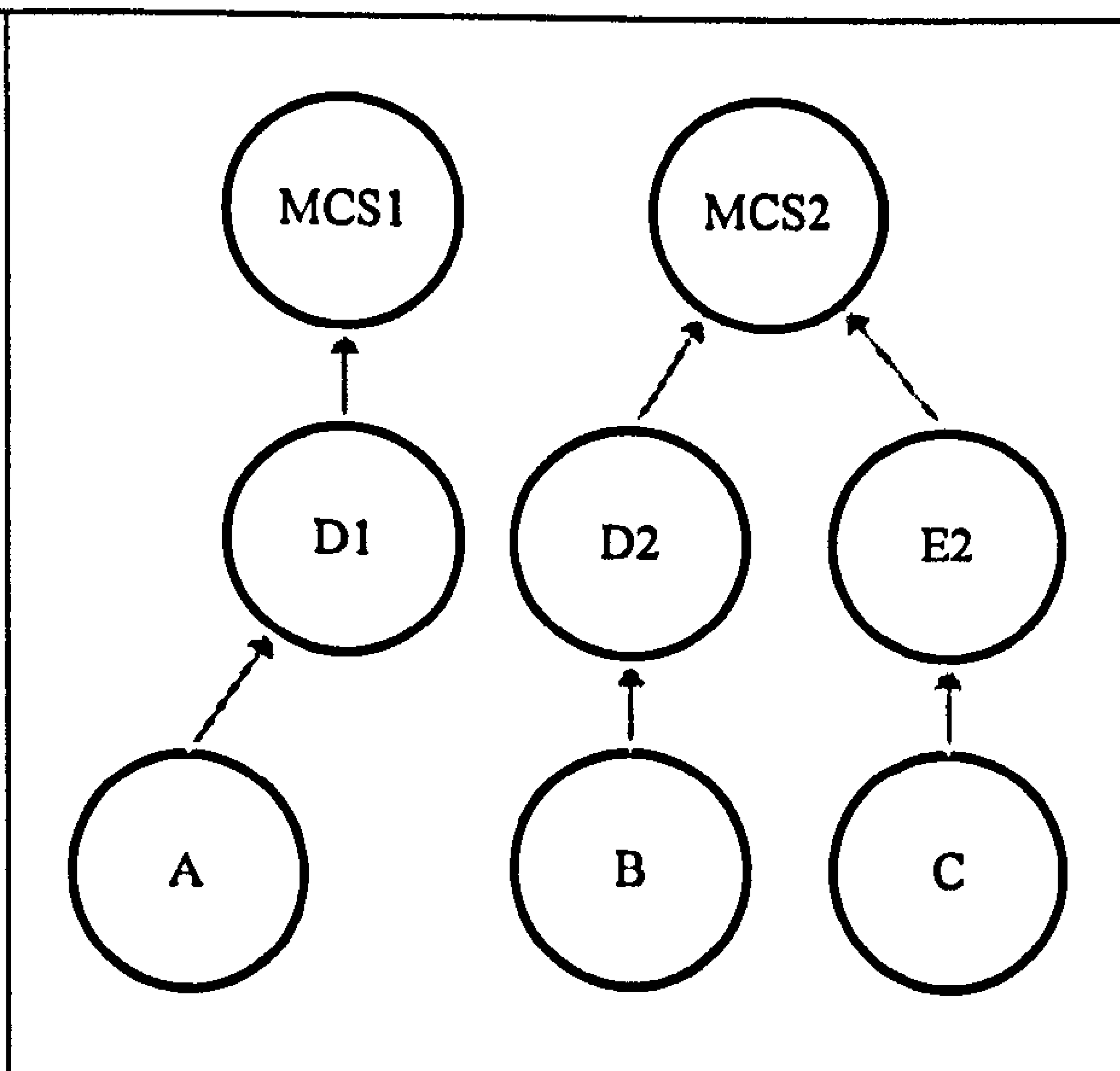


Figure 4-12 The incorrect backtracking outcome of the example

4.5.5 The Conditional Probability Table (CPT) of the Bayesian Network model

Having established the Directed Acyclic Graph associated with the Minimal Cut Sets of an accident, the process turns to encoding the Conditional Probability Tables for each node in the graph in order to accomplish the corresponding Bayesian Network model before being able to perform the quantitative analysis of the accident. As mentioned in section 4.5.1, the Conditional Probability Tables specify the probability distribution of every state of the nodes under the conditions given by their predecessors in the Bayesian Network. Basically, there is a probability distribution for every state of the child node considering every combination of the states of the parent nodes. In other words, if the conditions of the node are influenced by the node's direct predecessor(s), the posterior probability distributions values are given. If the node has no predecessor, the prior probability distributions of the node are entered into the Conditional Probability Tables. The dimensions of a Conditional Probability Table are determined by the number of parents, the state numbers of each parent and the number of states of the child node. Generally speaking, a Conditional Probability Table is a *matrix of conditional probabilities* (Eleye-Datubo, 2005). A conditional probability is a probability of one event, given that another event has occurred. More generally, for variable A with a set of states $\{a_1, a_2, \ldots, a_n\}$ and variable B with a set of states $(b_1, b_2, \ldots, b_m)$, the conditional probability matrix $P(a|b)$ representing the conditional probability of A given B is as follows:

$$P(a|b) = \begin{bmatrix} P(a_1 \mid b_1) & P(a_1 \mid b_2) & \ldots & P(a_1 \mid b_m) \\ P(a_2 \mid b_1) & P(a_2 \mid b_2) & \ldots & P(a_2 \mid b_m) \\ \vdots & \vdots & \vdots & \vdots \\ P(a_n \mid b_1) & P(a_n \mid b_2) & \ldots & P(a_n \mid b_m) \end{bmatrix}$$

Once all the data of the Conditional Probability Tables for each node has been given, the Bayesian Network is able to calculate the marginalisation (or unconditional) probabilities for each node. This is also the likelihood outcome for each node which is shown in the Bayesian Network model. It is important to note that the likelihood outcomes shown in the model are unconditional probability distribution although the data given in the Conditional Probability Tables is conditional. Theoretically, the best figures entered in the Conditional Probability Tables are derived from the historical statistic data according to other studies or researches if they are available. If the data does not exist, then experts' judgements are used as an alternative. These judgements can be done by an individual or a group of experts. If a group of experts is applied, it is preferred to obtain a consensus figure rather than several individual figures representing their opinions. Besides, a crisp value is essential due to the requirement of the

Conditional Probability Table. In order to harmoniously apply experts' judgements, a method is proposed to deal with group consensus issue and is detailed in Chapter 7.

After finalising the Conditional Probability Tables of a Bayesian Network model, the quantitative analysis is now able to proceed. As noted previously, in the Bayesian Network model of Minimal Cut Sets, the Top Event of an accident is represented by several Minimal Cut Sets nodes rather than a single object. Each node of Minimal Cut Sets represents one of the WoOs of the accident with the likelihood outcome. Nevertheless, the likelihood figures for each Minimal Cut Set are normally different because they consist of different combinations of Causal Factors. It should be noted that, in this model, the likelihood of the accident (i.e. the Top Event) is neither represented by any one of the Minimal Cut Sets nor simply their summation of likelihood outcomes. It has to resort to the Minimal Cut Set upper bound equation of FTA (see Equation (4.2) in section 4.4.3) with all the Minimal Cut Sets involved to obtain the approximate answer, or directly refer to the Top Event model depicted in section 4.3.5.

A: (B: and C:)

occur	not
0.1	0.9

E1: (E2:, D1: and D2:)

occur	not	A/B/C
1	0	occur
0	1	not

MCS1_1 (and MCS1_2:)

occur	not	E1(D1)
1	0	occur
0	1	not

MCS2:

occur	not	D2	E2
1	0	occur	occur
0	1	occur	not
0	1	not	occur
0	1	not	not

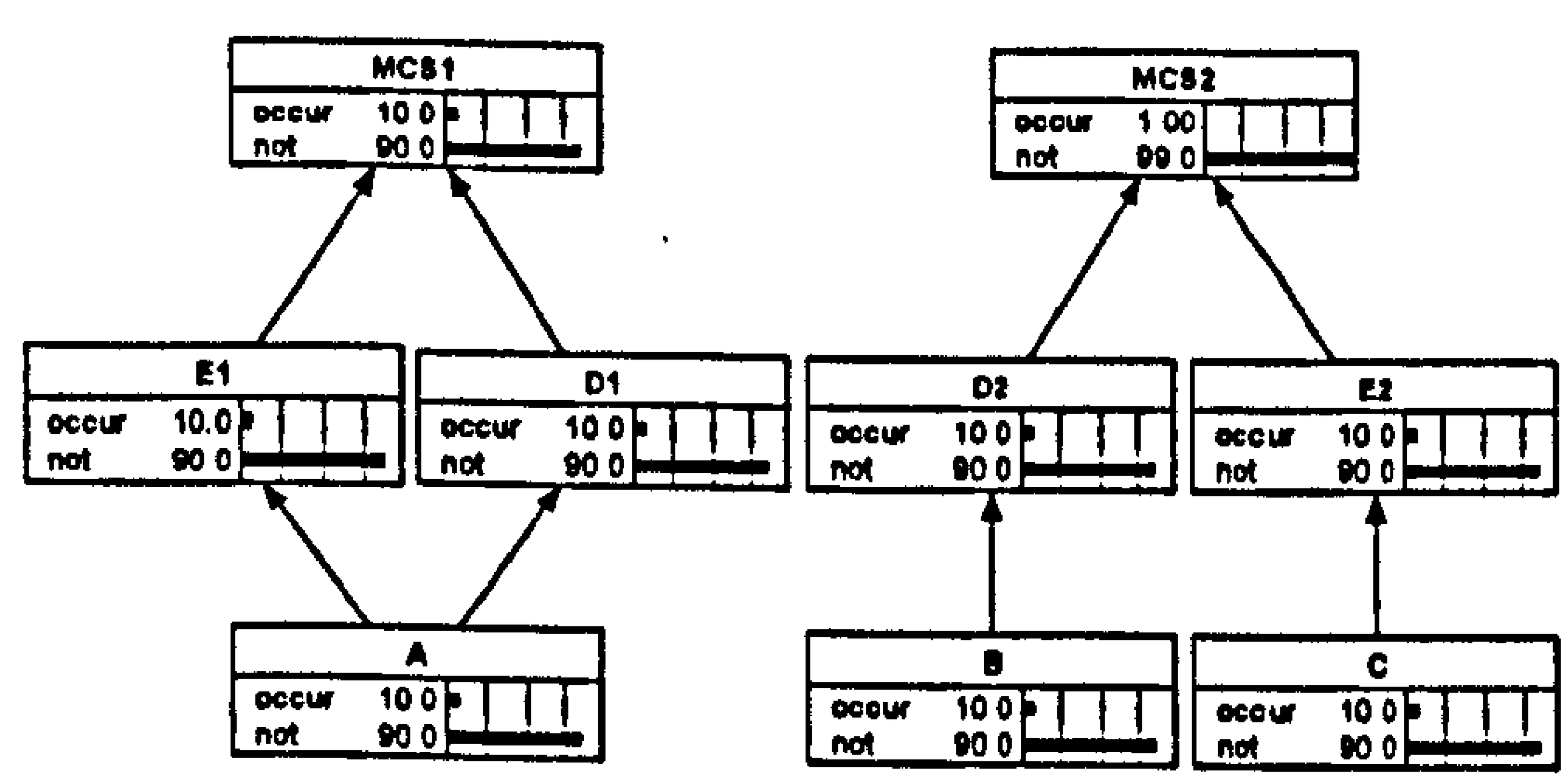


Figure 4-13 The Bayesian Network model of the repeated Basic Event example

In Figure 4-13, the Bayesian Network model associated with the repeating Basic Event example shown in Figure 4-11 is utilised to illustrate the notion. The Conditional Probability Tables are shown on the left hand side whilst the corresponding Bayesian Network model is on the right hand side. Each row of these tables depicts the probability distributions on the left half of the tables whilst the conditions given by its predecessors appear on the right of the same row. If a table subjects to no condition (e.g. the tables for nodes *A*, *B* and *C*), then prior probability distributions are given. In addition, the quantitative results displayed in the Bayesian Network model (on the right hand side of Figure 4-13) are the marginalised (or unconditional) likelihood outcomes in a percentage manner for each node. There are two nodes representing the *MCS1* in the model of the example; they are Node *MCS1_1* and Node *MCS1_2*. They are utilised to highlight that event *A* cannot either trigger event *D* or event *E* to cause the Top Event to happen. Any one of them should not be overlooked. Therefore, two nodes are shown in the model representing *MCS1*, but only one of their quantities will be applied to calculate the likelihoods of the Top Event. If the Minimal Cut set upper bound approach is applied, the computation details are shown in Equation (4.9), in which the probability figure applied for events *A*, *B* and *C* are 0.1 (or 10%) for each.

$$P(TE) \leq 1-(1-\mathrm{MCS1})(1-\mathrm{MCS2}) = 1-(1-0.1)(1-0.01) = 0.109 \tag{4.9}$$

The result shown in the equation means the likelihood of the Top Event is not larger than 10.9% which coincides with the answer obtained via Equation (4.1). The equality exists when no factor appears in more than one Minimal Cut Set. It implies that the result obtained in light of the Minimal Cut Set upper bond formula will be somewhat overestimated providing that there are common factors amongst Minimal Cut Sets. That is, the more the common factors involved, the larger the result overestimated. It is very important to bear in mind with this feature whilst applying this approach for the analysis. However this approach is still suitable for comparison purposes if the precise answer is not mandatory.

So far, the applied Bayesian Network software is only able to accept single crisp value for the entries of the Conditional Probability Tables. A practical problem may arise if there is more than one expert providing their estimations for the data of Conditional Probability Tables. It is unavoidable that they will disagree with each other regarding the values of the tables sometimes. A method which applies fuzzy set theory to obtain a consensus values, as the compromise, for the data of Conditional Probability Tables of the Bayesian Network model is proposed and detailed in Chapter 7. In the method, the consensus values for each node are derived and aggregated from every expert's opinion. However, it does not mean that this method intends to ignore the differences of the judgements, but simply proposes one solution to aggregates the expert opinion and may allow a resolution of the disputes amongst these experts.

4.5.6 The propagation of the Bayesian Network model for "what if" examination

The propagation (or Bayesian inference) is another useful feature that the Bayesian Network can provide. "Bayesian inference is a process by which observation of a real-world situation are used to update the uncertainty about one or more variables characterising the aspects of that situation. It relies on the use of *Bayes' Rule/Theorem* as its rule of inference, defining the manner in which uncertainties ought to change in light of newly made observations" (Wang and Trbojevic, 2007). It implies this feature can be used to examine the possible outcomes of every Causal Factor of the accident, based on the established Bayesian Network model, as "*what if*" examinations,. In addition, it can also be used to examine the possible solutions to prevent the similar accidents from happening again. Later, in section 5.5.6, the case study will show that the countermeasures which against some of the Intermediate Events are sometimes one of the efficient ways to prevent the similar accidents to happen again. This means that, from the view of Swiss Cheese Model, the Top Event can be prevented or relieved via blocking one of the holes represented by the Intermediate Events and resulting in the closure of the associated WoO of the accident.

The "*what if*" examination is an application of propagation function. By giving a new figure of the uncertainly to one of the nodes in the Bayesian Network model, the updated node will then update its likelihood (or belief). Consequently, it also triggers a chain reaction to the other nodes as an epicentre. Those nodes which have connections with the updated nodes will update their likelihoods according to the dependencies associated with the epicentre. Hence the updated node becomes the supreme influencing nodes of the Bayesian Network model and all the other nodes turn out to be its influenced nodes at the time even though those whom are its predecessors. Although the updated node has changed the influencing direction to the predecessors at that time, the dependencies between the node and its predecessor and others successors remain the same. In other words, the conditional dependencies amongst them depicted in the Conditional Probability Tables are still unchanged. In order to explain how it works out, it is necessary to cover some theoretical details about the feature before carrying on with the example application.

In fact, the propagation feature is only part of Bayesian inference mechanism. Together with the concept of conditional independence and the techniques of marginalisation, it provides a basic tool for Bayesian belief updating. It should be noted that the arrowheads in the Directed Acyclic Graph only represent the real causal connections rather than the flow of information during the inferring. In other words, the information can be propagated in any direction in a Bayesian Network. Therefore, the key features of conditional independences and/or dependency-separation (i.e. *D-Separation*) have to be clarified before performing the propagation. Actually, *D-Separation* is another method to determine conditional independence. Both of them indicate the same thing. However, *conditional independence* is defined in terms of probabilities and *D-separation* in terms of paths in a graph (Eleye-Datubo, 2005).

Eleye-Datubo (2005) further specifies that the characteristics of conditional independence may be experienced when two nodes are in a Bayesian Network model but the evidence about one cannot influence the other. To determine conditional independence in this setting, one must also consider all the undirected paths between these two nodes. Any node on any paths in the model may "*block*" the dependence along that path, and therefore if all the paths between the two nodes are blocked at least once, the two nodes will be independent (i.e. *D-separated*). This characteristic is crucial to fully understand the propagation function when it is applied to "*what if*" examination. Otherwise, the influencing paths might be blocked unexpected and the outcome of the propagation might be incorrect. Besides, the D-separation feature can be utilised as a mechanism to validate the correctness of the Directed Acyclic Graph of a Bayesian Network model. Yang (2006) suggests that the correctness of a qualitative Bayesian Network can be checked by carrying out the *belief updating* to each node and comparing the *D-separation* outcomes with the reality. In considering a node on a path in the network, Eleye-Datubo (2005) summaries the *D-Separation* can be distinguished from three types of connection: *serial*, *diverging* and *converging*. Each connection has its own propagation properties as follows:

Figure 4-14 *Serial, diverging* and *converging* connections to a node *C* on a path (from Eleye-Datubo, 2005)

- In a serial (head-to-tail) connection (i.e., $B \rightarrow C \rightarrow A$), any evidence entered at node *A* or node *B* can be transmitted along the directed or undirected path respectively (as in Figure 4-14 (a)(i)) providing that no intermediate node *C* on the path is instantiated (which thereby blocks further transmission by D-separation as in Figure 4-14(a)(ii)).
- In a converging (head-to-head) connection (i.e., $B \rightarrow C \leftarrow A$), entering evidence at node *B* will update node C but will have no effect on node *A* (Figure 4-14 (b)(i)). Evidence can only be transmitted between parents (i.e. nodes *A* and *B*) when the child (converging) node *C* has received some evidence (See Figure 4-14(b)(ii)).
- In a diverging (tail-to-tail) connection (i.e., $B \leftarrow C \rightarrow A$), evidence can be transmitted between child nodes (i.e. nodes *A* and *B*) of the same parent (i.e., node *C*) providing that the parent is not instantiated (Figure 4-14 (c)(i)).

Otherwise, nodes A and B are *conditionally independent* (i.e., due to *D-separation*) given evidence at node C (Figure 4-14(c)(ii)).

In the following example, the special case of belief updating called "*Evidence*" is applied, in which according to the information obtained, some particular nodes can only be one of the states stood (Jensen, 2001). For illustration, the *MCS2* of the repeated Basic Event case, which is the example shown in Figure 4-13 in section 4.5.5, is utilised as the example. During the examination, the event *D2* is assumed to occur (i.e. its likelihood is set as 100%) with evidence supported (see the right hand side of Figure 4-15). Consequently, the likelihood values of Node *MCS2* and Node *B* are both increased 10 times as they were before. However, the Node *E2* and Node *C* are not influenced because of the converging *D-Separation* of Node *MCS2*. This means that the propagation information is not transmitted to Nodes *E2* and *C* through *MCS2*. The outcome can be interpreted as event *B* being believed to have happened and the *MCS2* increasing the likelihood from 1% to 10% due to the "*evidence*" showing that factor *D2* happens. For quick referencing, the Conditional Probability Tables for Node *D2* and Node *MCS2* are shown on the left hand side of the figure. They are the same as the data shown in Figure 4-13 and will be utilised in the illustration of propagation calculation regarding Nodes *MCS2* and *B*.

D2:

occur	not	B
1	0	occur
0	1	not

MCS2:

occur	not	D2	E2
1	0	occur	occur
0	1	occur	not
0	1	not	occur
0	1	not	not

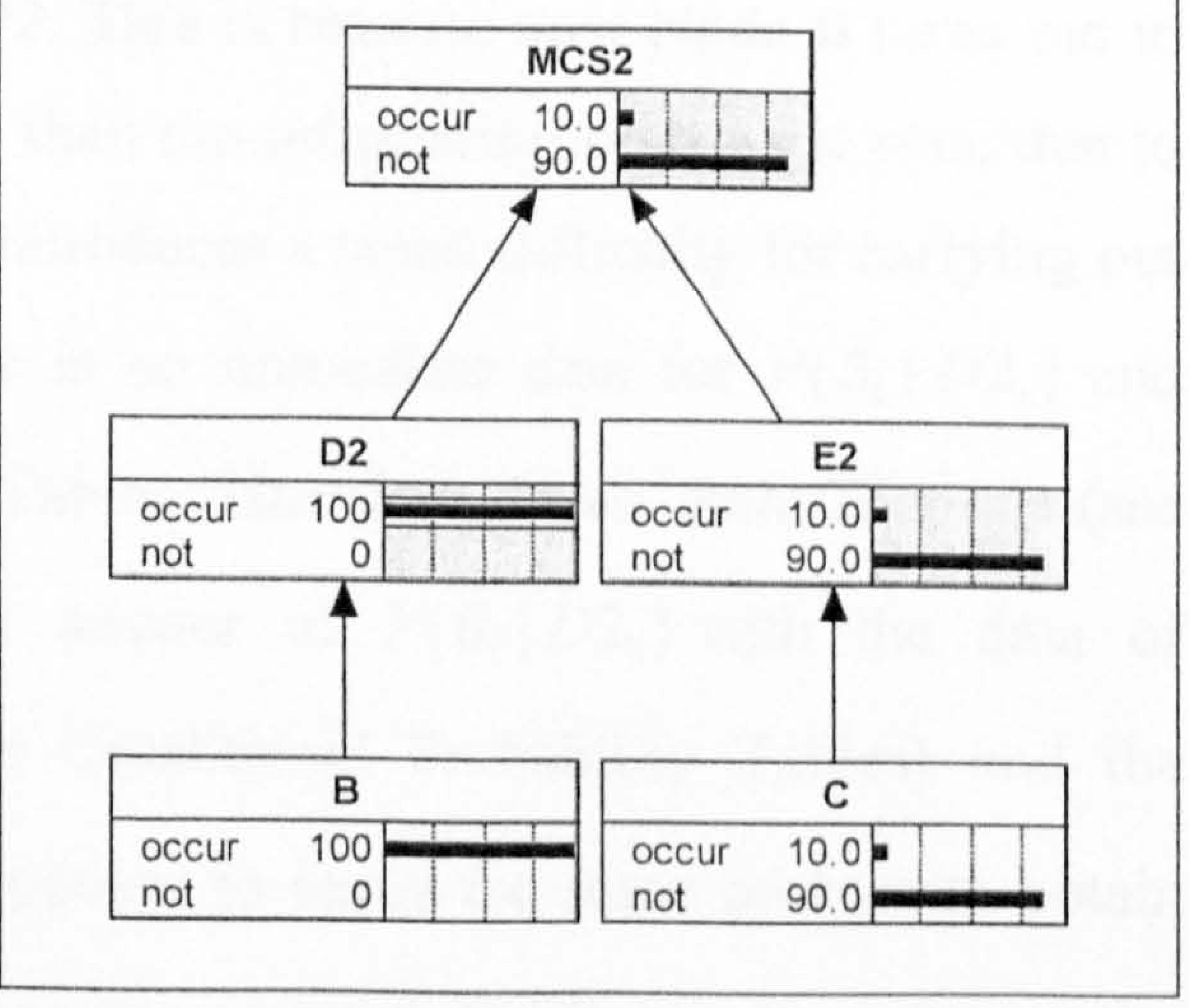


Figure 4-15 The illustration of the propagation of the repeated Basic Event example

The propagation and marginalisation details for $P(MCS2_1)$, which represents the unconditional probability of the state "*occur*" of Node *MCS2* under the condition that Node *D2* has been updated by "*evidence*", are shown in Equation (4.10). The computation just simply applies Equation (4.7) to update its likelihood. However, the probability data with regard to Node *D2* no longer applies from the Conditional Probability Table for the calculation, but from the "*evidence*" instead. In this example, the $P(D2_1)$ and $P(D2_2)$ are replaced by 100% and 0% respectively. To keep the calculation details short, only one of the states (i.e. the state of "*occur*") is illustrated. Since there are only two states within Node *MCS2* and there is 1's complement relationship between them, the likelihood of the other state of the node (i.e. state "*not*") can be obtained by simply subtracting the likelihood of the state "*occur*" by one (i.e. $1-P(MCS2_1)$).

$$\begin{aligned}
P(MCS2_1) &= \sum_{\substack{i=1\\j=1}}^{\substack{i=2\\j=2}} P(MCS2_1 \mid D2_i, E2_j) \times P(D2_i)P(E2_j) \\
&= (1\times1\times0.1)+(0\times1\times0.9)+(0\times0\times0.1)+(0\times0\times0.9) \\
&= 0.1+0+0+0 \\
&= 0.1
\end{aligned} \tag{4.10}$$

In contrast to Node *MCS2*, the propagation details for Node *B* is more complicate since Node *B* is the predecessor of Node *D2*. This is because now Node *B* turns out to be the influenced node of Node *D2*, rather than the influencing node as it was, due to the "*evidence*" updating of Node *D2*. This introduces a small difficulty for carrying out the marginalisation of $P(B_1)$ because there is no immediate data for $P(B_1 \mid D2_1)$ and $P(B_1 \mid D2_2)$ in the Conditional Probability Tables. Therefore *Bayes' Rule/Theorem* (see Equation (4.6)) is applied to obtain the answer of $P(B_1 \mid D2_1)$ with the data of $P(D2_1 \mid B_1)$ (i.e. the data depicted in the Conditional Probability Tables) and the marginalised $P(D2_1)$ before updating. It supposes to apply the same process to obtain the answer for $P(B_1 \mid D2_2)$. However, since the updated $P(D2_2)$ is zero, no matter what value the $P(B_1 \mid D2_2)$ is, the answer of $P(B_1 \mid D2_2)P(D2_2)$ is always zero. Hence, the calculation for $P(B_1 \mid D2_2)$ can be omitted. Therefore, the updated $P(B_1)$ is acquired via the calculation shown in Equation (4.11). For $P(MCS2_2)$, the updated $P(B_2)$ is also achievable via subtracting the acquired $P(B_1)$ from one as the short cut.

$$
\begin{aligned}
&P(B_1) = \sum_{i=1}^{i=2} P(B_1 \mid D2_i) \times P(D2_i) = P(B_1 \mid D2_1)P(D2_1) + P(B_1 \mid D2_2)P(D2_2) \\
&P(B_1 \mid D2_1) = P(D2_1 \mid B_1)P(B_1)/P(D2_1) = (1 \times 0.1)/0.1 = 1 \\
&P(B_1 \mid D2_2) = P(D2_2 \mid B_1)P(B_1)/P(D2_2) \\
&\because \\
&P(D2_1) = 1 \ \& \ P(D2_2) = 0 \\
&\therefore \\
&P(B_1) = (P(B_1 \mid D2_1) \times 1) + (P(B_1 \mid D2_2) \times 0) = (1 \times 1) + (0 \times 0) = 1
\end{aligned}
\tag{4.11}
$$

By applying the propagation function of the Bayesian Network model, the analyst is not only able to determine which countermeasures can effectively reduce the likelihood of the accident, but also more confident to say which factors take the significant role in causing the accident to happen. It also means that the Bayesian Network model would be a convenient tool for the accident investigation authorities to objectively conclude the critical Causal Factors as well as the effective countermeasures of the accident. This is because the Bayesian Network models can offer a comprehensive view for the analyst to score all the Causal Factors involved not only qualitatively but also quantitatively. In the next section, the validation of the Bayesian Network model will be the topic to be addressed. It is of vital importance for the correctness of the analysis results.

4.6 The Sensitivity Analysis (SA) over a Bayesian Network model

"*Sensitivity Analysis* is the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. The Sensitivity Analysis is hence considered by some as a prerequisite for model building in any setting, and in any field where the model is used" (Saltelli, 2002). It implies that the Sensitivity Analysis can be utilised to determine how "*sensitive*" a model is to the change in the value of the parameters and to the change in the structure of the model. Since the structure of the Bayesian Network model (i.e. the qualitative analysis results) is established through a systematic procedure, the Sensitivity Analysis applied within this proposed method will only focus on two issues: (1) validating the Conditional Probability Tables data and (2) finding the critical factors of the model. This study will only address these two issues, further applications might be revealed in the future.

It is believed that validating the model and finding the critical factors of a Bayesian Network model are imperative for the correctness of the analysis conclusions. In order to achieve these two goals, the technique applied is called *Parameters Sensitivity* examination, which is one of the applications of Sensitivity Analysis. In the examination, a series of parameters and values of the parameters are tested in order to appreciate the behaviour of the model which is changed due to the change of the parameters (Breierova and Choudhari, 1996). By showing how the model's behaviour responses to the change of the parameters value, Sensitivity Analysis is therefore applied, as the principle, to fulfil these two goals by evaluating the variations of the Bayesian Network model. Although the principle is the same, the procedures for achieving these two goals are different. Validating the model focuses on whether the outcomes of the entire model are in accord with the reality whilst finding the critical factors concentrates on the behaviours of individual nodes. Both of them have to resort to the mechanism of propagation of Bayesian Network in order to carry out the examination. Therefore, a Bayesian Network software, Netica (2008), was utilised to perform the computation and the propagation of the model.

4.6.1 The validation of the Bayesian Network model

Once a Bayesian Network model has been constructed by following the procedure described in the preceding sections, the correctness of the model becomes an imminent issue and has to be ensured before further progressing. That is, the validation of the Bayesian Network model is imperative and has to be made before the model is further used for the official accident analysis. As stated earlier, this process can resort to the technique of *Parameter Sensitivity* examination. By choosing some significant Causal Factors identified in the accident, variant probability values are given to the corresponding nodes in the Bayesian Network model as the "*updated belief*" to trigger the propagation of the model. Each time only one Causal Factor is selected and the inputted value is changed from 0% to 100% step by step, for example 10% as the interval of the steps. Then the outcomes of the Bayesian Network model are changed accordingly and will be observed thoroughly. That is, the likelihoods for each node of the model will be updated according to the dependencies through the propagation function when the testing probability value is given to the selected node(s). The results of those Minimal Cut Sets (i.e. the proxies of the Top Event) are then recorded as the outputted data of the model. This examination process will be imposed to every selected factor, one by one, until all the selected factors have been tested thoroughly. Please note that each Causal Factor may be represented by more than one node in the Minimal Cut Set model. Therefore all the nodes in association with that particular factor have to be given the "*updated belief*" at the same time. If the Minimal Cut Set model is employed, the updated belief of the Top Event is acquired via the Minimal Cut Set upper bound formula (see Equation (4.2) in section 4.4.3) with those outcomes. This procedure is summarised as follows.

1. Update the belief of the node(s) which represent one particular Causal Factor from 0% to 100% step by step, for example 10% as the interval of the steps.
2. Record the updated result of Top Event as the output of the model or compute the updated result of those Minimal Cut Sets through Equation (4.2) to acquire the answer.
3. Iterate previous steps until all the selected Causal Factors have been examined thoroughly.

Having accomplished this process to all the selected Causal Factors, the figures with regard to the likelihood of the Top Event against those "*updated belief*" to each Causal Factor are acquired (see Figure 5-10 as an example). From those figures, the tendency of each selected Causal Factor can be revealed and compared. With the help of those figures, several requirements can be examined as the criterion. They are:

1. These tendencies should be in line with the reality of the accidents. This is, the worse the negative behaviour of the factors, the higher the likelihood of the accident.
2. The curves which are converted from those figures should converge to a small area, on the positive behaviour side, as the trend. This phenomenon is derived from the notion of WoO that if any one of the holes to line up the window has

been shut, the WoO no longer exists. That is, no matter which hole has been shut, the window should be closed.

3. As long as all the Causal Factors have been set with the most adverse figures, the likelihood of the Top Event should reach the maximum figure. This is also rational correspondence to the reality. Since these selected Causal Factors were identified as the causes of the accident, the accident should happen whilst all the Causal Factors occur.

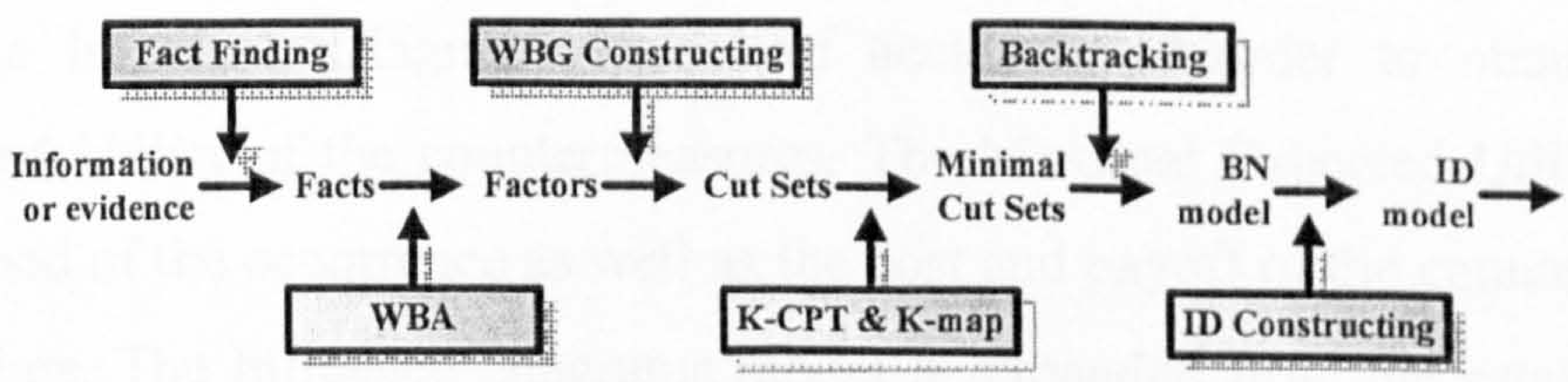
A proper validation process can help the analyst to highlight the inadvertent error(s) of the Bayesian Network model. From the point of view of practicability, the proposed validation process is reasonable and achievable for being part of the method. Although the proposed validation process is sound for the purpose of the method, a further comprehensive validation method to improve the process may be considered in the future.

4.6.2 Finding the critical Causal Factors of the accident

Having validated a Bayesian Network model, finding the critical factors of the model is the aim of the next step. Yang (2006) suggests that, in a Bayesian Network, it is possible to differentiate the importance of the input nodes in terms of the individual safety contribution to the output variable by giving the same variation of input probabilities and comparing their influence magnitudes on the output node(s). A study also points out that a node (or parameter) whose specific value(s) can significantly influence the outcome of the model is identified as the critical factor, which greatly changes the system's behaviour with the change of the node's value (Breierova and Choudhari, 1996). They recommend that "A good sensitivity analysis should conduct analyses over the full range of plausible values of key parameters and their interactions, to assess how impacts change in response to changes in key parameters". Therefore, the proposed process to find out the critical Causal Factors of the accident is performed by examining all the nodes in the Bayesian Network model with full range of plausible values for each node. These values are deemed as the "*updated belief*" of the nodes to trigger the propagation of the model and compare their influence magnitude to the output node(s). This must be done systematically and thoroughly for ensuring that none of the nodes will be overlooked. Apparently, it would be time consuming and error prone if this process is carried out manually. Fortunately, this requirement can be achieved easily through a built-in function of the utilised Bayesian Network software – Netica (2008). The explanation of the functionalities provided for *sensitivity finding* is described in Appendix-C.

Before executing this function via the software, a target node has to be assigned. After appointing one of the nodes representing the Minimal Cut Sets as the target node for the finding process, the software examines the sensitivity regarding the target node for every node in the model, one by one, step by step. A text report is provided at the end of the execution as the results. The report is divided into two parts; the details for individual node are in the first part and the comparison data is in the second part. The first part of the report provides detailed information associated with a "finding node", whilst the second part of the report provides a summary list of the sensitivities for each node. The second part of the report also shows the ranking of the "finding nodes" listed, from high to low, according to the sensitivities results. By having the report, it is helpful for the analyst to identify which Causal Factors are more sensitive (or crucial) to one of the WoOs (i.e. the Minimal Cut Sets) of the accident. After applying this process to all the WoOs of the accident, one by one, and analysing these reports, it is now easier for the investigators to objectively identify which factors are crucial with a comprehensive picture. With these identified crucial factors, it would be helpful for the investigation authorities to objectively conclude the comments and the recommendations in the investigation reports. It is recommended that this process should be executed before any recommendation of the countermeasures has been made. The countermeasures issue which is considered as the *Risk Control Options* will be discussed in the next sections.

4.7 Influence Diagrams (ID) for Risk Control Option (RCO)



An Influence Diagrams is a graphical framework for representation and analysis of (Bayesian) decision making under uncertainty. It can solve "a decision problem amounts to (i) determining an optimal strategy that maximises the expected utility for the decision maker and (ii) computing the Maximal Expected Utility of adhering to this strategy (Kjærulff and Madsen, 2008)". In addition, Jensen (2001) articulates a definition as that an Influence Diagrams consists of a Directed Acyclic Graph over *chance* nodes, *decision* nodes and *utility* nodes with the following structural properties:

- there is a directed path comprising all decision nodes;
- the utility nodes have no children.

For the quantitative specification, we require that:

- the decision nodes and the chance nodes have a finite set of mutually exclusive state;
- the utility nodes have no states;
- to each chance node A is attached a Conditional Probability Table $P(A|pa(A))$;
- to each utility node U is attached a real-valued function over $pa(U)$.

From the view of the decision makers, the countermeasures against a particular type of accident may be seen as a decision problem. In the thought of ***cost-benefit***, it would be improper if one only considers the likelihood of the occurrence without taking into account the cost and the payoffs of the countermeasures. A previous study (Eleye-Datubo, 2005) has shown that the Maximal Expected Utility of Influence Diagrams can be applied as the tools to evaluate the cost-benefit issue for safety-based marine and offshore decision making. In that study, the utility figures are relative to *Implied Cost of Averting Fatality* (IACF), which is a typical approach used in the offshore industry (Wang and Trbojevic, 2007). Instead of IACF, the study assumes that the same technique (i.e. the Maximal Expected Utility) can be utilised to analyse the accident for all the possible countermeasures considering the cost-benefit issue. Hence, the proposed methodology treats these countermeasures as the *Risk Control Options* incorporating into the Influence Diagrams model of accidents in order to obtain the Maximal Expected Utility of the countermeasures. The Maximal Expected Utility considers the likelihood of the occurrence as well as the cost and payoff of the countermeasures at the same time. The Influence Diagrams model is expanded from the established Bayesian Network model of the accident. In other words, the Bayesian Network model is the foundation of the Influence Diagrams model, in which the analysed results of the accident clarified in the preceding processes are the basis. Hence, the Influence

Diagrams model is eligible to be considered as a dedicated model which corresponds to the reality of the accident. Having established this model, it would be beneficial for the decision makers to assess all the available countermeasures, considering the cost-benefit issue, in order to choose the best solution to prevent the (or similar) type of accident from happening again.

A concise summary regarding *Influence Diagrams*, *Expected Utility* and *Maximal Expected Utility* is given as follows.

Influence Diagrams:

"An influence diagram is a compact representation of a joint expected utility function" (Kjærulff and Madsen, 2008). In order to provide decision-making capabilities, a Bayesian Network can be expanded with utility functions and with variables representing decisions to form an Influence Diagrams. That is,

"Influence Diagrams" = "Bayesian Network" + {decisions & utilities}

Besides, a utility table *U(D, S)* depicting the utility for each configuration of decision alternative, d, $d \in D$, and outcome states, *S*, for the determining variable has to be yielded in order to assess the decision alternatives in *D*.

Expected Utility:

The *Expected Utility* (*EU*) of a given decision alternative *d* is:

$$EU(d) = \sum_{S} P(S \mid d) U(d,S) \tag{4.12}$$

where *U(d,S)* are the utility function of *(d, S)* encoded in the utility table of node *U*. The conditional probability *P(S|d)* represents the belief in *S* given that *d* is performed (Kjærulff and Madsen, 2008).

Maximum Expected Utility (MEU):

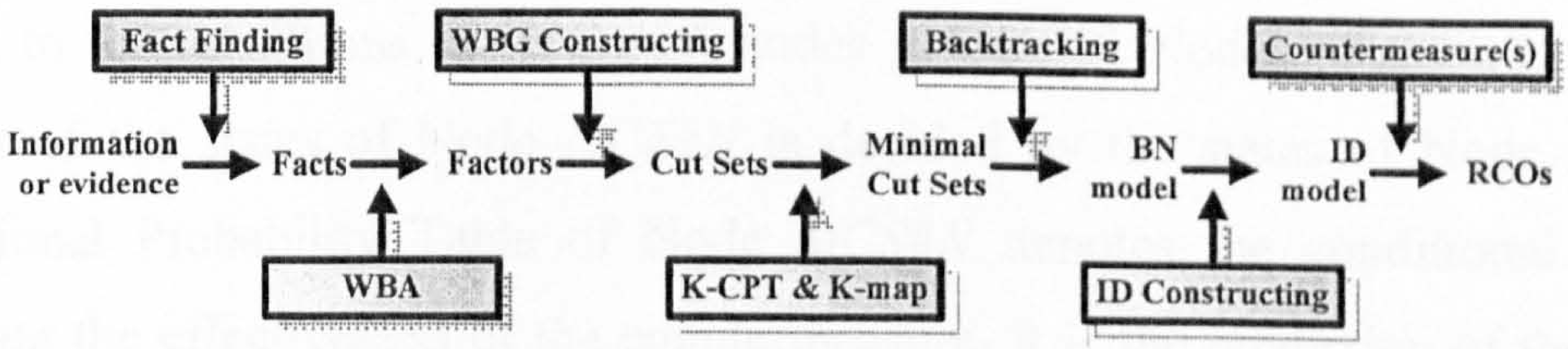
A rational decision-maker should choose an action that maximises expected utility of outcome states. Thus, given that $d_1, d_2, \ldots, d_k$ are the mutually exclusive decision alternatives of *D*, the decision alternative *d* that gives *MEU* is:

$$MEU(d) = \max_{d} \{EU(d_1), EU(d_2), \ldots, EU(d_k)\} \tag{4.13}$$

Evaluation of the Influence Diagrams can be done by setting the decision node to a particular choice of action (i.e., the best RCO) and treating the node just as a nature node with a known value that can further influence the values of other nodes (Eleye-Datubo, 2005).

In Influence Diagrams, the *Decision* nodes (usually drawn as rectangles or squares) represent the decision alternatives which are available to the decision makers. The nodes include a specification of the available decision options (i.e. choices). Edges into decision nodes indicate time precedence: an edge from a random variable to a decision variable indicates that the value of the random variable is known then the decision will be taken. By the same token, an edge from one decision variable to another decision node indicates the chronological order of the corresponding decisions. In contrast, the *Utility* nodes (normally drawn as diamond-shaped or hexagons) represent the figure of merit for a decision alternative. Each utility node has utility functions associating each utility with each states of its parents (Utility nodes do not have children). The probabilities of the nodes involved in the model are influenced by the decisions taken. Therefore the expected utility for each decision alternative can be computed accordingly (the global utility function is the sum of all the local utility functions) (see Equation (4.12)). The alternative with the highest expected utility is chosen; this is known as the *Maximum Expected Utility principle* shown in Equation (4.13) (Eleye-Datubo, 2005).

4.7.1 Applying Influence Diagrams for selecting the Risk Control Option



An instance of Influence Diagrams which has considered the occurrence likelihood of analysed accident as well as the cost and payoff of countermeasures is proposed and shown in Figure 4-16. It does not mean that this is the only solution to implement this notion, instead other implementations are still possible. In other words, it is an example to show how Influence Diagrams to cope with the cost-benefit issue for decision makers in order to choose the most efficient countermeasure against the accident. In the following paragraphs, the proposed solution is depicted with the calculation details.

Payoff	*MCS#*	*RCO*	*Cost*
$U_p(n_1)$	$P(s_1)$	d_1	$U_c(d_1)$
$U_p(n_2)$	$P(s_2)$	d_2	$U_c(d_2)$

MCS#N

	s_1		s_2	
	d_1	d_2	d_1	d_2
n_1	$P(n_1\|s_1,d_1)$	$P(n_1\|s_1,d_2)$	$P(n_1\|s_2,d_1)$	$P(n_1\|s_2,d_2)$
n_2	$P(n_2\|s_1,d_1)$	$P(n_2\|s_1,d_2)$	$P(n_2\|s_2,d_1)$	$P(n_2\|s_2,d_2)$

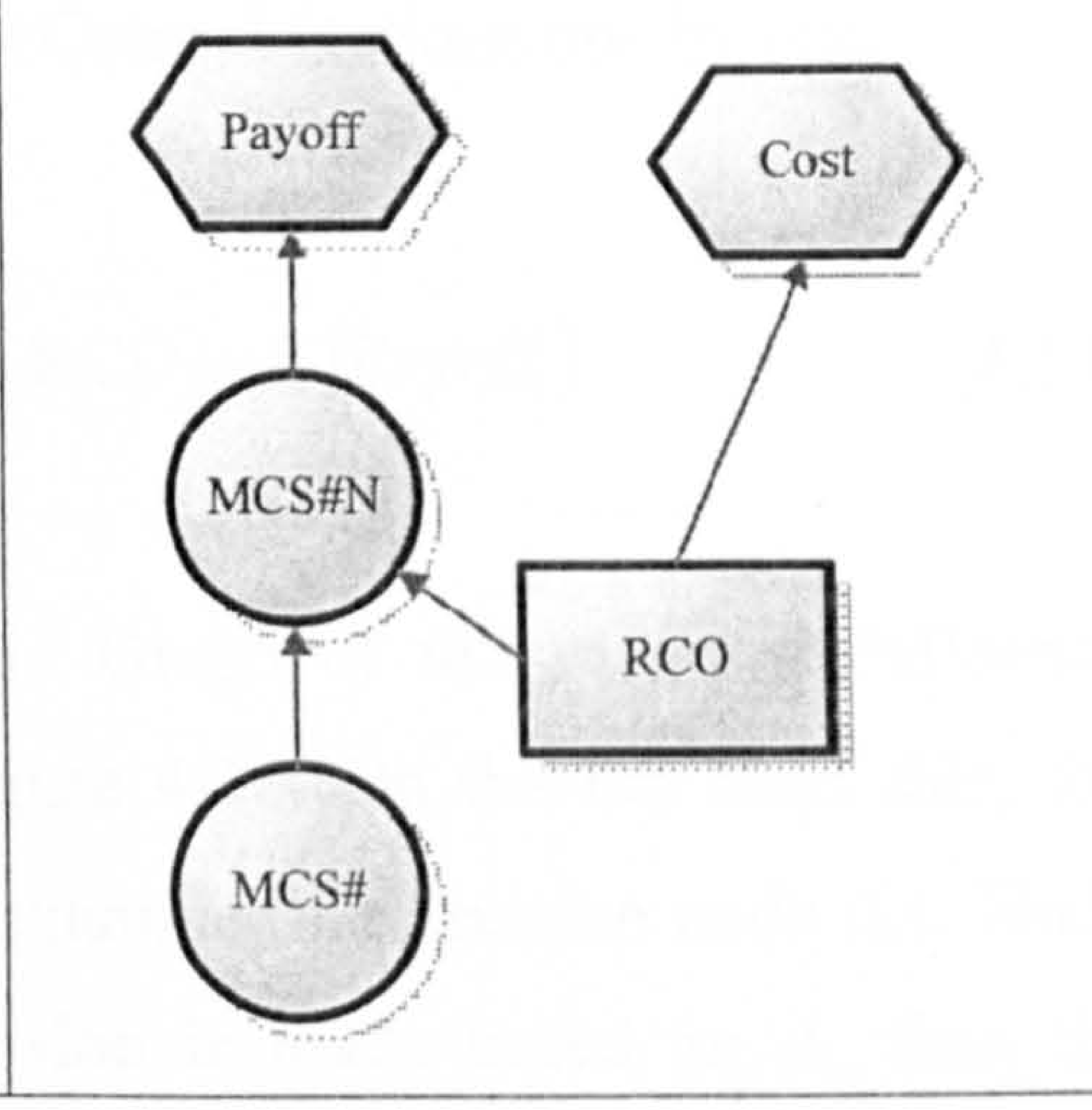


Figure 4-16 The example of Influence Diagrams for Risk Control Option selection

An Influence Diagram can be obtained by expanding the Bayesian Network model of an accident, in which one *Decision* node (labelled as *RCO)* and one *Utility* node (labelled as the *Cost*) are added into the established Bayesian Network model. In addition, for each Minimal Cut Set of the accident, which is represented by a *Chance* node (labelled as the *MCS#;* $\# \in N$), an extra *Chance* node (labelled as the *MCS#N*) is attached with a *Utility* node (labelled as the *Payoff*) followed (see Figure 4-16 for the illustration). Node *RCO* denotes the available countermeasures for decision making. Node *Cost* specifies the costs for each Risk Control Option, and the number of utility function of the node depends on the state number that Node *RCO* has (i.e. the numbers of the alternative). Node *MCS#N* represents the posterior status of the occurrence subject to the conditions of its parent nodes given (i.e. Nodes *MCS#* and *RCO*). The number of the states of Node *MCS#N* is decided by the states of Node *MCS#*. The Conditional Probability Table of Node *MCS#N* denotes the conditional probability regarding the effectiveness of the countermeasure. It is the prediction of the likelihood of the Top Event (or Minimal Cut Sets) if the Risk Control Options are imposed. The symbol "#" represents one digit of natural (or counting) number (i.e. $\# \in N$). For example, *MCS1* or *MCS1N* is instantiated if # is "1". Node *Payoff*, which has the same number of utility functions as the state number that its parent node has (i.e. Node *MCS#N*), specifies the benefits which can be acquired if one of the states of Node *MCS#N* occurs. For calculating the expected utility, Equation (4.14) is applied. Each alternative of the decision is calculated with the corresponding data of the nodes specified in the tables to obtain the answers of Risk Control Options one by one.

$$\mathrm{EU(RCO)} = \mathrm{U(Cost)} + \sum \mathrm{P(MCS\#\,N \mid MCS\#, RCO)} \times \mathrm{U(Payoff)} \tag{4.14}$$

For further illustration, the Directed Acyclic Graph of the proposed Influence Diagrams is shown on the right hand side of Figure 4-16. On the left hand side, the tables encoding these nodes are revealed. In this example, the decision node (i.e. Node *RCO*) has two alternatives: d_1 and d_2. If a decision is made based on d_1, then the expected utility is quantified via EU(d_1), which is shown in the first part of Equation (4.15). If a decision is based on d_2, EU(d_2) is applied, which is shown in the second part of the equation.

$$\begin{aligned}
\mathrm{EU}(d_1) = & \, U_c(d_1) \\
& + P(s_1) \times \left[P(\mathrm{n}_1 \mid s_1, d_1) U_p(\mathrm{n}_1) + P(\mathrm{n}_2 \mid s_1, d_1) U_p(\mathrm{n}_2)\right] \\
& + P(s_2) \times \left[P(\mathrm{n}_1 \mid s_2, d_1) U_p(\mathrm{n}_1) + P(\mathrm{n}_2 \mid s_2, d_1) U_p(\mathrm{n}_2)\right] \\
\mathrm{EU}(d_2) = & \, U_c(d_2) \\
& + P(s_1) \times \left[P(\mathrm{n}_1 \mid s_1, d_2) U_p(\mathrm{n}_1) + P(\mathrm{n}_2 \mid s_1, d_2) U_p(\mathrm{n}_2)\right] \\
& + P(s_2) \times \left[P(\mathrm{n}_1 \mid s_2, d_2) U_p(\mathrm{n}_1) + P(\mathrm{n}_2 \mid s_2, d_2) U_p(\mathrm{n}_2)\right]
\end{aligned} \tag{4.15}$$

When the values of the expected utilities (i.e. EU(d_1) and EU(d_2)) are acquired, the decision alternative d that provides the Maximal Expected Utility is given by:

$$\mathrm{MEU}(d) = \max_{\mathrm{EU}} \{EU(d_1), EU(d_2)\}$$

Theoretically, the Influence Diagrams model cannot only perform the Maximum Expected Utility functionality, but also execute the "*what if*" propagation testing since it is derived from Bayesian Network. This feature provides an extraordinary merit when Influence Diagrams are applied as the tool for assessing the best Risk Control Option. This is because this application can offer the decision makers a wider flexibility to examine the effectiveness of the countermeasures by testing variant conditions of the circumstances. Moreover, it also adheres to the accident analysis results and the cost-benefit consideration as a whole. A more comprehensive example which applies the proposed Influence Diagrams pattern to deal with the assessment of Risk Control Options for Herald of Free Enterprise case is shown in section 5.7. In that case study, the proposed pattern is used to construct the Influence Diagrams model which is based on the qualitative and quantitative analysis results of the accident. In that section, the calculation details are also illustrated in order to appreciate the underlying computation of the process.

4.8 Discussion

The hypothesis of the proposed methodology implementing the *WoO* of Reason's *Swiss Cheese Model* via the *Minimal Cut Set* of FTA is inspired by the similarity of the definitions between the *WoO* and the *Minimal Cut Set*. Having this notion as the principle of the method, the gathered information or evidence of an accident during investigation stage are transformed into the listed facts, the Causal Factors, the Cut Sets, and then the Minimal Cut Sets in turn to acquire the qualitative analysis results. Subsequently the quantitative analysis results are obtained through the corresponding Bayesian Network model which is constructed according to the qualitative analysis results. Furthermore the Influence Diagrams model extending from the Bayesian Network model provides a *cost-benefit* analysis tool, in light of the analysis results, for the decision makers to select the best Risk Control Option. The entire relay-like procedure of the methodology adheres to the *Swiss Cheese Model* with several sound risk assessment techniques, as a whole, to achieve the goal of analysing an accident qualitatively and quantitatively. In addition, having established the Bayesian Network and/or Influence Diagrams model of the accident, a dedicated simulator of the accident is available, with the feature of propagation of Bayesian Network, to perform a series of "*what if*" examinations, which offers an opportunity to objectively appreciate the influences that have effect on all the factors involved in the accident. In summary, from the perspective of data processing, the progress of the analysis procedure which is shown in Figure 1-3, and in several corresponding sections, is illustrated in Figure 4-17 again. In the figure, the main stream is the evolution of the analytic data whilst the rectangles depict the relevant processes applied.

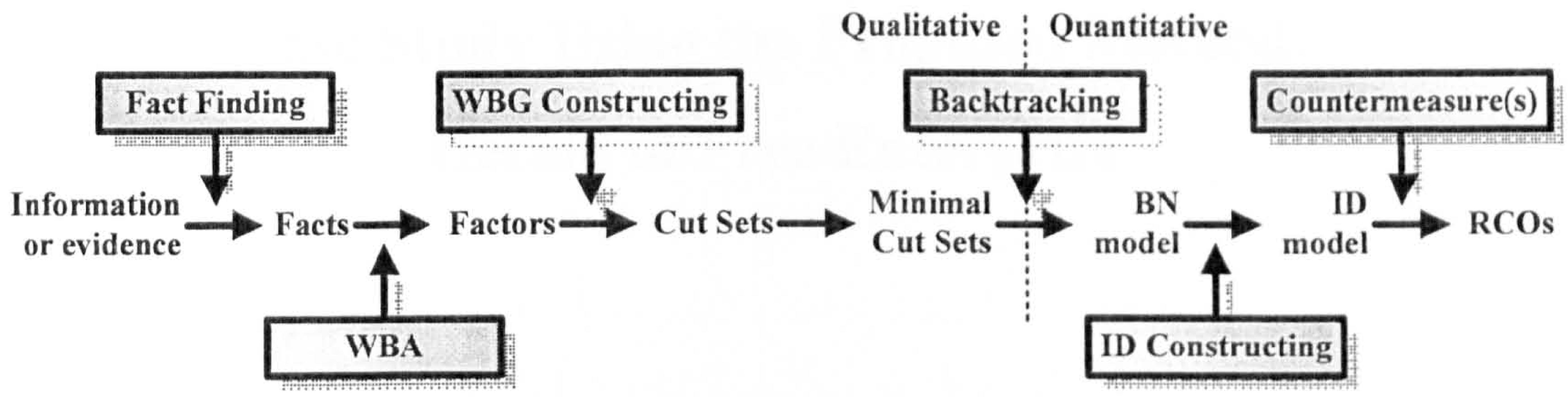


Figure 4-17 The data processing of the method

Predictably, this method can be utilised not only for the accident analysis but also for the preliminary assessment on safety case at other social-tech applications if the proper mathematic models of the topics are not in place. The features of the proposed methodology are briefly listed as follows.

- A systematic procedure to sort out the Minimal Cut Sets of the occurrences, as the qualitative analysis results, is in line with the WoO of Reason's Swiss Cheese Model.
- Both the qualitative and quantitative analysis results of the occurrences can simultaneously be shown on a Bayesian Network model as well as an Influence Diagrams model.
- The Bayesian Network model established according to the qualitative and quantitative analysis results can be seen as a dedicated simulator of the occurrences to perform a series of *what if* examination.
- An Influence Diagrams model based on the established Bayesian Network model of the occurrence is a useful tool for decision makers to evaluate the best Risk Control Option, whilst considering the cost-benefit issue, amongst variant available countermeasures.

Chapter Five –
Case Study Using the Proposed Method:
Herald of Free Enterprise

Summary

In this chapter, the tragedy of Herald of Free Enterprise (HoFE) is used as a case study to demonstrate the proposed method for identifying the Causal Factors involved in the accident and analysing the causation. This occurred on 6th March 1987 soon after leaving the harbour at Zeebrugge, Belgium The techniques applied by the method in analysing an accident qualitatively and quantitatively have been explicitly introduced in Chapter 4. They are: Why-Because Analysis (WBA), Karnaugh map (K-map), Fault Tree Analysis (FTA), Bayesian Network and Influence Diagrams. The method also utilises the Sensitivity Analysis to validate the analysed outcomes and to find out the critical Causal Factors of the accident. In this chapter, the entire relay-like procedure is performed, with these techniques, onto the HoFE case in order to provide a thorough overview of the analysis method. In the final stage of the procedure, the analysed results of the case study is further extended into an Influence Diagrams model, and the Expected Utility of Influence Diagrams is used to evaluate several possible Risk Control Options (RCOs) in order to demonstrate the way of finding the best countermeasure with the consideration of cost-benefit.

5.1 Introduction to the analysis

As noted previously, the first intention of the analysis is to clarify the Causal Factors of an accident and the causations amongst them. Thus, the factors involved in the accident have to be identified in advance. Therefore the aim of the first process is to identify all the Causal Factors involved in the accident basing on the information or evidence gathered during the investigation stage. Then, as stated in section 5.2.2, the Causal Factors for each Intermediate/Top Event and the causations amongst them are identified in turn. Next, the overall Why-Because (or Cause-Consequence) relationship amongst these Causal Factors will be depicted in a Why-Because Graph (WBG), according to the analysis outcome of WBA (section 5.2.3). However, this is not necessarily the final result of qualitative analysis since the analysed results might contain some irrelevant or redundant Causal Factors. In section 5.3, these Causal Factors (or Cut Set) are further clarified in order to obtain the Minimal Cut Set(s) for each Intermediate Event through the approximate simplification process (section 5.3.1). Hence, the Minimal Cut Set(s) of the accident are able to be obtained by using the Fault Tree Analysis techniques (section 5.4). The entire qualitative analysis can be achieved at this stage.

For quantitative analysis of an accident, a Bayesian Network technique is mainly utilised (section 5.5). A Bayesian Network model of Top Event can be obtained by transforming the established Why-Because Graph into a Directed Acyclic Graph (DAG) with the associated Conditional Probability Tables (section 5.3.2). The DAG of the Minimal Cut Set model is constructed by resorting to the proposed backtracking process (section 5.5.1), in which the simplified Minimal Cut Set equations acquired from the preceding approximate simplification process are the blueprint. In conjunction with the associated Conditional Probability Tables (section 5.5.4), the Bayesian Network model of Minimal Cut Sets of the accident can be established accordingly. In terms of validation, the Sensitivity Analysis is applied to ensure that the quantitative analysis results are rational (section 5.6). Finally, in section 5.7, the Influence Diagrams technique is utilised as the means to evaluate the possible Risk Control Options (i.e. the countermeasures to prevent reoccurrence) from the cost-benefit viewpoint.

The entire analysis procedure mainly relies on the gathered information and evidence collected during the investigation period. Subject expertise is also used, from time to time, to compensate the deficiency of the data, especially in the processes of WBA, approximate simplification, Conditional Probability Table of Bayesian Network and Influence Diagrams. Some assumptions on the data used for analysing the HoFE tragedy have been made by the author in order that the proposed methodology can be demonstrated.

5.2 Why-Because Analysis (WBA) for identifying the Cut Sets

The technique applied for identifying the Causal Factors and Cut Sets that involve in an accident is primarily the WBA, but the order and the number of the processes applied in the proposed method are different from the original WBA. This is because some of the mechanisms the WBA provides can be substituted by the other processes proposed in the method. For instance, the "quality assurance process" of WBA is substituted by the proposed Sensitivity Analysis technique depicted in section 5.6. Therefore, the processes which involve WBA are limited in identifying the Causal Factors for each Intermediate/Top Event and constructing the Why-Because Graph. In the end of the WBA process, a list of Causal Factors is produced as one of the data pool for the subsequent analysing processes. It should be noted that the WBA is highly dependent upon the subject expertises during the analysis. A brief description of WBA applied in the proposed method is covered in section 4.2.

5.2.1 Gathering information and determining the facts of the accident

In general, the gathered information with regard to an accident is mainly collected and organised during the investigation stage. The guidelines proposed by the International Maritime Organization (IMO) for the investigation into marine accidents are enumerated in section 4.2.1 where the codes, resolutions and circulars adopted by the IMO are tabulated, and these have to be considered ensuring the correctness and thoroughness of the data when an investigation is carried out. In order to focus on the application of the method, the case study does not consider this issue. Instead, it is assumed that the information gathered in this chapter is correct and sufficient.

All the identified facts or events listed in the following paragraph are extracted from the accident investigation report (DoT, 1987), which is available from Marine Accident Investigation Branch (MAIB) website (http://www.maib.gov.uk). In addition, a video documentary from the National Geographic Channel (Seconds from Disaster – Capsized in the North Sea, which is available form YouTube website (NGC, 2008)) is also utilised. They are the major data sources used for demonstrating this analysis example. Facts extracted from these data sources are then transformed into a collection of listed statements and become the major data pool for identifying the Causal Factors in the analysis. For referencing purposes, a short description in parentheses, as the notation of the "(source index)", at the end of each listed statement denotes which part of the DoT report the statements are derived from. For example the "(10.1; pp.8)", in the second listed statement below, denotes that the statement is extracted from section 10.1 on page 8 of the DoT report.

These listed statements are enumerated as follows. The mechanism to perform the facts finding process is indicated in section 4.2.2.

1. The chief officer relieved the 2nd officer from the duty of loading officer and then he left the bow door area without ensuring that the assistant bosun was present (10.5-10.8; pp.8-9).
2. The assistant bosun failed to carry out his duty to close the bow doors at the time (10.1; pp.8).
3. The master ordered a ship speed of 18 knots (9.2; pp.7).
4. A large quantity of water entered G deck and caused an initial lurch to port due to free surface instability – reached 30° (9.3; pp.7).
5. The Court was satisfied that at departure the HERALD had a mean draught of between 5.68 m and 5.85 m with a trim by the head about 0.8m (8.5; pp.6).
6. The ship was in fact overloaded significantly at departure (8.5; pp.6).
7. The ship was trimmed by the head in order to load E deck (8.1; pp.5).
8. The Court identified a need for more information about the weight cargo actually loaded and the desirability of fitting draught indicator (8.5; pp.7).
9. It was necessary to trim the ship by the head to allow the raised ramp to reach E deck (7.3; pp.5).
10. The ballast system could fill or empty No.14 ballast tank at a rate of 115-120 tones per hours (7.3; pp.5) (meaning that it would take at least 2 hrs to fill or empty the tank).
11. The company employed a Master and two deck officers on this run (7.2; pp.5).
12. Frequently the order "harbour station" was given before loading was completed (11.1; pp.10) (indicating pressure to leave the berth).

13. The lack of time available at Dover to handle both discharge and loading together with storing, was often mitigated by an early sailing from Zeebrugge in the previous voyage (11.3; pp.11).

14. "Master came to rely upon the absence of any report at the time of sailing as satisfying them that their ship was ready for sea in all respects. That was, of course, a very dangerous assumption" (12.3; pp.12). This was encouraged by the standing order 01.09 specifying that "In the absence of such report the Master will assume, at the due sailing time, that the vessel is ready for sea in all respects" (12.3; pp.12).

15. Before this disaster there had been no less 5 occasions when one of the company's ship had proceeded to sea with bow or stern door open ... the management had not drawn them to the attraction of the other Masters (12.5; pp.12).

16. The fact that...Captain Lewry had a personal responsibility for taking his ship to sea in an unsafe condition...he was seriously negligent in the discharge of his duties. The negligence was one of the causes contributing to the casualty (12.6; pp.13).

17. Senior Master Captain Kirby adopted a set of General Instructions issued by Captain Martin in July 1984. "2. The officer loading the main vehicle deck, G deck, to ensure that the water tight and bow/stern doors are secured when leaving port." (13.2; pp.14). He was content to accept without demur the Ship's Standing Orders issued by the company...If he had read the orders he would certainly have appreciated their defects ... Captain Kirby must bear his share of the responsibility for the disaster (13.3; pp.14).

18. The failure on the part of shore management to give proper and clear directions was a contributory cause to the disaster (14.1; pp.14).

19. It was the failure to give clear order about the duties of the Officers on the Zeebrugge run which contributed so greatly to the cause of this disaster (14.2; pp.15).

20. The worst features of the Standing Orders were that (1) they made no reference to closing the bow and stern doors, and (2) they appear to have led Captain Lewry to assume that his ship was ready for sea in all respects merely because he had had no

report to the contrary (15.3; pp.16).

21. There is no indication on the bridge as to whether the most important watertight doors are closed or not....Indicator lights on the very excellent mimic panel could enable the bridge to monitor the situation in such circumstances (A memorandum issued by Captain Blowers on 28th June 1985) (18.4; pp.23).

22. The matter was raised again on 17th May 1986, a memorandum issued by Captain Kirby and Captain de Ste Croix, suggested that "17. Bow and stern doors. Open/Closed indication to be duplicated on bridge" (18.6; pp.24). But on the 21st October 1986, Mr Alcindor replied "...the Bridge indication is a 'no go'" (18.7; pp.25).

23. Captain Lewry told the Court ... that no attempt had been made to read the draught of his ship on a regular basis...Fictitious figures were entered in the Official Log which took no account of the trimming water ballast (19.2; pp.26).

24. The ship was operating outside her conditions as set out in (and, was therefore not complying with) the conditions under which the Passenger Ship Certificate was issued (19.3; pp.26).

25. Mr. Develin, a director of the Company and former "Chief Marine Superintendent", did not appreciate that the stability of the HERALD could be significantly affected if the ship was trimmed by the head (19.2; pp.26). Mr. Develin ought to have been alert to the serious effects of operating at large trims. Furthermore he should have been concerned about Captain Martin's remarks about stability in a memorandum sent on 24th October 1983 (19.3; pp.26).

26. Mr. Ayers, who was at the relevant time a director of the Company, told the Court that in his view it was impossible for the officers to read the draught mark of the HERALD (19.5; pp.27).

27. Normal ballasting requirements are for Nos. 1 and 14 tanks ... to be filled for arrival Zeebrugge and emptied upon completion of loading ... Using one pump the time to either fill or empty the two tanks is approximately 1hr.55mins. Using two pumps ...can be reduced to approximately 1hr.30mins (20; pp.29).

28. Mr. Develin did not agree with the need for a high capacity ballast pump (20; pp.29). An estimate was obtained for the installation of a pump at a cost of

£25,000. This cost was regarded by the Company as prohibitive (20; pp.30).

29. The "Marine Department" did not listen to the complaints or suggestions of their Masters. Those areas were: (a) complaints that ship proceeded to sea carrying passengers in excess of the permitted number. (b) The suggestion to have lights fitted on the bridge to indicate whether the bow and stern doors were open or closed. (c) Draught marks could not be read. Ships were not provided with instruments for reading draughts. At times ships were required to arrive and sail from Zeebrugge trimmed by the head, without any relevant stability information. (d) The suggestion to have a high capacity ballast pump to deal with the Zeebrugge trimming ballast (16.2; pp.17).

30. Water in large quantities continued to flood trough the open bow doors aperture (9.3; pp.7).

5.2.2 Determining the Why-Because subset for each Intermediate/Top Event

Once all the information and evidence with respect to the accident are listed and organised as statements one by one, the causality among them becomes the most important issue in order to find out the answer of how and why the accident happened. Therefore, the aim of this process is to identify the Causal Factors as well as to clarify the causations between them according to the listed statements described in the preceding section. In this section, the Causal Sufficiency Criterion (CSC) of WBA is the major tool to transform these listed statements into Causal Factors and to clarify the causality among them. For the details of the process, section 4.2.3 is worth visiting.

Recall the definition of CSC that "*between a set of Causal Factors $A_1 \cdots A_N$ and a consequence event B, it is impossible for B not to have happened if all of $A_k; k \in [1,N]$ have happened* (Paul-Stüve, 2005)". This is similar to the definition of Cut Set of FTA; a *Cut Set* is a collection of *Basic Events* such that if they all occur the *Top Event* must also occur (Andrews and Moss, 2002). As mentioned before, the similarity between these two definitions is the reason why CSC is chosen as the tool to identify the Cut Set of Intermediate/Top events. The Cut Set is a set of direct Causal Factors which is sufficient to trigger a particular *Intermediate/Top Event* to occur where *Intermediate Events* are those events between *Top Event* and *Basic Event* in the fault tree. The process repeatedly goes through these listed statements with CSC to identify the direct Causal Factors relating to each Intermediate Event, one by one, from the top (i.e. Top Event) to the bottom (i.e. Basic Event) of the fault tree. In each step, the process only concentrates on one particular Intermediate Event in order to find out the sufficient direct Causal Factors for that event. Therefore, a Why-Because subset can be set accordingly. In the end, once all the Why-Because subsets relating to each Intermediate Event have been sorted out, the Why-Because Graph is able to be drawn for further analysis in the following steps (see Figure 5-1 below).

Normally each listed statement should be represented by a Causal Factor in which an event symbol (e.g. *A* or *L8*) is assigned in the analysis procedure. However, they are not necessarily one-to-one relationship although it is preferred. Sometimes, more than one Causal Factor refers to a single listed statement (see Figure 5-1 and LoF in section 5.2.3). Conversely, it is also possible that a single event symbol refers to more than one listed statement. For example, in the Why-Because Graph in Figure 5-1, event *J* shows the symbols (10) and (27) meaning that the corresponding facts are listed in statements No.10 and No.27 in section 5.2.1.

In this example, the process starts from the Top Event (i.e. the capsizing of Herald of Free Enterprise) by examining all the facts organised in the listed statements with the criteria (i.e. CSC) to identify all the direct Causal Factors which cause the Top Event to happen. In this way, the examination found that the factor "large quantity of water entered G deck (specified in sentence (4) of section 5.2.1)" is one of the direct Causal Factors that caused the Top Event (i.e. the capsize of the ship) to happen. This Causal Factor is hence added and labelled *A*, and an arrow arc is drawn from factor *A* to the Top Event as shown in Figure 5-1. Meanwhile factor *A* is also queued for further CSC examination. These arrow arcs infer that the direct Causal Factors (i.e. "Because" events) are the factors that cause the pointed event (i.e. "Why" event) to happen. In addition to Causal Factor *A*, there are two more Causal Factors existing; they are Causal Factors *B* and *C*. Causal Factor *C* is also identified from statement (4) and is defined as "lurch to port due to no enough upright GM force against Free Surface Instability (FSI)". Nevertheless, under the examination of CSC, factors *A* and *C* do not seem to be sufficient enough to trigger the Top Event to occur. The justification for including Causal Factor *B* is that, theoretically, a large amount of water inside the ship will not definitely cause the Free Surface Instability to occur. Ships can only capsize due to Free

Surface Instability when subject to three conditions simultaneously. These are: large amount of liquid inside the ship, no anti-FSI devices and the righting GM force of the ship is counteracted by excessive rolling. Therefore, a factor *B* of "No anti-FSI device" is justified to be added as the third Causal Factor of the Top Event. This addition is supported by a documentary program (Seconds from Disaster – Capsized in the North Sea) from National Geographic Channel (NGC, 2008). It is revealed that the absence of anti-FSI devices at the time should be accounted as one of the Causal Factors of the disaster. Examples of anti-FSI devices on vessels are longitudinal bulkheads (common, for example, on oil tankers), fast-draining scuppers or pumps (to remove water from the deck), transverse bulkheads/barriers to limit quantity and flow of water entering vessel. This examination results in three direct Causal Factors (i.e. factor *A*, *B* and *C*) being identified as the lined up holes of a Windows of Opportunity (WoO) in the Swiss Cheese Model, and are added into the Why-Because Graph with arrow arcs connecting to Top Event as the result. Up to this stage, the first CSC check against the Top Event is now accomplished.

In the next step, factors *A*, *B* and *C* become the Intermediate Events and their direct Causal Factors need sorting in turn. Since event *A* has events *D* and *F* as the direct Causal Factors (see Figure 5-1), Events *D* and *F* are queued for further CSC examination. Eventually there is no further CSC examination for event *H1* because it is assumed that its Causal Factors are out of the scope of the information gathered during the investigation or are not concerned in the analysis. Hence *H1* is treated as a Basic Event. That is, the process is iterated until reaching the limit of the information the investigation gathered or the boundary the analysis intended. Detailed CSC examinations for the rest of Intermediate Events of the accident are not specified further. Figure 5-1 contains the entire results. In the graph, the rectangles represent those Intermediate Events which are connected (or supported) by their direct Causal Factors while the circles denote those Basic Events which are the end of a branch of the fault tree.

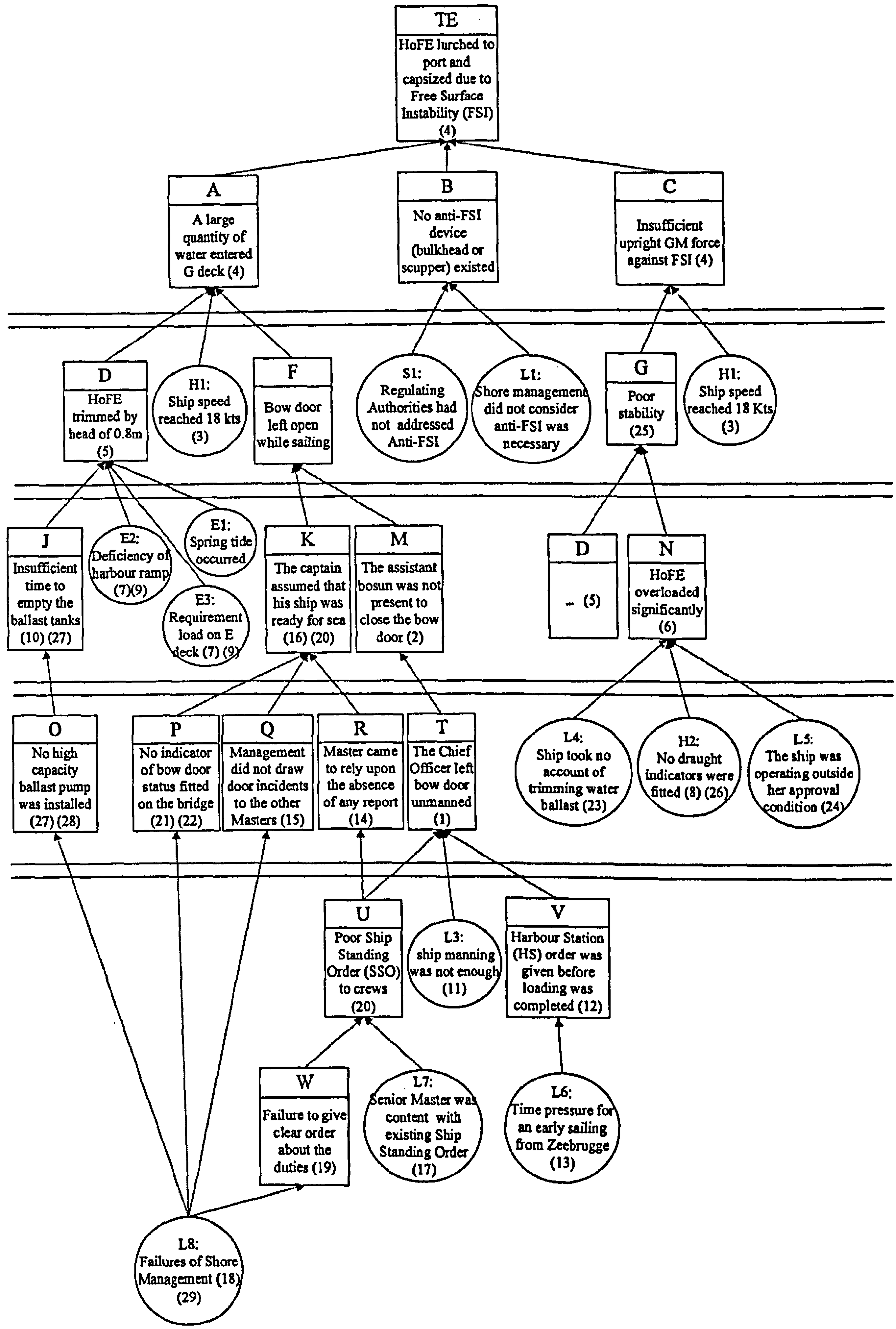


Figure 5-1 The Why-Because Graph of HoFE accident

5.2.3 Constructing the Why-Because Graph (WBG) and List of Factors (LoF)

In this process, as stated in sections 4.2.4 and 4.2.5, there are two goals. The first goal is to integrate all Why-Because subsets regarding every Intermediate Event (including the Top Event). The outcome of the integration is the Why-Because Graph (see Figure 5-1 as an example). This graph is built according to the results derived from the previous CSC examination, step by step, from the top to the bottom. The second goal is to organise a list of Causal Factors which are involved in the accident. At the tail of the description for each factor, a number, in parenthesis, indicates where a listed statement is derived from. This provides an index for rapid referencing between the listed factors and the listed statements. For example, "(4)" at the end of the description of factor *A* shows that factor *A* is derived from the listed statement No. 4 in section 5.2.1. Most of the listed statements have at least one corresponding event in the WGB whilst some of the symbols are concluded from two or more listed statements. For example, factors *A* and *C* are supported by the listed statement No. 4 while factor *J* is concluded from listed statements No. 10 and No. 27.

The following list is the complete LoF of the HoFE case and can be seen as a quick reference of the Causal Factors. It is also a useful auxiliary reference for the following processes.

- ⇨ TE (Top Event): HoFE lurched to port side and capsized due to Free Surface Instability (FSI)
- ⇨ A: A large quantity of water entered G deck (4)
- ⇨ B: No Anti-FSI device (bulkhead or scupper) existed
- ⇨ C: Insufficient upright GM force against FSI (4)
- ⇨ D: HoFE Trimmed by head of 0.8m (5)
- ⇨ E1: Spring tide occurred
- ⇨ E2: Deficiency of harbour ramp to load ship in all conditions (7)(9)
- ⇨ E3: Requirement load on E deck (7) (9)
- ⇨ F: Bow door left open while sailing (30)
- ⇨ G: Poor stability (25)

- ⇨ H1: Ship speed reached 18 Kts (3)
- ⇨ H2: No draught indicators were fitted (8) (26)
- ⇨ J: Insufficient time to empty the ballast tanks (10) (27)
- ⇨ K: The captain assumed that his ship was ready for sea (16) (20)
- ⇨ L1: Shore management did not consider anti-FSI was necessary
- ⇨ L3: Ship manning was not enough (11)
- ⇨ L4: Ship took no account of trimming water ballast (23)
- ⇨ L5: The ship was operating outside her approval condition (24)
- ⇨ L6: Time pressure for an early sailing from Zeebrugge (13)
- ⇨ L7: Senior Master was content with existing Ship's Standing Orders (17)
- ⇨ L8: Failures of Shore Management (18) (29)
- ⇨ M: The assistant bosun was not present to close the bow door (2)
- ⇨ N: HoFE overloaded significantly (6)
- ⇨ O: No high capacity ballast pump was installed (27) (28)
- ⇨ P: No indicator of bow door status fitted on the bridge (21) (22)
- ⇨ Q: Management did not draw door incidents to the other Masters (15)
- ⇨ R: Master came to rely upon the absence of any report (14)
- ⇨ S1: Regulating Authorities had not addressed FSI
- ⇨ T: The Chief Officer left bow door unmanned (1)
- ⇨ U: Poor Ship's Standing Order (SSO) to crews (20)
- ⇨ V: Harbour Station (HS) order was given before loading was completed (12)
- ⇨ W: Failure to give clear order about the duties (19)

5.3 Simplifying the approximate Minimal Cut Sets (MCS) and constructing the Bayesian Network model of Top Event

There are two goals in this process. They are: (1) clarifying the Minimal Cut Sets for each Intermediate Event and (2) constructing the Bayesian Network model of Top Event. So far, the analysed results obtained for each Intermediate Event are Cut Sets rather than Minimal Cut Sets. As stated earlier, the difference between Minimal Cut Sets and Cut Sets is that a Minimal Cut Set consists of *necessary and sufficient* Causal Factors whilst a Cut Set consists of *sufficient* Causal Factors. Thus, two techniques, *Karnaugh map* (K-map) and *K-style Conditional Probability Table* (K-CPT), are utilised in order to transform the Cut Sets into Minimal Cut Sets if they are achievable. In short, the approximate Minimal Cut Set is named as Minimal Cut Set hereafter. Later in the second half of this section an example will be illustrated to show how these two techniques work together to achieve the first goal. The theoretical background is covered in section 4.3. Having completed this transformation, a list of Boolean equations depicting the Minimal Cut Set(s) for each Intermediate Event is provided as one of the outcomes of the process. These Boolean equations are essential for constructing a Bayesian Network model of Minimal Cut Sets of an accident which is depicted in section 5.5.

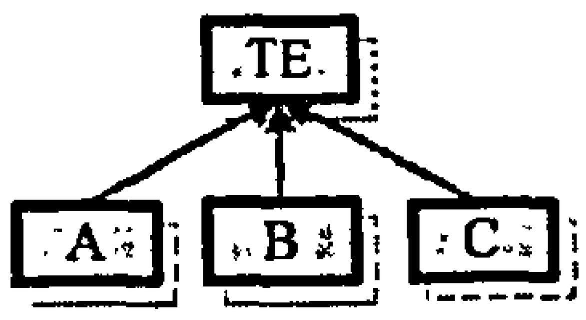
5.3.1 Determining the approximate Minimal Cut Set(s) for Intermediate Events

In the determining process (see Figure 5-2 as an example), the corresponding Why-Because Graph of an Intermediate Event (i.e. a Why-Because subset) is shown on the left of the figure, and the Boolean equation for the Minimal Cut sets is shown on the right. In the middle, the associated K-CPT and K-map are tabulated. Each row represents a subset and the transforming results are produced from the left to the right in turn according to the data in the column on the left, as the input source. Experts' estimates might be needed in K-CPT if the historical statistic data is not available, and the simplification rules of Karnaugh map (revealed in section 4.3.2) are applied for obtaining the minimised *sum-of-products* Boolean expressions for each Intermediate Event. In the following paragraph, the determining process applied on the Why-Because subset of Intermediate Event *A* is demonstrated as an example. The entire processing results are shown in Figure 5-2, Figure 5-3 and Figure 5-4. A list of Boolean expressions regarding the Minimal Cut sets of Intermediate Events of the case study is shown at the end of this section.

The determining process starts from the Top Event (i.e. the accident) and visits each Intermediate Event, which is drawn in a rectangle symbol in the Why Because Graph. Then, the execution of the process is similar to factorisation in algebra and only stops at the end of the branch, which is a Basic Event shown in a circle symbol. Therefore, each time, the process only necessarily focuses on one Why-Because subset for reasoning. For example, in the subset with regard to Intermediate Event A, the reasoning is only concentrated on event A and its direct Causal Factors; they are factors D, F and $H1$ (see Figure 5-2). The details of processing the rest of the Intermediate Events are not included, but the entire results of the process are shown in a means of graphs, maps, tables and Boolean equations in Figure 5-2, Figure 5-3 and Figure 5-4.

In event A, it is shown that about two thousands tonnes of sea water entered into the ship within 30 seconds because the bow door of the ship was widely opened (i.e. factor F) and the ship's speed reached 18 knots (i.e. factor $H1$) whilst the ship was trimmed by head (TBH) around 0.8m (i.e. factor D), according to the accident investigation report (DoT, 1987). Hence, it is presumed that the experts assign a value of "0.95" depicting the occurrence probability of event A subjecting to this condition. Therefore, the value is inputted into the entry of the K-CPT which represents factors $H1$, F and D appearing simultaneously (i.e. $H1=1$, $F=1$ and $D=1$ are given as the condition). Meanwhile, in the entry of "$(H1, F, D) = (1,1,0)$", "0.9" is given as the occurrence probability, which is almost the same as the previous one. This is because factor D is considered as a minor influencing factor when the bow wave reaches 4 metres above sea level due to the ship's speed reaches 18 knots and comes up with the shallow water effect occurring at the same time. In such circumstance, the entire bow door area was engulfed by the bow wave and factor D becomes relatively insignificant although it had been considered as an important Causal Factor at the first investigation.

This consideration had been confirmed by a full scale sea trial with her identical sister ship *Pride of Free Enterprise* which took place 9 weeks after the disaster. Both the model tests and the *Pride* experiment indicated clearly that at *Combinator 6*, which is a speed indication of about 18 knots, the bow wave welled up the bow doors, i.e. perhaps 2 m above the level of the top of the spade (DoT, 1987). The *Pride* sea trial also revealed that there was almost no bow wave reaching the bow door over the spade if the speed was under 15 knots, even though the ship (*Pride of Free Enterprise*) was ballasted and trimmed by head about 1 metre. Therefore, it is appropriate to assume that the probability given that $(H1, F) = (0, 1)$ is "0.1" no matter factor D existed or not. This means that the accident would almost not have happened if the ship's speed had not reached 18 knots in the entrance of the harbour, even though she (HoFE) was trimmed by head about 0.8 M with her bow door was opened. This also explains why the disaster had not happened before the HoFE accident, even though at least five incidents had been reported where the ships sailed with bow door open when proceeding to sea (DoT, 1987). Unfortunately, HoFE did not make it this time, due to a series of human errors compounded by her higher speed in the harbour and her heavy condition of loading. For the rest of the entries, as the bow door is closed ("$F=0$"), the probability values are very low and assigned "0.01". Once the K-CPT of event A has been accomplished, the associated K-map can be obtained if an appropriated approximate criterion is applied. For example, a value (in K-map) is deemed as one if it is larger than 0.8 (in K-CPT), and as zero (in K-map) if it is small than 0.2 (in K-CPT). Having set up the K-map, a simplified Boolean expression associated with the approximate Minimal Cut Sets of event A can be obtained following a K-map simplification procedure. An illustrated example is $A \approx H1 \cdot F$.



TE: capsized
A: flooding
B: no anti-FSI
C: reach CP

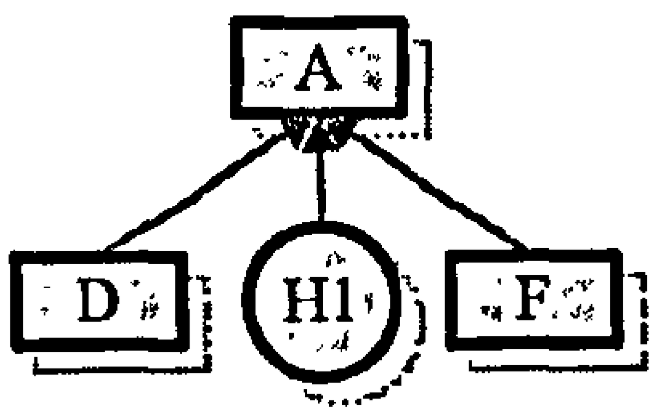
K-CPT:

	A=0	A=1
BC=00	0.01	0.05
BC=01	0.1	0.2
BC=11	0.1	0.99
BC=10	0.01	0.1

K-map:

	A=0	A=1
BC=00	≈0	≈0
BC=01	≈0	≈0
BC=11	≈0	≈1
BC=10	≈0	≈0

$$TE \approx A \cdot B \cdot C$$



A: flooding
D: TBH 0.8m
H1: over 18Kts
F: bow door opened

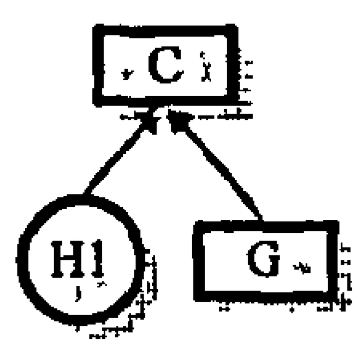
K-CPT:

	D=0	D=1
H1F=00	0.01	0.01
H1F=01	0.1	0.1
H1F=11	0.9	0.95
H1F=10	0.01	0.01

K-map:

	D=0	D=1
H1F=00	≈0	≈0
H1F=01	≈0	≈0
H1F=11	≈1	≈1
H1F=10	≈0	≈0

$$A \approx H1 \cdot F$$



C: Insufficient GM
H1: over 18Kts
G: poor stability

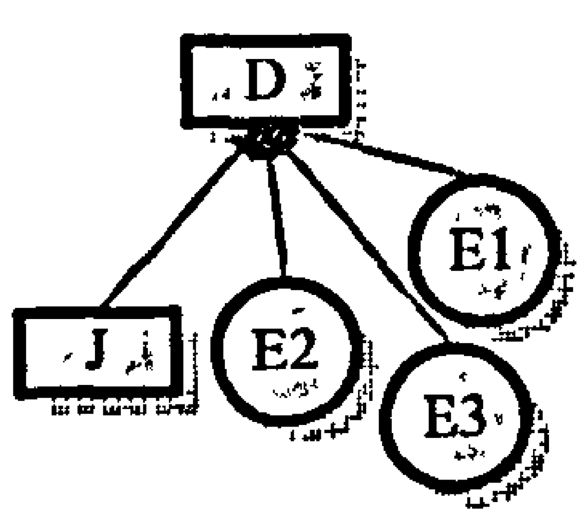
K-CPT:

	H1=0	H1=1
G=0	0.05	0.2
G=1	0.8	0.95

K-map:

	H1=0	H1=1
G=0	≈0	≈0
G=1	≈1	≈1

$$C \approx G$$



D: TBH 0.8m
E1: spring tide
E2: ramp deficiency
E3: E deck loading
J: more than 2hrs

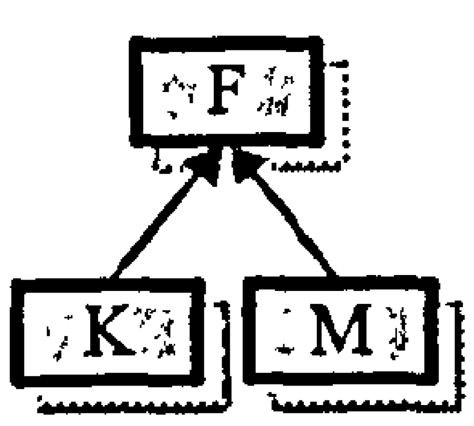
K-CPT:

	E1J=00	E1J=01	E1J=11	E1J=10
E2E3=00	0.01	0.01	0.01	0.01
E2E3=01	0.05	0.1	0.1	0.05
E2E3=11	0.05	0.9	0.9	0.05
E2E3=10	0.01	0.1	0.1	0.01

K-map:

	E1J=00	E1J=01	E1J=11	E1J=10
E2E3=00	≈0	≈0	≈0	≈0
E2E3=01	≈0	≈0	≈0	≈0
E2E3=11	≈0	≈1	≈1	≈0
E2E3=10	≈0	≈0	≈0	≈0

$$D \approx E2 \cdot E3 \cdot J$$



F: bow door opened
K: no re-check
M: Ass. Bosun was absent

K-CPT:

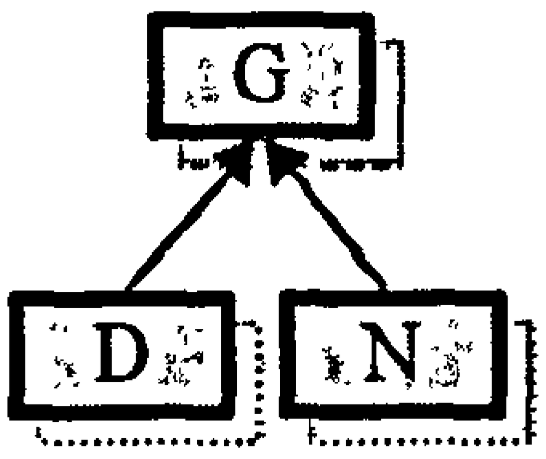
	K=0	K=1
M=0	0.01	0.01
M=1	0.1	0.99

K-map:

	K=0	K=1
M=0	≈0	≈0
M=1	≈0	≈1

$$F \approx K \cdot M$$

Figure 5-2 The determining process for approximate MCS (1/3)



G: poor stability
D: TBH 0.8m
N: overloaded

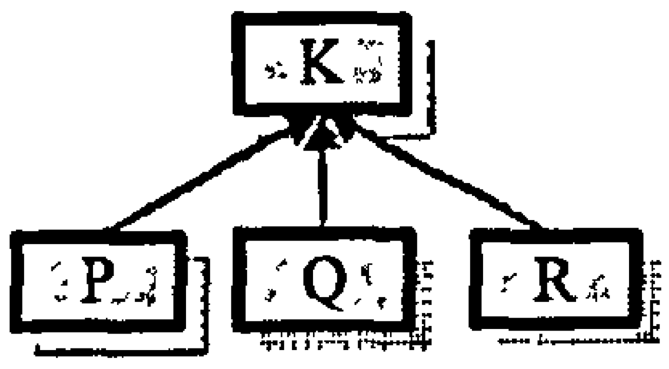
K-CPT:

	D=0	D=1
N=0	0.05	0.1
N=1	0.2	0.95

K-map:

	D=0	D=1
N=0	≈0	≈0
N=1	≈0	≈1

$$G \approx D \cdot N$$



K: no re-check
P: no BD indicator
Q: Master didn't know the incidents
R: no report is ready for sea

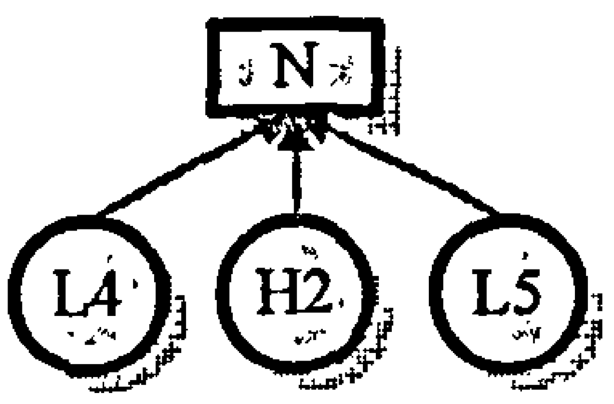
K-CPT:

	P=0	P=1
QR=00	0.01	0.6
QR=01	0.05	0.8
QR=11	0.9	0.99
QR=10	0.01	0.7

K-map:

	P=0	P=1
QR=00	≈0	≈1
QR=01	≈0	≈1
QR=11	≈1	≈1
QR=10	≈0	≈1

$$G \approx P + (Q \cdot R)$$



N: overloaded
H2: no draught indicator fitted
L4: not accounted ballast water
L5: operated outside the safe condition

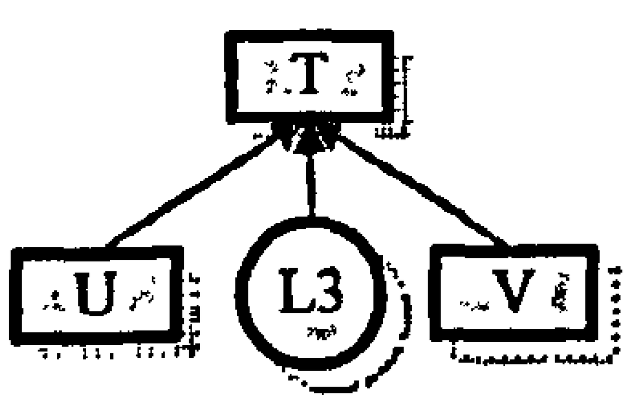
K-CPT:

	H2=0	H2=1
L4L5 =00	0.05	0.1
L4L5 =01	0.2	0.8
L4L5 =11	0.2	0.95
L4L5 =10	0.1	0.8

K-map:

	H2=0	H2=1
L4L5 =00	≈0	≈0
L4L5 =01	≈0	≈1
L4L5 =11	≈0	≈1
L4L5 =10	≈0	≈1

$$N \approx (H2 \cdot L4) + (H2 \cdot L5)$$



T: CO left earlier
L3: short of crew
U: poor SSO
V: earlier HS order

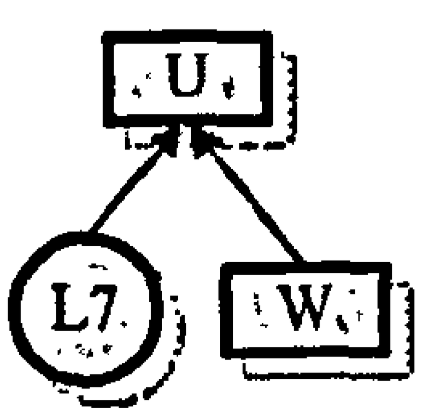
K-CPT:

	L3=0	L3=1
UV=00	0.05	0.8
UV=01	0.1	0.9
UV=11	0.9	0.99
UV=10	0.1	0.95

K-map:

	L3=0	L3=1
UV=00	≈0	≈1
UV=01	≈0	≈1
UV=11	≈1	≈1
UV=10	≈0	≈1

$$T \approx L3 + (U \cdot V)$$



U: poor SSO
W: order unclear
L7: content with existing SSO

K-CPT:

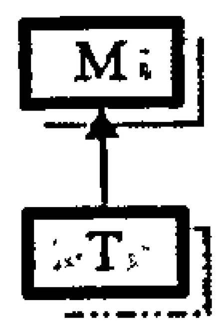
	W=0	W=1
L7=0	0.05	0.2
L7=1	0.1	0.95

K-map:

	W=0	W=1
L7=0	≈0	≈0
L7=1	≈0	≈1

$$U \approx W \cdot L7$$

Figure 5-3 The determining process for approximate MCS (2/3)



K-CPT:

T=0	0.01
T=1	0.8

K-map:

T=0	≈0
T=1	≈1

$M \approx T$

M: Ass. Bosun was absent
T: CO left earlier

The same procedure for:

J: insufficient time to empty the tanks
O: no high power ballast pump fitted
P: no bow door indicator fitted
Q: Masters was unaware the door incidents
R: Masters relied on the absent of any reports
V: HS order was given earlier
W: fail to give clearer order

Therefore:

$J \approx O$

$O \approx L8$

$P \approx L8$

$Q \approx L8$

$R \approx U$

$V \approx L6$

$W \approx L8$

Figure 5-4 The determining process for approximate MCS (3/3)

Once all of the Intermediate Events in the Why-Because Graph have passed the simplification process, the direct Causal Factors remaining in each Minimal Cut Set of the Intermediate Events can be considered as *Necessary Causal Factors*. This also means that they are the *necessary and sufficient* factors. A summary of the Boolean equations for the Minimal Cut Sets of these Intermediate Events is shown in Equation (5.1). However, it should be noted that the *Necessary Causal Factors* defined in the proposed method are those significant factors which can highly likely, instead of definitely, cause the Intermediate/Top Events to happen if they all occur. This is the side effect of the proposed approximate simplification law that some factors will be ignored due to the simplification. That is the simplification compromises the details of the Causal Factors in order to reveal the individual Window of Opportunities of the accident.

$$
\begin{aligned}
TE &\approx A\cdot B\cdot C \\
A &\approx H1\cdot F \\
C &\approx G \\
D &\approx E2\cdot E3\cdot J \\
F &\approx K\cdot M \\
G &\approx D\cdot N \\
J &\approx O \\
K &\approx P+(Q\cdot R) \\
M &\approx T \\
N &\approx H2\cdot(L4+L5)=(H2\cdot L4)+(H2\cdot L5) \\
O &\approx L8 \\
P &\approx L8 \\
Q &\approx L8 \\
R &\approx U \\
T &\approx L3+(U\cdot V) \\
U &\approx W\cdot L7 \\
V &\approx L6 \\
W &\approx L8
\end{aligned}
\tag{5.1}
$$

5.3.2 Constructing the Bayesian Network of Top Event of an accident

Having accomplished the first goal, the next task is to construct the Bayesian Network model of Top Event of an accident. By directly transforming the Why-Because Graph into the Directed Acyclic Graph and forming the Conditional Probability Table derived from the K-CPT, a Bayesian Network model in relative to the Top Event can be constructed accordingly. Figure 5-5 illustrates the corresponding Bayesian Network model of Top Event of the case study, and the data regarding the Conditional Probability Tables is tabulated in Appendix-A. Up to this stage, a Top Event model, without the details of Minimal Cut Sets, is accomplished and the quantitative analysis can be proceeded if the WoOs of the accident is not the issues concerned. The difference between these two models is that the Top Event model only shows the aggregated influences of the Causal Factors with respect to the accident, rather than the individual WoOs. In section 3.2, more details regarding this issue are covered. Again, as noted earlier and specified in section 4.3, the Minimal Cut Sets model of an accident is obtained by compromising the accuracy of the Causal Factors involved in order to gain the extra information of WoOs. The distortion of the analysis outcomes is unavoidable because of the approximate simplification of the method.

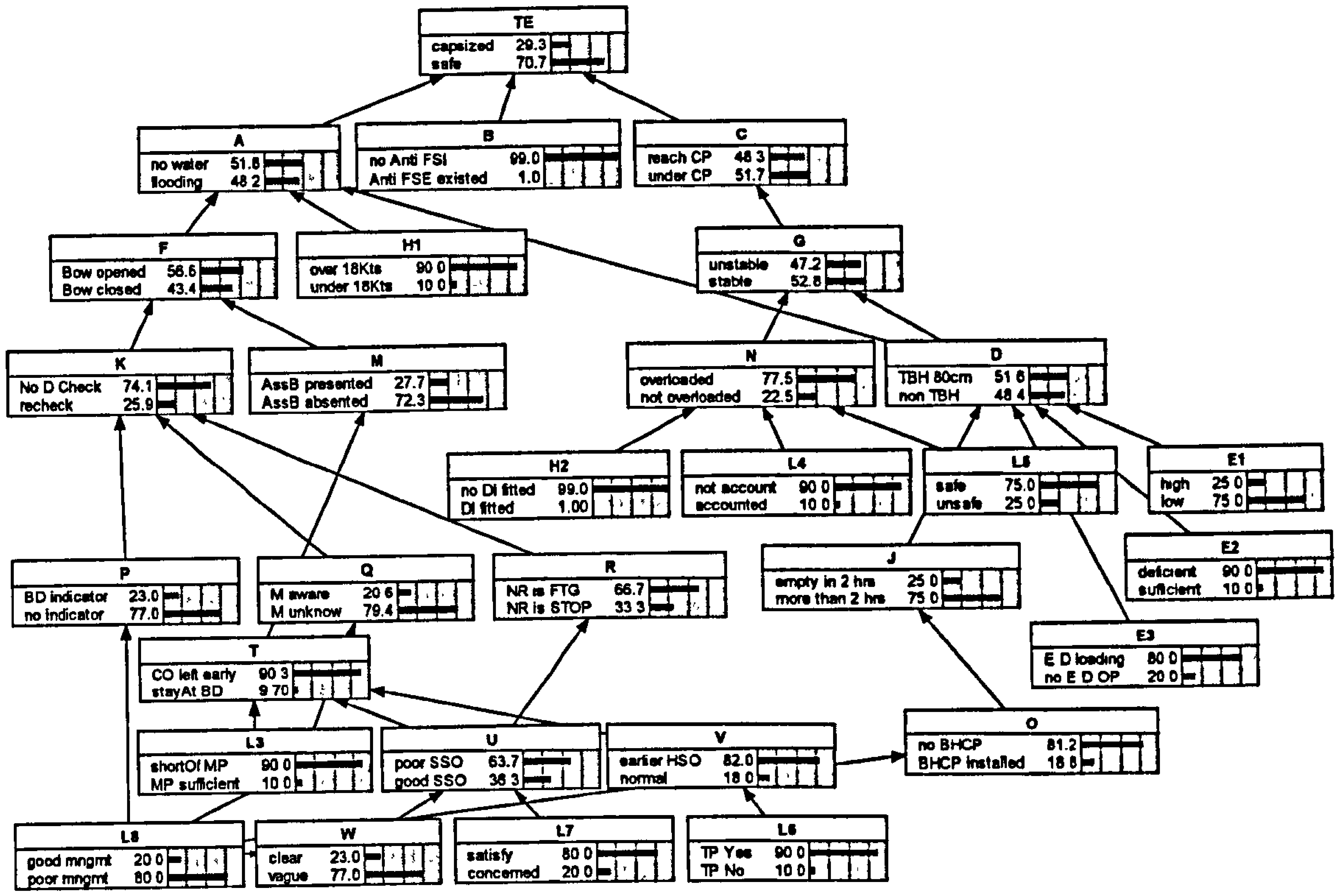


Figure 5-5 The Bayesian Network model of Top Event of HoFE

5.4 Applying Fault Tree Analysis (FTA) for finalising the qualitative analysis

Eventually, having clarified the Minimal Cut Sets for each Intermediate Event, the Minimal Cut Sets of an accident can be clarified by performing a factorisation operation with those Minimal Cut Sets of every Intermediate Event, in which Boolean algebra is used again. The theoretical explanations regarding this process are described in section 4.4. At the end of this process, all the possible Minimal Cut Set(s) of the accident will be revealed as part of the qualitative analysis results of the accident. As mentioned before, each Minimal Cut Set of the accident represents one of the Window of Opportunities to cause the accident to happen, which is represented by a combination of identified Basic Events. However, these Basic Events are not the only identified Causal Factors to cause the accident to happen, but simply the representatives. These Basic Events are the Causal Factors of those Intermediate Events whilst those Intermediate Events are the Causal Factors of the accident (i.e. Top Event). Those Intermediate Events are located in the middle of the causation branch and should not be overlooked even though they are not shown in the Minimal Cut Set(s) of Top Event. Later, in section 5.5, the case study will illustrate a comprehensive picture to discover those Intermediate Events through a backtracking process. Before backtracking, the Minimal Cut Set(s) of the accident has to be determined first. The tragedy of Herald of Free Enterprise is still the example utilised in the following process. For the theoretical details of the process, it is worthy to revisit the explanations in section 4.4.

5.4.1 Determining the approximate Minimum Cut Sets of the accident

Although factors *S1* and *L1* have been denoted in the Why-Because Graph of the accident as the Necessary Causal Factors of event *B* (i.e. No Anti-FSI device (bulkhead or scupper) existed) in the preceding section, there is no intention to discuss it further since there is no official evidence to support this speculation. Therefore there is no factorisation operation for event *B*. This means that event *B* will not be substituted by factors *S1* and *L1* in the following process.

The determining process starts from the Top Event again. In the first row of Equation (5.2), the Top Event is replaced by "$A \cdot B \cdot C$", which is shown on the right hand side of the approximation sign. This determination derives from the summary of Minimal Cut Sets of Intermediate/Top Events, which are concluded in section 5.3.1. It shows that there are three events deemed as the Necessary Causal Factors of the Top Event. Subsequently, in the second row of the equations events *A* and *C* are replaced by $(H1 \cdot F)$ and *G* respectively, according to the summary. Then event *F* is replaced by $(K \cdot M)$, and *G* is replaced by $(D \cdot N)$, and so on for the rest of succeeding Intermediate Events. This means that these Intermediate Events are iteratively replaced by their Minimal Cut Set(s), and then the Minimal Cut Set(s) replaced by their Necessary Causal Factors, until reaching the bottom of the Why-Because Graph, which is a circle symbol in the graph denoted as a Basic Event. In the end, there are only Basic Events left in the equations, such as *H1* and *L8*, etc. During the determining process, the properties or axiom laws of Boolean algebra have to be applied in order to obtain the most simplified results. The absorption property, for example, reduces the number of the terms for event *A* from four down to two in the last second row of the equation. This is because that two identical $(\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L7} \cdot \mathrm{L6})$ items can be simplified into one (i.e. $A + A = A$ or $A \vee A = A$) in Boolean algebra.

Finally there are only four Minimal Cut Sets yielded as the result of the process; they are *MCS1~MCS4*. This means that the accident can occur provided that any one of the Minimal Cut Sets occurs. When an insight is taken into these equations, it reveals that all of the factors involved can be divided into three major parts; they are portions *A*, *B* and *C*. For example, in Equation (5.2) the $(H1 \cdot \mathrm{L8} \cdot L3)$ is denoted as *A1* and the $(E2 \cdot E3 \cdot \mathrm{L8} \cdot H2 \cdot L4)$ is as *C1* for *MCS1*. It also can be seen as that factors *H1*, *L8* and *L3* eventually trigger event *A* to occur and the combination of factors *E2*, *E3*, *L8*, *H2* and *L4* makes event *C* happen. However there is another combination of the factors that can trigger event *A* to happen; this is $(H1 \cdot \mathrm{L8} \cdot \mathrm{L7} \cdot \mathrm{L6})$ denoted as *A2* in short. The same as event *A*, there are two combinations of the factors that can provoke event *C*; they are $(E2 \cdot E3 \cdot \mathrm{L8} \cdot H2 \cdot L4)$ denoted as *C1* and $(E2 \cdot E3 \cdot \mathrm{L8} \cdot H2 \cdot L5)$ denoted as *C2* respectively. As long as events *A*, *B* and *C* occur at the same time, the Top Event occurs no matter which combination of these factors triggers events *A* and *C* to happen. That is why there are four possible combinations of the factors that could make the accident happen.

$$
\begin{aligned}
& TE \approx A \cdot B \cdot C \\
& \approx (H1 \cdot F) \cdot B \cdot G \\
& \approx (H1 \cdot K \cdot M) \cdot B \cdot (D \cdot N) \\
& \approx [H1 \cdot (P + \mathrm{Q} \cdot R) \cdot T] \cdot B \cdot \{(E2 \cdot E3 \cdot J) \cdot [(H2 \cdot L4) + (H2 \cdot L5)]\} \\
& \approx [H1 \cdot (P + \mathrm{Q} \cdot R) \cdot (L3 + U \cdot V)] \cdot B \cdot \{(E2 \cdot E3 \cdot O) \cdot [(H2 \cdot L4) + (H2 \cdot L5)]\} \\
& \approx [(H1 \cdot P \cdot L3) + (H1 \cdot P \cdot U \cdot V) + (H1 \cdot \mathrm{Q} \cdot R \cdot L3) + (H1 \cdot \mathrm{Q} \cdot R \cdot U \cdot V)] \cdot B \cdot \\
& \quad [(E2 \cdot E3 \cdot O \cdot H2 \cdot L4) + (E2 \cdot E3 \cdot O \cdot H2 \cdot L5)] \\
& \approx [(\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \langle W \cdot L7 \rangle \cdot \mathrm{L6}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot U \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot U \cdot \langle \mathrm{W} \cdot \mathrm{L7} \rangle \cdot \mathrm{L6})] \\
& \quad \cdot \mathrm{B} \cdot [(\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L4}) + (\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L5})] \\
& \approx [(\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \langle \mathrm{L8} \cdot \mathrm{L7} \rangle \cdot \mathrm{L6}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \langle \mathrm{W} \cdot \mathrm{L7} \rangle \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \langle \mathrm{L8} \cdot \mathrm{L7} \rangle \cdot \mathrm{L6})] \\
& \quad \cdot \mathrm{B} \cdot [(\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L4}) + (\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L5})] \\
& \approx [(\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L7} \cdot \mathrm{L6}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \langle \mathrm{L8} \cdot \mathrm{L7} \rangle \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L7} \cdot \mathrm{L6})] \\
& \quad \cdot \mathrm{B} \cdot [(\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L4}) + (\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L5})] \\
& \approx [(\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L3}) + (\mathrm{H1} \cdot \mathrm{L8} \cdot \mathrm{L7} \cdot \mathrm{L6})] \cdot \mathrm{B} \cdot [(\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L4}) + (\mathrm{E2} \cdot \mathrm{E3} \cdot \mathrm{L8} \cdot \mathrm{H2} \cdot \mathrm{L5})] \\
& \approx MCS1 + MCS2 + MCS3 + MCS4
\end{aligned}
\tag{5.2}
$$

where:

$$MCS1 = (H1 \cdot L8 \cdot L3) \cdot B \cdot (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4) = A1 \cdot B \cdot C1$$
$$MCS2 = (H1 \cdot L8 \cdot L3) \cdot B \cdot (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5) = A1 \cdot B \cdot C2$$
$$MCS3 = (H1 \cdot L8 \cdot L7 \cdot L6) \cdot B \cdot (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4) = A2 \cdot B \cdot C1$$
$$MCS4 = (H1 \cdot L8 \cdot L7 \cdot L6) \cdot B \cdot (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5) = A2 \cdot B \cdot C2$$
$$A1 = (H1 \cdot L8 \cdot L3)$$
$$A2 = (H1 \cdot L8 \cdot L7 \cdot L6)$$
$$C1 = (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4)$$
$$C2 = (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5)$$

The Minimal Cut Sets which could cause the accident to happen have been revealed through a systematic procedure.. Nevertheless it is dangerous to only focus on these Basic Events and overlook those Intermediate Events since they do not emerge in the Minimal Cut Sets. One thing should be kept in mind is that these Intermediate Events are still the Causal factors (the same as Basic Events) to make the holes exist in the layers forming the *Window of Opportunities.* Later, in section 5.6, the case study will show an example that the accident can be prevented by blocking any one of the holes due to these holes can be shut by reducing the occurrence probabilities of one or few associated Causal Factors, including those Intermediate Events. It will also show why the likelihoods of different Minimal Cut Sets are not the same.

FTA technique is capable of doing qualitative analysis as well as quantitative analysis provided all the Basic Events are mutually independent. This assumption is almost impossible to comply with in the method because the identified Basic Events involved in an accident are normally correlative to each other. Therefore another appropriate technique has to be applied in order to overcome this difficulty. Bayesian Network is hence chosen as the technique to handle the quantitative analysis of an accident. In the following section, the way to carry out the quantitative analysis with Bayesian Network is under the spotlight.

5.5 Applying Bayesian Network (BN) for quantitative analysis

In this section, the processes to establish a corresponding Bayesian Network model regarding the Minimal Cut Sets of an accident, according to the qualitative analysis results acquired in the preceding sections, for the quantitative analysis are discussed. It is crucial to ensure that the established Bayesian Network model is able to present all the identified Causal Factors without overlooking any Intermediate Event. Therefore, a backtracking process, which consists of two operations, to sort out the Intermediate Events involved and the correlation between them has to be done before constructing the model of the accident. The backtracking process mainly reveals the clues as to which Basic Events in the Minimal Cut Sets can influence those Intermediate Events. It is a step by step process, from those Basic Events to the Top Event. These backtracking paths, which are highlighted by the circles and arrows shown in Equations (5.4) and (5.5), are very useful for finding the backtracking equations. These equations will then become the essential blueprints for constructing the corresponding Bayesian Network model in the next stage. For the purpose of quick reference, all the Intermediate Events involved in the model are summarised in the second half part of the equations (i.e. the "*where*" part) with their influencing events (i.e. the Causal Factors shown on the right hand side of the approximation sign). For validation, it is very important to examine the equivalency, in the equations, between the factorisation part and backtracking part from time to time. It is also the way to ensure that the backtracking outcomes are correct otherwise some Intermediate Events will easily be overlooked. Later, in section 5.5.3, an incorrect example will be demonstrated to show a potential problem which is prone to overlooking those Intermediate Events and a proposed validation mechanism to avoid it.

5.5.1 Backtracking the Intermediate Events via the factorisation equations of Minimum Cut Sets

In section 5.4, the Minimal Cut Sets of an accident are represented by sets of Basic Events. However the Intermediate Events lying between those Basic Events and the Top Event in the fault tree should be taken into account as well. The process to sort out those Intermediate Events involved starts from the Minimal Cut Sets of the accident. By utilising the Why-Because causation (i.e. the factorisation equations), the process can track back the corresponding Cause-Consequence relationship from the Basic Events of the Minimal Cut Sets through the associated Intermediate Events to the Top Event, and then sort out the backtracking paths and Intermediate Events involved. For more details regarding this issue, section 4.5.2 is worthy to revisit. The systematic procedure to track back the Intermediate Events of the case study is described in the following sections.

5.5.1.1 Factorisation operation (Downward Why-Because)

In section 5.4, it has been showed that the HoFE tragedy was triggered by four Minimal Cut Sets, which are represented by sets of Basic Events. In order to clearly demonstrate how the backtracking process works, the Necessary Causal Factors of event A (including the in-between Intermediate Events) are used as an example. The process starts from revisiting the factorisation equations related to event A and finds that it has two Minimal Cut Sets involved; they are $A1=(H1\cdot L8\cdot L3)$ and $A2=(H1\cdot L8\cdot L7\cdot \mathrm{L6})$. They are two Sets of Basic Events representing those Necessary Causal Factors to provoke event A to occur. Equation (5.3) is elicited from the portion associated with event A in the factorisation equations (i.e. Equation (5.2)) in order to present a clearer view of the process without unnecessary clutter.

In Equation (5.3), it shows where *A1* and *A2* derive from. It also implies the *Why-Because* causation between each row, and the row above/below. For instance, the differences between the second and third rows show that event *K* (the consequence) is triggered when either event *P* occurs or events *Q* and *R* happen simultaneously. In addition, the reasons why events *P* or *Q* can occur are because factor *L8* exists in the fifth row while event *R* is influenced by event *U*, and so on. The factorisation operation described in Equations (5.2) and (5.3) can be seen as the Downward *Why-Because* path leading from the Top Event at the top of the fault tree to the Basic Event at the bottom of the tree.

$$
\begin{aligned}
A &\approx H1\cdot F\\
&\approx H1\cdot(K\cdot M)\\
&\approx H1\cdot(P+Q\cdot R)\cdot M\\
&\approx (H1\cdot P\cdot M)+(H1\cdot Q\cdot R\cdot M)\\
&\approx (H1\cdot L8\cdot T)+(H1\cdot L8\cdot U\cdot T)\\
&\approx (H1\cdot L8\cdot T)\\
&\approx H1\cdot L8\cdot(L3+U\cdot V)\\
&\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot U\cdot V)\\
&\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot W\cdot L7\cdot L6)\\
&\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L8\cdot L7\cdot L6)\\
&\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L7\cdot L6)\\
&\approx A1+A2\\
&\textit{where}:\\
A1 &= (H1\cdot L8\cdot L3)\\
A2 &= (H1\cdot L8\cdot L7\cdot \mathrm{L6})
\end{aligned}
\qquad (5.3)
$$

5.5.1.2 Backtracking operation (Upward Cause-Consequence)

Although, the details regarding the downward operation of the equations have been shown above, further analysis of the equations is required in order to sort out the Cause-Consequence correlation (i.e. backtracking equations) to build the Bayesian Network model of the accident for the quantitative analysis. That is, a backtracking operation of the equations is needed and is illustrated as follows.

As mentioned before, event *A* is neither directly triggered by events *H1*, *L8* and *L3* (i.e. the Minimal Cut Set *A1*) nor events *H1*, *L8, L7* and *L6* (i.e. the Minimal Cut Set *A2*), but through a series of Intermediate Events. The reverse *Why-Because* path (i.e. the Cause-Consequence correlation) from these Basic Events to event *A* have to be clarified in order to identify which Intermediate Events are involved. This process starts from the last row of the factorisation equations which are labelled as *A1* and *A2.* When backtracking to event *T*, it reveals that (*L3*) and (*UV*) are the Minimal Cut Sets of event *T* respectively, and that is the main reason why there are two Minimal Cut Sets for event *A*. Therefore a new symbol *T1* is utilised to denote the situation that event *T* is triggered via event *L3* (i.e. $T1 \approx L3$). Meanwhile another symbol *T2* denotes that event *T* is triggered by events *U* and *V* when they occur simultaneously (i.e. $T2 \approx U \cdot V$). Now, event *T* can also be expressed as *(T1+T2)* in the backtracking equations resulting from the two Minimal Cut Sets triggering event *T* to occur. Subsequently, the propagation of event *T* results in the propagation of event *M.* That is, two extra symbols (i.e. *M1* and *M2*) are applied to depict that event *M* is triggered by which Minimal Cut Sets of event *T* respectively (i.e. $M1 \approx T1$ and $M2 \approx T2$). This is justified from the factorisation of $M \approx T$ denoted in Equation (5.1). In the same way, symbol *K1* is used to denote event *K* is triggered by event *P* (i.e. $K1 \approx P$) as well as symbol *K2* for it is provoked when event *Q* and *R* occur at the same time (i.e. $K2 \approx Q \cdot R$).

When backtracking the Minimal Cut Set *A2* for event *A*, there are two factors *L8* identified (as shown in row 9 of equation (5.4)), one derived from event *W* (see the circle mark with an arrow in row 9 of Equation (5.4)), and the other one from event *Q* or *P* (in row 4). However, only one *L8* is left in the end of the factorisation equations because of the idempotency property (i.e. $A + A = A$ or $A \cdot A = A$) of Boolean algebra (see row 10 of Equation (5.4)). Thus event *L8* should be restored to two instances before tracking back to event *W* (from row 9 to row 8) while joining with event *L7* (i.e. $W \cdot L7$)

for event U (row 7). In addition, event $L6$ (in row 8 of the equation (5.4)) comes from event V (row 7). It is revealed when rows 7 and 8 of the equations are compared. In Equation (5.4), there is always a corresponding *backtracking/upward equation* on the right hand side in addition to the *factorisation/downward equations.* Although the backtracking equations look slightly different from their counter part on the left hand side, both of them are equivalent except using different symbols to denote the same thing. For example, in row 7 of Equation (5.4), event T was replaced by $(L3+U\cdot V)$ during factorisation. This means that it has two Minimal Cut Sets which are represented by $(L3)$ and $(U\cdot V)$ respectively. Hence, the symbol $T1$ is utilised to denote the condition influenced by $L3$ and the symbol $T2$ for the condition of $U\cdot V$ (row 6) during backtracking. Thas is, despite the expressions on both sides are slightly different, the equivalency between both sides should be kept. In a similar fashion, another two symbols $F1$ and $F2$ (row 1) are added into the backtracking outcome for event F to denote the situation of $(K1\cdot M1)$ and $(K2\cdot M2)$ respectively (i.e. $F1\approx K1\cdot M1$ and $F2\approx K2\cdot M2$), and eventually revealing $A1\approx H1\cdot F1$ and $A2\approx H1\cdot F2$ to end the backtracking operation. In the end, the backtracking equations for event A, consisting of Minimal Cut Set $A1$ and $A2$ in factorisation part, are summarised in the "*where*" part of Equation (5.4).

Factorisation

$$
\begin{aligned}
&1.)\ A \approx H1\cdot F\\
&2.)\ \approx H1\cdot(K\cdot M)\\
&3.)\ \approx H1\cdot(P+Q\cdot R)\cdot M\\
&4.)\ \approx (H1\cdot P\cdot M)+(H1\cdot Q\cdot R\cdot M)\\
&5.)\ \approx (H1\cdot L8\cdot T)+(H1\cdot L8\cdot U\cdot T)\\
&6.)\ \approx (H1\cdot L8\cdot T)\\
&7.)\ \approx H1\cdot L8\cdot(L3+U\cdot V)\approx(H1\cdot L8\cdot L3)+(H1\cdot L8\cdot U\cdot V)\\
&8.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot W\cdot L7\cdot L6)\\
&9.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L8\cdot L7\cdot L6)\\
&10.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L7\cdot L6)\\
&11.)\ \approx A1+A2
\end{aligned}
$$

Backtracking

$$
\begin{aligned}
&1.)\ A \approx H1\cdot(F1+F2)\\
&2.)\ \approx H1\cdot[(K1\cdot M1)+(K2\cdot M2)]\\
&3.)\ \approx (H1\cdot K1\cdot M1)+(H1\cdot K2\cdot M2)\\
&4.)\ \approx (H1\cdot P\cdot M1)+(H1\cdot Q\cdot R\cdot M2)\\
&5.)\ \approx (H1\cdot L8\cdot T1)+(H1\cdot L8\cdot U\cdot T2)\\
&6.)\ \approx H1\cdot L8\cdot(T1+T2)=(H1\cdot L8\cdot T1)+(H1\cdot L8\cdot T2)\\
&7.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot U\cdot V)\\
&8.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot W\cdot L7\cdot L6)\\
&9.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L8\cdot L7\cdot L6)\\
&10.)\ \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L7\cdot L6)\\
&11.)\ = A1+A2
\end{aligned}
\tag{5.4}
$$

where:

$A1 \approx (H1 \cdot L8 \cdot L3) \approx (H1 \cdot P \cdot T1) \approx (H1 \cdot K1 \cdot M1) \approx H1 \cdot F1$

$A2 \approx (H1 \cdot L8 \cdot L7 \cdot L6) \approx (H1 \cdot L8 \cdot L8 \cdot L7 \cdot L6) \approx (H1 \cdot L8 \cdot W \cdot L7 \cdot V) \approx (H1 \cdot L8 \cdot U \cdot V)$

$\quad \approx (H1 \cdot L8 \cdot U \cdot U \cdot V) \approx (H1 \cdot L8 \cdot U \cdot T2) \approx (H1 \cdot Q \cdot R \cdot M2) \approx (H1 \cdot K2 \cdot M2) \approx H1 \cdot F2$

$F1 \approx K1 \cdot M1$

$F2 \approx K2 \cdot M2$

$K1 \approx P$

$K2 \approx Q \cdot R$

$M1 \approx T1$

$M2 \approx T2$

$T1 \approx L3$

$T2 \approx U \cdot V$

$P \approx L8$

$Q \approx L8$

$R \approx U$

$U \approx W \cdot L7$

$V \approx L6$

$W \approx L8$

The backtracking process for event *A* is now completed. So far, there is no backtracking process for event *B* since no factorisation has taken place.

In the backtracking of event *C*, the operation starts at the end of the factorisation equations of event *C*. However the following discussion will only focus on the details of the backtracking part without discussing the factorisation of event *C*. Equation (5.5) contains the factorisation details (on the left hand side, elicited from Equation (5.2)) and the backtracking equations (on right) for event *C*. There are two Minimal Cut sets represented by two set of Basic Events that can provoke event *C* to occur. They are $(E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4)$ and $(E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5)$, and are labelled as *C1* and *C2* respectively in the factorisation equations. Moreover, event *L8* (in row 5) replaces event *O* (in row 4) for both *C1* and *C2* in the factorisation part of Equation (5.5). Therefore, in the backtracking equations, it is obvious that event *O* was caused by event *L8*. In other words, event *L8* is the only factor to determine whether event *O* occurs or not. Meanwhile, event *J* is influenced by event *O*. In addition, event *N* was replaced by "$(H2 \cdot L4)+(H2 \cdot L5)$" (row 3) when performing the factorisation. Hence, during the backtracking, two different symbols, *N1* and *N2*, are utilised to label these two Minimal Cut Sets of event *N* respectively (i.e. *N1* $\approx$ $(H2 \cdot L4)$ and *N2* $\approx$ $(H2 \cdot L5)$). This means that either *N1* or *N2* can provoke event *N* to happen. It is also similar to the occurrence of event *G*. Therefore two new symbols, *G1* and *G2*, are added to depict the provoking condition of $(D \cdot N1)$ and $(D \cdot N2)$ respectively for event *G*. It is quite straightforward to define event *D* since it consists of events *E2*, *E3* and *J* (row 3). Eventually, the backtracking results for event *C* with regard to correlative Intermediate Events are finalised and summarised in the "*where*" part of the equations. In these equations, the factors on the right hand side of the approximation sign are the Necessary Causal Factors to the Intermediate Events (on left). Again, for validation, the equivalency between both sides of the equations has to be kept from time to time. As noted previously, these backtracking equations are the essential information, as the blueprints, to construct the Bayesian Network model of Minimal Cut sets of an accident. It is vital to secure the backtracking results are correct. Finally, the backtracking process is completed and is possible to conduct the Bayesian Network model constructing process, which mainly relies on the summarised backtracking equations shown in Equation (5.4) for event *A*, and Equation (5.5) for event *C*.

Factorisation	Backtracking
1.) $C \approx G$	1.) $C \approx G1 + G2$
2.) $\approx D \cdot N$	2.) $\approx D \cdot (N1 + N2) = (D \cdot N1) + (D \cdot N2)$
3.) $\approx (E2 \cdot E3 \cdot J) \cdot [(H2 \cdot L4) + (H2 \cdot L5)]$	3.) $\approx (E2 \cdot E3 \cdot J) \cdot (N1 + N2)$
4.) $\approx (E2 \cdot E3 \cdot O \cdot H2 \cdot L4) + (E2 \cdot E3 \cdot O \cdot H2 \cdot H5)$	4.) $\approx (E2 \cdot E3 \cdot O \cdot N1) + (E2 \cdot E3 \cdot O \cdot N2)$
5.) $\approx (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4) + (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5)$	5.) $\approx (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4) + (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5)$
6.) $\approx C1 + C2$	6.) $\approx C1 + C2$

(5.5)

$$
\begin{aligned}
&where: \\
&C1 \approx (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L4) \approx (E2 \cdot E3 \cdot O) \cdot (H2 \cdot L4) \approx (E2 \cdot E3 \cdot J) \cdot N1 \approx D \cdot N1 \approx G1 \\
&C2 \approx (E2 \cdot E3 \cdot L8 \cdot H2 \cdot L5) \approx (E2 \cdot E3 \cdot O) \cdot (H2 \cdot L4) \approx (E2 \cdot E3 \cdot J) \cdot N2 \approx D \cdot N2 \approx G2 \\
&G1 \approx D \cdot N1 \\
&G2 \approx D \cdot N2 \\
&D \approx E2 \cdot E3 \cdot J \\
&N1 \approx H2 \cdot L4 \\
&N2 \approx H2 \cdot L5 \\
&J \approx O \\
&O \approx L8
\end{aligned}
$$

5.5.2 Constructing the Directed Acyclic Graph (DAG) of the Bayesian Network model for Minimal Cut sets

Having accomplished the backtracking process, lists of backtracking equations are revealed. In the HoFE example, the backtracking equations are shown in the "*where*" part of Equations (5.4) and (5.5). They are the blueprints for constructing the DAG of Bayesian Network of the accident in this process. The way to establish the DAG is described in section 4.5.3 and is briefed as follows. An arc connects from an influencing (parent or predecessor) node to an influenced (child or successor) node and has the arrowhead toward the child node (Wang and Trbojevic, 2007). Therefore, at the beginning, the DAG starts the construction from the Top Event, which is now represented by four Minimal Cut Sets (i.e. *MCS1~MCS4*). Since the process has to deal with them in turn, *MCS1* is the first one to be handled. The *MCS1* consists of $A1 \cdot B \cdot C1$, according to Equation (5.2) in section 5.2.1. This implies that *MCS1* is provoked (or influenced) by these three Causal Factors. Thus, node *MCS1*, which is one of the proxies of Top Event, is placed first. Subsequently, nodes *A1*, *B* and *C1* are added into the DAG respectively with an arc, depicting the influence relationship, toward node *MCS1* to establish the correlations amongst them (see Figure 5-6). These connections are in light of the equations (i.e. $MCS1 \approx A1 \cdot B \cdot C1$), which means that node *MCS1* is the successor of these three new added nodes. In addition, according to the backtracking equations (5.4) summarised in section 5.5.1, factor *A1* is influenced by factors *H1* and *F1* (i.e. $A1 \approx H1 \cdot F1$). Therefore, two new added nodes, *F1* and *H1*, are joined as the predecessor of node *A1*. In a similar fashion, another arrow arc connects node *C1* with node *G1* expressing *G1* is the predecessor of *C1*, according to $C1 \approx G1$ depicted in the backtracking equations (5.5). After further step by step processing through the backtracking equations in turn, the DAG of Bayesian Network for *MCS1* is eventually accomplished when all the Intermediate Events, as well as Basic Events, involved have been placed in the DAG accordingly. The process is carried out on the other Minimal Cut Sets in the same way and finally builds up the entire DAG of Bayesian Network model for the Minimal Cut sets of the accident. In the end, Figure 5-6 is the whole picture showing the DAG with around forty nodes included.

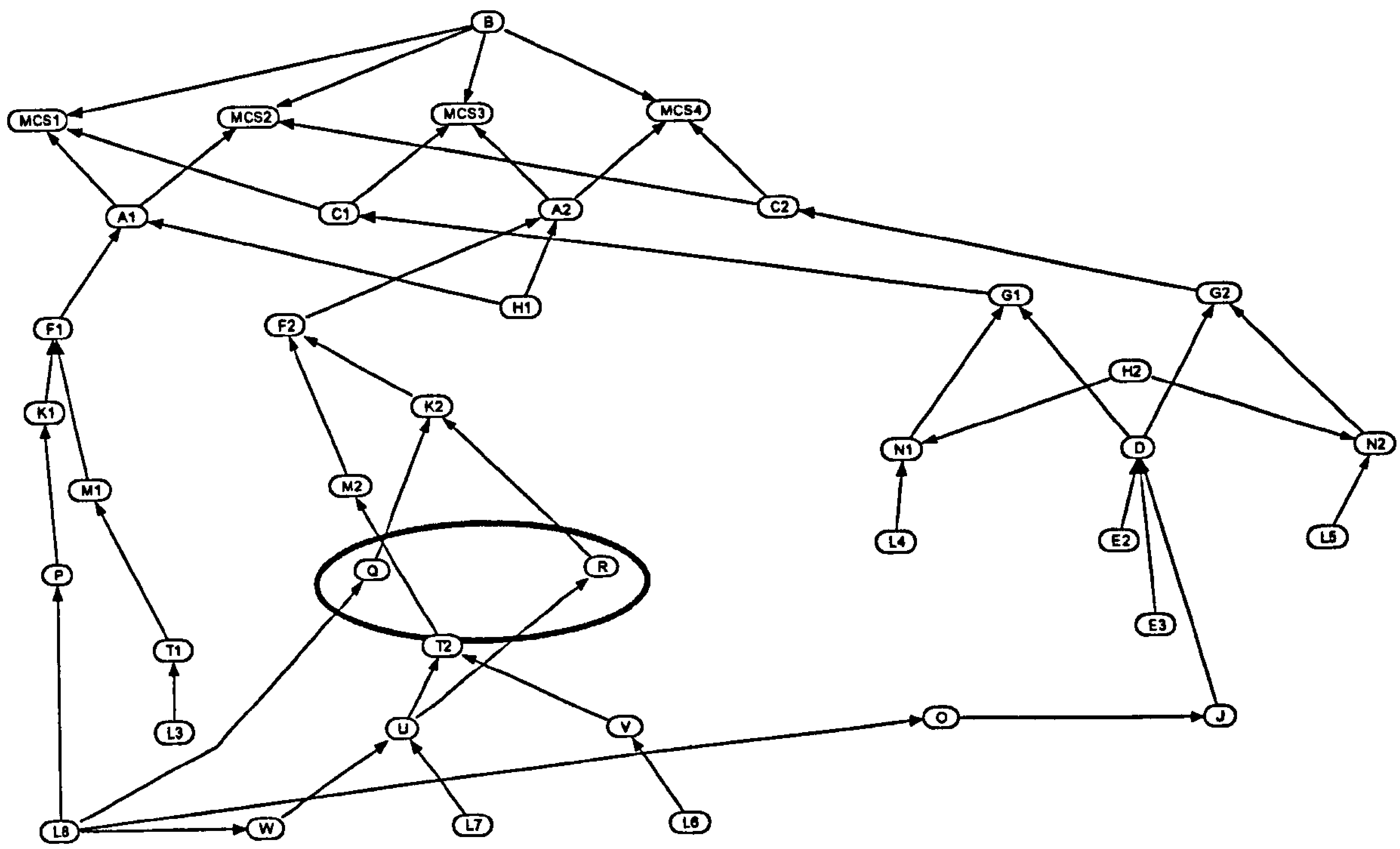


Figure 5-6 The Bayesian Network model for HoFE accident

5.5.3 The absorption problem while backtracking

Although the construction of the DAG of Bayesian Network model for the accident has been accomplished in the preceding section, there is one aspect regarding the backtracking process that needs further consideration. As specified in section 4.5.4, it is the problem caused by absorption, in which the Intermediate Events are wrongly tracked back due to the fact that more than one backtracking path, from the Basic Events to the Top Event, is available. For instance, the absorption problem might occur in the backtracking of event *A* in the HoFE example.

In order to highlight this issue, part of Equation (5.2) in section 5.4.1 regarding event *A* is extracted and shown in Equation (5.6). This equation shows that only two groups of Basic Events are left in the end of the factorisation due to the absorption property of Boolean algebra. Since the second and fourth groups (i.e. *A2* and *A4*) are identical, they are absorbed into one group. Meanwhile, the third group denoted as *A3* is also absorbed into *A1*, and eventually only two groups of Basic Events have been left as the Minimal Cut Sets of event *A*. The absorption property is frequently applied in Boolean algebra equations for simplification purposes, but this might cause confusion while carrying out the backtracking.

$$
\begin{aligned}
&A \approx \left[(\mathrm{H1}\cdot\mathrm{L8}\cdot\mathrm{L3})+(\mathrm{H1}\cdot\mathrm{L8}\cdot\mathrm{L7}\cdot\mathrm{L6})+(\mathrm{H1}\cdot\mathrm{L8}\cdot\langle\mathrm{L8}\cdot\mathrm{L7}\rangle\cdot\mathrm{L3})+(\mathrm{H1}\cdot\mathrm{L8}\cdot\mathrm{L7}\cdot\mathrm{L6})\right]\\
&= A1+A2+A3+A4=(\mathrm{H1}\cdot\mathrm{L8}\cdot\mathrm{L3})+(\mathrm{H1}\cdot\mathrm{L8}\cdot\mathrm{L7}\cdot\mathrm{L6})\\
&\textit{where}\\
&A1 = H1\cdot L8\cdot L3\\
&A2 = H1\cdot L8\cdot L7\cdot L6\\
&A3 = H1\cdot L8\cdot L7\cdot L3\\
&A4 = H1\cdot L8\cdot L7\cdot L6
\end{aligned}
\tag{5.6}
$$

An invalid example which is shown in Equation (5.7) and Figure 5-7 is the outcome resulting from this type of confusion. In contrast, Equation (5.4) in section 5.5.1.2 is the valid version and is compared with. The incorrect Equation (5.7) shown below looks similar to the valid one, but actually these two equations are not equivalent. The difference between them is in the backtracking part. The omission of some of the Intermediate Events associated with item *A2* is under the spotlight when these two equations are compared. Precisely speaking, events *Q* and *R* are omitted in Equation (5.7). This results from the absorption of factor *L8* in factorisation and wrongly tracking back in backtracking process. If the backtracking equations were not verified before building the DAG of Bayesian Network, the Bayesian Network model would look like the one shown in Figure 5-7. When it is compared with the valid version (i.e. the one shown in Figure 5-6), nodes *Q* and *R* are omitted in the DAG, which is pointed out by an ellipse in Figure 5-7. It is assumed that the mistake occurs when the process merely tracks factor *L8* back to factor *P*, rather than factors *P* and *Q* at the same time. This problem can happen when the group (or item) *A2* is the only start point to launch the backtracking in this case, rather than from the groups *A2* and *A4* at the same time. Consequently, the Intermediate Events *Q* and *R*, which are also influenced by the *L8*, are overlooked due to the absorption in the factorisation operation. The overlooking of some Intermediate Events in the DAG can happen when the backtracking is performed from a single absorbed item rather than from all the identical items.

Fortunately this mistake can be picked up by checking the equivalence between the backtracking equations and the factorisation equations in the process. For instance, one of the inconsistencies is highlighted in Equation (5.7) by the ellipses. In this example, the equation (in row 4) on the left hand side does not equivalent to the one on the right hand side, because factor *P* is neither equal to $(Q \cdot R)$ nor one of the proxies of them. In order to avoid this type of mistake, the good practice is to initiate the backtracking from all the items before any absorption takes place and to check the backtracking equations with the factorisation counterparts for equivalence all the time during the backtracking process.

$$
\begin{array}{ll}
\text{Factorisation} & \text{Backtracking} \\
A \approx H1\cdot F & \\
\approx H1\cdot(K\cdot M) & \\
\approx H1\cdot(P+Q\cdot R)\cdot M & \\
\approx (H1\cdot P\cdot M)+(H1\cdot Q\cdot R\cdot M) & \neq (H1\cdot P\cdot M1)+(H1\cdot P\cdot M2) \\
\approx (H1\cdot L8\cdot T)+(H1\cdot L8\cdot U\cdot T)=(H1\cdot L8\cdot T) & \approx (H1\cdot L8\cdot T)\approx (H1\cdot L8\cdot T1)+(H1\cdot L8\cdot T2) \\
\approx H1\cdot L8\cdot(L3+U\cdot V) & \approx H1\cdot L8\cdot(T1+T2)=(H1\cdot L8\cdot T1)+(H1\cdot L8\cdot T2) \\
\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot U\cdot V) & \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot U\cdot V) \\
\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot W\cdot L7\cdot L6) & \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot W\cdot L7\cdot L6) \\
\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L8\cdot L7\cdot L6) & \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L8\cdot L7\cdot L6) \\
\approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L7\cdot L6) & \approx (H1\cdot L8\cdot L3)+(H1\cdot L8\cdot L7\cdot L6) \\
\approx A1+A2 & \approx A1+A2
\end{array}
\tag{5.7}
$$

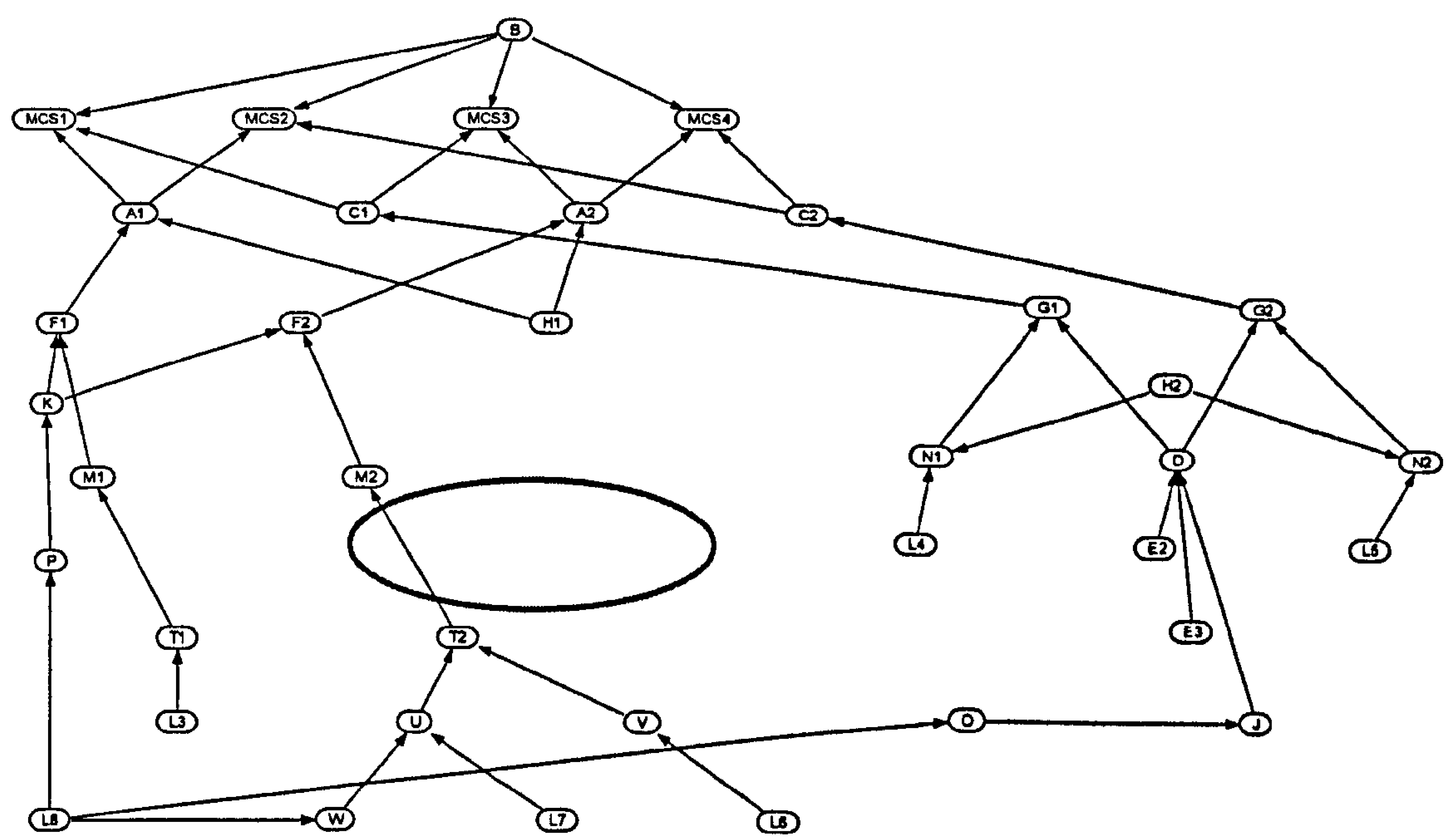


Figure 5-7 An incorrect Bayesian Network model caused by absorption

5.5.4 The Conditional Probability Table (CPT) of the Bayesian Network model

After constructing the Directed Acyclic Graph of the accident, the *Conditional Probability Tables* of the model have to be completed before the corresponding Bayesian Network model being able to perform the quantitative analysis of the accident.

These tables specify the *probability distributions* for each state of the nodes, contained in the Directed Acyclic Graph, under certain conditions. In other words, the Conditional Probability Table tabulates the conditional probability distribution of each node according to Bayes' rule specified in section 4.5.1. Once all the data of the Conditional Probability Tables have been given, the Bayesian Network model is able to calculate and show the outcomes of *marginalisation* (or *unconditional*) likelihood for each node. It is worth revisiting section 4.5.5 if further technique details are required. Figure 5-8 shows the established Bayesian Network model regarding the HoFE example applied in this case study. The likelihood outcomes shown on the display are marginalised (or unconditional) although the data entered is conditional probability distribution. Regarding the data for these Conditional Probability Tables, there is no doubt that the historical statistic data is the first choice to derive from. However, if the historical statistic data is not available at the time, experts' judgement will be one of the practical solutions to resort to. In this example, all the data given for the Conditional Probability Tables is presumed to be rationally correct although it is neither associated with historical statistic data nor expert judgements, but the researcher's estimation for the demonstration only.

In Table 5-1, the Conditional Probability Tables for nodes *L8*, *L7*, *W* and *U* of the established Bayesian Network model are shown. The entire Conditional Probability Table of the model is tabulated in Appendix-B. Instead of working out the marginalisation of the nodes by hand, a Bayesian Network software package (i.e. Netica) is utilised to perform this tedious job. The tables which belong to the nodes that have predecessor(s) consist of two parts; the data part (the data shows on the left hand side of the tables) and the conditions part (given by their parent or predecessor nodes on the right hand side of the tables). If there is no condition part in the tables, it means that this node has no predecessor and the data is depicted by *prior* probability distributions. Otherwise it is depicted by *posterior* probability distributions. For not distracting the concentration of the explanation, only two states are imposed onto every node in this case; but more than two states are still practical. The label of each state of the nodes follows the title of the node with a subscript number to distinguish them. For example, the $L8_1$ denotes the state No.1 of node *L8*. Each entry of these tables depicts the probability distributions subject to the condition given on the right hand side (i.e. the condition part) of the tables. For example, the cell located at the cross of row one and column one in the data part of the table for node *U* depicts the probability of state U_1 under the condition of W_1 and $L7_1$.

Table 5-1 The Conditional Probability Table for nodes *L8*, *L7*, *W* and *U* of the Bayesian Network model

L8: (Shore Management)

good management ($L8_1$)	poor management ($L8_2$)
0.2	0.8

L7: (Senior master was content without demur the SSO)

Satisfy ($L7_1$)	Concerned ($L7_2$)
0.8	0.2

W: (status to give clear order about the duties)

Clear (W_1)	Vague (W_2)	L8
0.95	0.05	good management ($L8_1$)
0.05	0.95	poor management ($L8_2$)

U: (Ship Standing Order (SSO) to crew)

poor SSO (U_1)	good SSO (U_2)	W	L7
0.1	0.9	Clear (W_1)	Satisfy ($L7_1$)
0.05	0.95	Clear (W_1)	concerned($L7_2$)
0.95	0.05	Vague (W_2)	Satisfy ($L7_1$)
0.2	0.8	vague (W_2)	concerned($L7_2$)

5.5.5 The quantitative analysis results of the Bayesian Network model

Although the Netica software will perform the marginalisation of all the nodes in a second, it is worthy to demonstrate the calculation details in light of equation (4.7) in section 4.5.1 in order to appreciate how it works. The demonstration takes only four nodes, nodes *L8*, *L7*, *W* and *U*, of the established model (see Figure 5-6) as the example and tabulates their Conditional Probability Tables in Table 5-1. The data depicted in the tables for nodes *L8* and *L7* are unconditional (or *prior*) probability distribution since they have no predecessor. Hence the demonstration will only concentrate on the marginalisation of nodes *W* and *U* respectively. Before carrying out the marginalisation process for node *U*, the unconditional probability distribution of node *W* has to be acquired beforehand. Therefore the marginalisation process for node *W* is the first to be dealt with and each state of the node has to be handled individually. The marginalisation process for node W is illustrated in Equation (5.8) where the data for nodes W and $L8$ refer to Table 5-1. In the equation, the $P(W_1 \mid L8_1)$ depicts the probability of state W_1 under the condition given by state $L8_1$ of node $L8$. The data in the cell crossed at column W_1 and row $L8_1$ in the table of node W is referred to and the value of 0.95 is the answer for $P(W_1 \mid L8_1)$. Besides, $P(L8_1)$ is the unconditional probability distribution of state $L8_1$ of node $L8$. Since node $L8$ is depicted by prior probability distribution in the table, the figures shown in the cell can be directly referred to as $P(L8_1)$ and 0.2 is the result. By the same token, the remaining parts of the equation are handled with the associated data in the tables. Eventually the answer with regard to $P(W_1)$ turns out to be 0.23 and the answer for $P(W_2)$ is acquired as 0.77.

$$
\begin{aligned}
P(W_1) &= \sum_{j=1}^{2} P(W_1 \mid L8_j) \times P(L8_j) = P(W_1 \mid L8_1)P(L8_1) + P(W_1 \mid L8_2)P(L8_2) \\
&= (0.95 \times 0.2) + (0.05 \times 0.8) = 0.19 + 0.04 = 0.23 \\
p(W_2) &= \sum_{j=1}^{2} P(W_2 \mid L8_j) \times P(L8_j) = P(W_2 \mid L8_1)P(L8_1) + P(W_2 \mid L8_2)P(L8_2) \\
&= (0.05 \times 0.2) + (0.95 \times 0.8) = 0.01 + 0.76 = 0.77
\end{aligned}
\tag{5.8}
$$

After finalising the calculation of $P(W_1)$ and $P(W_2)$, the marginalisation of node U is now able to proceed with the Conditional Probability Table data of nodes U and $L7$ specified in Table 5-1. The calculations for $P(U_1)$ and $P(U_2)$ are a little more complicated than $P(W_1)$ and $P(W_2)$ since node U has two parent nodes rather than just one as node W has. Nevertheless, the principle is still the same except the workload of the calculation is twice as for node W. The details of the calculation are illustrated in Equation (5.9). The answers for $P(U_1)$ and $P(U_2)$ are 0.6367 and 0.3633 respectively. Although these manual calculation results look slightly different from the results displayed on the Netica software shown in Figure 5-8, they are correct. The study presumes that the differences resulted from the round and display function of the software. That is, 0.6367 is displayed as 0.637 due to the use of only 3 digits after the decimal point are taken and rounded in the software.

$$
\begin{aligned}
P(U_1) &= \sum_{\substack{i=1\\j=1}}^{\substack{i=2\\j=2}} P(U_1 \mid W_i, L7_j) \times P(W_i)P(L7_j) \\
&= P(U_1 \mid W_1, L7_1)P(W_1)P(L7_1) + P(U_1 \mid W_1, L7_2)P(W_1)P(L7_2) \\
&\quad + P(U_1 \mid W_2, L7_1)P(W_2)P(L7_1) + P(U_1 \mid W_2, L7_2)P(W_2)P(L7_2) \\
&= (0.1 \times 0.23 \times 0.8) + (0.05 \times 0.23 \times 0.2) + (0.95 \times 0.77 \times 0.8) + (0.2 \times 0.77 \times 0.2) \\
&= 0.0184 + 0.0023 + 0.5852 + 0.0308 = 0.6367
\end{aligned}
$$

$$
\begin{aligned}
P(U_2) &= \sum_{\substack{i=1\\j=1}}^{\substack{i=2\\j=2}} P(U_2 \mid W_i, L7_j) \times P(W_i)P(L7_j) \\
&= P(U_2 \mid W_1, L7_1)P(W_1)P(L7_1) + P(U_2 \mid W_1, L7_2)P(W_1)P(L7_2) \\
&\quad + P(U_2 \mid W_2, L7_1)P(W_2)P(L7_1) + P(U_2 \mid W_2, L7_2)P(W_2)P(L7_2) \\
&= (0.9 \times 0.23 \times 0.8) + (0.95 \times 0.23 \times 0.2) + (0.05 \times 0.77 \times 0.8) + (0.8 \times 0.77 \times 0.2) \\
&= 0.1656 + 0.0437 + 0.0308 + 0.1232 = 0.3633
\end{aligned}
\tag{5.9}
$$

Having finalised the Directed Acyclic Graph and Conditional Probability Tables of the Bayesian Network model for the accident, the quantitative analysis is now able to proceed. Both the qualitative and quantitative analysis results are presented in Figure 5-8. As mentioned before, the Top Event is no longer represented by a single object in the model, but four Minimal Cut Sets instead. This is because there are four possible combinations of these factors that can lead the ship to the accident according to the preceding qualitative analysis result. Each Minimal Cut Set represents one of the Window of Opportunities of the accident but their likelihoods are different. The marginalisation results for each node, including these four Minimal Cut Sets, are shown in a percentage manner with their short notation. For example, "capsized 28.2"of node *MCS1* denotes the likelihood of capsizing of the ship is 28.2% under the threat of those factors represented by *MCS1*.

It should be noted that the overall likelihood of the accident is not the likelihood represented by any one of the Minimal Cut Set acquired in the Bayesian Network model. This is because, in a Bayesian Network model of Minimal Cut Sets, the Top Event of the accident is represented by several Minimal Cut Sets rather than a single object as it is in FTA. As elucidated in section 3.2, each Minimal Cut Set only represents one of the possible combinations of those Necessary Causal Factors to trigger the accident to occur, the quantity of each Minimal Cut Set can only bear part of the total responsibility. Thus, the way to obtain the answer of the overall likelihood of the accident is not simply summing up these likelihoods. It has to resort to the FTA Minimal Cut Set upper bound formula (see Equation (4.2) in section 4.4.3), although a certain amount of overestimate is introduced. This overestimate is unavoidable as long as there are common factors existing among those Minimal Cut Sets. That is, the more the common factors, the larger the overestimate. However, if there is no common factor among those Minimal Cut Sets, this formula still has a chance to obtain an accurate figure.

Equation (5.10) shows the calculation details of the total likelihood of this example according to the upper bound formula. This means the likelihood of the accident (i.e. capsizing of the ship) is not larger than 66.32%. The reason why the equation is "not larger than" rather than "equal to" is that the calculated result in light of this formula will be somewhat overestimated due to those common factors have been counted more than once. It is very important to bear in mind with this feature while applying this formula for analysis; this figure is only suitable for comparison and not for the precise answer. It is recommended that the overall accident likelihood should refer to the Bayesian Network model of Top Event which is introduced in section 5.3.2 and discuss the individual Minimal Cut set figures via this Minimal Cut Set model.

$$P(TE) \leq 1-(1-0.282)(1-0.205)(1-0.268)(1-0.194)=0.6632 \qquad (5.10)$$

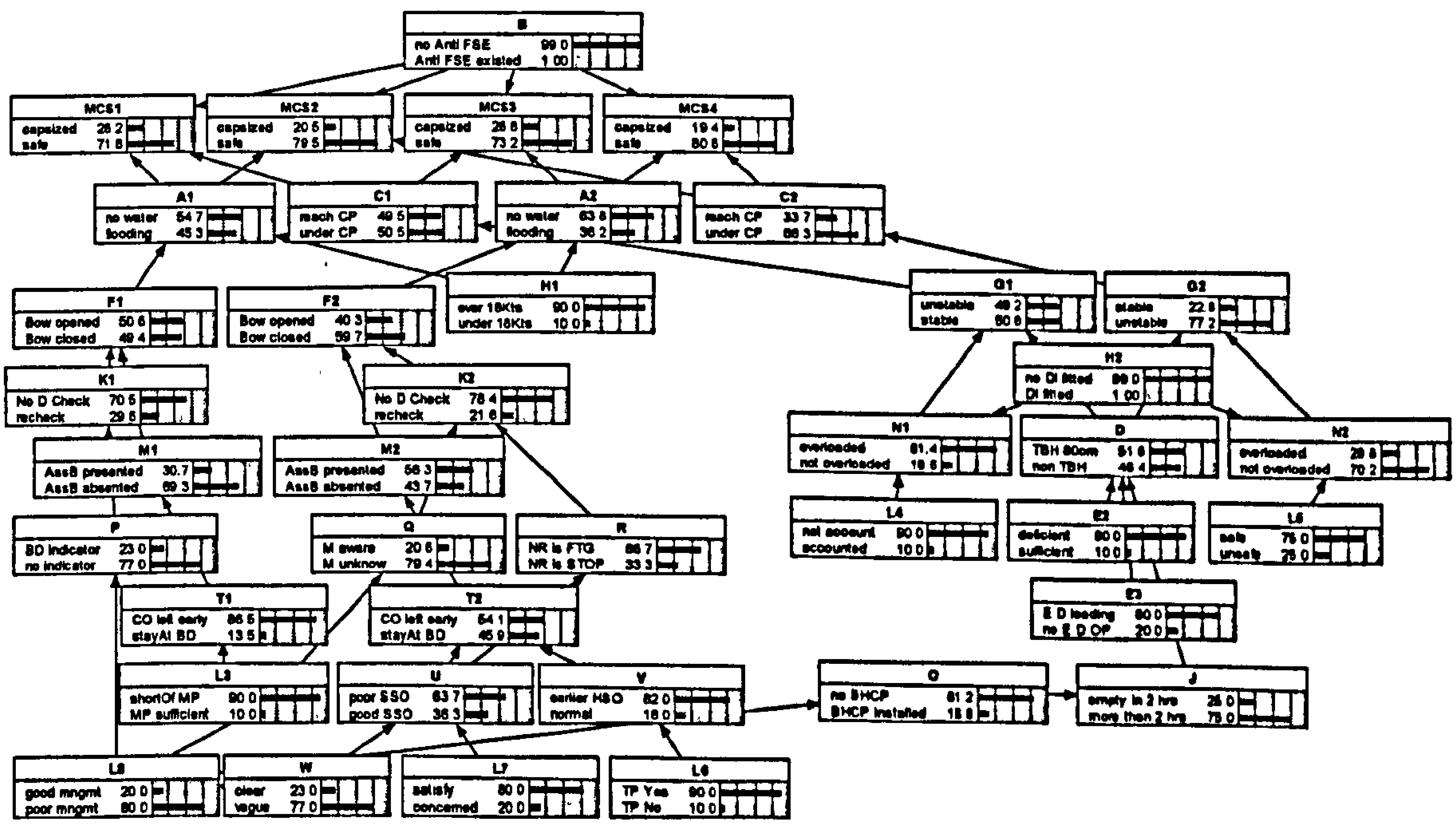


Figure 5-8 The Bayesian Network model of Minimal Cut Sets of the accident

5.5.6 The propagation of the Bayesian Network model

The propagation is another powerful feature of Bayesian Network. This feature can be used to perform "*what if*" examination in order to predict the possible outcomes of each factor involved in the model under the conditions given, as well as the possible solutions to prevent the similar accidents from happening again. It is worthy to revisit section 4.5.6 for the theoretical details regarding the propagation of Bayesian Network. In this section, some assumed examples will be used to illustrate how this functionality works and how it can be utilised for inferring. For instance, the accident report indicated that the "poor shore management" should take a significant part of the responsibility of the tragedy (DoT, 1987). In other words, if the shore management had listened to the complaints, suggestions or wishes of their Masters, the accident could have been prevented. For verifying this allegation, the established Bayesian Network model of the accident can now be used to examine if this argument is rational. Instead of adjusting the shore management factor (i.e. *L8*: shore management) directly, the demonstrated example amends factor *W* (i.e. failure to give clear order about the duties) for illustrating some particular features of propagation. It is assumed that if the orders given regarding the duties were clear then the probability of $P(W_1)$ in the model would be increased from 20% to 100%. Consequently, the likelihoods of *MCS1~MCS4* shown in the established model (see Figure 5-9) reduce to 13.4%, 10.2%, 10.8% and 8.5% respectively. They are almost 50% less than the previous outcomes when Figure 5-9 and Figure 5-8 are compared.

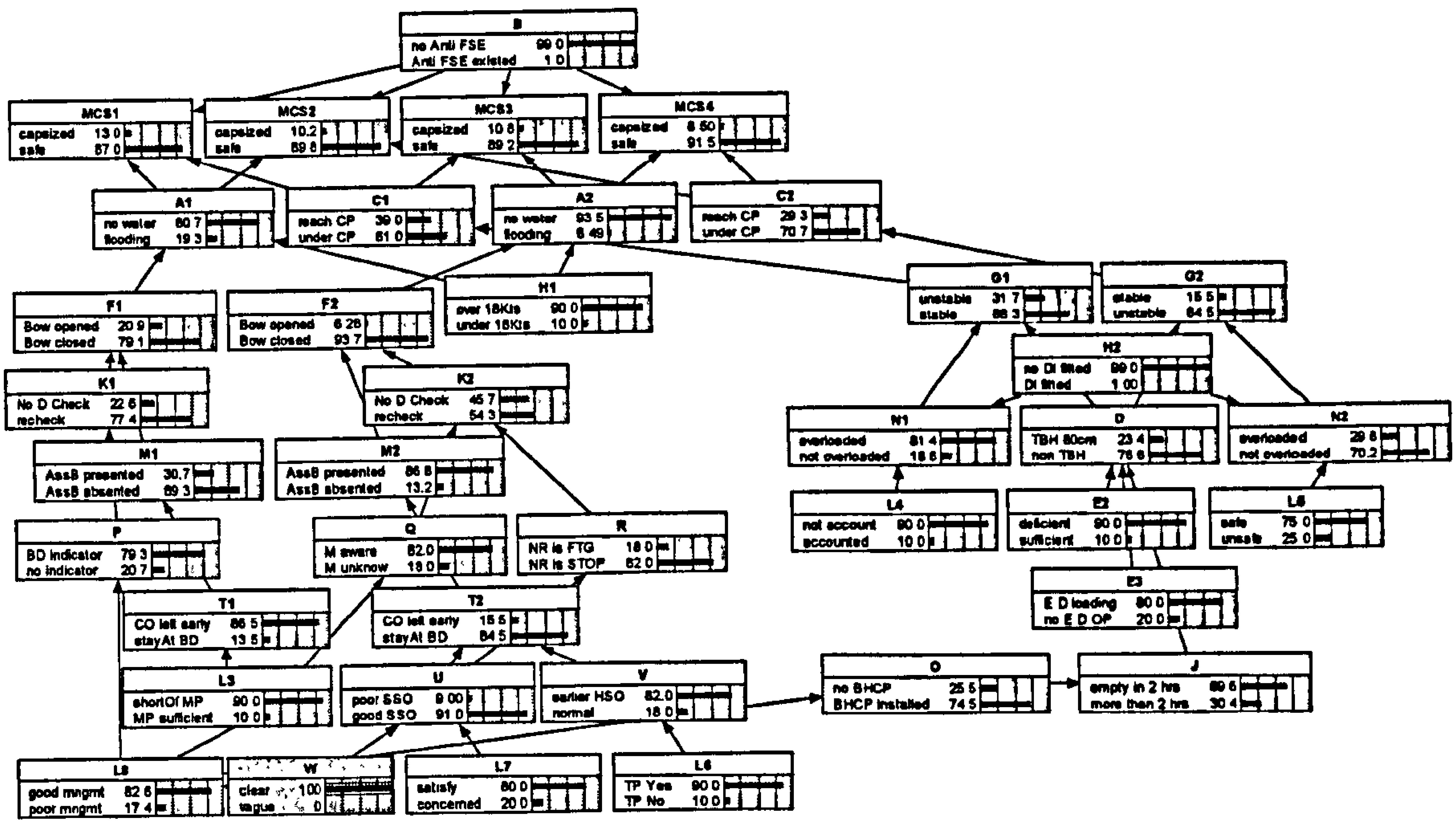


Figure 5-9 The propagation outcomes with the value of node *W* changed

From the Bayesian Network model shown in Figure 5-9, it approves this argument. This is achieved by updating the belief of node *W* assuming a new piece of evidence has been found. It makes node *W* act like an epicentre and a chain reaction of belief update is triggered over the Bayesian Network model. All the other nodes in the model are influenced and updated according to the dependencies to the epicentre node (i.e. node *W*). Hence the epicentre node becomes the supreme influencing node over the Bayesian Network model and all the other nodes turn out to be its influenced nodes at the time even though those used to be its predecessors. However the dependencies between them remain the same, only the influencing direction has been reversed. This means that node *L8* now becomes one of the influenced nodes, rather than an influencing node, of node *W*, although the dependency between them is still the same as before. Since nodes *L8* and *U* are directly connected with node *W*, the calculation details for their belief updating are illustrated as an example. Because node *U* is still a successor of node *W* as it was, the marginalisation equations for node *U* remain the same as Equation (5.9) except the probability of $P(W_1)$ and $P(W_2)$ are changed; they are now 100% and 0% respectively. Thus, the likelihood values of $P(U_1)$ and $P(U_2)$ become 9% and 91% accordingly (see Equation (5.11)).

$$\begin{aligned}
P(U_1) &= \sum_{\substack{i=1\\ j=1}}^{\substack{i=2\\ j=2}} P(U_1 \mid W_i, L7_j) \times P(W_i)P(L7_j) \\
&= (0.1\times1\times0.8)+(0.05\times1\times0.2)+(0.95\times0\times0.8)+(0.2\times0\times0.2) \\
&= 0.08+0.01+0+0=0.09 \\
P(U_2) &= \sum_{\substack{i=1\\ j=1}}^{\substack{i=2\\ j=2}} P(U_2 \mid W_i, L7_j) \times P(W_i)P(L7_j) \\
&= (0.9\times1\times0.8)+(0.95\times1\times0.2)+(0.05\times0\times0.8)+(0.8\times0\times0.2) \\
&= 0.72+0.19+0+0=0.91
\end{aligned} \tag{5.11}$$

Nevertheless, the situation for node *L8* is different because it becomes the influenced node of node *W*. This means that the influencing direction is now reversed, from node *W* to node *L8* instead. Therefore, the unconditional Probability distributions depicted in the Conditional Probability Table for node *L8* are not the proper data to be directly applied and have to be acquired through the marginalisation formula shown as Equation (5.12).

$$\begin{aligned}
P(L8_1) &= \sum_{j=1}^{2} P(L8_1 \mid W_j) \times P(W_j) = P(L8_1 \mid W_1)P(W_1) + P(L8_1 \mid W_2)P(W_2) \\
p(L8_2) &= \sum_{j=1}^{2} P(L8_2 \mid W_j) \times P(W_j) = P(L8_2 \mid W_1)P(W_1) + P(L8_2 \mid W_2)P(W_2)
\end{aligned} \tag{5.12}$$

There is still a problem due to the fact that no corresponding data with respect to $P(L8 \mid W)$ is available in the Conditional Probability Table. Fortunately, the $P(L8 \mid W)$ can be derived from $P(W \mid L8)$ via Bayes' rule since the dependency between nodes *L8* and *W* is still unchanged. The details of the calculation for $P(L8 \mid W)$ are shown in Equation (5.13). The entire updated outcomes of these nodes (i.e. the Bayesian Network model) are shown in Figure 5-9. From the figure, it shows that the shore management has been improved, from 20% to 82.6% if the orders given are always clear. It also shows that this remedy can dramatically reduce the likelihood of the overall occurrence around 50% when the likelihood outcomes of the four Minimal Cut Sets are compared with the outcomes shown in Figure 5-8. The overall likelihood of the accident is now 36.24% according to Equation (5.14).

However, this remedy cannot completely prevent the accident to happen because some other *Window of Opportunities* may still exist. It should be noted that the value to update node W (or any other node) does not necessarily have to be either 100% or 0% (it is just a special case of belief update called *Evidence*). Precisely speaking, the *Evidence* means that "the information obtains when some particular nodes can only be one of the states stood" (Jensen, 2001). Actually, the belief update can be any figure between 0 and 1 (i.e. $\in[0,1]$).

$$
\begin{aligned}
&P(L8_1 \mid W_1) = P(W_1 \mid L8_1)P(L8_1)/P(W_1) = (0.95\times 0.2)/0.23 = 0.826 \\
&P(L8_2 \mid W_1) = P(W_1 \mid L8_2)P(L8_2)/P(W_1) = (0.05\times 0.8)/0.23 = 0.174 \\
&P(L8_1 \mid W_2) = P(W_2 \mid L8_1)P(L8_1)/P(W_2) \\
&P(L8_2 \mid W_2) = P(W_2 \mid L8_2)P(L8_2)/P(W_2) \\
&\because \\
&P(W_1)=1 \ \ \& \ \ P(W_2)=0 \ \text{ to work with Equation (5.12)} \\
&\therefore \\
&P(L8_1)= P(L8_1 \mid W_1)P(W_1) + P(L8_1 \mid W_2)P(W_2) = 0.826 \\
&P(L8_2)= P(L8_2 \mid W_1)P(W_1) + P(L8_2 \mid W_2)P(W_2) = 0.174
\end{aligned}
\tag{5.13}
$$

$$P(TE)\leq 1-(1-0.13)(1-0.102)(1-0.108)(1-0.085)=0.3624 \tag{5.14}$$

By using the propagation function, it is not only able to determine which factors can effectively reduce the likelihood of the accident, but also has more "evidence" to say which factors highly likely caused the accident to happen. For instance, in the HoFE example, all the evidence has shown that the bow door of the ship was definitely opened while sailing and the ship's speed reached 18 knots at the time. Such evidence can be used to test the established Bayesian Network model to see if the *evidence* outcomes are in line with the reality. Having set up such new evidence, the updated likelihoods of these four Minimal Cut Sets soar dramatically while factors *F1* and *F2* (i.e. status of bow door) are both set to the status of "*Opened*" and factor *H1* to "*over 18 Kts*" (see Figure 5-10). Hence the likelihood of MCS1~MCS4 arise by around one more time. All the Causal Factors on the left of the figure are almost confirmed to happen. However the nodes on the right group only have little change. This updated outcome of the Bayesian Network model does confirm the situation that the ship capsized at that time.

$$P(T) \leq 1-(1-0.54)(1-0.39)(1-0.542)(1-0.392)=0.9219 \tag{5.15}$$

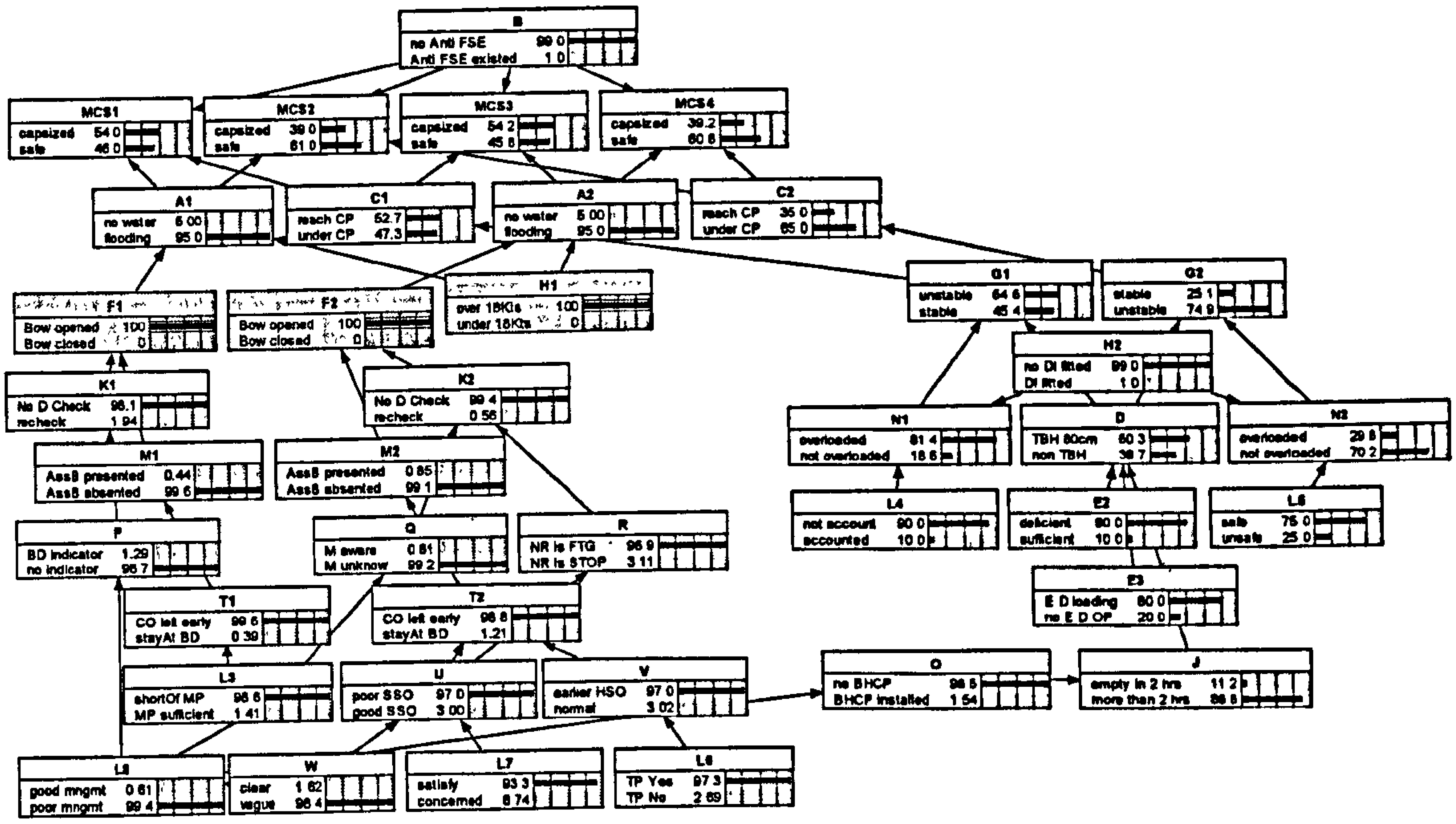


Figure 5-10 An application of *Evidence* examination in which "*bow door opened*" and "*ship speed over 18 Kts*" are confirmed

This functionality is very useful when the Bayesian Network model is applied for further analysis, because it can provide the investigators with a comprehensive view about the influences from one factor to the others over the network. It also means that the Bayesian Network model can provide the investigation authority a convenient tool to discover the critical factors and the effective countermeasures against the accident. Therefore, the authority may be able to conclude a qualitative and quantitative analysis of an accident more confidently. However it still remains an important issue unsolved yet – how to validate the established Bayesian Network model. The next section will provide an answer to this question.

5.6 Sensitivity Analysis of the Bayesian Network model

Sensitivity Analysis is a technique to determine how "*sensitive*" a model is to the change in the value of the parameters and to the change in the structure of the model (as discussed in section 4.6). Regarding the correctness of the structure of a Bayesian Network model, Yang (2006) also suggests that it can be checked by carrying out a *D-*

separation examination to each node and comparing the outcomes with the reality. Without distracting the discussion, it is presumed that the structure of the example model has been checked via *D-separation* examination and is correct. Hence, the Sensitivity Analysis applied for the proposed method merely focuses on two goals. They are firstly validating the Conditional Probability Tables of the established Bayesian Network model and secondly finding the critical factors of the model. Although further applications of Sensitivity Analysis associated with Bayesian Network might be possible, the study would first address these two goals and demonstrate the relative applications in the next two sections.

5.6.1 The validation of the established Bayesian Network model of the accident

The correctness, or at least reasonableness, of the established Bayesian Network model is the prerequisite of the following accident analysis as well as the fairness of the conclusions and recommendations of the analysis. Therefore, the validation of the established Bayesian Network model is the first aim to achieve before further progressing. The examination applied for this purpose is called *parameter sensitivity* examining, which is one of the applications of Sensitivity Analysis. For further information with respect to this application, it is worth revisiting section 4.6.1. In order to perform this examination, several significant Causal Factors have to be chosen in advance. By giving variant probability values, as the belief updates, to the selected node to trigger the propagations, the behaviours of the model are compared with the reality. If the model's behaviours are in line with the observations of the real world, it would be more confident to say that the established Bayesian Network model coincides with the reality. In this examination, the inputted values are ranged from 0% to 100% step by step, and 10% is the interval of the step.

Therefore, in this example, four human factors are selected as the significant Causal Factors to perform this parameters analysis examination. They are the *Assistant Bosun*, the *Chief Officer*, the *Captain* and the *Shore Management*. In the established Bayesian Network model these factors are represented by node *M* (the Assistant Bosun was not present to close the bow door), *T* (the Chief Officer left bow door early), *K* (the Captain assumed that his ship was ready for sea) and *L8* (the Shore Management) respectively. They were those crucial human factors that should be taken into account, according to the DoT accident report. This is also the reason why these four factors are chosen for the examination. Their inputted values, as the belief updates, will be applied to one of the chosen node and changed values step by step, in turn, in order to observe the changes of the outputs (i.e. *MCS1~MCS4*) according to the propagation outcome. Each time, only one of the factors will change the inputted value whilst the value is set from 0% (i.e. the most negative behaviour) to 100% (i.e. the most positive behaviour) with 10% as the interval for each step. Hence, when the propagation is triggered, the likelihoods of the nodes are updated according to the value inputted and the dependencies amongst them. It should be noted that some of Causal Factors may be represented by more than one node in the Minimal Cut Set model. For example, there are two nodes (i.e. node *M1* and *M2*) representing the *Assistant Bosun* in the model. Therefore all the nodes relating to that particular factor have to be changed accordingly if there are any. Having updated the belief of the corresponding nodes, the overall likelihood of the accident is observed via aggregating the likelihoods of these four Minimal Cut Sets with Equation (4.2). The examining outcomes and the comparison with regard to these four factors are showed in Figure 5-11. The brief conclusions of the outcomes are:

1. If the Probability distributions of these four human factors can be reduced, the likelihood of the accident decreases as well.

2. All the curves of these factors in the figure converge to a small area while the inputted value is set to 100%. It means that the eventual outcome of different countermeasures against any one of these four Causal Factors is almost the same since they all can shut the Window of Opportunity, no matter which holes of the window have been blocked.

3. The factor of "Assistant bosun was not present to close the bow door" seems to be the most critical factor in the model because its adversely influenced result is the worst due to its immediate feature to the accident.

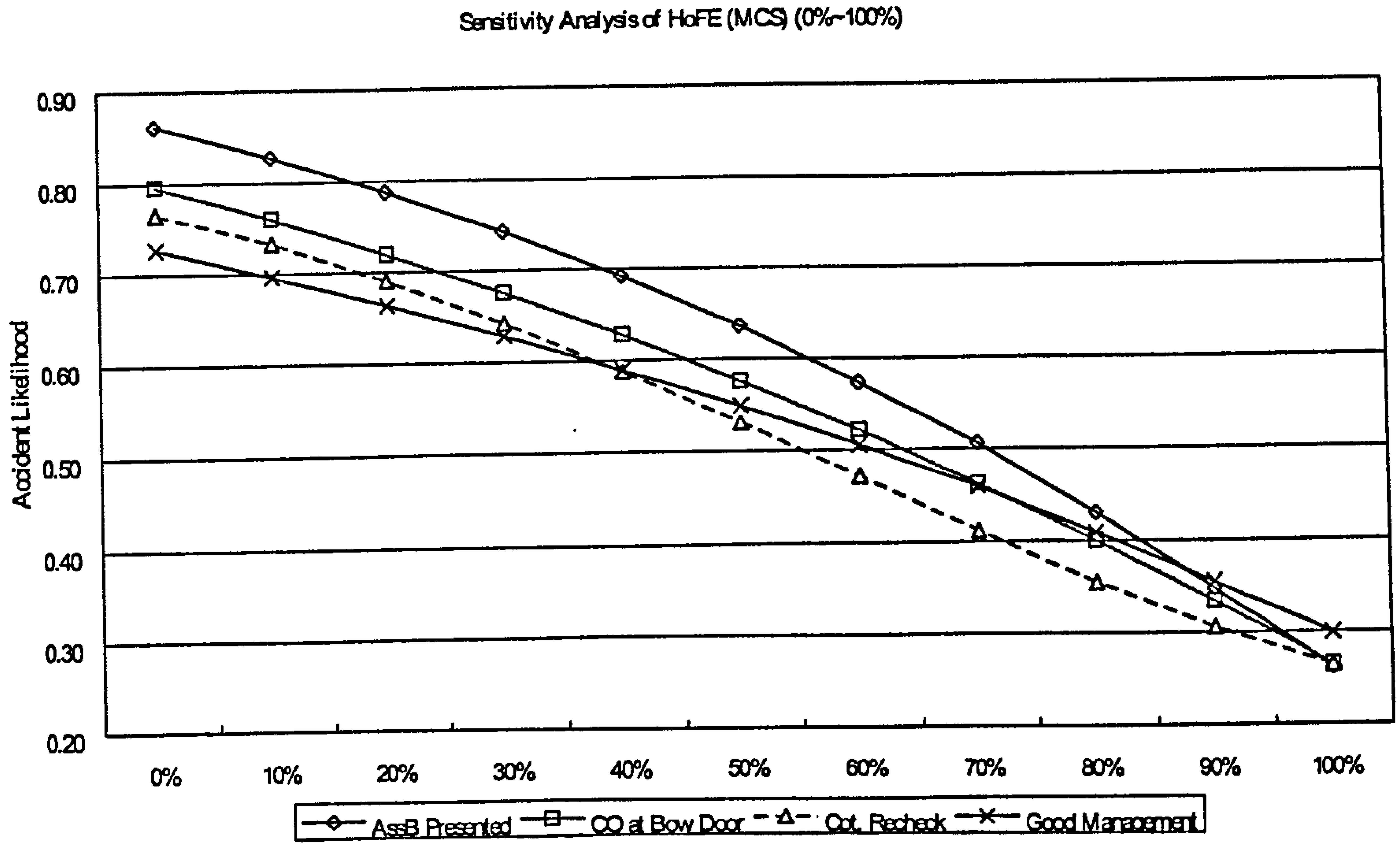


Figure 5-11 The Sensitivity Analysis results regarding these four critical human factors involved in the accident

These conclusions are in line with the reality of the accident and are considered respectively as follows.

Firstly, according to the outcomes of the parameter sensitivity examination, the worse the human factors performance (i.e. the *Assistant Bosun*, the *Chief Officer*, the *Captain* and the *Shore Management*), the higher the likelihood of the accident. This is concluded by interpreting the trends of these curves shown in the figure, in which the inputted values represent the performance of the human factors and 0% of the value is the worst case. The tendencies of these factors are the same. They all have the most adverse consequences (on the left of the curves) due to the adverse behaviours (i.e. 0% is the inputted values) and the lowest likelihood of the occurrence (on the right) when the alertness is given (i.e. 100% is the values).

Secondly, the bow door could have been closed if any one of them had been carried out their duties properly. Accordingly, the accident would not have happened if the bow door had been closed. In other words, these four factors line up the trajectory and can be seen as an instance of Window of Opportunity. Once any one of the holes in the window has been shut, the Window of Opportunity does no longer exist. That also explains why the curves converge to a small area. The convergence means the effectiveness of the countermeasures against any one of the selected factors are similar. These countermeasures are the means to ensure that the practitioners carry out their duties properly.

Thirdly, the *Assistant Bosun* is the most immediate factor to the accident and can be seen as the *active failure*. The curve representing the factor of *Assistant Bosun* has the most adverse outcome when comparing with the other three factors. In contrast to *Assistant Bosun*, the *Shore Management* is the most distant and indirect as the *latent condition*. In addition, the magnitude and the trend of the factor are apparently different from the curve of *Assistant Bosun*. This phenomenon may be utilised to distinguish the *active failure* and *latent condition* factors of the accident when the Bayesian Network model is applied. However, it should also be considered, from another point of view, as to why the *Assistant Bosun's* unintentional error could result in such disastrous consequences as though he was entrapped. The management pretended that the *Assistant Bosun* would never fail without any defence (or alarm) mechanism but after all he is still a human being. The management should have considered a mechanism to prevent this crucial function from failure, such as a positive reporting procedure. If the Ship Standing Orders had been designed so that the *Assistant Bosun* should be required to report that the bow door was closed actively, rather than passively, before setting out for the sea, the captain should have realised that something was wrong at that time.

5.6.2 Finding the critical factors of the model

In addition to the validation of the established Bayesian Network model, Sensitivity Analysis can also be used to indicate which parameters (or factors) are critical to the model. Having validated the model, finding the critical factors of the model is the next step. As noted in section 4.6.2, a node (or parameter) whose specific value(s) can significantly influence the outcome of the model is identified as the *critical factor*, which greatly changes the system's behaviour with the change of the node's value (Breierova and Choudhari, 1996). In order to ensure that any node has not been overlooked, this process should be performed systematically and thoroughly for all the nodes in the model. Having the help of a built-in function (i.e. Sensitivity to Finding) of the employed Bayesian Network software (i.e. Netica), this requirement can easily be achieved. Before performing this function, a target node has to be selected first. The selected target node is the node of concern at the moment. By checking all the nodes in the model and obtaining the sensitivity analysis results regarding the target node, the entire results can be acquired through a report.

By appointing node *MCS1* as the target node in this example, both Table 5-2 and Table 5-3 tabulate the sensitivities, to the target node, for each finding node (i.e. the other nodes except node *MCS1*) involved in the model. Table 5-2 shows one of the instances (i.e. node *M1*) in the first part of the report and Table 5-3 lists the entire second part of the *sensitivity finding* report. The second part of the report also ranks all the nodes listed, from high to low, according to the sensitivities to the target node. The meanings of these data shown in the tables are briefly tabulated in Table 5-4 and the details of the definitions are specified in Appendix-C. By analysing these tables, it is more confident to say that the factor "*Assistant bosun was not present to close the bow door*", which is presented by node *M1* in the model, is the most sensitive (or critical) human factor to *MSC1*, which represents one of the Window of Opportunity of the accident. This seems reasonable and is in line with one of the conclusions depicting in the last section.

Table 5-2 The first part of the report: the detailed information for each finding node

Sensitivity of 'MCS1' to findings at 'M1':				
Probability ranges:	Min	Current	Max	RMS Change
capsized	0.0626	0.2816	0.3785	0.1457
safe	0.6215	0.7184	0.9374	0.1457
Entropy reduction = 0.0906 (10.6 %)				
Belief Variance = 0.0212 (10.5 %)				

Table 5-3 The second part of the report: the summary list of the sensitivities

Sensitivity of 'MCS1' due to a finding at another node:		
Node	Mutual Info	Variance of Beliefs
MCS1	0.8577	0.2023
A1	0.2462	0.0633
C1	0.2217	0.0554
F1	0.1959	0.0493
M1	0.0906	0.0212
G1	0.0864	0.0234
K1	0.0723	0.0173
MCS3	0.0718	0.0214
MCS2	0.0537	0.0163
P	0.0492	0.0116
D	0.0457	0.0125
L8	0.0397	0.0094
Q	0.0368	0.0088
O	0.0357	0.0084
T1	0.0326	0.0073
J	0.0309	0.0078
W	0.0274	0.0069
L3	0.0175	0.0040
N1	0.0129	0.0033
H1	0.01	0.0025
U	0.0097	0.0026
R	0.008	0.0022
K2	0.007	0.0019
E3	0.0063	0.0017
A2	0.0056	0.0016
L4	0.0048	0.0012
T2	0.0044	0.0012
G2	0.0042	0.0012
F2	0.0041	0.0012
E2	0.0029	0.0008
M2	0.0028	0.0008
MCS4	0.0023	0.0007
B	0.0017	0.0004
C2	0.0012	0.0003
H2	0.0003	0
N2	0	0
L5	0	0
L7	0	0
L6	0	0
V	0	0

Table 5-4 The brief explanation of the meanings of the sensitivity report

Title	Definition
Min	Minimum belief that each state q of Q can take due to a finding at F. This provides a value for each state.
Max	Maximum belief that each state q of Q can take due to a finding at F. This provides a value for each state.
RMS Change	The square root of the expected change squared of the belief of state q of Q, due to a finding at F. This provides a value for each state. This is the standard deviation of P(q|f) about P(q) due to a finding at F, with the finding at F distributed by P(f).
Entropy reduction (Mutual Info)	The mutual information between Q and F (measured in bits). The expected reduction in entropy of Q (measured in bits) due to a finding at F.
Belief Variance	The expected change squared of the beliefs of Q, taken over all of its states, due to a finding at F.
Notation: Q: is the query variable F: is the varying variable q: is a state of the query variable f: is a state of the varying variable RMS: is "root mean square", which is the square root of the average of the values squared.	

After carrying out the same examination to all the WoOs (i.e. Minimal Cut Sets) of the accident, one by one, and gathering their results, the investigators are able to identify the critical factors with a broadened picture. Having concluded these identified critical factors according to the Bayesian Network model, it would be helpful for the authorities to decide which conclusions and recommendations are objective to the investigation report. These two Sensitivity Analysis processes may repeat if any improper value of the nodes has been found during the process. It is expected that this critical factors finding process can lead to the resolution of the experts' disagreements or arguments in terms of critical factors by appreciating the influences of each node to the model.

5.7 Influence Diagrams for the accident analysis

In this section, the study will demonstrate an instance that applies the Maximum Expected Utility (MEU) of Influence Diagrams as the tool to assess the Risk Control Options (RCOs) against the analysed accidents. The Influence Diagrams model is derived from the established Bayesian Network model of the accident, as the foundation, having considered cost-benefit issue. The Risk Control Options represented by the Expected Utilities in the model are the countermeasures to the analysed accident. From the view of decision making, it would be helpful if the countermeasures for preventing the type of accidents are evaluated in terms of ***cost-benefit*** and the effectiveness of all possible solutions. In order to illustrate this notion, a pattern of Expected Utility which is proposed in section 4.7 will be applied to the Herald of Free Enterprise example in the next two sections. Four presumed Risk Control Options are utilised as the countermeasures to construct the corresponding Influence Diagrams model for the demonstration.

5.7.1 Applying Influence Diagrams to assess the Risk Control Options (RCOs) against the accident

In order to demonstrate the process of applying Influence Diagrams, as the tool, to assess the Risk Control Options for accident analysis, the established Bayesian Network model for the accident of Herald of Free Enterprise is used and expanded. It is presumed that the established Bayesian Network model, constructed through the proposed method, is validated. For finding the best countermeasure from all of the possible solutions, an Influence Diagrams model which is constructed by adding several *Decision* and *Utility* nodes, including some *Chance* nodes, into the established Bayesian Network model is utilised. These new added nodes are four *Chance* nodes (i.e. node *MCS1N ~ MCS4N*), one *Decision* node (i.e. node *RCO*) and five *Utility* nodes (i.e. node *Payoff_1 ~ Payoff_4* and node *Cost*). This construction follows the proposed pattern of Expected Utility depicted in section 4.7.1 to construct the Influence Diagrams model in order to assess the four-alternative Risk Control Options for decision-making (see Figure 5-12). These four Risk Control Options are mainly against the (or similar) type of HoFE accident with estimated costs figures for demonstration purposes. All the assumptions used are based on a five year period of ship's expected operating life. All the costs for equipment include the maintenance fee (estimated at roughly 5% of purchase price per year). These four Risk Control Options are listed and depicted as follows.

- RCO0: Nothing has been improved except the crews have been replaced. No further corresponding countermeasures are taken. Hence there is no extra cost imposed.

- RCO1: Sufficient manpower is provided; it can be seen as ensuring that two crew members are always at the bow door to secure its closure before sailing. In this case, the extra cost is £20,000 per year.

- RCO2: A bow door monitoring system is installed; this allows the captain to check the status of the bow door anytime during the journey. £20,000 is the cost for installation and £1,000 is the maintenance fee per year.

- RCO3: It can be deemed as a set of tougher safety regulations is imposed (e.g. International Safety Management Code) or an Anti-FSI (Free Surface Instability) device is geared, such as the installation of a longitudinal bulkhead on the G deck. It is assumed that its initial cost is £200,000 and £10,000 is the annual expense.

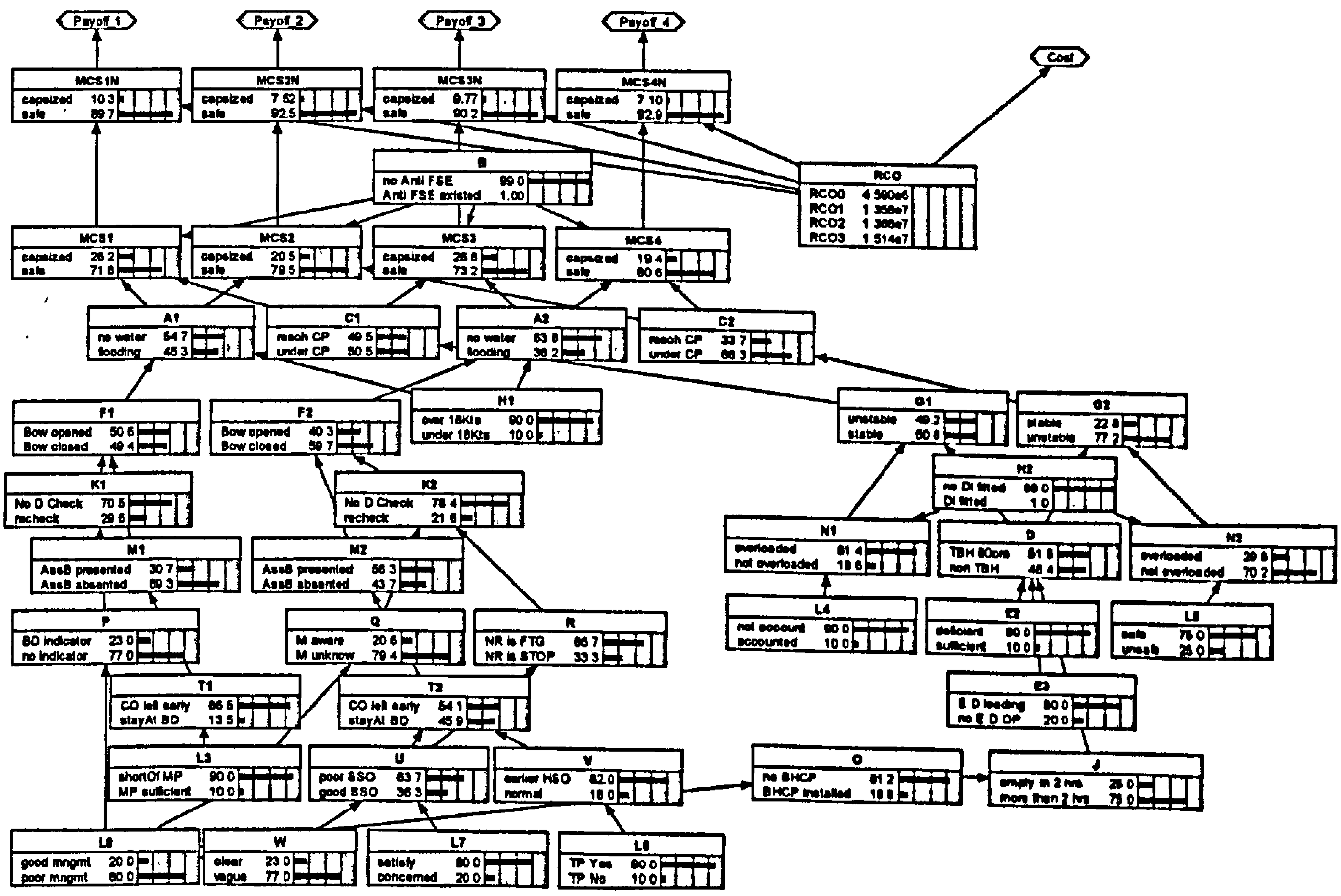


Figure 5-12 The Influence Diagrams for HoFE accident

In order to simplify the explanation, the following paragraph only concentrates on the calculation details of the Risk Control Options for *MCS1N*. The calculations regarding the rest of the Minimal Cut Sets over the Risk Control Options are not detailed further; instead Netica software is used. In the new constructed Influence Diagrams model, an extra *Chance* node is added following each Minimal Cut Set node, as a child node. Therefore four new *Chance* nodes (i.e. *MCS1N~MCS4N*) represent the posterior status (i.e. the remedied outcomes) of the Minimal Cut Sets after the Risk Control Options are implemented. Each such extra child node is named following its parent node with an extra "N" at the end of the label. For example *MCS1N* denotes the posterior status of *MCS1*. Table 5-5 shows the Conditional Probability Tables for nodes *MCS1N* ~ *MCS4N* whilst Table 5-6 shows the data for nodes *Payoff* and *Cost*. The conditional probability data for *MCS2N* ~ *MCS4N* is the same as *MCS1N*, and also refers to Table 5-5. Since the Conditional Probability Table data for the *Utility* nodes *Payoff_1* ~ *Payoff_4* are identical, only one instance is shown in Table 5-6. It has two entries: -£8,000,000 (if ship is capsized and totally lost) and £4,000,000 (if ship is safe in 5 years time and has the revenue returned). In addition, the posterior status of the Minimal Cut Sets (i.e. *MCS1N* ~ *MCS4N*) depicts the probability (or prediction) regarding the change of the likelihood of these Minimal Cut Sets (i.e. *MCS1* ~ *MCS4*) when these Risk Control Options are implemented. For example, in Table 5-5 the most left top data entry specifies the posterior occurrence probability for capsize is almost equal to one if *RCO0* is implemented and the condition given by *MCS1* happens. It means, in this example, that if the likelihood of capsize under the condition given by *MCS1* is 28.2% (as indicated for *MCS1* in Figure 5-12), then 99.9% of the 28.2% will be the likelihood for *MCS1N* to be capsized. In other words, the final likelihood outcome of node *MCS1N* depends on the likelihood result of its parent node (i.e. node *MCS1*).

Table 5-5 The Conditional Probability Table of nodes *MCS1N* ~ *MCS4N*

MCS(1~4)		capsized				Safe			
RCO		RCO0	RCO1	RCO2	RCO3	RCO0	RCO1	RCO2	RCO3
MCS(1~4)N	capsized	0.999	0.2	0.2	0.05	0.001	0.001	0.001	0.001
	safe	0.001	0.8	0.8	0.95	0.999	0.999	0.999	0.999

Table 5-6 The Utility tables for *Payoff* and *Cost*

	Payoff
capsized	£ -8,000,000
safe	£ 4,000,000

	Cost
RCO0	£ 0
RCO1	£ -100,000
RCO2	£ -25,000
RCO3	£ -250,000

By applying Equation (5.16) in section 5.7.2, the individual Expected Utility results against each Minimal Cut Set over all the possible countermeasures (i.e. Risk Control Options) are listed in Table 5-7. In the table, the row *MCS1 ~ MCS4* reveal the Expected Utilities results when only one particular Minimal Cut Set is considered over *RCO1 ~ RCO4* respectively. For instance, each entry in the row labelled as *MCS1* reveals the Expected Utility under the condition that *MCS1* is the only Minimal Cut Set considered in the model when these four Risk Control Options are imposed individually. Therefore the Expected Utility results with regard to one particular Minimal Cut Set over each Risk Control Option can be specified individually. This is achieved via the calculations detailed in section 5.7.2, in which the Expected Utilities for *MCS1* are the examples illustrated. Table 5-7 tabulates the manual calculation results as well as the Netica software readouts. This table provides an opportunity to appreciate how these Expected Utilities responsed to each Minimal Cut Set and then influence to the synthesis outcomes for each Risk Control Option. The row "*EU(Total)*" depicts the value that sums up the four entries which represent the individual Minimal Cut Sets in the same column. The row labelled as "*EU* (*corrected*)" is the result by taking out three times of "*cost*" value from the "*EU(Total)*" value in each column. This is because, in each row belonging to each Minimal Cut Set, the "*cost*" has already been taken into account once at every entry. There will be three times of redundant "*cost*" value overestimated if the figure for each Expected Utility simply sums up the data in the same column of the table without correction. Therefore, the redundant "*cost*" value should be taken out for correction. The figures shown in row "*Netica display*" are the Expected Utility outcomes over each Risk Control Option while these four Minimal Cut Sets are considered simultaneously. They are derived from the readout shown in the Influence Diagrams model of HoFE (see Figure 5-12). The differences between the data shown in row "*EU (corrected)*" and "*Netica display*" are minor and is reasonably believed to be from the effective decimal digits taken. Therefore, according to this outcome, there is no doubt that the RCO3 (i.e. gear up Anti-FSI devices for the ship) is the best choice of the countermeasure in five year time when considering the posterior occurrence probability and cost-benefit issue simultaneously. This is concluded from the ranking result of RCO3 > RCO2 > RCO1 > RCO0.

Table 5-7 The summary of Expected Utility for each RCO and MCS

(manual calculations)	RCO0	RCO1	RCO2	RCO3
MCS1	£ 610768	£ 3214584	£ 3289584	£ 3572184
MCS2	£ 1532920	£ 3398460	£ 3473460	£ 3617460
MCS3	£ 778432	£ 3248016	£ 3323016	£ 3580416
MCS4	£ 1664656	£ 3424728	£ 3499728	£ 3623928
EU (Total)	£ 4586776	£ 13285788	£ 13585788	£ 14393988
EU (corrected)	£ 4586776	£ 13585788	£ 13660788	£ 15143988
Netica display	£ 4590000	£ 13580000	£ 13660000	£ 15140000

P.S. the minor difference between the outcomes of "*Netica display*" and "*EU (corrected)*" results from the effective decimal digits taken (i.e. only four digits are rounded and shown in the Influence Diagrams model)

5.7.2 The Expected Utility (EU) calculation details for MCS1

In this section, the calculation details which acquire the Expected Utility results for *MCS1* over these four Risk Control Options are illustrated. The likelihood outcomes regarding *MCS1* ~ *MCS4* shown in the established Bayesian Network model are listed in Table 5-8 for the following calculations although only the data of *MCS1* will be utilised. The equation applied for the calculation is shown in Equation (5.16) below. The data involved in the calculation also refers to Table 5-5 and Table 5-6. The details of the calculation are illustrated in Equation (5.17), in which the individual Expected Utility results (i.e. *RCO0~RCO3*) for *MCS1* are illustrated one by one with the data involved. In the equation, some of the data has to refer to Table 5-5, which shows the posterior occurrence probability of each individual Minimal Cut Set when these Risk Control Options have been implemented.

Table 5-8 The likelihood for each MCS in the Bayesian Network model

	MCS1	MCS2	MCS3	MCS4
capsized	0.282	0.205	0.268	0.194
safe	0.718	0.795	0.732	0.806

$$\mathrm{EU}(\mathrm{MCS1},\mathrm{RCO}) = U(Cost) + \sum P(\mathrm{MCS1N} \mid \mathrm{MCS1},\mathrm{RCO}) \times U(Payoff) \qquad (5.16)$$

There are four parts in Equation (5.17). The first part of the equation (i.e. $\mathrm{EU}(\mathrm{MCS1},\mathrm{RCO0})$) reveals the calculation details for acquiring the Expected Utility given *MCS1* over *RCO0* whilst Equation (5.16) is applied. Therefore the $U(Cost)$ is inputted by zero when referring to the data entry of *RCO0* in Utility Table *Cost* (see Table 5-6). Then, for $P(\mathrm{MCS1N} \mid \mathrm{MCS1} = \mathrm{capisized}, \mathrm{RCO} = \mathrm{RCO0})$, it has to refer to Table 5-5 at column "*MCS1*=capsized" and "*RCO*=RCO0". This was 0.999 for "*capsized*" and 0.001 for "*safe*" respectively. In the Utility Table "*Payoff*", there are two states (i.e. "*capsized*" and "*safe*" in Table 5-6). This represents the revenue that the ship can obtain under these two different circumstances. Hence, the data for $U(Payoff)$ to be picked up, from the table, depend on which condition the $P(\mathrm{MCS1N} \mid \mathrm{MCS1})$ is given. For example, in Equation (5.17), $0.999 \times £\text{-}8{,}000{,}000$ is taken for "*MCS1N*=capsized" and $0.001 \times £4{,}000{,}000$ for "*MCS1N*=safe" when "*MCS1*=capsized". Finally, the answer acquired for $\mathrm{EU}(\mathrm{MCS1},\mathrm{RCO0})$ is £ 610,768 when Equation (5.16) and those data shown in the tables are applied. In order to validate the outcomes of Equation (5.17), an Influence Diagrams model regarding this demonstration is utilised and shown in Figure 5-13. The Expected Utility results are under the condition that only *MCS1* exists, and therefore the reading of node *RCO* can be utilised to validate the results acquired by the manual calculation. Although there are minor differences between the manual calculations outcomes and the software readings, they are reasonably equivalent. Again, such minor differences are believed resulting from the differences of the effective decimal digits taken (i.e. only three digits after the decimal point are taken for the manual calculation but there are far more than three digits in the software). For instance, the software reading shows the Expected Utility of *RCO1* is £3.215e6 (i.e. 3.215×10^6) whilst the result of the manual calculation is £ 3,214,584. They are not the same but the difference is minor.

$$
\begin{aligned}
\mathrm{EU}(\mathrm{MCS1}, \mathrm{RCO0}) &= £0 \\
&+ 0.282 \times (0.999 \times £\text{-}8{,}000{,}000 + 0.001 \times £4{,}000{,}000) \\
&+ 0.718 \times (0.001 \times £\text{-}8{,}000{,}000 + 0.999 \times £4{,}000{,}000) \\
&= £0 + 0.282 \times (£\text{-}7{,}992{,}000 + £4{,}000) + 0.718 \times (£\text{-}8{,}000 + £3{,}996{,}000) \\
&= £610{,}768 \\
\mathrm{EU}(\mathrm{MCS1}, \mathrm{RCO1}) &= £\text{-}100{,}000 \\
&+ 0.282 \times (0.2 \times £\text{-}8{,}000{,}000 + 0.8 \times £4{,}000{,}000) \\
&+ 0.718 \times (0.001 \times £\text{-}8{,}000{,}000 + 0.999 \times £4{,}000{,}000) \\
&= £\text{-}100{,}000 + 0.282 \times (£\text{-}1{,}600{,}000 + £3{,}200{,}000) + 0.718 \times (£\text{-}8{,}000 + £3{,}996{,}000) \\
&= £3{,}214{,}584
\end{aligned}
\tag{5.17}
$$

$$
\begin{aligned}
\mathrm{EU}(\mathrm{MCS1}, \mathrm{RCO2}) &= £\text{-}25{,}000 \\
&+ 0.282 \times (0.2 \times £\text{-}8{,}000{,}000 + 0.8 \times £4{,}000{,}000) \\
&+ 0.718 \times (0.001 \times £\text{-}8{,}000{,}000 + 0.999 \times £4{,}000{,}000) \\
&= £\text{-}25{,}000 + 0.282 \times (£\text{-}1{,}600{,}000 + £3{,}200{,}000) + 0.718 \times (£\text{-}8{,}000 + £3{,}996{,}000) \\
&= £3{,}289{,}584 \\
\mathrm{EU}(\mathrm{MCS1}, \mathrm{RCO3}) &= £\text{-}250{,}000 \\
&+ 0.282 \times (0.05 \times £\text{-}8{,}000{,}000 + 0.95 \times £4{,}000{,}000) \\
&+ 0.718 \times (0.001 \times £\text{-}8{,}000{,}000 + 0.999 \times £4{,}000{,}000) \\
&= £\text{-}250{,}000 + 0.282 \times (£\text{-}400{,}000 + £3{,}800{,}000) + 0.718 \times (£\text{-}8{,}000 + £3{,}996{,}000) \\
&= £3{,}572{,}184
\end{aligned}
$$

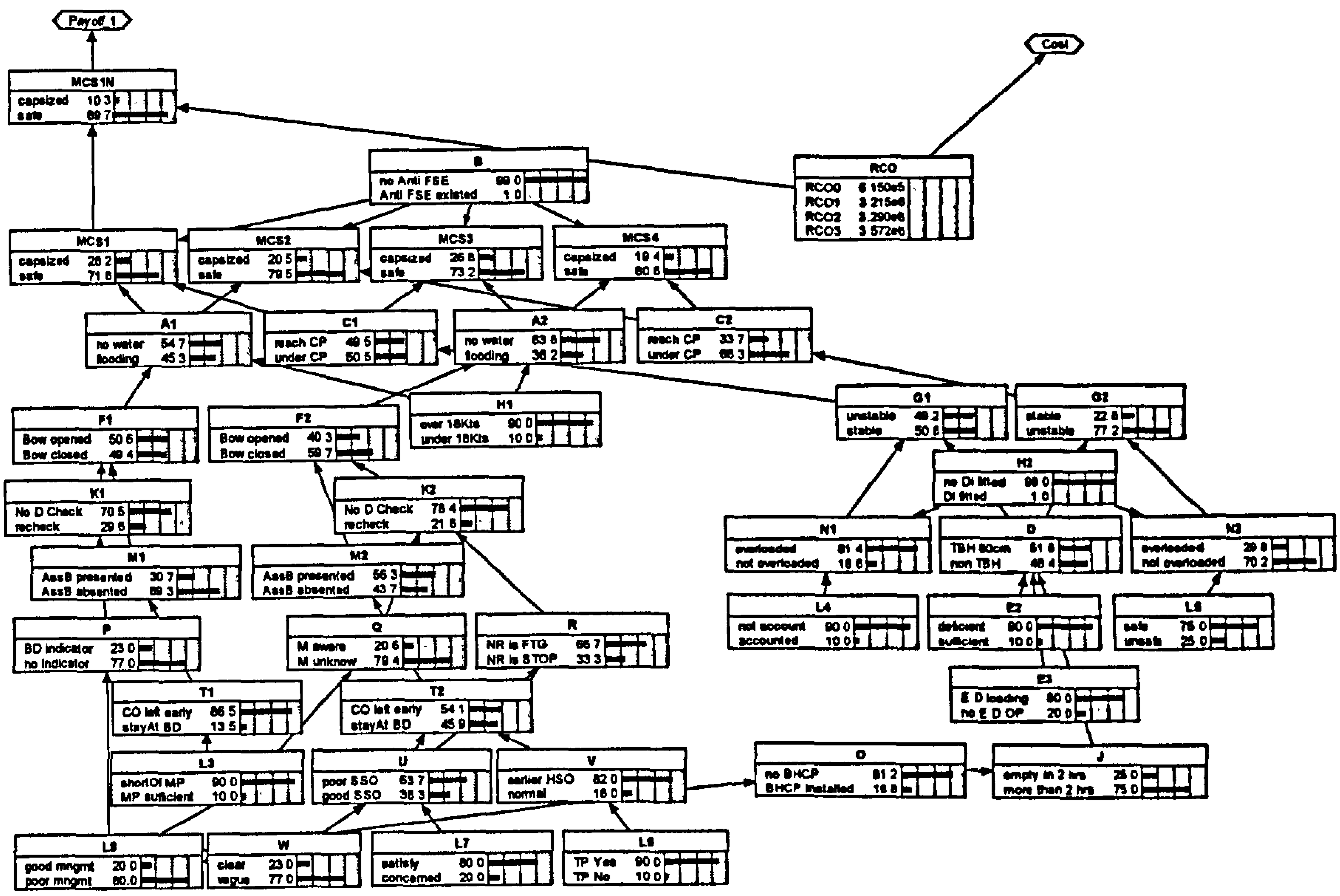


Figure 5-13 The Influence Diagrams of HoFE accident while only *MCS1* exists

5.8 Discussion

From the case study examined in this chapter, the hypothesis of implementing the Window of Opportunity of Reason's Swiss Cheese Model with the Minimal Cut Sets of FTA has been demonstrated, although it is an approximate outcome. It is not carried out via FTA alone, but several risk assessment techniques are used, one by one, step by step in the procedure. Each of these techniques (i.e. WBA, Karnaugh map, FTA, Bayesian Network and Influence Diagrams) provides a particular part of the procedure which has been formulated from Reason's Window of Opportunity in his Swiss Cheese Model. This method brings a comprehensive picture of the accident structure via the Bayesian Network model with results of both qualitative and quantitative analysis.

With the help of the Bayesian Network model, an insight into the occurrence that diagnosing the critical factors involved and predicting the interactions amongst these factors are available. This is achieved by employing the Bayesian Network propagation feature which enables "*what if*" examination to be performed in order to objectively figure out which factors are critical and what the possible influences from one factor to another will be. In addition to the Bayesian Network model, the Influence Diagrams model which is in conjunction with *Utility* and *Decision* nodes based on the established Bayesian Network model can offer the decision makers with a useful tool to examine the cost-benefit of the countermeasures from several choices in order to select one of the best Risk Control Option.

In summary, this case study has shown that the proposed method is capable of achieving the requirements of analysing an accident qualitatively and quantitatively as well as evaluating the best countermeasure efficiently. The advantages of the method are briefly listed as follows.

- A systematic procedure to sort out the Minimal Cut Sets of the accident as the qualitative analysis result is in line with the notion of Window of Opportunity of Reason's Swiss Cheese Model.
- Both the qualitative and quantitative analysis result of the accident can simultaneously be shown on a Bayesian Network model.
- A Bayesian Network model established according to the qualitative and quantitative analysis results can perform a series of "*what if*" examinations.
- The applied Sensitivity Analysis method is capable of relieving the problem of validating the analysed results as well as finding out the critical factors via a thorough and systematic process.
- An Influence Diagrams model based on the established Bayesian Network model of the accident is a useful tool for decision makers to select the best Risk Control Option from various countermeasures.
- The application of Expected Utility based on the accident analysis results has considered occurrence likelihood, effectiveness of the RCOs and payoff issues for decision makers to select the best countermeasures as a means of cost-benefit resolution.

From another perspective, although this method is dedicated to marine accidents analysis, it could be employed to other domains for the application of preliminary safety prediction, especially for the topics where no proper mathematic model is available.

Chapter Six – Human Factors Analysis and Classification System – for Maritime Accidents (HFACS-MA)

Summary

From the viewpoint of Human and Organisational Factors (HOFs) of maritime accidents and the prevailing human factors analysis methodology in the aviation industry, it is obviously worthwhile to develop a dedicated HOFs framework to deal with the human factor issue for the maritime industry. In this chapter, a prototype HOFs framework is proposed and named as Human Factors Analysis and Classification System for Maritime Accidents (HFACS-MA). Several advantages that the framework can offer are demonstrated in different sections. In section 6.2, the details of the proposed framework are specified level by level to show the hierarchy of HOFs. The benefits for the investigators in identifying the human factors issues during the investigation stage are described in section 6.3. Finally, in section 6.4, an example analysis showing the combination of the framework with the Fault Tree - Bayesian Network (FT-BN) analysis results of the accidents can provide investigators a more comprehensive picture of the influence of the human factors involved in the accident.

6.1 Introduction

"What makes the 'Swiss cheese' model particularly useful in accident investigation is that it forces the investigators to address latent failures within the causal sequence of events as well. ... However, a limitation of Reason's model is it fails to identify the exact nature of the 'hole' in the cheese" (Shappell and Wiegmann 2003b). Although the International Maritime Organization (IMO) guidelines have specified the procedure to be followed and the topics to be covered when the investigators collect the information or evidences for human factor involved in marine casualties and incidents, there is still no dedicated HOFs framework for the maritime industry to illustrate the hierarchy of the causal sequences. Therefore, the necessity to develop a specific HOFs framework for the maritime industry to help the investigators to identify the human factors involved, as well as to figure out the causality amongst these factors, should be considered.

This study therefore proposes the notion of HFACS-MA, which mainly follows the principles of the *Human Factors Analysis and Classification System* (HFACS) (see Figure 3-6) (Shappell and Wiegmann, 2003b) and the *Systemic Occurrence Analysis Methodology* (SOAM) (EUROCONTROL, 2005). Most importantly, it complies with the guidelines for the investigation of human factors in marine casualties and incidents (IMO A.884), which was adopted by IMO in 1999. Both HFACS and SOAM apply Reason's (1997) *Swiss Cheese Model* as the kernel concept of the framework. However, SOAM has also considered Hawkins's (1987) SHEL model (i.e. Software, Hardware, Environment and Liveware when identifying the causal factors which the sharp end personnel encountered at the time of the accidents. In contrast, HFACS has concentrated more on the contextual influences of active failures and latent conditions amongst different levels.

The proposed HFACS-MA framework mimics the classification of HFACS but the content of level one (i.e. *Unsafe Acts*) and level two (i.e. *Preconditions*) have been modified according to the requirements of IMO guidelines. In the proposed *Unsafe Acts* level, it incorporates aspects of Reason's (1990) *Generic Error Modelling System* (GEMS) including the differentiation between errors and violations. Furthermore, in the *Preconditions* level, it adheres to the SHEL model as the core to distinguish the types of factors involved. Figure 6-1 gives an overview of the framework, from which at least two advantages can be gained. In the first place, it is not only a dedicated HOFs framework, satisfying the requirements of maritime industry, but also suitable for the proposed Fault Tree Analysis – Bayesian Network (FTA-BN) analysis method, which is detailed in Chapters 4 and 5, to classify the identified critical factors into their proper categories. This classification of the HOFs is the foundation for further statistical study or data exchanging between authorities regarding safety issues. In the second place, it will help the investigators to gain a more comprehensive picture about the relative causal influences of various human factors aspects when gathering information or evidence during an accident investigation period.

The aviation industry has relied on HFACS in analysing the underlying human factors causes of accidents for many years (Wiegmann and Rantanen 2003; Wiegmann *et al.*, 2005; Scarborough *et al*,. 2005; Shappell and Wiegmann 2003a; Shappell *et al.*, 2007). HFACS has also made valuable contributions to investigations of railway accidents (Reinach and Viale, 2006; Baysari *et al.*, 2008). The present study considers that it should be beneficial to incorporate HFACS into the proposed framework for maritime accident analysis. The resultant HFACS-MA framework has the following aspects:

- The *Unsafe Acts* level takes into account Reason's GEMS model and can be seen as the centre component of the SHEL model (i.e. the central Liveware), which represents the conditions of sharp end personnel.
- The *Preconditions* level consists of the four components of the SHEL model and the Personnel Factors proposed in the original HFACS framework. This is in line with the study that has been made by Celik an Er (2007). They has pointed out the "integrated unit" (i.e. hardware) shall be considered within the HFACS in order to identify the design-based human factors. Thus the proposed approach presumes that the preconditions of sharp end personnel encountered at the time of an accident can be more comprehensively specified with the proposed *Preconditions* level. That is the investigators should consider Software, Hardware, Environment, peripheral Liveware, and Personnel Factors comprehensively at this level.
- In the IMO guidelines, no specific differentiation is made between Unsafe Supervision and Organisational Influences; both are considered as parts of the Management issue. This study recommends that the framework should remain as four levels as in the original HFACS approach. It is believed that it would benefit the maritime industry to make a clear distinction between the possible causal influences at Supervisory and at Organisational levels rather than simply counting them together as the factors of Management.

6.2 The framework of HFACS-MA

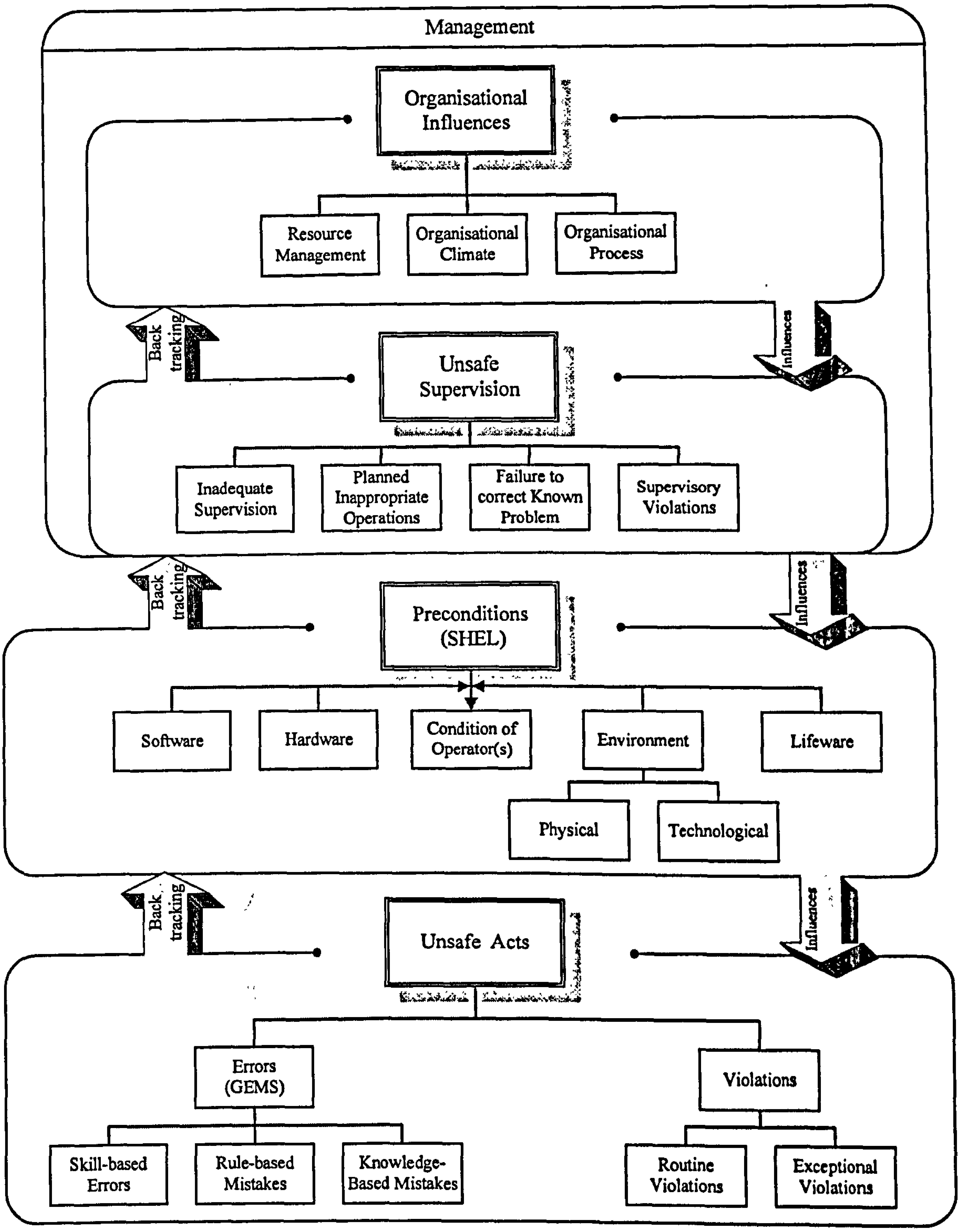


Figure 6-1 The overview of the HFACS-MA framework

In this section, each level of the proposed framework is specified, from the sharp end personnel level to the organisational level, with the categories contained in the level and the brief explanations of each category. The proposed HOFs framework (i.e. HFACS-MA) comprises four levels (see Figure 6-1); they are:

- ⇨ *Unsafe Acts* (i.e. the lowest level);
- ⇨ *Preconditions;*
- ⇨ *Unsafe Supervision;*
- ⇨ *Organisational Influences* (i.e. the highest level).

Each level consists of several categories. For example, there are three categories comprising the *Organisational Influences* level. Each category defines numerous items as the human factors of the type. It is intended that the specific items of each level can be varied according to the requirements of the applied fields or realm. Some of the levels contain a table listing examples of potential items in the categories. What the present study wants to emphasise is that the items given in these tables are only indicated as potentially relevant. They are not determined yet, but to illustrate the notion of the HOFs framework. Those items are mainly elicited from the definitions of human element in IMO guidelines A.884(21), in which the terms and the definitions are given.

In the following sections, the overview of the levels and the preliminary definition of each category will be shown. Nevertheless, the details of items for each category and the definitions of each item need to be carried out by other comprehensive studies, and is out of the scope of this study. At this stage, the study only gives an overview of the framework and its application in cooperating with the FTA-BN method for accident analysis.

6.2.1 Unsafe Acts

The first (or lowest) level of the proposed HOFs framework is *Unsafe Acts* level. The IMO guidelines suggest that "an *unsafe act* is defined as an *error* or *violation* that is committed in the presence of a hazard or potential unsafe condition" (IMO A.884). This definition seems to derive from Reason's suggestion that "an *unsafe act* is an *error* or a *violation* committed in the presence of a potential hazard: some mass, energy or toxicity that, if not properly controlled, could cause injure or damage" (Reason, 1990). Reason further defines "the psychological varieties of *unsafe acts* which are classified initially according to whether the act was *intended* or *unintended* and the distinction between *errors* and *violations*" (Reason, 1990) (see Figure 6-2).

Figure 6-2 The classification of "Unsafe Acts" (from Reason, 1990)

This differentiation between *error* and *violation* is also adopted by the HFACS when defining the unsafe acts of operators; it is loosely classified into two categories: *errors* and *violations*. *Errors* represent "the mental or physical activities of individuals that fail to achieve their intended outcome" whilst *violations* refer to "the wilful disregard for the rules and regulations that govern the safety" (Shappell and Wiegmann, 2003b). Meanwhile, U.S. Department of Defence (DoD) defines *unsafe acts* of their practice version as "those factors that are most closely tied to the mishap, and can be described as active failures or actions committed by the operator that result in human error or unsafe situation" (U.S. DoD, 2005).

Therefore, the proposed HOFs framework adopts Reason's Generic Error Modelling System (GEMS) to distinguish *errors* from *violations* in order to follow the suggestions of the IMO guidelines. The study suggests that the *unsafe acts* level consists of two categories; they are *errors* and *violations* (see Figure 6-3). Their detailed definitions are described in the next two sections.

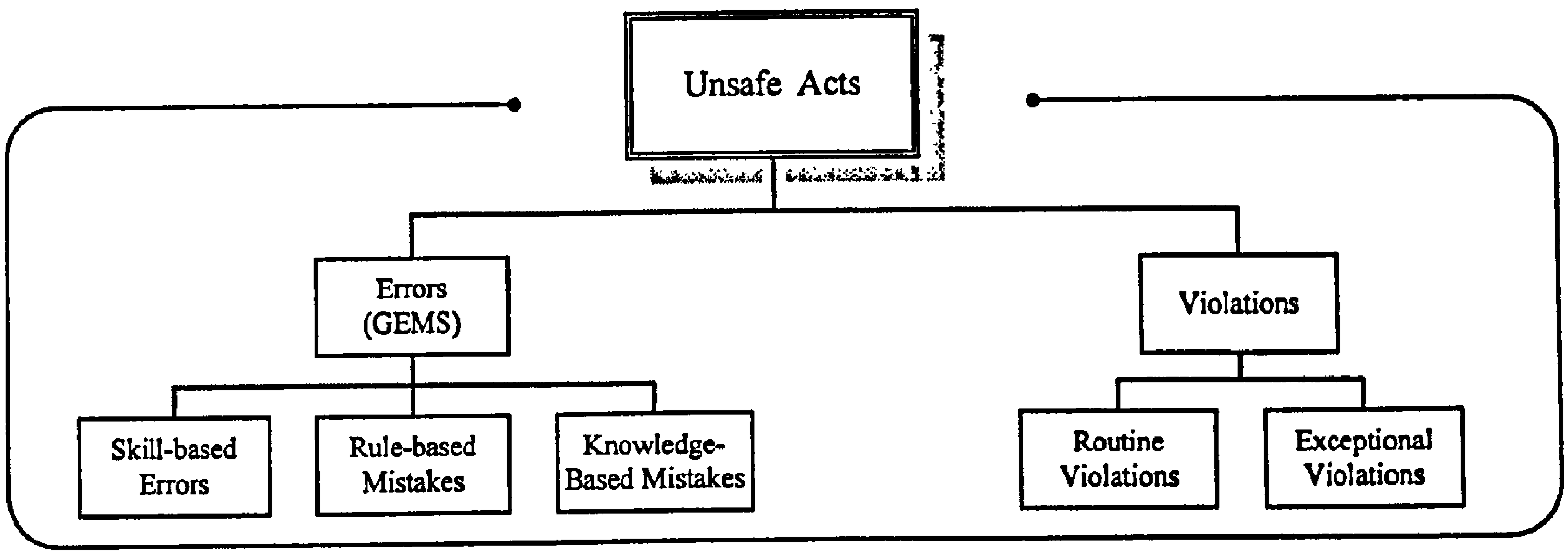


Figure 6-3 The "Unsafe Acts" level of HFACS-MA

6.2.1.1 Errors (GEMS)

In this category, the key feature is GEMS, which is asserted by Reason as that, "when confronted with a problem, human beings are strongly biased to search for and find a pre-packaged solution at the Rule-Based (RB) level before resorting to the far more effortful Knowledge-Based (KB) level, even where the latter is demanded at the outset" (Reason, 1990). This means that "errors (i.e. slips and lapse) occurring prior to problem detection are seen as being mainly associated with *monitoring failures*, whilst those that appear subsequently (RB and KB mistakes) are included under the general heading of *problem-solving failures*" (Reason, 1990). Figure 6-4 outlines the dynamics of the GEMS.

It is believed that errors or mistakes described in GEMS are derived in large part from Rasmussen's Skill-Rule-Knowledge classification of human performance and yield three basic human error types (Reason, 1990), in which errors are unintended and "a mistake is an intentional action, but there is no deliberate decision to act against a rule or plan" (IMO A.884) (see Figure 6-2). In other words, "errors are factors in a mishap when mental or physical activities of the operator fail to achieve their intended outcomes as a result of Skill-Based errors leading to an unsafe situation" (U.S. DoD, 2005). These are failures in execution, e.g. lapses or slips. In contrast, Rule-Base or Knowledge-Base mistakes are actions that are carried out as planned but the actions are inappropriate; these are failures in planning (IMO A.884).

Figure 6-4 The dynamics of the GEMS (from Reason, 1990)

In summary, these three types of errors or mistakes are defined as follows:

- **Skill-Based (slips and lapse) errors:** "slips are an unintentional action where the failure involves attention whilst lapses are an unintentional action where the failure involves memory" (IMO A.884). Here, "attention failures commonly occur during highly automatic behaviour and memory failure often appears as omitted items in a checklist, place losing, or forgotten intention" (Shappell and Wiegmann, 2003b).

- **Rule-Based mistakes:** They are the mistakes involving "the inappropriate matching of environmental signs to the situational component of well-tried *troubleshooting* rules" (Reason, 1990). The control mechanism operating at the Rule-Based level is goal-oriented, but it is a feed-forward control which is structured by the large number of rules stored.

- **Knowledge-Based mistakes:** They happen "when the individual has *run out* of applicable problem-solving routines and is forced to resort to attention processing within the conscious workspace. Mistakes at the Knowledge-Based level have hit-and-miss qualities not dissimilar to the errors of beginners and will be less predictable in their forms" (Reason, 1990).

6.2.1.2 Violations

Violations are "factors in a mishap when the actions of the operator represent wilful disregard for rules and instructions, and lead to an unsafe situation" (U.S. DoD, 2005). These rules and instructions, including regulations, govern safe behaviour. Unlike errors, violations are deliberate and occur much less frequently since they often involve fatalities (Shappell and Wiegmann, 2003b). Meanwhile, the IMO guidelines state that "a violation is a planning failure where a deliberate decision to act against a rule or plan has been made" (IMO A.884). Both the IMO guidelines and HFACS suggest that the violations can be divided into two types: *Routine* and *Exceptional*.

- **Routine violations:** routine violations are those factors which "tend to be habitual by nature and often tolerated by governing authority" (Shappell and Wiegmann, 2003b). "Routine violations occur everyday as people regularly modify or do not strictly comply with work procedures, often because of poorly designed or defined work practices" (IMO A.884). "If a routine violation is identified, one must look further up the supervisory chain to identify those individuals in authority who are not enforcing the rules" (Shappell and Wiegmann, 2003b).

- **Exceptional violations:** exceptional violations appear as "isolated departures from authority, not necessarily indicative of individual's typical behaviour pattern, nor condoned by management" (Shappell and Wiegmann, 2003b). An exceptional violation "tends to be a one-time breach of a work practice, such as safety regulations being deliberately ignored to carry out a task. Even so, the intention was not to commit a malevolent act but just to get the job done" (IMO A.884). Shappell and Wiegmann (2003b) point out that most exceptional violations are usually "heinous and have an extreme nature. They are considered exceptional because they are neither typical of the individuals, nor condoned by the authority".

6.2.2 Preconditions (SHEL)

Preconditions are the second level of the framework and are deemed as latent states which create potential for a wide variety of unsafe acts. Each precondition can contribute to a large number of unsafe acts, depending upon the prevailing conditions. This means that, at this level, the "some-to-many mapping between preconditions and unsafe acts play a significant part in both provoking and shaping an almost infinitely large set of unsafe acts" (Reason, 1990). Hence "the only sensible way of dealing with these unsafe acts is, first, to eliminate their preconditions as far as possible and, second, to accept that, whatever the measures taken, some unsafe acts will still occur, and so provide defences that will intervene between the acts and their adverse consequences" (Reason, 1990).

The original HFACS suggests that the process involves analysing preconditions of unsafe acts should include the condition of the operators, environmental and personnel factors (Shappell and Wiegmann, 2003b). However, the IMO guidelines recommend that the first step in the human factors investigation process is the collection of "work-related information regarding the personnel, tasks, equipment, and environmental conditions involved in the occurrence" (IMO A.884). Precisely speaking, the guidelines recommend the use of the SHEL model as an organisational tool for the investigators avoiding that critical information will be overlooked or lost during an investigation.

The original SHEL model, named after the initial letters of its components, *Software* (S), *Hardware* (H), *Environment* (E) and *Liveware* (L), was first developed by Edwards (1972). Later, Hawkins developed the Edwards's SHEL model from the view of the interfaces between a central Liveware element (i.e. the sharp end personnel) and other components to construct a "building block" style model. In this model the four components surround the central Liveware and affect the behaviour of the central

Liveware (see Figure 6-5 (a)). In the model, the edges of the blocks are not simple and straight since interfaces are rarely, if ever, perfectly aligned, and the central Liveware is usually the one has to adapt to incompatibility (Hawkins, 1987). This model helped the subsequent study of the human factors involved in flight. However, both models are based on the exactly same concepts.

(a) SHEL model (b) multiple SHEL model

Figure 6-5 The demonstration of the SHEL model (from Hawkins, 1987)

Moreover, in a complex system (e.g. involving distributed cognition), it is often necessary to have multiple *Software*, *Hardware*, *Environmental* and *Liveware* elements existing (see Figure 6-5 (b)). In the SHEL model's viewpoint, the mismatch of the interfaces between the operators and the surrounding components can be the sources of human error. In this sense, the categories proposed in the *Preconditions* level are: *condition of operator*, *software*, *hardware*, *environment* and *Liveware* (see Figure 6-6). The application of the SHEL model leads to some dramatic differences from the original HFACS approach. This is because the "identification of a mismatch may be the identification of a safety deficiency in the system" (IMO A.884). In summary, *Preconditions* are factors in a mishap if active and/or latent preconditions - such as conditions of the operators, software, hardware, environmental or other personnel (i.e. Liveware) practices, conditions or actions of individuals - result in human error or an unsafe situation. Thus, investigators must dig deeper into this level to explore why the unsafe acts occurred. Each category of the level is detailed in the following sections.

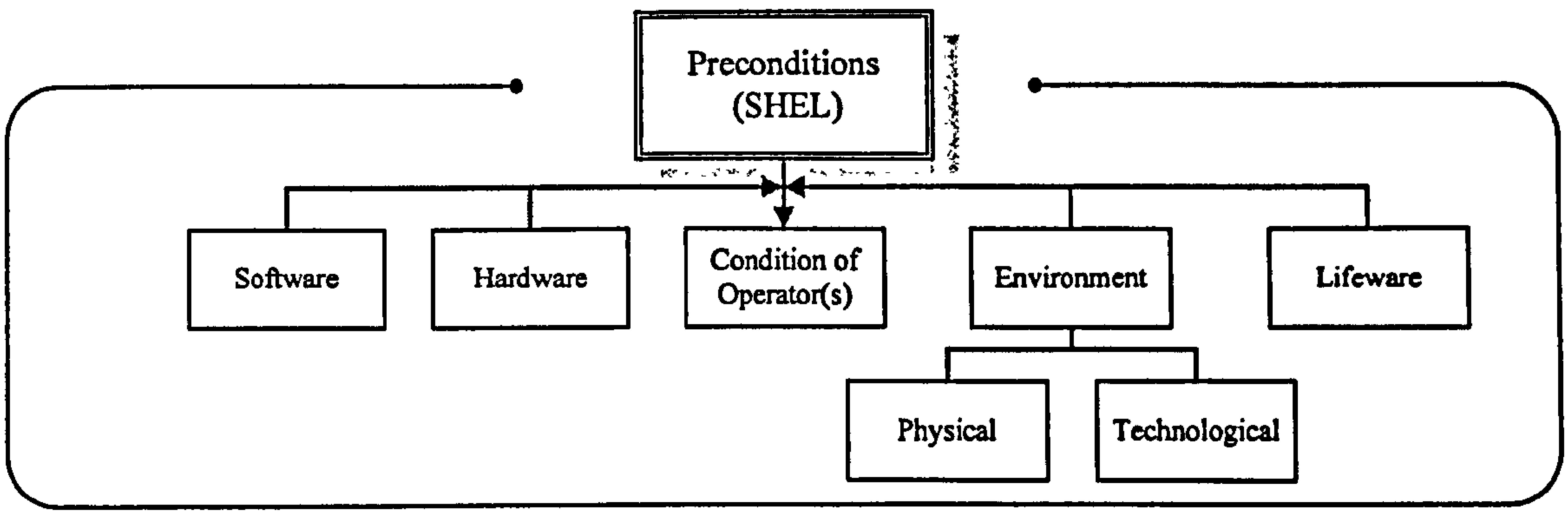


Figure 6-6 The "Preconditions" level of HFACS-MA

6.2.2.1 Condition of Operator(s)

The human element placed at the centre of the SHEL model is "the most valuable and flexible in the system. Each person brings their own capabilities and limitations to the work" (IMO A.884). Hence, "the condition of an individual can, and often does, influence the performance on the job" (Shappell and Wiegmann, 2003b). HFACS suggests that three conditions of operators can directly impact the performance; they are adverse mental states, adverse physiological states and physical/mental limitations. Also personal readiness should be counted in this category because a compromise in personal readiness can lead to the failure of physical or mental preparation for duty.

6.2.2.2 Software

Software is the non-physical part of the system including organisational policies, procedures, manuals, checklist layouts, charts, maps, advisories and, increasingly, computer programs (IMO A.884). "They are often less tangible than those associated with the Liveware-Hardware interface and encompass the non-physical aspects of the system, e.g. symbology" (Hawkins, 1987).

6.2.2.3 Hardware

Hardware refers to "the equipment part of a transportation system. It includes the design of work stations, displays, controls, seats, etc." (IMO A.884). "The natural human characteristic of adapting to Liveware-Hardware mismatches masks, but does not remove, their existence and the operators may never be aware of the deficiency, even when it finally leads to disaster" (Hawkins, 1987).

6.2.2.4 Environment

Environmental factors are "factors in a mishap if physical or technological factors affect practices, conditions and actions of an individual and result in human error or an unsafe situation" (U.S. DoD, 2005). Sometimes the broad political and economic constraints under which the system operates are included in this category. The regulatory climate is a part of the environment because it affects communications, decision-making, control and co-ordination" (IMO A.884).

- **Physical:** Physical environment aspects are factors in a mishap if environmental phenomena such as "internal and external weather, climate, temperature, visibility, vibration, noise and other conditions, which constitute the conditions within which people are working", affect the actions of individuals and result in human error or an unsafe situation (IMO A.884). This subcategory mainly focuses on the nature of environmental factors.
- **Technological:** Technological environment aspects are "factors in a mishap when workspace design factors or automation affects the actions of individuals and result in human error or an unsafe situation" (U.S. DoD, 2005). These factors encompass a variety of issues including the design of workplace and controls, information exchanging characteristics, task factors and automations. This subcategory emphasizes the importance of artificial environmental factors, e.g. harbour, waterway and traffic control issues, and so on.

6.2.2.5 Liveware

The peripheral Liveware refers to "the system's human-human interactions, including such factors as management, supervision, crew interactions and communications" (IMO A.884). This is because, increasingly, "attention is being turned to the team-work of the system from the individual since group influence can be expected to play a role in determining behaviour and performances" (Hawkins, 1987).

In summary, the *Preconditions* level focuses on revealing the underlying factors behind the act or decision of an individual or group. Therefore, it is important to determine whether there were any factors in the work system that may have facilitated the expression of the given failure mode at the Unsafe Acts level. They can be found by examining the work system information, and are organised using the SHEL or GEMS model (IMO A.884). Table 6-1 lists some example items for each category involved in the Preconditions level. These items are elicited from the IMO guidelines and are not a complete listing. The aim of showing the list is to provide a conceptual image of the scope. The details of the items can be varied according to the requirements of different domains or different authorities, and additional research is needed for determining them.

Table 6-1 The example items of Preconditions

➢ Condition of Operator(s) • personality • physical condition • activities prior to accident/occurrence • assigned duties at time of accident/occurrence • actual behaviour at time of accident/occurrence • attitude ➢ Software • procedures and standing orders • regulations ➢ Hardware • ergonomic design of working, living and recreation areas and equipment • ship design • state of maintenance • equipment (availability, reliability) • cargo characteristics, including securing, handling and care	➢ Environment ▸ Physical • adequacy of living conditions • adequacy of food • level of ship motion, vibrations, heat and noise • weather and sea conditions • ice conditions ▸ Technological • port and transit conditions (VTS, pilots, etc) • traffic density • level of automation ➢ Liveware • communication • on-board management and supervision • teamwork, • ship-shore communication • surveys and inspections (international, national, port, classification societies, etc.) • organisations representing ship owners and seafarers

(Note: This is a partial listing)

6.2.3 Unsafe Supervision

In practice, a mishap event can often be traced back to the supervisory chain of command. Reason (1990) originally names this level as *line management deficiencies*, which are defined as the consequences of higher-level decision making, but it is not purely a function of these decisions. This is because the incompetence of any set of supervisions could exacerbate the adverse effects of high-level decisions or even good decisions to have bad effects. "Conversely, competence at the supervisory level could do something to mitigate the unsafe effects of fallible decisions, make neutral decisions have safer consequences, and transform good decisions into even better ones" (Reason, 1990). "There is a many-to-many mapping between possible unsafe supervision and the various preconditions of unsafe acts, and the interaction between them is extremely complex". Any precondition could be the product of several different unsafe supervisions; the converse is also true. In this sense, four categories are proposed for the *Unsafe Supervision* level; they are: *Inadequate Supervision*, *Planned Inappropriate Operations*, *Failed to correct Known Problem*, and *Supervisory Violations* (Shappell and Wiegmann, 2003b). These categories follow the suggestion of the HFACS and are in line with Reason's Swiss Cheese Model of accident causation associated with supervisors who influence the condition of operators and the operation environment. Each of these categories is briefly described in the following sections.

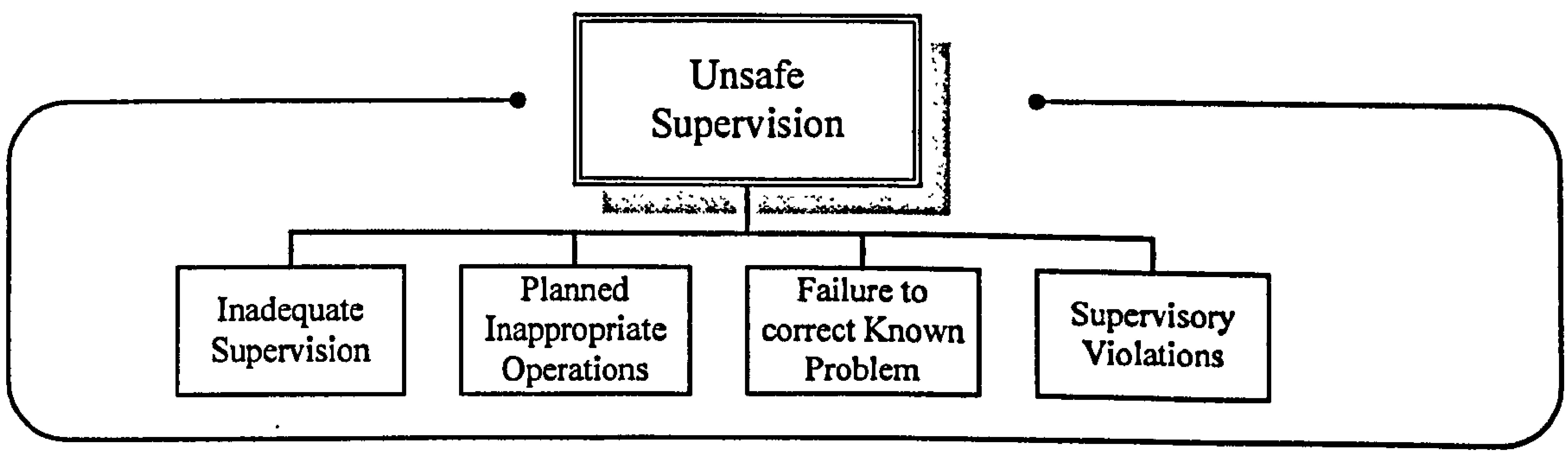


Figure 6-7 The "Unsafe Supervision" level of HFACS-MA

6.2.3.1 Inadequate Supervision

The role of any supervisor is to provide his/her personnel with the opportunity to succeed. Hence, they have to provide whatever it takes to ensure that the job is done safely and efficiently. Therefore, "any thorough investigation of accident causal factors must consider the role supervision plays in the genesis of human error", despite "empowering individuals to make decisions and function independently" (Shappell and Wiegmann, 2003b). Thus, the category of Inadequate Supervision is defined as a factor in a mishap when supervision has failed to identify a hazard, recognise and control risk, provide guidance, training and/or oversight, etc., and results in human error or an unsafe situation (U.S. DoD, 2005; 10).

6.2.3.2 Planned Inappropriate Operation

Planned Inappropriate Operation is "a factor in a mishap when supervision fails to adequately assess the hazards associated with an operation and allows for unnecessary risk. It is also a factor when supervision allows non-proficient or inexperienced personnel to attempt missions beyond their capability or when crew makeup is inappropriate for the task or mission" (U.S. DoD, 2005). Examples of these issues are the improper crew pairing and improper manning during a period of downsizing.

6.2.3.3 Failure to correct Known Problem

This refers to those instances where "deficiencies among individuals, equipment, training or other related safety areas are "known" to the supervisor, yet are allowed to continue uncorrected" as well as "the failures to consistently correct or discipline inappropriate behaviour certainly fosters an unsafe atmosphere and prompts the violation of rules" (Shappell and Wiegmann, 2003b). Likewise, the failure to report these unsafe tendencies and initiate corrective actions is another example. They can be deemed as a factor in a mishap when supervision fails to correct known deficiencies in documents, processes or procedures, or fails to correct inappropriate or unsafe actions of individuals, and this lack of supervisory action creates an unsafe situation (U.S. DoD, 2005; 11).

6.2.3.4 Supervisory Violations

Supervisory Violations are those instances when existing rules, regulations and doctrine are disregarded or violated by the supervisors when they manage organisational assets". Likewise, "flaunting authority, which is the same as failing to enforce existing rules and regulations, is a violation at the supervisory level and invariably sets the stage for the tragic sequence of events that predictably follow" (Shappell and Wiegmann, 2003b). In other words, they are factors in a mishap when supervision, whilst managing organisational assets, wilfully disregards instructions, guidance, rules, or operating instructions and this lack of supervisory responsibility creates an unsafe situation (U.S.

DoD, 2005). Table 6-2 lists some of the example items which refer to the IMO guidelines.

Table 6-2 Selected examples of Unsafe Supervision

➢ Unsafe Supervision ▸ Planned Inappropriate Operation • division of tasks and responsibilities • composition of the crew • manning level • workload/complexity of tasks • working hours/rest hours • planning (voyages, cargo, maintenance) • opportunities for recreation • assignment of duties	▸ Inadequate Supervision • organization of on-board training and drills ▸ Failure to correct known problem ▸ Supervisory Violation • Certificates (authorized unqualified crews or equipment)

(Note: This is a partial listing)

6.2.4 Organisational Influences

Fallible decisions of upper-level management can directly affect supervisory practices, as well as the preconditions and actions of operators. Unfortunately, these organisational errors often go unnoticed by safety professionals (Shappell and Wiegmann, 2003b). In considering fallible decisions, it is important to be aware that "system accidents have their primary origins in fallible decisions made by designers and high level managerial decision makers". Since they are "an inevitable part of the design and management process, the question is not so much how to prevent them from occurring, as how to ensure that their adverse consequences are speedily detected and recovered" (Reason, 1990). Therefore, the *Organisational Influences* are defined as "factors in a mishap if the communications, actions, omissions or policies of upper-level management directly or indirectly affect supervisory practices, preconditions or actions of the operator(s) and result in system failure, human error or an unsafe situation" (U.S. DoD, 2005). These latent conditions generally involve issues related to *Resource Management*, *Organisational Climate*, and *Organisational Process* and are detailed as follows.

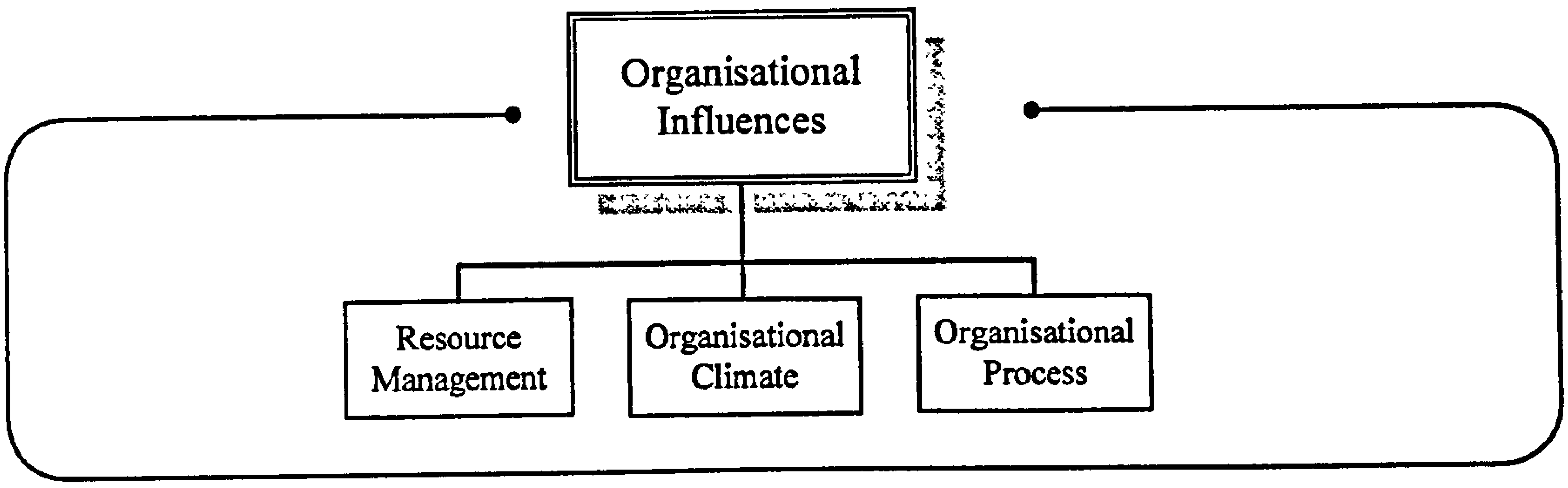


Figure 6-8 The "Organisational Influences" level of HFACS-MA

6.2.4.1 Resource Management

"This category encompasses the realm of corporate-level decision-making regarding the allocation and maintenance of organisational assets such as human resources (personnel), monetary assets, equipment, and facilities". Such resources are typically based upon two, sometimes conflicting, objectives – the *goal of safety* and the *goal of on-time, cost-effective operations* (Shappell and Wiegmann, 2003b). This is because all organisations have to allocate resources to two distinct goals: *production* and *safety*. In the long term, they are clearly compatible, but there are occasionally short-term conflicts of interest due to the fact that all resources are finite (Reason, 1990). Unfortunately, history tells us that "safety is often the loser in such battles, and as such, it is the first to be cut in organisations having financial difficulties" (Shappell and Wiegmann, 2003b). Management should ensure that "human-factors engineering principles are known and utilised and that existing specifications for equipment and workplace design are identified and met". Hence, *Resource Management* is defined as a factor in a mishap "if resource management processes or policies, directly or indirectly, influence system safety and results in poor error management or creates an unsafe situation" (U.S. DoD, 2005).

6.2.4.2 Organisational Climate

Organisational Climate can be seen as the working atmosphere referring to a broad class of variables that influence worker performance within the organisation. The HFACS suggests that the climate can be broken down into three categories; they are *structure, policies* and *culture*. The *structure* reflects the chain-of-command, delegation

HFACS suggests that the climate can be broken down into three categories; they are *structure*, *policies* and *culture*. The *structure* reflects the chain-of-command, delegation of authority, communication channels, and formal accountability for actions. The *culture* refers to the unofficial or unspoken rules, values, attitudes, beliefs, and customs of an organisation. In other words, culture is "the way things really get done around there". Meanwhile, the *policies* are "official guidelines that direct management's decisions about such things as hiring and firing, promotion, retention, sick leave, and a myriad of other issues important to the everyday business of the organisation" (Shappell and Wiegmann, 2003b). All these issues affect attitudes about safety and the value of a safe working environment. Hence it is defined as "a factor in a mishap if organisational variables including structure, policies and culture influence individual actions and results in human error or an unsafe situation" (U.S. DoD, 2005).

6.2.4.3 Organisational Process

This category refers to "corporate decisions and rules that govern the everyday activities within an organisation....Other organisational factors such as operational tempo, time pressure, and work schedules are all variables that can adversely affect safety." It can be subdivided into three subcategories; they are *operations*, *procedures* and *oversight* (Shappell and Wiegmann, 2003b). *Operations* refer to "the characteristics or conditions of work that have been established by management". *Procedures* are "the official or formal procedures as to how the job is to be done". *Oversight* is viewed as "monitoring and checking of resources, climate and processes to ensure a safe and productive work environment". Generally speaking, *Organisational Processes* can be defined as "a factor in a mishap if organisational processes such as operations, procedures and oversight negatively influence individual, supervisory and/or organisational performance and results in unrecognised hazards and/or uncontrolled risk which leads to human error or an unsafe situation" (U.S. DoD, 2005).

Again, Table 6-3 is just an example of the listing. Another study to figure out the details of the items is needed and is out of the scope of this research.

Table 6-3 Selected examples of Organisational influences

➢ Organisational influences ▸ Resource Management • policy on recruitment ▸ Organisational Climate • safety policy and philosophy (culture, attitude and trust) • general management policy	▸ Organisational Process • management commitment to safety • scheduling of leave periods • port scheduling • contractual and/or industrial arrangements and agreements

(Note: This is a partial listing)

6.2.5 The management factors and m-SHEL model

The m-SHEL model (see Figure 6-9) was first introduced by Kawano when he carried out a human factors research project for Tokyo Electric Power Company. This model is derived and expanded from SHEL model in order to solve the problem of not incorporating the management factors when it is applied to the human factors involved in an organisation (Kawano, 1997). In m-SHEL, the management (m) factor is defined as "the corporate organisation, administration and system, and the efforts to develop a desirable atmosphere at job site and safety culture," when it cooperates with the original SHEL model. Subsequently, a few studies (Itoh *et al.*, 2002; Hiroaki, 2004) published in Japan have referred this (m) factor when the m-SHEL model is applied for human factors analysis. However, in these papers, there is no further definition being given as to how the (m) factor interacts with, or influences, the other components (i.e. Software, Hardware, Environment and peripheral and central Liveware).

(a) m-SHEL model (b) multiple m-SHEL model

Figure 6-9 The illustration of m-SHEL model (from Itoh *et al.*, 2002)

Although there is no specific definition associated with management factors in IMO guidelines A.884(21), Appendix 3 of the guideline (i.e. the section of "definitions common human element terms") has specified that the management factor involves the following situations.

- Failure to maintain discipline
- Failure of command
- Inadequate supervision
- Inadequate communication
- Inadequate physical resources
- Inadequate manning
- Poor job design
- Poor regulations or practices
- Misapplication of policies, procedures or practices

In addition, in the section of "process for investigating human factors" (i.e. Appendix 1) of the guidelines, the *underlying factors* are described as the causes behind the act or decision of an individual or group which may have facilitated the expression of the given failure mode in the work system. These factors can be found by examining the work system information collected and organised using the SHEL model or Reason's Swiss Cheese Model. In other words, they are the latent condition of the factors identified in the *Preconditions* or *Unsafe Acts* level of the proposed framework. Hence the identification of potential safety problem is based extensively on what factors were identified in the lower level of the framework.

In this sense, if the management factors are deemed as the factors in *Organisational Influences* and/or *Unsafe Supervision* of the HFACS-MA framework (see Figure 6-1), it can explain how the management factor interacts with or influences the other factors in the m-SHEL model and also complies with the requirements of the IMO guidelines. In other words, the consideration of including management factors in the HFACS-MA has the merit to implement the notion of m-SHEL whilst complying with the IMO guidelines and being in line with Reason's Swiss Cheese Model. In this fashion, the *Management Factors* can therefore be deemed as a factor in a mishap if adverse supervision and/or organisational influences result in poor management or creates an unsafe precondition situation.

6.3 The applications of HFACS-MA during the investigation stage

Once the HFACS-MA framework is in place, it offers the analyst a clearer vision with respect to the definitions of human factors and the structure of the HOFs hierarchy. This framework can assist investigators in categorising the human factors identified and also in spurring on further investigation of the latent conditions regarding the identified factors during the investigation period.

This framework would help the investigators in two aspects.

Firstly, a clearer definition for the HOFs hierarchy and human factors can help the investigators to more clearly classify the identified human factors involved in the accident. Such as the framework that has been established by U.S. DoD (2005), it organises all the human factors which have been identified from the investigated accidents and details the typical characteristics of them. Additionally, it has also repeatedly been applied to numerous U.S. military and civil aviation accident investigations. It is obvious that an official HOFs definition can dramatically improve the classification of the factors identified by avoiding individual investigators use the same terminology in different ways. The definitions of factor and category for every level of the HOFs framework also improve the precision of the framework by specifying what should be classified as a human factor and by indicating exactly what should be categorised at which level. Meanwhile, the framework provides a well defined basis to facilitate quantification of the identified human factors involved in accident investigations. This also has the benefit of providing a platform for data exchange. If data from separate accident investigations can be quantified using the same criteria, it will be easier for further statistical analyses to be made thus broadening the view of human factor issues. For instance, several studies (Wiegmann and Shappell 2001; Shappell and Wiegmann, 2003a; Shappell *et al.*, 2007) are able to carry out a broader statistical analysis regarding the analysed accidents since they are achieved by following the same framework to gain the benefit of clear classifications and specifications of the identified factors.

Secondly, a HOFs hierarchy associated with causality can offer the investigators a clearer view to track back through the causal sequence amongst the factors identified.

For example, if a preconditions factor has been identified, the framework will encourage the investigators to consider whether any *Unsafe Supervision* or *Organisational Influences* factors, as the latent conditions of the identified factors, is overlooked. In other words, it can clearly point out the deficiency of the information or evidence associated with the identified factors in the lower level (i.e. *Unsafe Acts* or *Preconditions* level) when no related factor in the higher level is discovered. This mechanism will help the investigators to decide if any underlying factor needs to be explored in greater depth. Besides, this framework can also helps the investigators to figure out the causalities (or trajectories) amongst identified factors from the higher level to the lower level. With the clearer hierarchy of HOFs and the classification of factors, the causal sequences between factors are no longer vague since their categories are determined. It implies that the factor in the lower level is always provoked by the factor in the higher level, and the reverse direction is very unusual. This is because the relationship between factors should be in line with the principle of the framework (i.e. Reason's Swiss Cheese Model), otherwise either some evidence is still missing or the supposed connections amongst the factors are incorrect.

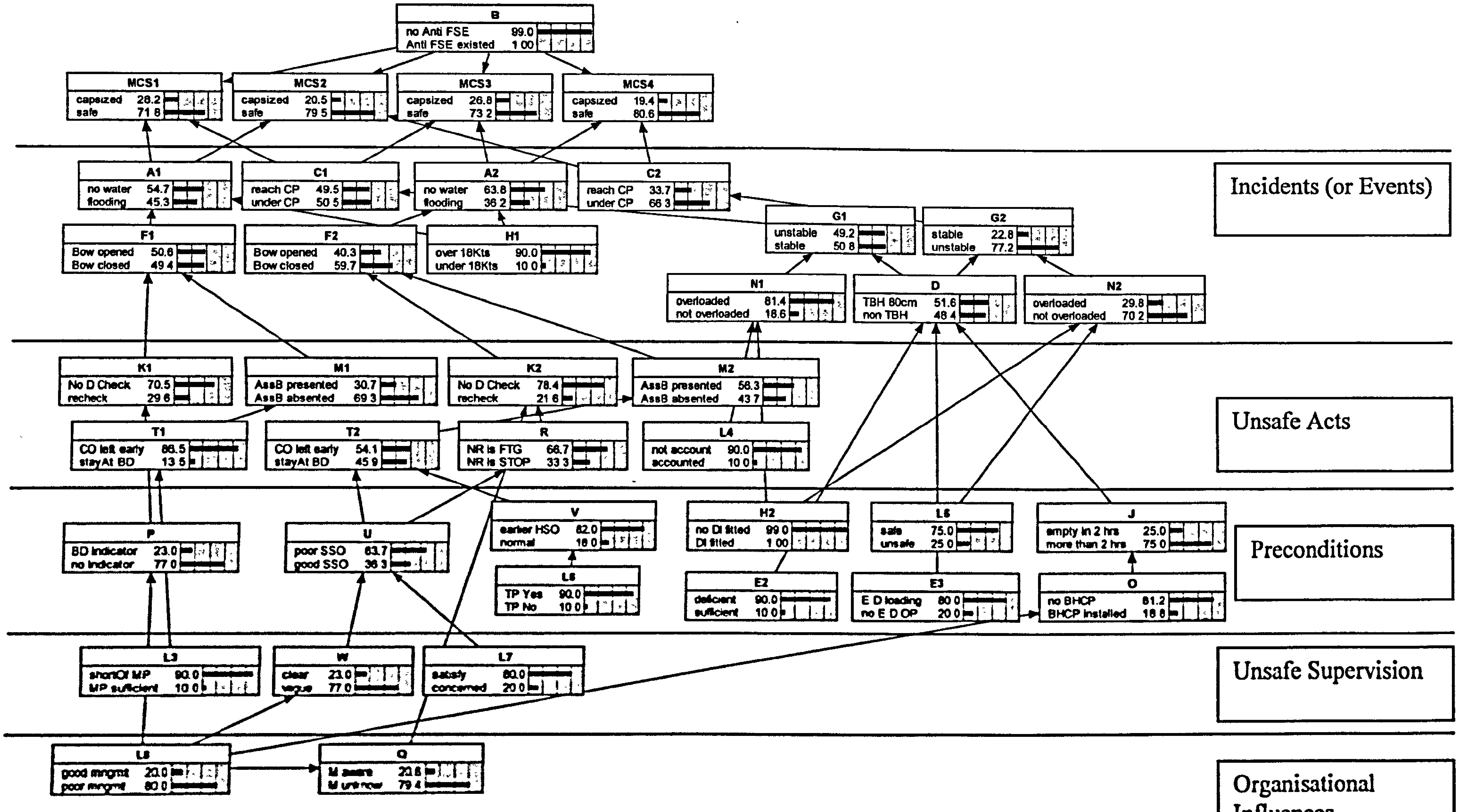


Figure 6-10 The FTA-BN analysis results of HoFE masked with HFACS-MA framework

6.4 The integration of HFACS-MA with the Fault Tree – Bayesian Network (FT-BN) analysis results

As noted previously, the proposed HFACS-MA framework can not only be used at the investigation stage, but also be a very useful auxiliary tool for the subsequent analysis. By projecting the HFACS-MA framework, as a mask, onto the FT-BN analysis results, a comprehensive picture associated with the causalities amongst these identified human factors at different levels of the framework can be acquired. Furthermore, the factors located in the lower levels (i.e. *Unsafe Acts* or *Preconditions* level) without provoking factors in the higher levels also give the investigators an unambiguous indication that further investigation associated with these lower level factors should be considered. The example shown in Figure 6-10 illustrates the FT-BN analysis results of the Herald of Free Enterprise (HoFE) analysis, which is the integrated outcome with respect to the case study described in Chapter 5, with the mask of HFACS-MA framework. In this illustration all of the identified factors are placed in the levels according to their characteristics referring to the definitions of HFACS-MA framework. Each node includes indications showing the marginalised probabilities in terms of events occurrence likelihood in percentage manner. From the figure, the following features emerge in a comprehensive way:

1. The illustrations of the Window of Opportunity (WoO) of Reason's Swiss Cheese Model and the trajectories to penetrate the WoO. For example, the path starts from Node *L8* through Nodes *P*, *K1*, *F1* and *A1*, and finally reach Node *MCS1* or *MCS2* is one of the instances of the trajectories whilst the combination of the factors of *MCS1* or *MCS2* represents one of the WoOs.

2. The influences of the factors from the higher level to the lower level. It portrays the principle of HFACS-MA framework (i.e. Reason's Swiss Cheese Model) that the causal sequence moves from fallible decisions, through the intervening planes to an accident.

3. The deficiencies of information or evidence regarding some of the identified factors in the lower levels. This is highlighted by the lack of connections between underlying factors. For instance, there is no factor in the higher levels influencing Node *H1* in the FT-BN analysis result shown in Figure 6-10.

However, there should be some reasons (i.e. unsafe acts) to specify why the ship's speed was over 18 knots at the time, but no such explanation has been given.

4. The numerical or statistical indications pin point which part of the system is more vulnerable. It is obvious, from Figure 6-10, that there are many potential factors for consideration at the *Preconditions* level, although they are now deemed as consequences instead of causes. In addition, if a series of accidents are reviewed and compared under the same framework, it can conveniently provide a chance to analyse these accidents statistically and offer a broader view which can highlight the weak point(s) of the system. For example, if some *Unsafe Supervision* factors are repeatedly identified as the critical factors in a series of incidents or accidents, these analysis results can subsequently be compared, organised and aggregated as an statistically figure. This figure can help the authorities to pin point the critical part(s) of the system before another serious accident occurs.

6.4.1 The procedure to integrate the FT-BN analysis results with HFACS-MA framework

Having accomplished the FT-BN analysis results according to the method proposed in Chapter 4, the results should be able to map onto the HFACS-MA framework since the definition of the Minimal Cut Sets of the results is in line with the principle of HFACS-MA (i.e. Reason's Swiss Cheese Model). By following the definitions of each level of HFACS-MA framework, each node in the Bayesian Network should be able to find a location in one of the levels. Having organised each node to the levels which it belongs to, these factors should be able to divide into six groups; they are *accidents*, *incidents (or events)*, *unsafe acts*, *preconditions*, *unsafe supervision*, and *organisational influence* levels respectively, from the top to the bottom. The nodes allocated in the *incidents* level are the Intermediate Events which are the consequence of unsafe acts or preconditions, and the accidents are provoked or triggered by the combinations of these incidents. As noted previously, the accident is represented by several nodes named MCS# ($\# \in N$, e.g. 3) in the Bayesian Network model, and is no longer a single object as it is in FTA. Hence, in the *accidents* level, each node represents one of the Minimal Cut Sets of the accident and can be seen as one of the WoO with a numerical figure to indicate its likelihood. In summary, the integration process can be achieved by the following steps:

1. Drawing lines in the Bayesian Network model of the accident to separate the area and to indicate the different levels of the HFACS-MA framework.
2. Organising each node to the levels to which it belongs according to its characteristic and the definitions of each category in the HFACS-MA framework.
3. Rechecking the allocation of each node to ensure that every influencing direction is from the higher level to the lower level. If not, either the relative nodes have been placed to the wrong level or, even worse, the Bayesian Network model might be invalid. This is because it is very rare that the factors in the higher lever can be influenced by the factor in the lower level.

6.4.2 Some considerations of the combination

One may ask why the FT-BN analysis result and the HFACS-MA framework can be integrated together. Can any framework integrate into the FT-BN analysis result? The answer is Reason's Swiss Cheese Model. As long as the framework is based on the Swiss Cheese Model, it can be integrated with the FT-BN analysis result, though the items or categories for each level will vary. In other words, an individual can vary the framework and work with the FTA-BN methods providing that the levels of the framework still coincide with the principle of Reason's Swiss Cheese Model. This is because the principles of both HFACS-MA and FTA-BN method are in line with Reason's Swiss Cheese Model. In FT-BN, each Minimal Cut Set is one of the instances of a WoO, and the WoO is the core of the Swiss Cheese Model. Meanwhile, the HFACS-MA, which is transformed from HFACS, is an instance of the Swiss Cheese Model with more specific definitions relating to items and categories involved at each level. Both FTA-BN and HFACS-MA are derived from the same principle but are expressed differently, therefore they are compatible. They simply interpret the same thing from a different aspect.

In the integrated outcome, the FTA delivers the qualitatively analysed results whilst the Bayesian Network performs the quantitative analysis with the HOFs framework of HFACS-MA. Having integrated the framework with the FT-BN analysis result (see Figure 6-10 as an example), it clearly depicts which levels of the framework the factors belong to, as well as the occurrence likelihood of them. It can also highlight which part of the system in the lower levels is more vulnerable due to the defects in the higher level. Each path in the figure, from the higher level through the intervening planes and eventually leading to the nodes representing the Minimal Cut Sets, is the route map of influences (or causality) between levels. The paths also illustrate how the trajectories penetrate the multiple defences of the system. Each node in the various paths shows the quantified figure regarding the degree of influences, whilst the likelihood of each Minimal Cut Set indicates how big the "window" is. Predictably, the levels (or layers) of the framework can make the causality appear less disordered and ambiguous and even highlight the defects or deficiencies of the system explicitly and distinctly. This combination of information can provide the analyst with a crystal clear indication of causative links between identified factors. In summary, there are at least three advantages can be obtained from the combination.

Firstly, It can reveal the likelihoods of every factor and the causality of the accidents with an overview of HOFs framework as a whole, in which the vulnerable part of the system is under the spotlight immediately. For instance, the example in Figure 6-10 shows that there are more human factors identified in the *Preconditions* and *Unsafe Acts* level. Undoubtedly, this outcome will attract the attention of the analyst. However the operatives at this level can now be seen as the victims rather than the pathogen. The outcome clearly illustrates that a few defects at the decision level can cause lots of problem in the operation level. The influences not only affect on the factors in the lower level, but also the combinations of these factors (i.e. Minimal Cut Sets), and the effectiveness on them are different from one to another.

Secondly, it can help the investigators to decide if any factor in the higher level is still missing. In other words, if there is any lack of explanation to support the occurrence of an identified factor in the lower level. If so, a further investigation should be carried out. For instance, in Figure 6-10 there is no factor in the higher level connecting to event "L6 (time pressure for an early sailing from Zeebrugge)" and "E2 (Deficiency of harbour ramp)" whilst these two factors are categorised as *Preconditions*. Although these two factors in this example have not affected the Top Event (i.e. the Minimal Cut Sets) significantly. They just reduce the likelihood value of the Top Event by 0.004 and 0.05 respectively if these two factors were not considered (or did not exist).

However, there is still something missing regarding the defects of the higher level from the point of view of HOFs framework. In other words, the framework clearly points out that further work is needed in order to figure out if there is any latent condition existing at the *Unsafe Supervision* and *Organisational Influences* levels to make events *L6* and *E2* likely to happen.

Thirdly, the hierarchy of the framework can also help the analyst to validate the FT-BN analysis results. Theoretically, the factors in the higher level cannot be influenced by the factors in the lower level. It means that if all the nodes of the FT-BN results are placed in the correct levels according to the HFACS-MA framework, the influence arcs between the nodes should be always from the higher level (e.g. *Organisational Influences*) to the lower level (e.g. *Unsafe Acts*). If it is not the case, something must have gone wrong and the FT-BN analysis result should be re-examined. This is because the direction of influence within the HOF framework should always be from the higher levels to the lower levels. Thus, it provides a mechanism to validate the FT-BN analysis results.

6.4.3 Further work regarding the framework

The proposed HOFs framework in this chapter is a preliminary attempt using this approach. The present study has no intention to prove that the proposed framework is practically applicable. Yet, it points out the benefits of having a HOFs framework for the maritime industry and illustrates its possible applications. In other words, there are many refinements needed before the framework can be utilised in practical. Since these topics are either beyond the scope of the research, or more expertise is required, the study only highlights these considerations without further discussion. They are:

1. A consensus HOFs framework with detailed items defined for the maritime industry. A further study, to define the items and categories of the framework for the maritime industry, such as that done by U.S. DoD (2005), would be helpful for the investigators to follow in order to identify and depict the human factors. Furthermore, this definition also provides a basis to set up a platform for data exchange in order to share the information regarding the identified causal factors involved in variant accidents.

2. A protocol for data exchanging amongst authorities or organisations. If a data exchange protocol based on the consensus (or similar) HOFs framework is in place in the maritime industry, it would help authorities to gather and exchange the causal data of the analysed accidents with regard to HOFs. Individual enterprises in the industry could also benefit by following the same framework when investigating and analysing their own incidents; hence broadened applications of the quantified accident analysis data can be acquired. Therefore more comprehensive and efficient countermeasures can be introduced faster if the analysed accident data can be quantified, based on the same HOFs framework, and exchanged within the industry.
3. The consideration of an additional *Administration and legislation* level. If an addition level is defined and added above the *Organisational Influences* level, the framework can extend the application scope to examine the deficiencies or defects associated with regulations or legislations, or even the authorities. This means that the method and the framework can also be helpful in identifying the deficiencies or defects occurring at the government level. This would be useful to deal with the issues beyond the organisational level.

6.5 Discussion

Although the IMO has realised the crucial role that the human factor plays in an accident and have specified numerous guidelines distributed in various documents (see section 4.2.1), a dedicated HOFs framework still remains to be established. The proposed HOFs framework – HFACS-MA – outlined in this chapter is an illustration to point out the benefits which would follow from such a dedicated approach.

Once established, a dedicated framework for the maritime industry could assist an investigation by identifying the human factors involved, and by combining the proposed FTA-BN method to provide a more comprehensive insight into the analysed accident. In other words, it should be of benefit to the investigators in carrying out their investigations and in analysing the results.

The HFACS-MA framework proposed in this chapter incorporates key aspects of four major models which are prominent in the Human Factors' literature - Reason's Generic Error Modelling System, Reason's Swiss Cheese Model, Hawkins's SHEL model and Itoh's m-SHEL model. Most importantly, it complies with the IMO guidelines for the investigation of human factors involvement in marine casualties and incidents.

In the previous sections, the advantages of integrating the FT-BN outcomes and the HFACS-MA have been shown - in which, the HOFs framework is imposed onto the accident analysis results as a mask. This combination can not only indicate the causation amongst factors, but also reveal the influences between levels. This enables a comprehensive picture that has qualitative and quantitative information associated with the human factors involved in an accident to be gained. In short, from the view of Reason's Swiss Cheese Model, each Minimal Cut Set reveals the *Window of Opportunity*, and the likelihood of each Minimal Cut Set indicates the width (or extent) of the window (see Figure 6-10 as an example). This Minimal Cut Set explicitly instantiates that "disasters are very rarely the product of a single monumental blunder; usually they involve the concatenation of several, often quite minor, errors committed either by one person or, more often, by a number of people" (Reason, 1990).

In summary, this combination provides a systematic method to perform the qualitative and quantitative analysis of an accident with a clearer causality overview over HOFs as a whole. At the analysis stage, the framework can provide a clear indication to show which part of the system is more vulnerable. This is because it highlights the following information.

1. The perspectives of WoOs of the accident. It shows how the identified factors located in different levels comprise each one of the windows with the likelihood values for every factor and an overview of HOFs framework as a whole.

2. The influences of the factors from the higher level to the lower level. This portrays the principle of the HFACS-MA framework that the causal sequence moves from fallible decisions, through the intervening planes to an accident.

3. The deficiencies of information or evidence. The framework can facilitate the investigators to spotlight the factors identified in the lower levels without further explanation or underlying factors connected. It can help the investigators to check if any factor in the higher level is overlooked and warrants further investigation.

4. The vulnerable parts of the system. The numerical or statistical data can easily be acquired from the analysed accidents if they are under the same HOFs framework. This is the base to carry out a broadened analysis in order to highlight the weak points of the system.

It has also been demonstrated in sections 6.3 that the proposed framework can provide a HOFs hierarchy to investigate the human factors involved in an accident. In other words, it can provide, for the investigators during the investigation stage, a definite taxonomy to classify the identified human factors involved in an accident and a clearer aspect to gather the evidence or information regarding those factors discovered. This is because:

1. It provides a clear framework and definition which help the investigators to identify the human factors involved in an accident and to classify the categories of the factors.

2. It offers a clearer causality hierarchy associated with HOFs for the investigators to track the causal sequence amongst the factors identified.

Since human factors still dominate almost 80% of the accidents in maritime industry (Akten, 2004; Harati-Mokhtari et. al., 2007), the researcher would like to address the main benefits of the proposed HOFs framework. It provides:

1. A dedicated HOFs framework with detailed levels and categories which is specifically suitable for the maritime industry.

2. A platform for data exchanging amongst authorities or organisations. It is based on the dedicated HOFs framework for every entity in the maritime industry to share their analysed accident data.

3. The consideration of an additional *Administration and legislation* level. This would be useful to examine the defects or deficiencies at the governmental level.

Chapter Seven – Similarity Aggregation Method (SAM) for group consensus of uncertainty

Summary

Group consensus is always a difficult issue to cope with. Unfortunately, historical statistical data will not be always available for some of the entries of the Conditional Probability Table regarding the established Bayesian Network model of an accident. The main feasible alternative is to use the judgement of a number of experts. However, the difficulty of obtaining a group consensus emerges. In order to overcome this problem, the present study proposes a method which provides a systematic and objective procedure to aggregate the experts' estimates. In addition, this method has also considered the uncertainty of the judgements and the experts' contentment about the consensus outcome. The method adopted applies the Positive Trapezoidal Fuzzy Number (PTFN) and the Similarity Aggregation Method to deal with the estimates aggregation and the *f-weighted* valuation functions to obtain the crisp value of the PTFN. Occasionally, the Delphi method has to be utilised in order to reach a common ground associated with those PTFNs given by the experts if their estimates differ significantly. Eventually, the group consensus is achieved, through the proposed aggregation method, and the outcome of the consensus takes into consideration the importance of the opinions given by individual experts involved.

7.1 Introduction

When historical statistical data is not available, it is a common practise to use experts' judgements to evaluate the likelihood of the events of the accident. However, a question is frequently encountered as to whether or not their estimates should be aggregated when the views of the experts do not coincide. From the viewpoint of decision makers, it is preferred to have a group consensus, rather than several individual figures, to depict the accident analysis results.

Traditionally, the aggregated result of the experts' estimates for the likelihood of the events can be the mean (or median) of the figures given. However, this simple practice may not be practicable all the time. Firstly, there may be a significant disagreement among experts with regard to some particular events. For example, two individual experts award 10% and 90% to a particular event respectively as the likelihood of the occurrence. It would be unrealistic for both of them to accept the average of 50% as the final consensus. Secondly, there will be doubt as to whether the single crisp value is of a suitable form to express the experts' opinion or not.

Having considered these concerns (above) when solving the group consensus problem, an aggregation method is proposed in this chapter. The PTFN (see section 7.2) has the advantage to handle the uncertainty of the judgements considering randomness and fuzziness. Furthermore, it can also facilitate the common ground of the judgements to be reached when the Delphi method, which is a communication tool developed by Dalkey (1969), is applied (see section 7.5). Subsequently, the Similarity Aggregation Method (SAM), which is proposed by Hsu and Chen (1996), is utilised to aggregate these PTFNs when the common ground of the estimates is reached (see section 7.3). Eventually, the crisp value regarding a corresponding entry of the Conditional Probability Table of the Bayesian Network model, is acquired when the consensus PTFN is attained. This crisp value is obtained by transforming (or defuzzifying) the PTFN into a single figure value via the *f-weighted* valuation functions (see section 7.4), which is a defuzzification function proposed by Yager (1981).

In summary, the flowchart shown on the right hand side of Figure 7-1 is the proposed procedure for dealing with a group of experts in order to obtain the group consensus. Furthermore, this method can also be used by a single expert to express his/her estimate if uncertainty is the problem to cope with. If this is the case, the flowchart shown on the left hand side of the figure is more suitable to be followed (as the Delphi method can be omitted). In the following sections, the PTFN, SAM, *f-weighted* valuation function and the Delphi method, which form the proposed aggregation method, will be introduced in turn.

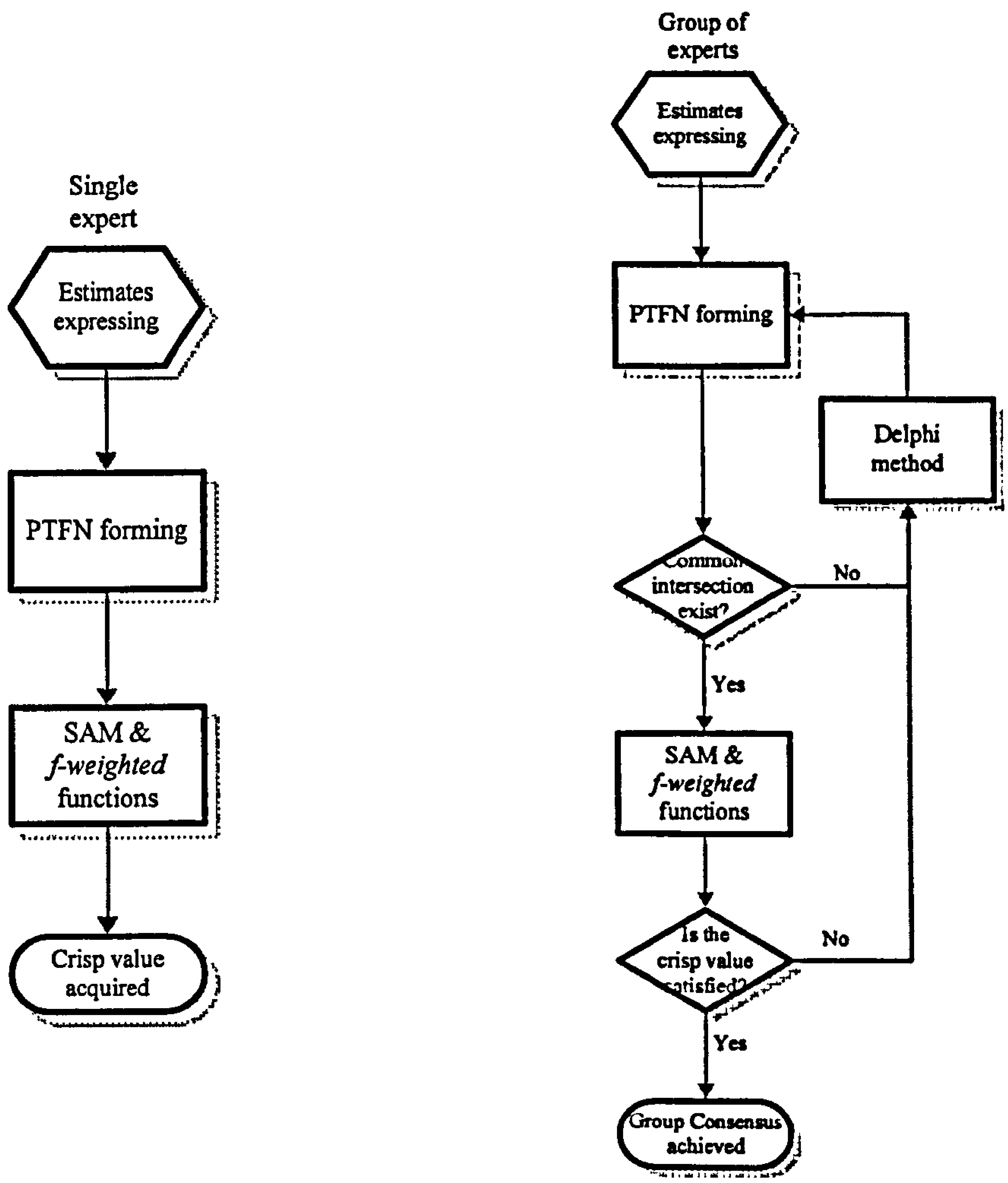


Figure 7-1 The flowchart of the aggregation method

7.2 Positive Trapezoidal Fuzzy Number (PTFN)

A PTFN consists of two intervals which are the most likely interval $[b_i, c_i]$ (i.e. the core) and the largest interval $[a_i, d_i]$ (i.e. the support) where $a_i \le b_i \le c_i \le d_i$ (see Figure 7-2 for the illustration). It means that "a_i" represents the lower least likely value, "b_i" and "c_i" the most likely value, and "d_i" the upper least likely value. In the proposed methodology, each expert $E_i(i=1,2,\ldots,n)$ can construct a PTFN ($\tilde{R}_i$) with member functions $\mu_{\tilde{R}_i}(x) \in [0,1]$, $x \in [0,1]$ to represent his subjective estimate regarding a given entry of the Conditional Probability Table of a Bayesian Network node. A trapezoidal fuzzy set is undoubtedly a better choice to represent the experts' estimates. Nevertheless, a triangular fuzzy set is also practicable, as a substitute, since it is a special trapezoidal fuzzy set. "A triangular fuzzy set can be seen as a special trapezoidal fuzzy set when the core set (i.e. the most likely interval $[b_i, c_i]$) of the trapezoidal fuzzy set takes the form of a single point" (Ren *et al.*, 2008).

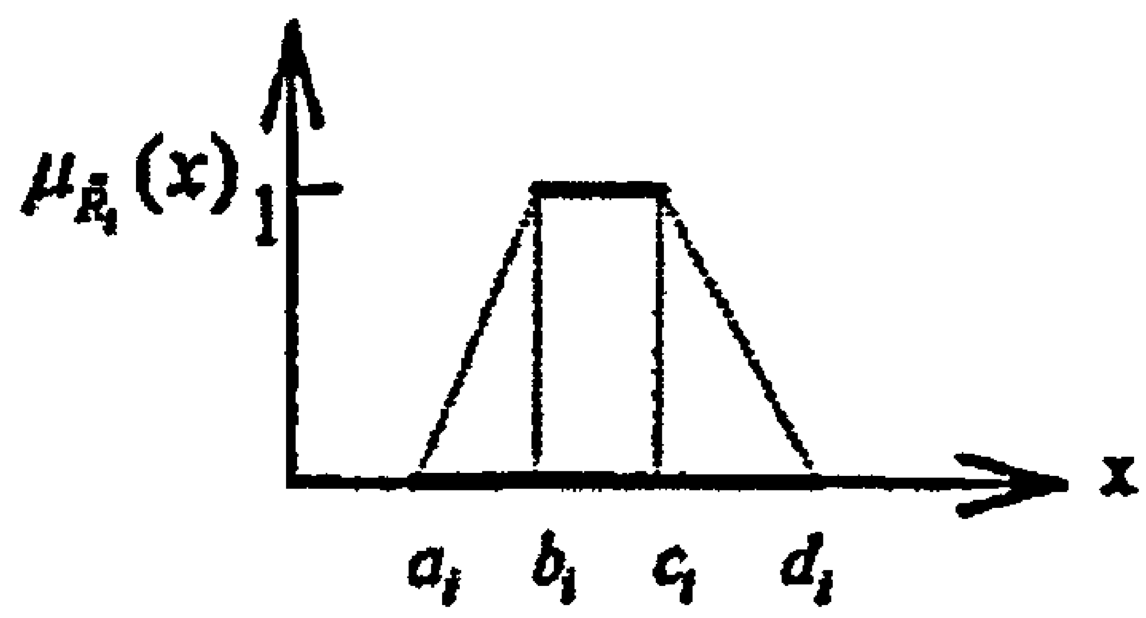


Figure 7-2 The illustration of Positive Trapezoidal Fuzzy Number (PTFN)

Since the Bayesian Network software 'Netica' cannot accept fuzzy sets as the data for the entries of the Conditional Probability Table, the PTFN which represent the experts' estimates have to be defuzzified before introducing them to the corresponding entries. As the defuzzification function in the method, the *f-weighted* valuation function is applied and specified in section 7.4. Theoretically, this function is capable of defuzzifying trapezoidal or triangular fuzzy sets. Conversely, other defuzzification functions are also applicable provided that the outcome is able to cooperate with the proposed methodology.

7.2.1 Considerations of applying PTFN

The reason why the present study does not consider a linguistic format for the estimate rating of the experts' judgements is that it has no value to the Bayesian Network model in presenting the outcomes of likelihood. Therefore, only the numerical forms are considered to represent the experts' judgements. However, this numerical form has to be intuitive and of a form that uncertainty and aggregation can be dealt with in order to reflect the consensus opinion. Hence, the PTFN is selected as the way forward with the following considerations:

⇨ Fuzzy theory provides a means to qualify subjective opinion. Mukaidono (2004) has asserted that "The goal of fuzzy theory is to establish a mathematical theory to deal with subjectivity, given any membership values. ... It is a mathematical theory to deal with ambiguities using quantified descriptions in exact method". This means that fuzzy sets (or numbers) can provide a suitable form to quantify an expert's subjective opinion.

- ⇨ The uncertainties of the estimate can be represented by the membership functions of the fuzzy number according to the intuitive feeling/judgement of individual. The uncertainty of the estimate (i.e. fuzziness) is represented by the area under the membership function of the fuzzy number. In other words, the larger the area, the higher the uncertainty. Furthermore, the membership function can be manipulated by a method defined in fuzzy theory (Mukaidono, 2004). This means that fuzzy sets are also a suitable form to depict the uncertainty of the estimate as well as to aggregate the group's opinions.
- ⇨ Zadeh expands fuzzy theory to the possibility theory, where membership values are interpreted as a possibility (i.e. randomness) of events. Mukaidono (2004) has specified this viewpoint as such "Probability is based on set theory. Fuzzy theory is based on fuzzy set theory. Since the (crisp) set of labels of a fuzzy set is a crisp set, we can consider the probabilities of them. This means that both theories can work together". This means fuzzy sets can be a form of interpreting the possibility of events.
- ⇨ Ren and the co-authors (2008) have shown that the fuzzy number can cooperate with Bayesian Network to analyse the collision risk for Floating Production, Storage and Offloading (FPSO) units.

Therefore the practicability of applying a fuzzy number to represent the subjective estimates regarding the nodes of the Bayesian Network model indeed has merit. According to the considerations denoted above, the PTFN is therefore chosen as the form representing the experts' judgement whilst the proposed methodology is applied.

7.2.2 PTFN and Uncertainty

This section provides an example of how the PTFN works within the proposed methodology for estimation. The example deals with two experts who provide estimates as the judgements. Both of the experts assign a PTFN, instead of a crisp value, to a given entry of the Conditional Probability Table representing their estimates. Expert *A* expresses a vague estimate whilst expert *B* offers a more precise estimation; the details are as follows.

With reference to expert *A*'s opinion, the lower least likely value (i.e. a_l) of the PTFN is 10% which means that the likelihood of the occurrence must be higher than

10% according to his/her judgement. In a similar fashion, the most likely values (i.e. b_i, c_i) that the expert assigns are 60% and 80% respectively. This means that between this interval the event is most likely to happen. Finally, the upper least likely value (i.e. d_i) is given as 90% which depicts that he would not believe the likelihood of the occurrence to be beyond this value. Therefore the fuzzy number representing expert *A*'s opinion is denoted as $\tilde{R}_a = (10, 60, 80, 90)$ which results in 60% as the crisp value when the *f-weighted* function is applied for defuzzification (see Figure 7-3). In the same way, expert *B* assigns another PTFN $\tilde{R}_b = (50, 55, 65, 70)$ to represent his estimate, and 60% is the crisp value as well.

It is clear to see that, from the equivalency of the crisp values, PTFN has the merit to assistant the experts to express their estimates even though their judgements are vague, but the outcomes can be the same as any definite one. Furthermore, the format of PTFN has another advantage that it can facilitate the achievement of the aggregation amongst experts for obtaining a common ground. Section 7.6 provides two examples which show that the features of PTFN would not only help the experts to express their judgement, but also facilitate the achievement of a group consensus.

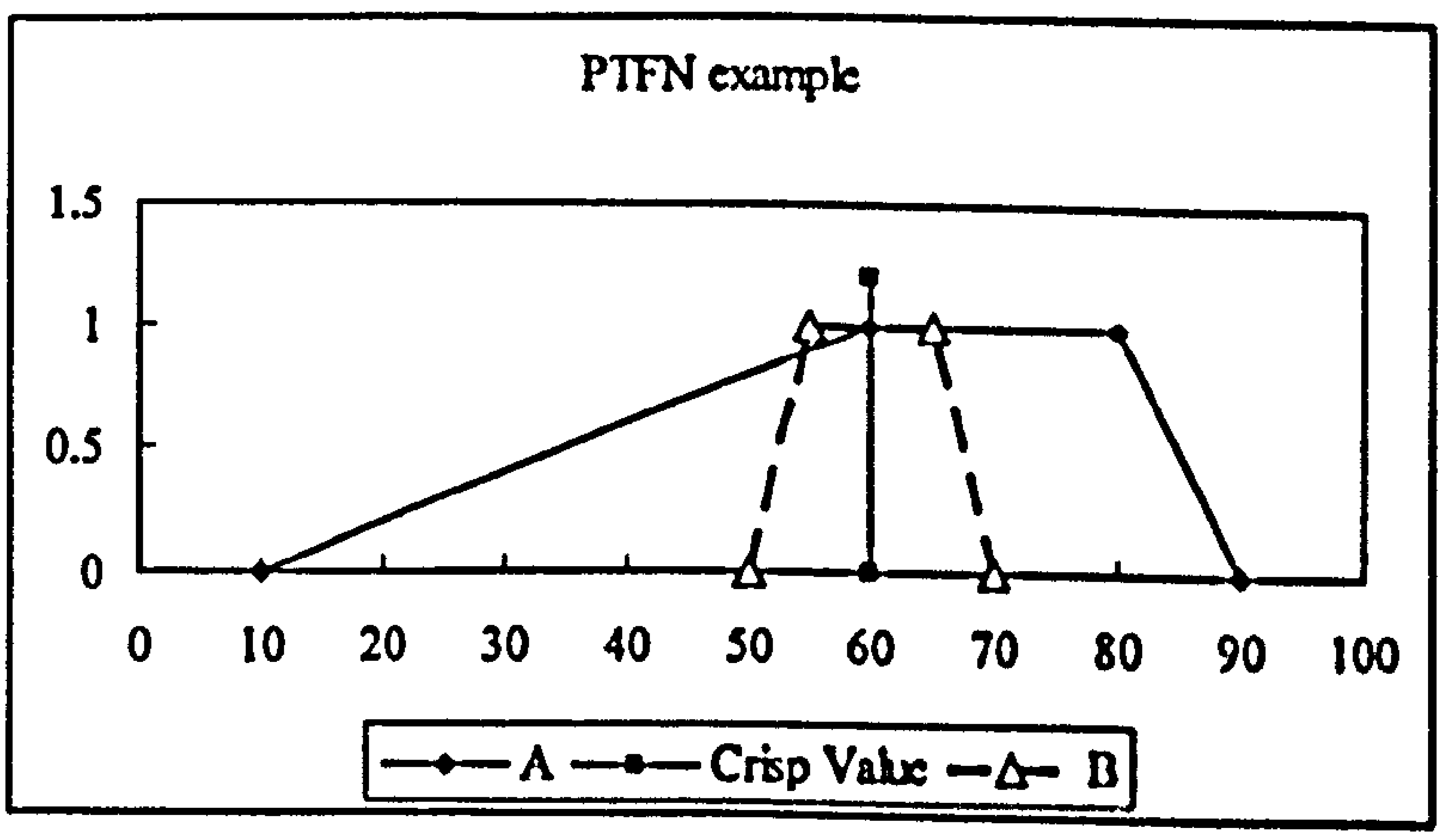


Figure 7-3 An PTFN example

7.3 The Similarity Aggregation Method (SAM)

Having acquired each estimate derived from every expert's judgement regarding an entry of the Conditional Probability Table required in the Bayesian Network model, the next problem is how to obtain the group consensus estimate of that entry. In this section, SAM is proposed as the solution to this problem. The SAM, which is proposed by Hsu and Chen (1996), is a method to achieve the aggregation of a group consensus opinion from several individual opinions through a systematic procedure. Here, the individual opinion is represented by a PTFN, denoted as $\tilde{R}_i$ (i=1,2, ..., n), and the group consensus opinion, denoted as $\tilde{R} = f(\tilde{R}_1, \tilde{R}_2, \ldots, \tilde{R}_n)$, is the outcome of the aggregation function which aggregates these experts' estimates.

7.3.1 The main features of the SAM

The functionality of the SAM is to aggregate several PTFNs into a consensus PTFN according to three indexes: the similarities between PTFNs, the importance of the expert and the bias preference (i.e. towards objective or subjective). The aggregation function has embedded two coefficients that allow users to regulate the aggregation process whether the consensus PTFN is bias toward objectivity or subjectivity. This method also has an advantage to implement a computer program due to the systematic characteristic of the procedure. Thus a prototype program has been implemented in the present study and has been applied in section 7.6 as the tool for the experiments.

Another outstanding feature of the SAM is that the aggregation function has considered the "importance of the experts" and the "similarity of the estimates" simultaneously when deciding the degree of influence (or contribution) of an expert's judgement into the group consensus. In other words, this method can regulate the overall consensus outcomes biased to the degree of importance of the experts or the agreement degree (or similarity) of each estimate. The "importance of the experts" subjectively decides the weight for each expert's judgement whilst the "similarity of the estimates" objectively judges the weight for one's estimate according to the relative similarity when these estimates are compared with each other in turn. In other words, the "importance of the experts" offers a flexibility of allowing one's opinion to be more important than the others. However the "similarity of the estimates" firmly adheres to the results of similarity measure function. This means that, in the aggregation function of the SAM, there are two regulators affecting the outcome of group consensus opinion. One regulators can control the overall consensus outcome to bias to either subjective "importance of the expert" or objective "similarity of the estimates", meanwhile the other fine-tunes the degree of importance for each expert's judgement.

One may appreciate the features mentioned above from the details of the procedure depicted in the next section.

7.3.2 The procedure of the SAM

According to the suggestions made by Hsu and Chen (1996), the SAM can be achieved by following the eight steps outlined below.

Step 1:

Each expert $E_i(i=1,2,\ldots,n)$ constructs a PTFN $\tilde{R}_i$ representing his/her subjective estimate to a given circumstance and has to ensure a demanded common intersection among these estimates exists. The given circumstance associated with the proposed FTA-BN method is the entries of the Conditional Probability Table of Bayesian Network. Therefore the subjective estimates are the figures given to the entries. Precisely speaking, the experts, based on their own judgments, assign a PTFN to each entry of the Conditional Probability Table relating to the established Bayesian Network model in order to depict the likelihood of the events involved in the accident. In other words, every estimate derived from the experts' subjective judgments is represented by a PTFN to a given entry of the Conditional Probability Table of the nodes in the Bayesian Network model. It is highly likely that the initial estimates given by some experts have no common intersection at first. Hence the Delphi method is applied to modify the values of (a_i, b_i, c_i, d_i) of these PTTNs in order to obtain a common intersection at a fixed α-level cut. The details of the Delphi method are covered in section 7.5. It should be noted that the intersection between each pair of PTFNs is a prerequisite to perform this SAM. This means that the assumption of $\tilde{R}_i^\alpha \cap \tilde{R}_j^\alpha \neq 0, \forall i,j \in \{1,2,\cdots,n\}$ must stand for each PTFN in a set before continuing the following steps.

Step 2:

The aim of this step is to calculate the *agreement degree* $S(\tilde{R}_i, \tilde{R}_j)$ of the opinions between each pair of estimates. This can be determined by the proportion of the consensus area (i.e. $\tilde{R}_i \cap \tilde{R}_j$) to the total area (i.e. $\tilde{R}_i \cup \tilde{R}_j$). The $S(\tilde{R}_i, \tilde{R}_j)$ is also known as the *similarity measure function* and is defined by Equation (7.1) by Zwick, Carlstein and Budescu (1987). If both of the experts have the same opinion then $S(\tilde{R}_i, \tilde{R}_j) = 1$, and if the opinions of two experts are completely different then $S(\tilde{R}_i, \tilde{R}_j) = 0$. This means $0 \leq S(\tilde{R}_i, \tilde{R}_j) \leq 1$, and the higher the percentage of consensus area, the higher the agreement degree.

$$S(\tilde{R}_i, \tilde{R}_j) = \frac{\int_x \min\{\mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x)\} dx}{\int_x \max\{\mu_{\tilde{R}_i}(x), \mu_{\tilde{R}_j}(x)\} dx} \tag{7.1}$$

Step 3:

In this step, the work is to construct an *agreement matrix* (AM). Once all of the *agreement degrees* between each pair of experts have been measured, an agreement matrix can be constructed. This matrix gives an insight into the similarities among these experts' opinion.

$$AM = \begin{bmatrix} 1 & S_{12} & \cdots & S_{1j} & \cdots & S_{1n} \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ S_{i1} & S_{i2} & \cdots & S_{ij} & \cdots & S_{in} \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nj} & \cdots & 1 \end{bmatrix}$$

$$\text{where } S_{ij} = S(\tilde{R}_i, \tilde{R}_j) \text{ for } i \neq j$$
$$S_{ij} = 1 \text{ for } i = j$$

Step 4:

Once the *agreement matrix* has been sorted out, the *average agreement degree* $A(E_i)$ for each expert $E_i (i = 1, 2, \ldots, n)$ is able to be acquired. The $A(E_i)$ for each expert is achieved by Equation (7.2). Here, S_{ij} gives the *agreement degree* (i.e. the similarity of the estimates) of expert E_i when comparing with one of the other experts.

$$A(E_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ j \neq i}}^{n} S_{ij} \tag{7.2}$$

Step 5:

Calculate the *relative agreement degree* (i.e. RAD_i) for each expert $E_i(i=1,2,\ \ldots,n)$. The RAD_i is computed by using Equation (7.3). It represents the similarity of the opinion of an expert in contrast with the other experts of the group. It also implies a certain weight regarding the expert's opinion for further calculation.

$$\mathrm{RAD}_i=\frac{A(E_i)}{\sum_{i=1}^{n}A(E_i)} \tag{7.3}$$

Step 6:

Define the *degree of importance* W_i for each expert $E_i(i=1,2,\ \ldots,n)$. Sometimes, the relative importance of experts, such as team leader or head of department, is wildly different from the other experts and the different weight for different experts' opinion must be considered. Hence, the W_i is defined as Equation (7.4).

$$W_i=\frac{r_i}{\sum_{i=1}^{n}r_i},i=1,2,\cdots,n \tag{7.4}$$

where r_i is the importance weight of the expert and is acquired by the following procedure. First select the most important expert among the group and assign him the weight as one (i.e. $r_i=1$). Then the j_{th} expert is compared with the most important expert to obtain the weight $r_{j\to i}\in[0,1], j=1,2,\cdots,n$. If the importance of each expert is equal then $w_1=w_2=\cdots=w_n=\frac{1}{n}$.

Step 7:

Calculate the *consensus degree coefficient* (i.e. CDC_i) for each expert $E_i(i=1,2,\ \ldots,n)$. After the *relative agreement degree* (i.e. RAD_i) and the *degree of importance* (i.e. W_i) have been acquired, the CDC_i for each expert E_i can be derived from Equation (7.5).

$$\mathrm{CDC}_i=\beta\cdot w_i+(1-\beta)\cdot \mathrm{RAD}_i$$
$$\text{where } 0\le\beta\le1 \tag{7.5}$$

β can regulate the weight between *agreement degree* (i.e. RAD_i) and the *degree of importance* (i.e. W_i). If the degree of importance of each expert is not considered, then β is assigned zero (i.e. $\beta = 0$). The CDC_i of each expert is an efficient measurement to evaluate the relative worthiness of each expert's opinion.

Step 8:

Aggregate the consensus opinions according to the *consensus degree coefficient* (i.e. CDC_i) of expert $E_i(i = 1, 2, \ldots, n)$. Let $\tilde{\mathrm{R}}$ be the consensus fuzzy number of the group experts' opinion. The aggregated result of $\tilde{\mathrm{R}}$ is defined in Equation (7.6).

$$\tilde{\mathrm{R}} = \sum_{i=1}^{n} (\mathrm{CDC}_i (\cdot) \tilde{\mathrm{R}}_i) \tag{7.6}$$

where $(\cdot)$ is the fuzzy multiplication operation.

7.3.3 The properties of the SAM

Hsu and Chen (1996) suggest that the SAM holds some properties that should be noted when this method is applied. For rapidly referring, these properties are briefly summarised, without further discussion, as follows.

1. Agreement preservation: if $\tilde{R}_i = \tilde{R}_j$ for all *i, j,* then $\tilde{R} = \tilde{R}_j$. This means that if all the estimates of the experts are identical, the aggregated result should be equivalent to any of their estimates.
2. Order iridependence: *if* $\{(1),(2),\ldots,(n)\}$ *is a permutation of* $\{1,2,\ldots,n\}$, *then* $\tilde{\mathrm{R}} = f(\tilde{\mathrm{R}}_1, \tilde{\mathrm{R}}_2, \ldots, \tilde{\mathrm{R}}_n) = f(\tilde{\mathrm{R}}_{(1)}, \tilde{\mathrm{R}}_{(2)}, \ldots, \tilde{\mathrm{R}}_{(n)})$. This means that the result of the SAM does not depend on the order in which the estimates are taken.
3. Let the uncertainty measure $H(\tilde{R}_i)$ of individual estimate $\tilde{R}_i$ be defined as the area under its member function (i.e. $H(\tilde{R}_i) = \int_{\infty}^{\infty} \mu_{\tilde{R}_i}(x)dx$). The uncertainty after the aggregation made by the SAM is the 'mean' of the uncertainties of every estimate.
4. If an expert's estimate is far from the others, then his estimate is less important.

5. If a crisp value is considered to be possible for the aggregated result, then it should also be accepted by at least one estimate.

6. The common intersection area of all estimates is included in the aggregated result (i.e. $\bigcap_{i=1}^{n} \widetilde{R}_i \subseteq \widetilde{R}$).

7. If every expert's opinion can be represented by a PTFN, the aggregated result is also a PTFN.

7.4 *f*-weighted valuation function for defuzzification

It is said that the problem of comparing and ordering fuzzy numbers is the reason why the defuzzification methods are introduced. A general idea to this problem is to find a single scalar value (i.e. the crisp value) to represent the associated fuzzy number, and then the fuzzy numbers are compared via these represented scalar values (Yager and Filev, 1999). An approach to this method was introduced by Yager (1981), in which the expected value type of the valuations is based upon the transformation of a fuzzy subset into an associated probability distribution.

Having acquired the aggregated PTFN as the group consensus opinion, the following process aims to obtain the crisp (or scalar) value of the fuzzy number. This is because the applied Bayesian Network software is not able to handle the fuzzy numbers generated so far, thus the PTFN has to be transformed into crisp values before being further utilised. The associated valuation process is also known as defuzzification process, in which a corresponding computation process is performed in order to acquire a represented scalar value. More precisely, the defuzzification process involves a process in which a fuzzy subset is used to generate a probability distribution. This probability distribution is then used to obtain an expected value, which can be used as the evaluation of the fuzzy subset (Yager and Filev, 1999). Therefore, the present study follows the same idea of transforming a crisp value from a PTFN which represents the experts' judgement acquired for the Conditional Probability Table of the Bayesian Network model. In this way, all the PTFNs applied in this method will be defuzzified according to the following process to obtain the corresponding crisp value before being used as the likelihood data of the nodes.

In order to obtain a crisp value, *Val(F)*, as the proxy of a fuzzy subset *F*, Yager suggests using

$$\mathrm{Val}(F) = \int_0^1 \mathrm{Average}(F_\alpha) \cdot d\alpha \tag{7.7}$$

Here $F_\alpha = \{x \mid F(x) \geq \alpha\}$ is the α -level set of the fuzzy subset *F* and $\mathrm{Average}(F_\alpha)$ is the average of the elements in the α -level set. In order to associate probability distribution, Yager and Filev (1999) extended this formulation and developed a generalised formulation for a class of valuation functions.

$$\mathrm{Val}(F) = \frac{\int_0^1 \mathrm{Average}(F_\alpha) \cdot f(\alpha) \cdot d\alpha}{\int_0^1 f(\alpha) \cdot d\alpha} \tag{7.8}$$

As shown in Equation (7.8), $f(\alpha)$ is a mapping from [0,1] to [0,1] (i.e. f: [0,1]→ [0,1]). If $f(\alpha)$ is monotone, it tends to put additional emphasis on the element with high cardinality, the core set (i.e. [b_i, c_i]), while $f(\alpha)$ anti-monotone puts more emphasis on the support set (i.e. [a_i, d_i]) (Yager and Filev, 1999). If a PTFN, F(a, b, c, d), is set by : F (left support, left core, right core, right support), it will have the membership functions shown below.

$$F(x) = \begin{cases} 0 & \text{for } x < a \\ \dfrac{x-a}{b-a} & \text{for } a \leq x \leq b \\ 1 & \text{for } b \leq x \leq c \\ \dfrac{d-x}{d-c} & \text{for } c \leq x \leq d \\ 0 & \text{for } x > d \end{cases} \tag{7.9}$$

By following the notion of Equation (7.8), the $\mathrm{Average}(F_\alpha)$ of a trapezoidal fuzzy number can be computed according to Equation (7.10) (Detyniecki and Yager, 2000)

$$\text{Average}(F_\alpha) = \frac{u_\alpha + v_\alpha}{2} \tag{7.10}$$

Therefore u_α and v_α can be obtained with the help of the membership functions.

$$u_\alpha = (b-a)\cdot\alpha + a \text{ and } v_\alpha = d-(d-c)\cdot\alpha$$

Then the valuation formula (i.e. Equation (7.8)) becomes:

$$\text{Val}(F) = \frac{\frac{1}{2}\int_0^1 [(b+c)\cdot\alpha + (1-\alpha)\cdot(a+d)]\cdot f(\alpha)\cdot d\alpha}{\int_0^1 f(\alpha)\cdot d\alpha} \tag{7.11}$$

This equation can be put into the following form:

$$\text{Val}(F(a,b,c,d)) = \left(\frac{b+c}{2}\cdot w\right) + \left(\frac{a+d}{2}\cdot(1-w)\right) \tag{7.12}$$

where 'w' is computed by:

$$w = \frac{\int_0^1 \alpha\cdot f(\alpha)\cdot d\alpha}{\int_0^1 f(\alpha)\cdot d\alpha} \tag{7.13}$$

One evident result obtained is that, according to Equation (7.12), the valuation of the equation will be a weighted-mean between the average of the core and the average of the support. In other words, the valuation for any function *f* will be between the middle point (or average) of the core and the middle point (or average) of the support (because $w \in [0,1]$) (Detyniecki and Yager, 2000). Figure 7-4 gives an example illustrating the middle point of the core, the middle point of support, and the middle point of the average of core and support. In this example, the fuzzy set denoted in the figure is: F (1, 6, 8, 9), and the crisp value of the trapezoidal fuzzy set depends on the *f*-weighted valuation function $f(\alpha)$. For the increasing (or monotone) case (i.e. $f(\alpha) = \alpha^q; q \geq 0$), the valuation of the defuzzification is between 6 and 7. For the decreasing (or anti-monotone) case (i.e. $f(\alpha)=(1-\alpha)^q; q \geq 0$), the valuation of the defuzzification is between 5 and 6.

Figure 7-4 Variability of the valuation for Yager and Filev's *f*- weighted function (from Detyniecki and Yager, 2000)

For generality, let *f*-weighted valuation function $f(\alpha)=1$ in Equation (7.11) and/or w =1/2 in Equation (7.13). The $\mathrm{Val}(F(a,b,c,d))$ becomes:

$$\mathrm{Val}(F(a,b,c,d))=\frac{\left(\frac{b+c}{2}\right)+\left(\frac{a+d}{2}\right)}{2} \tag{7.14}$$

This means that the transformed crisp value of the PTFN is the mean of the average of the core and the average of the support if Equation (7.14) is applied. However, if *f*-weighted valuation function (i.e. Equation (7.13)) is utilised, experts are able to fine-tune the crisp values, to either bias to core or bias to support of the PTFN, in order to represent their judgements (Ren *et al.*, 2008). Therefore the defuzzification method utilised in the proposed methodology applies Equation (7.12) as the valuation function. Thus, by using w ($w \in [0,1]$) as the regulator, the valuation function for defuzzifying a PTFN can place emphasis on the core or the support, or the somewhere between the average of the core and the support.

7.5 Delphi method

The Delphi method is originally derived from a project named "RAND" (an acronym for *Research and Development*), which was funded by the U.S. Air Force in order to establish and propose a procedure to elicit and refine group judgement (Dalkey, 1969). In the mid-1960s, this method was utilised to deal with a large amount of experiments with regard to technological forecasting (Fowles, 1978). In short, Delphi is "a procedure to obtain the most reliable consensus of opinion of a group of experts ... by a series of intensive questionnaires interspersed with controlled opinion feedback" (Dalkey and Helmer, 1963 cited in Fowles, 1978). From the view of Dalkey – one of the major researchers of the project, this method has three major features; they are: (1) anonymous response, (2) iteration and controlled feedback, and (3) statistical group response (Dalkey, 1969). Additionally, Linstone and Turoff (2002) in their book define that "Delphi may be characterized as a method for structuring a group communication process so that the process is effective in allowing a group of individuals, as a whole, to deal with a complex problem". In other words, according to the initial suggestion that has been made, the Delphi method is "a set of procedures for formulating a group judgement for subject matter where precise information is lacking" (Dalkey *et al.*, 1969). In general, the procedures mainly consist of three parts. They are (1) obtaining individual answers to pre-formulated questions either by questionnaire or some other formal communication technique; (2) iterating the questionnaire one or more times, where the information feedback between rounds is carefully controlled by the exercise manager; and (3) taking as the group response a statistical aggregate of final answers (Dalkey *et al.*, 1969).

7.5.1 The original Delphi process

To undertake the Delphi method, Fowles (1978) suggests the following ten steps:

1. Formation of a Delphi team to undertake and to monitor the project.
2. Selection of one or more panels to participate in the exercise. Customarily, the participants are experts in the investigation area.
3. Development of the first round Delphi questionnaire.
4. Testing the questionnaire for proper wording (e.g., ambiguities, vagueness).
5. Transmission of the first questionnaires to the panellists.

6. Analysis of the first round responses.
7. Preparation of the second round questionnaires (and possible testing).
8. Transmission of the second round questionnaires to the panellists.
9. Analysis of the second round responses. (Steps 7 to 9 are reiterated as long as desired or necessary to achieve stability in the results.)
10. Preparation of a report by the analysis team to present the conclusions of the exercise.

Several experiments made by Brockhoff (1983) suggest that under ideal circumstances, groups as small as four can perform well, even though Dalkey found that a suitable minimum panel size is seven. Other studies (Erffmeyer *et al.*, 1986; Fischer, 1978) indicate that up to four times of the iteration of the rounds is sufficient to extract a consensus result. In practice, these conclusions are valuable to be followed when the Delphi method is applied.

7.5.2 The critiques of the Delphi method

Although there are advantages of using the Delphi method, it is not always supported. Woudenberg (1991) argued that "Delphi is extremely efficient in obtaining consensus, but this consensus is not based on genuine agreement; rather, it is the result of strong group pressure to conformity". Coates (1975) underlines the fact that "Delphi is a method of last resort in dealing with extremely complex problems for which there are no adequate models". The most extensive critique of the Delphi method was made by Sackman (1975 cited in Twiss, 1976) who criticizes the method as being unscientific. Martino (1970) asserts that the results of the method are bias on one's intuition about the behaviour of a Delphi panel. However, he still admits that improvements in the methodology for combining the panel members' estimates will enhance the utility of Delphi (Martino, 2003). In other words, "the Delphi method is useful in answering one, specific, single-dimension question. There is less support for its use to determine complex forecasts concerning multiple factors. Such complex model building is more appropriate for quantitative models with Delphi results serving as inputs". This view point is proposed by Gordon and Hayward (1968). They further state that a shortcoming of the Delphi method to be that "potential relationships between the forecasted events may be ignored and the forecasts might well contain mutually reinforcing or mutually exclusive items". Hence, a method - *Cross Impact Analysis* - has been developed by them as an extension of Delphi techniques in order to remedy the deficiency of the method. Gordon and Hayward (1968) have stated that "the probabilities of an item in a forecasted set can be adjusted in view of judgment relating to potential interactions of the forecast items".

7.5.3 The proposed process whilst applying Delphi

By considering the pros and cons of the Delphi method, the proposed method decides to only apply Delphi as a tool to reach a common ground among those PTFNs given by the experts instead of obtaining the consensus PTFN of the group directly. In other words, the Delphi method is merely applied for ensuring that each set of PTFNs have a common intersection at certain α-level cut, rather than trying to acquire a consensus PTFN as the group opinion. Instead, every consensus PTFN for each set of PTFNs is computed using the SAM. Each set of PTFNs represents the estimated probability distributions, derived from the experts, regarding a Conditional Probability Table entry of the Bayesian Network nodes. This application is also in line with the suggestions made by Gordon and Hayward mentioned in the last section. By following the recommendations mentioned above, the Cross Impact Analysis should have been integrated with Delphi for acquiring the common intersection of the PTFNs. However, the proposed methodology does not need to do so since the Conditional Probability Table of Bayesian Network has already contained the functionality of conditional probability that the Cross Impact Analysis implies. To incorporate the Delphi method into the proposed methodology, the applied Delphi procedure is modified as follows:

1. Formation of a Delphi team to undertake and to monitor the process.
2. Selection of one or more panels (4 to 7 panels is preferable) to participate in the exercise. Customarily, the participants are the experts who are involved in the analysis task.
3. Development of the first round of the Delphi questionnaire regarding the analysed Conditional Probability Table entries, in which the corresponding set of PTFNs have difficulties to reach the common intersection at certain α-level cut at first.
4. Testing the questionnaire for proper wording (e.g., ambiguities, vagueness).
5. Distribution of the first questionnaires to the panellists.

6. Aggregating the first round responses following the SAM. If the group consensus of the set is reached, then jump to Step 10, otherwise carry on the next step.
7. Preparation of the second round questionnaires (and possible testing).
8. Distribution of the second round questionnaires to the panellists.
9. Aggregation of the second round responses. (Steps 7 to 9 are reiterated as long as desired or necessary to achieve stability in the results.)
10. Defuzzification of the consensus PTFN via the proposed *f*-weighted valuation function for the corresponding Conditional Probability Table entry.

7.6 Experiments

In this section, two examples are utilised to illustrate the process which aggregates a set of estimated PTFNs in order to acquire a consensus crisp value. These PTFNs are given by a group of experts and the consensus crisp value is acquired by using the proposed aggregation method depicted in the preceding sections. The crisp value represents the group consensus to a given entry of a Bayesian Network node. Both of the cases are under the condition that every expert is equally important and the overall aggregation outcome is decided by the "*relative agreement degree* of the estimate" rather than the "*importance degree* of the experts". This means that the weight for each expert's opinion depends on the similarity of the estimated PTFN when it is compared with others' (see section 7.3 for the detailed explanation). It is assumed that there are four experts involved in both cases and every expert has to construct a PTFN to express their judgements regarding the likelihood of the events before carrying out the aggregation process. If these estimates are not able to reach a common intersection at certain α-level, the Delphi method will be applied and iterated until this requirement is fulfilled. Once the consensus PTFN has been acquired via the SAM with a common intersection standing amongst these estimates, the *f-weighted* valuation function is applied to compute the crisp value according to the consensus PTFN for the target entry of the Bayesian Network nodes. The crisp value is the figure representing the probability distribution of an event associated with a given condition shown in the Bayesian Network node.

In the following cases, the first case presumes that only one expert's estimate is distant from the others. In contrast, in the second case, more than two experts' opinions are significantly apart. Each case simulates different scenarios and many other scenarios are still possible. However, while applying the aggregation process with unmentioned situations, the execution approach may be slightly different but the principle of the process should remain the same. This principle is that a common intersection of the estimated PTFNs has to be obtained before carrying out the aggregation process.

7.6.1 Case 1: only one expert's opinion is distant

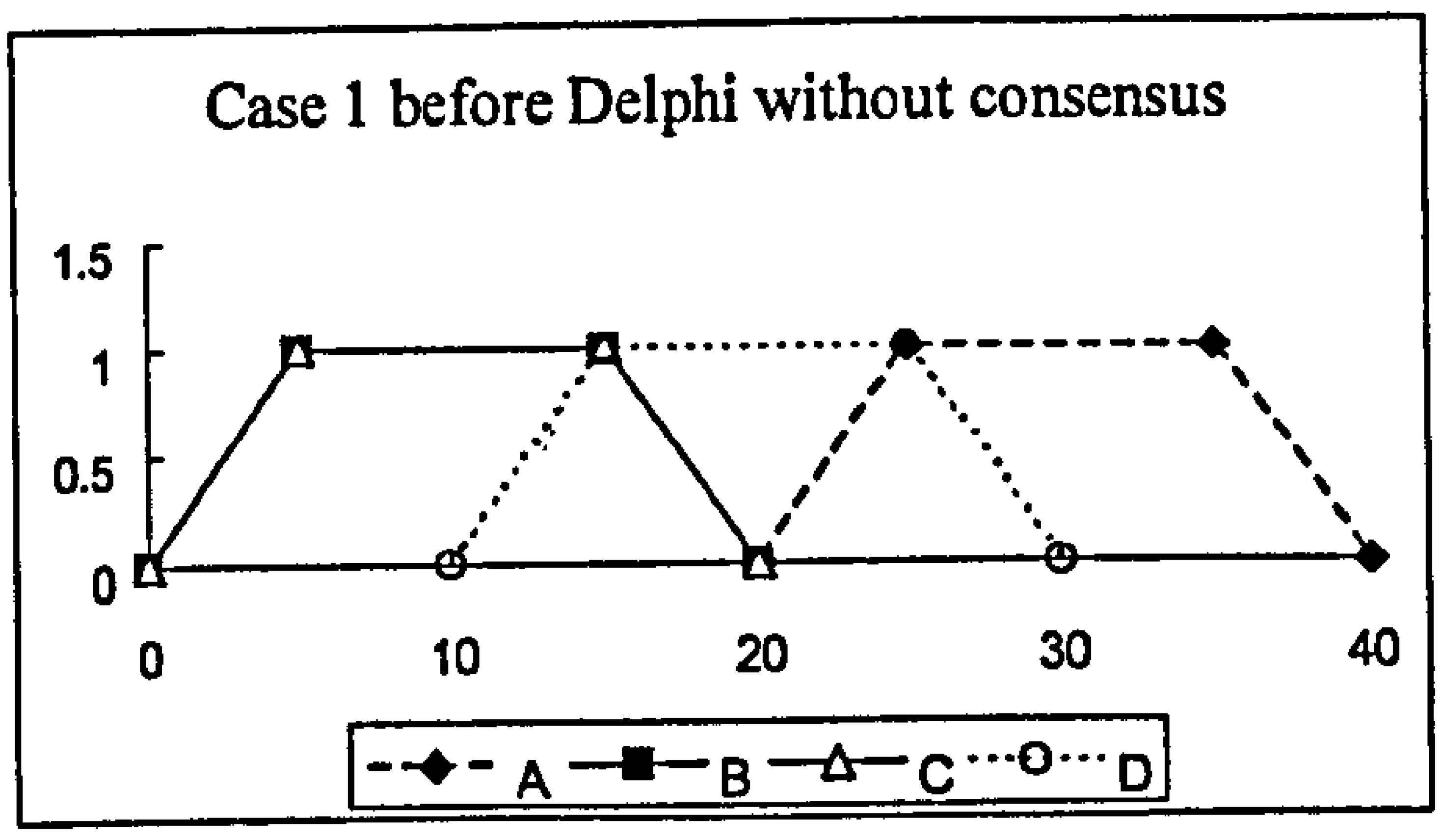
In this example, it is assumed that only one of the experts' estimates is distant from the judgement of the others. Under this circumstance, a quicker way to achieve the group consensus is to ask the most distinct expert to modify his estimate alone by following the Delphi procedure proposed in the preceding sections. The rest of the estimates should remain unchanged. Table 7-1 tabulates the assumed estimates given by each expert; here, the column "After Delphi" lists the estimates when a common intersection among these estimated PTFNs is reached after the Delphi process is applied. In contrast, the column "Before Delphi" depicts the estimates given before carrying out the Delphi process.

In this example, the most distant estimate is made by expert A; this is (20, 25, 35, 40) having 30 as the crisp value (i.e. the result after defuzzification) of the estimate. Therefore, expert A is the only expert who will be asked to modify his estimate following the Delphi process with a sub-consensus PTFN as the modification reference provided. The sub-consensus PTFN is the consensus PTFN without taking expert A's estimate into account and $\widetilde{R}_{sub} = (1.4, 6.4, 16.4, 21.4)$ with a crisp value of 11.42 as the result. The data entries for experts B, C and D in column "Before Delphi" of the table are the same as in column "After Delphi". This is because their estimates are unchanged during the Delphi process. Eventually, a common intersection amongst these PTFNs is reached when $\widetilde{R}_a = (15, 25, 35, 40)$ representing expert A's opinion is given after the Delphi process. This compromise results in the consensus PTFN $\widetilde{R} = (4, 9, 19, 24)$ being obtained with 13.88 as the crisp value.

Figure 7-5 illustrates the PTFNs representing the estimates given by every expert before and after the Delphi process, and the group consensus if there is one. On the left of the figure, the estimated PTFNs for each expert are shown, in which no common ground of the PTFNs has been reached. In addition, the group consensus PTFN with a crisp value derived from the updated estimates after performing the Delphi process are drawn on the right of the figure. It is evident that the common intersection of these PTFNs is located in the range between 15 and 20, which is the common ground among these PTFNs. However, although the consensus PTFN is achieved, the crisp value – 13.88 – is difficult to be accepted by expert *A*, as the group consensus, due to being outside the range of his estimate. Under this circumstance, all the involved experts may have to comprise their judgements, so that an acceptable outcome can be obtained.

Table 7-1 The estimates made by each expert in Case 1

	Before Delphi		After Delphi	
	PTFN	Crisp value	PTFN	Crisp value
Expert *A*	(20, 25, 35, 40)	30	(15, 25, 35, 40)	28.75
Expert *B*	(0, 5, 15, 20)	10	(0, 5, 15, 20)	10
Expert *C*	(0, 5, 15, 20)	10	(0, 5, 15, 20)	10
Expert *D*	(10, 15, 25, 30)	20	(10, 15, 25, 30)	20
consensus			(4, 9, 19, 24)	13.88



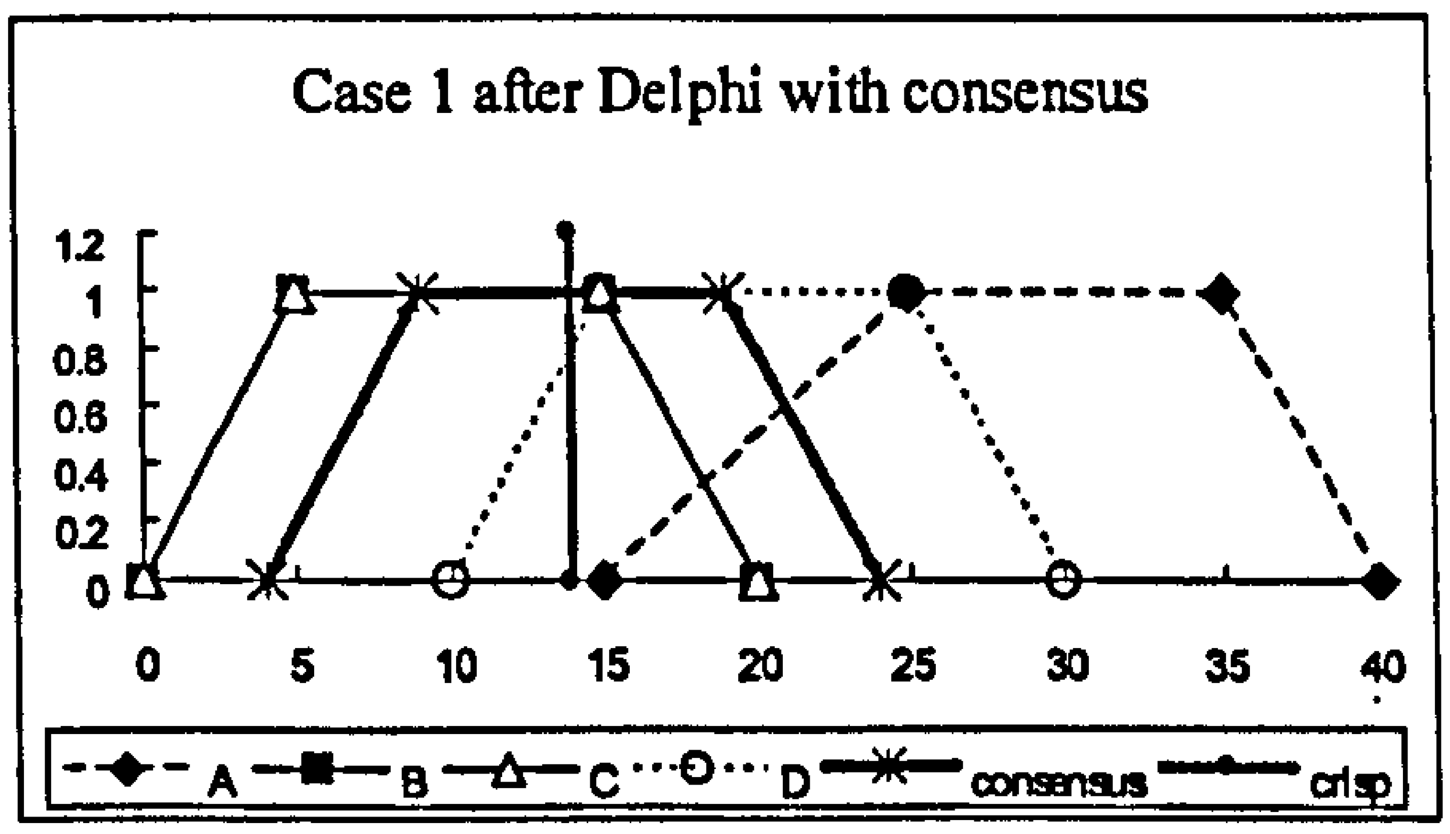


Figure 7-5 The illustration of the PTFNs for case 1

7.6.2 Case 2: more than two experts are apart

In this example, it is presumed that disagreement among these experts still remains unsolved in the first run (e.g. the situation shown in the preceding case). This situation could be caused by either the most distant expert refuses to modify his/her estimate further or more than one expert's opinions are apart from one another. This difficulty results in no group consensus being obtained unless all the experts are willing to compromise their judgements together. Under this situation, there is no other alternative but to ask every expert to participate the Delphi process in order to reach a common intersection.

Table 7-2, as in Case 1, shows the PTFNs of the estimates made by four experts before and after the Delphi process. Before updating their judgements, a median value (i.e. 72.19) of their initial estimations is given as the reference value for re-estimation. It is assumed that these experts are willing to modify their estimates and that the larger the difference, the larger the compromise. Therefore the consensus PTFN is obtained following the Delphi and the SAM aggregation method when the common intersection amongst these updated estimates is reached. These updated estimates and the consensus PTFN are shown on the right hand side (i.e. the column "After Delphi") of the table. Thus the consensus PTFN $\widetilde{R} =$ (62, 77, 87, 94) and the crisp value of the PTFN (i.e. 79.82) are acquired.

Eventually, after the Delphi process, the crisp value of the consensus PTFN is inside the common intersection of every expert's estimates (see the figures shown on the right hand side of Figure 7-6). This outcome should be accepted by all the experts as the group consensus. This assumption is made by assuming that every expert will be content with the outcome as long as the crisp value is inside their estimates although the value may locate in the margin of the estimations. In this example, none of the expert's opinion has been ignored despite the crisp value is in the margin of one of the estimations.

Table 7-2 The estimates made by each expert in Case 2

	Before Delphi		After Delphi	
	PTFN	Crisp value	PTFN	Crisp value
Expert #A	(85, 90, 100, 100)	93.75	(65, 80, 90, 100)	83.75
Expert #B	(30, 35, 45, 50)	40	(50, 55, 65, 80)	62.5
Expert #C	(55, 60, 70, 75)	65	(65, 75, 85, 90)	78.75
Expert #D	(80, 85, 95, 100)	90	(60, 80, 90, 95)	81.25
consensus			(62, 77, 87, 94)	79.82

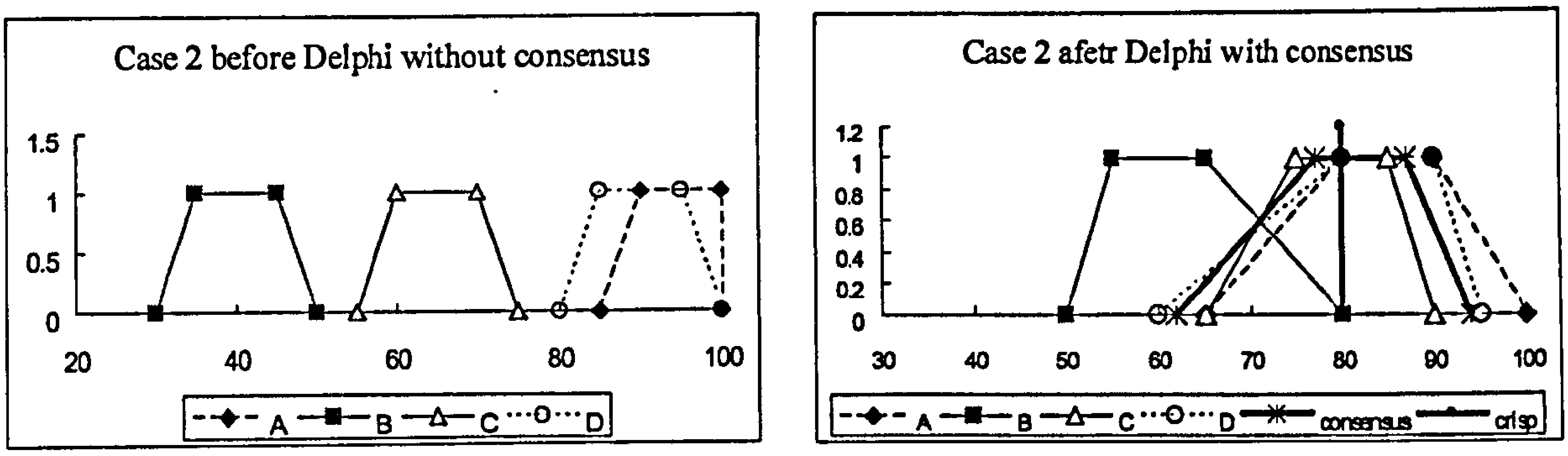


Figure 7-6 The illustration of the PTFNs for case 2

It should be noted that the key point of the aggregation of group opinions is not an issue of computation, but an issue of human satisfaction. Any expert can disagree with the aggregation outcome by all means. It is unlikely that there is an aggregation function or procedure which can satisfy every expert regarding the aggregation outcome and solve all the problem of group consensus. The aggregation function is just a tool to facilitate the goal (i.e. group consensus). Although the proposed aggregation method and procedure are not able to solve all the problems, it is still practical to deal with the most of the cases. Other solutions are possible but the present study has no intention of discussing this further since the satisfaction of human beings involves psychological issues which are beyond the scope of the present study.

7.7 Discussion

It is highly likely that the required historical statistical data is not always available for the established Bayesian Network model associated with the analysed accident. Therefore, experts' judgements usually become the alternative to solve the problem of lacking of data. However, the group consensus issue arises when a group of experts are involved in providing their estimates for the Conditional Probability Table data of the Bayesian Network model. Hence, an aggregation method and/or procedure are needed in order to overcome this problem. Furthermore, the systematisation and objectivity of the method and the contentment of the experts have to be considered as well.

The proposed aggregation method for the group consensus is based on the SAM as the core to deal with the numerical computation of a set of PTFNs. In addition, it needs to cooperate with the *f-weighted* valuation function for defuzzification as well as the

Delphi method for the common ground of the estimates. The aim of the proposed aggregation method is to seek a systematic and objective way to carry out a process that can help a group of experts to reach their group consensus for the estimated values regarding the entries of the Conditional Probability Table of Bayesian Network nodes. These Bayesian Network nodes are the events associated with an analysed accident which is depicted in the preceding chapters.

It is obvious that, from the view of a decision maker, it would be easier for him/her to make a decision if a group consensus derived from a group of experts is reached. For example, the judge of the court will find it difficult to make a verdict if the members of the jury are not able to reach a group consensus. Theoretically, the SAM and *f-weighted* valuation function can handle the aggregation computation if the PTFNs given are close to each other. However, this would not be always the case since the experts' opinions might be significantly apart. Thus, compromise amongst the experts becomes essential, and the Delphi method is the communication tool to resort to in order to facilitate a common ground to be reached.

It has been shown, in the preceding sections, the proposed aggregation method can assist with the proposed methodology to fulfil the requirements of obtaining a group consensus with the following features:

- ⇨ The form of PTFN has the advantages to intuitively express an expert's estimate as well as the uncertainty of the estimate. The larger the uncertainty, the larger the area of the PTFN covered. Furthermore, this form can not only fulfil the aggregation of the estimates in the SAM process, but also facilitate the common intersection of the estimates (i.e. the common ground) to be reached within the Delphi process.
- ⇨ The consensus PTFN can only be achieved if and only if the common intersection of the estimates exists. Since the common intersection is always under the coverage of the consensus PTFN, it can be deemed as the consensus PTFN is constructed based on the common ground of the group opinion although not all the experts may be content with the crisp value of the PTFN at first.
- ⇨ The SAM aggregation function considers the "importance of the experts" when deciding the degree of influence (or contribution) for each estimate to

the group consensus. Moreover, this method can also regulate the overall consensus outcomes bias to the "degree of importance of the experts" or the "agreement degree (or similarity) of the estimates".

- ⇨ The outcome of the *f-weighted* valuation function can be regulated to the range between the average of the core and the average of the support of the PTFN when defuzzifying the PTFN for the crisp value.
- ⇨ The Delphi method can ensure a common intersection of the estimates to be reached, and the crisp value of the consensus PTFN to be accepted by all the experts involved.
- ⇨ The SAM and *f-weighted* valuation function can still be applied even though only one expert's estimate is utilised. This is because the form of PTFN has the advantage to deal with the uncertainty of randomness and fuzziness.

Chapter Eight – Conclusions

Summary

This chapter summarises, in section 8.1, the features and the contributions of the proposed methodology which can be utilised in qualitatively and quantitatively analysing human errors in maritime accidents. The improvements of the methodology and ideas for the future work of the research are also given in section 8.2. Finally in section 8.3 the study concludes that the methodology would be of benefit in assisting the investigator to find the real causes of the accident, and it is the start, rather than the end, of the research in this topic area.

8.1 Summary of Research Findings

In Chapter 1, it was shown that Human factors (or elements) are gradually being recognised as the primary causal contributors to the accidents in maritime transportation sector, and the International Maritime Organization (IMO) has taken the conscious decision to concentrate its efforts on the human element. A methodology which can qualitatively as well as quantitatively analyse the Human and Organisational Factors (HOFs) involved in an accident is desperately needed by the investigator in order to find the real causes of the accidents and to respond to the public enquiry and lesson learning. This is because a sufficiently thorough and comprehensive accident/incident investigation procedure to clarify the significance, frequency and impact of the factors involved is of vital importance. Therefore, the present study (see Figure 8-1, which has also been shown in Chapter 1) proposes a methodology which implements the notion of Reason's *Swiss Cheese Model* with the set theory and the probability theory in conjunction with several well-defined Formal Safety Assessment (FSA) techniques, e.g. Why-Because Analysis, Fault Tree Analysis, Bayesian Network and Influence Diagrams, etc., to form a systematic procedure that possesses the following features.

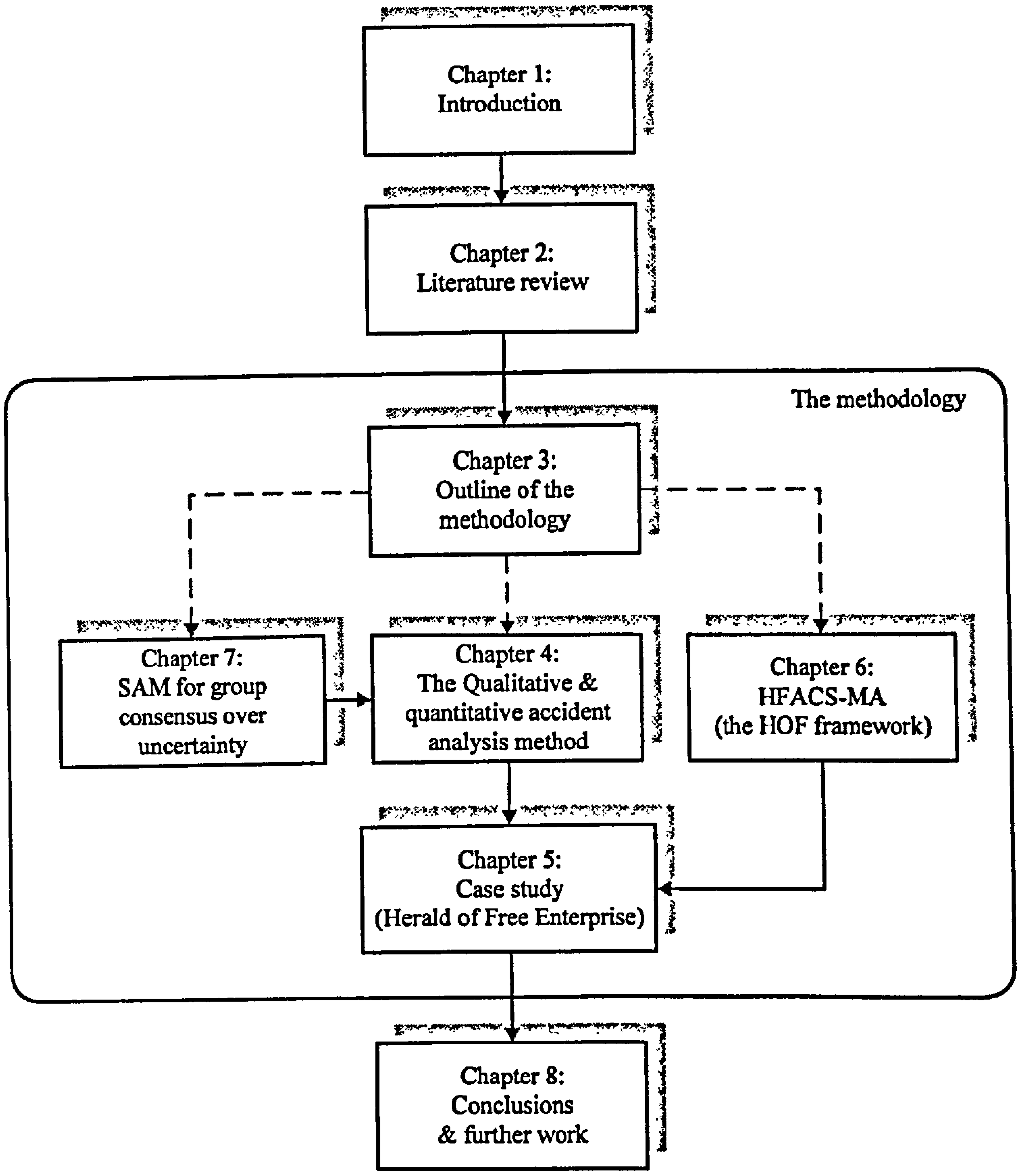


Figure 8-1 The structure of the thesis

- The analysis outcomes covered in Chapters 4 and 5 show the Bayesian Network can not only display the causation of the factors involved, but also explore the significance, frequency and impact of the factors where the qualitative results represent the instances of the Window of Opportunities (WoOs) identified in an accident, and the quantitative results reveal the width or extent of the WoOs.
- The proposed HOFs framework developed in Chapter 6 – HFACS-MA – is a modification derived from the original Human Factors Analysis and Classification System (HFACS) and has taken Reason's GEMS and Hawkin's SHEL models into account in order to fulfil the requirements of the maritime industry. The framework is an application of the Swiss Cheese Model, from which the identified human factors can be classified into different levels and categories. Hence, a

comprehensive insight into the causation of the accident analysed can be obtained by integrating the qualitative and quantitative analysis results with the HOFs framework.

- The applied Similarity Aggregation Method (SAM) and the Positive Trapezoidal Fuzzy Number (PTFN) are developed in Chapter 7 using fuzzy set theory in order to handle the group consensus problem. This can help solve the problem encountered when experts' judgements are used to calibrate the Bayesian Network due to a lack of historical statistic data during the quantitative analysis period. Both the randomness and fuzziness of the uncertainty have been considered in the aggregation method to handle the issue of subjective probability. This feature makes the methodology more resilient.
- The systematic procedure is another important feature of the methodology. This feature can make the methodology more feasible and practical by reducing the unnecessary speculations of the analysts and diminishing the influences of individual bias. This is achieved by ensuring that the analyst only concentrate on every limited scope of questions and infer their rational answers to the questions at each stage and step, without having to concern the whole picture of the accident. All analysis outcomes are therefore accumulated and integrated together to obtain the final results.

The challenges in analysing an accident/incident thoroughly and comprehensively to clarify the significance, frequency and impact of the factors involved can be fulfilled, although in certain cases, it could be overly time consuming to conduct the analysis using the proposed methodology for some minor incidents. It is believed that some of the developed methods possess valuable potential as useful aids and effective alternatives to assist the decision makers in safety planning, and will gain increased usage in other safety related operations and management. It is also believed that these methods can be tailored to the applications of dealing with the safety problems in the other industries. The major contributions of the novel methods or notions proposed are as follows:

- The implementation of Swiss Cheese Model with the set theory and the probability theory opens another possibility way to view the Swiss Cheese Model. It shows that the Swiss Cheese Model is not only suitable as an abstract notion of human errors, but also capable of substantiating with physical figures to quantitify the factors behind these holes and/or WoOs.

- The proposed HOFs framework – HFACS-MA – clearly classifies the human factors which can cause an accident to occur in different levels of the system. It can also be applied during the investigation stage to assist the investigator in avoiding overlooking those latent conditions in the shadow. When it is integrated with the qualitative and quantitative analysis results produced by the proposed methodology, a comprehensive insight into the causation of the causal factors reveals the interactions between those *active failures* and *latent conditions*.
- The innovation of Backtracking process and its validation mechanism can transform a fault tree into a Bayesian Network in a form of Minimal Cut Set, in which the Top Event is no longer represented by a signal object, but several nodes as Minimal Cut Sets. This formation can facilitate the diagnosis and prediction of the network to be performed, offering more valuable details about an accident that the Top Event format can provide
- The introduction of K-CPT and Approximate Simplification Law provides a method to find the minimum *sum-of-product* Boolean expression depicting the deterministic correlation between a node and its parent nodes in a Bayesian Network regarding an accident. This method can simplify a Bayesian Network of the accident into a simplified fault tree. It cannot only broaden the usage of Bayesian Network, but also extends the application of FTA.
- The notion of the *List Statement* utilised in Fact Finding process provides a data format and index mechanism which can facilitate the logical organisation of information and evidence in the proposed analysis procedure.

8.2 The improvements of the methodology and future work

The hypothesis is fulfilled through a rather sophisticated combination of FSA techniques and methods. However, the mission has yet been accomplished since the novel methodology is still at preliminary stage. Improvements in the methodology and the potential application of the method are still expecting. Although it has been shown that the proposed methodology has potential for the analysis, due to the time and research constraints, the present study has not been able to explore all aspects of what may be concerned and desirable in accident analysis. They can be identified as follows:

1. The applicability and limitation of the methodology: it would be useful if more test cases are applied in order to further clarify the details of the issues. Then the deficiencies of the methodology will be revealed, and the direction of future improvement will be emerged.
2. The detailed classification and definition of the proposed HOFs framework: the proposed HFACS-MA is only developed without specifying the detailed items and their definition in each category and/or level. A profound study to establish a dedicated HOFs framework which can fulfill the requirements of the maritime industry is urgently needed.
3. The solution to the simplification of K-CPT if the variables are more than six: due to the limitation of Karnaugh-map, the simplification of K-CPT can only be carried out provided that the number of the variables is less than six. An alternative is needed to cope with this issue when it is encountered.
4. A proper procedure to perform the diagnosis and prediction of the analysis results: the analysis results are formed in a Bayesian Network and/or Influence Diagrams model, which can be used to diagnose its causes and predict possible consequences based on observable evidence. A sufficient and thorough procedure to execute those functionalities is yet uncertain, and needs to be clarified.
5. An achievable process to establish a Temporal Bayesian Network model for accidents: this would allow modelling an accident in light of its evolution over time. In other words, a Bayesian Network model is generated according to a specific time of the occurrence, and then the same structure of the model denoting different period of time of interest is repeated. Thus, the proposed methodology can be extended to deal with the time sequence issue of accidents.
6. Different type of Influence Diagrams models for variant requirements of countermeasures: the proposed Influence Diagrams model is only suitable for considering cost-benefit as the criteria of the Risk Control Options. Different types of Influence Diagrams model should be introduced when the requirements of the countermeasures are changed.

7. Other methods for subjective estimation and/or group consensus: although the applied method (i.e. SAM + PTFN) is capable of handling this issue, it still has deficiencies for pragmatic utilisation due to the bothersome requirements of PTFN. For example, each estimate needs four numbers to compose a PTFN. In contrast, linguistic expressions may be a friendlier way for the experts to express their estimations and worthy of investigation.

The proposed methodology can therefore be improved and its applicability can be extended to other safety related fields in other transport sectors and indeed virtually any other industry.

8.3 Final Conclusion

Hybrid methods are recognized as an effective way to deal with the multidisciplinary nature of organisational safety and corresponding assessment frameworks (Lin and Wang, 1997). The proposed methodology follows this idea by composing a hybrid technique integrating qualitative and quantitative analysing perspectives, and offers a flexible risk-informed decision-making tool. It can be used as an approach for accident analysis to particularly carry out the analysis in those situations where probabilistic distributions of the events or factors, involved in the accident, are difficult or impossible to obtain.

The proposed methodology is still in an early stage of development, it needs time and more case studies to find out the best way of using it as well as ways of improving it. The detailed items and categories, even the levels, of the HFACS-MA also need a profound study to finalise a dedicated HOFs framework which can fulfil the needs of the maritime industry in investigating and analysing HOFs involved in an organisational accident. One thing that can be assured is that this study shall not be the end but the start of the research in this topic. Further work regarding the proposed methodology is still required.

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Appendix A – The Conditional Probability Tables for Top Event model

Source of the data used in the Conditional Probability Tables

	Historical Statistic	Experts Judgement	Author's Assumption
TE		×	
A		×	
B			×
C			×
D		×	
E1			×
E2			×
E3			×
F			×
G			×
H1			×
H2			×
J			×
K			×
L3			×
L4			×
L5			×
L6			×
L7			×
L8			×
M			×
N		×	
O			×
P			×
Q			×
R			×
T			×
U			×
V			×
W			×

Netica (CoGF) 4.08 Win, (C) 1992-2008 Norsys Software Corp.
Command Line: HeraldFE-TE.neta
Compiled to 20 cliques, with total table size (including sepsets) of 332.

TE:

capsized	safe	A	C	B
0.1	0.9	no water	reach CP	no Anti FSE
0.1	0.9	no water	reach CP	Anti FSE existed
0.01	0.99	no water	under CP	no Anti FSE
0.01	0.99	no water	under CP	Anti FSE existed
0.99	0.01	flooding	reach CP	no Anti FSE
0.2	0.8	flooding	reach CP	Anti FSE existed
0.1	0.9	flooding	under CP	no Anti FSE
0.05	0.95	flooding	under CP	Anti FSE existed

A:

no water	flooding	H1	F
0.05	0.95	over 18Kts	Bow opened
0.99	0.01	over 18Kts	Bow closed
0.9	0.1	under 18Kts	Bow opened
0.99	0.01	under 18Kts	Bow closed

B:

no Anti FSE	Anti FSE existed
0.99	0.01

C:

reach CP	under CP	G
0.8	0.2	unstable
0.2	0.8	stable

D:

TBH 80cm	non TBH	E2	E3	E1	J
0.05	0.95	deficient	E D loading	high	empty in 2 hrs
0.9	0.1	deficient	E D loading	high	more than 2 hrs
0.05	0.95	deficient	E D loading	low	empty in 2 hrs
0.9	0.1	deficient	E D loading	low	more than 2 hrs
0.01	0.99	deficient	no E D OP	high	empty in 2 hrs
0.1	0.9	deficient	no E D OP	high	more than 2 hrs
0.01	0.99	deficient	no E D OP	low	empty in 2 hrs
0.1	0.9	deficient	no E D OP	low	more than 2 hrs
0.05	0.95	sufficient	E D loading	high	empty in 2 hrs
0.1	0.9	sufficient	E D loading	high	more than 2 hrs
0.05	0.95	sufficient	E D loading	low	empty in 2 hrs
0.1	0.9	sufficient	E D loading	low	more than 2 hrs
0.01	0.99	sufficient	no E D OP	high	empty in 2 hrs
0.01	0.99	sufficient	no E D OP	high	more than 2 hrs
0.01	0.99	sufficient	no E D OP	low	empty in 2 hrs
0.01	0.99	sufficient	no E D OP	low	more than 2 hrs

E1:

high	low
0.25	0.75

E2:

deficient	sufficient
0.9	0.1

E3:

E D loading	no E D OP
0.8	0.2

F:

Bow opened	Bow closed	K	M
0.01	0.99	No D Check	AssB presented
0.99	0.01	No D Check	AssB absented
0.001	0.999	recheck	AssB presented
0.1	0.9	recheck	AssB absented

G:

unstable	stable	N	D
0.95	0.05	overloaded	TBH 80cm
0.2	0.8	overloaded	non TBH
0.1	0.9	not overloaded	TBH 80cm
0.05	0.95	not overloaded	non TBH

H1:

over 18Kts	under 18Kts
0.9	0.1

H2:

no DI fitted	DI fitted
0.99	0.01

J:

empty in 2 hrs	more than 2 hrs	O
0.1	0.9	no BHCP
0.9	0.1	BHCP installed

K:

No D Check	recheck	P	Q	R
0.05	0.95	BD indicator	M aware	NR is FTG
0.01	0.99	BD indicator	M aware	NR is STOP
0.9	0.1	BD indicator	M unknow	NR is FTG
0.01	0.99	BD indicator	M unknow	NR is STOP
0.8	0.2	no indicator	M aware	NR is FTG
0.6	0.4	no indicator	M aware	NR is STOP
0.99	0.01	no indicator	M unknow	NR is FTG
0.7	0.3	no indicator	M unknow	NR is STOP

L3:

Short Of MP	MP sufficient
0.9	0.1

L4:

not account	accounted
0.9	0.1

L5:

safe	unsafe
0.75	0.25

L6:

TP Yes	TP No
0.9	0.1

L7:

satisfy	concerned
0.8	0.2

L8:

good mngmt	poor mngmt
0.2	0.8

M:

AssB presented	AssB absented	T
0.2	0.8	CO left early
0.99	0.01	stayAt BD

N:

overloaded	not overloaded	H2	L4	L5
0.8	0.2	no DI fitted	not account	safe
0.95	0.05	no DI fitted	not account	unsafe
0.1	0.9	no DI fitted	accounted	safe
0.8	0.2	no DI fitted	accounted	unsafe
0.1	0.9	DI fitted	not account	safe
0.2	0.8	DI fitted	not account	unsafe
0.05	0.95	DI fitted	accounted	safe
0.2	0.8	DI fitted	accounted	unsafe

O:

no BHCP	BHCP installed	L8
0.1	0.9	good mngmt
0.99	0.01	poor mngmt

P:

BD indicator	no indicator	L8
0.95	0.05	good mngmt
0.05	0.95	poor mngmt

Q:

M aware	M unknow	L8
0.99	0.01	good mngmt
0.01	0.99	poor mngmt

R:

NR is FTG	NR is STOP	U
0.99	0.01	poor SSO
0.1	0.9	good SSO

T:

CO left early	Stay At BD	L3	U	V
0.99	0.01	shortOf MP	poor SSO	earlier HSO
0.95	0.05	shortOf MP	poor SSO	normal
0.9	0.1	shortOf MP	good SSO	earlier HSO
0.8	0.2	shortOf MP	good SSO	normal
0.9	0.1	MP sufficient	poor SSO	earlier HSO
0.1	0.9	MP sufficient	poor SSO	normal
0.1	0.9	MP sufficient	good SSO	earlier HSO
0.05	0.95	MP sufficient	good SSO	normal

U:

poor SSO	good SSO	W	L7
0.1	0.9	clear	satisfy
0.05	0.95	clear	concerned
0.95	0.05	vague	satisfy
0.2	0.8	vague	concerned

V:

earlier HSO	normal	L6
0.9	0.1	TP Yes
0.1	0.9	TP No

W:

clear	vague	L8
0.95	0.05	good mngmt
0.05	0.95	poor mngmt

Appendix B – The Conditional Probability Tables for Minimal Cut Sets model

Source of the data used in the Conditional Probability Tables

	Historical Statistic	Experts Judgement	Author's Assumption
MCS1		×	
MCS2		×	
MCS3		×	
MCS4		×	
A1		×	
A2		×	
B			×
C1			×
C2			×
D		×	
E2			×
E3			×
F1			×
F2			×
G1			×
G2			×
H1			×
H2			×
J			×
K1			×
K2			
L3			×
L4			×
L5			×
L6			×
L7			×
L8			×
M1			×
M2			×
N1		×	
N2		×	
O			×
P			×
Q			×
R			×
T1			×
T2			×
U			×
V			×
W			×

Netica (CoGF) 4.08 Win, (C) 1992-2008 Norsys Software Corp.
Command Line: HeraldFE-MCS.neta"
Compiled to 34 cliques, with total table size (including sepsets) of 654.

MCS1:

capsized	safe	A1	B	C1
0.1	0.9	no water	no Anti FSE	reach CP
0.1	0.9	no water	Anti FSE existed	reach CP
0.01	0.99	no water	no Anti FSE	under CP
0.01	0.99	no water	Anti FSE existed	under CP
0.99	0.01	flooding	no Anti FSE	reach CP
0.2	0.8	flooding	Anti FSE existed	reach CP
0.1	0.9	flooding	no Anti FSE	under CP
0.05	0.95	flooding	Anti FSE existed	under CP

MCS2:

capsized	safe	A1	B	C2
0.1	0.9	no water	no Anti FSE	reach CP
0.01	0.99	no water	no Anti FSE	under CP
0.1	0.9	no water	Anti FSE existed	reach CP
0.01	0.99	no water	Anti FSE existed	under CP
0.99	0.01	flooding	no Anti FSE	reach CP
0.1	0.9	flooding	no Anti FSE	under CP
0.2	0.8	flooding	Anti FSE existed	reach CP
0.05	0.95	flooding	Anti FSE existed	under CP

MCS3:

capsized	safe	A2	B	C1
0.2	0.8	no water	no Anti FSE	reach CP
0.01	0.99	no water	no Anti FSE	under CP
0.2	0.8	no water	Anti FSE existed	reach CP
0.01	0.99	no water	Anti FSE existed	under CP
0.99	0.01	flooding	no Anti FSE	reach CP
0.1	0.9	flooding	no Anti FSE	under CP
0.2	0.8	flooding	Anti FSE existed	reach CP
0.05	0.95	flooding	Anti FSE existed	under CP

MCS4:

capsized	safe	A2	B	C2
0.2	0.8	no water	no Anti FSE	reach CP
0.01	0.99	no water	no Anti FSE	under CP
0.2	0.8	no water	Anti FSE existed	reach CP
0.01	0.99	no water	Anti FSE existed	under CP
0.99	0.01	flooding	no Anti FSE	reach CP
0.1	0.9	flooding	no Anti FSE	under CP
0.2	0.8	flooding	Anti FSE existed	reach CP
0.05	0.95	flooding	Anti FSE existed	under CP

A1:

no water	flooding	H1	F1
0.05	0.95	over 18Kts	Bow opened
0.99	0.01	over 18Kts	Bow closed
0.7	0.3	under 18Kts	Bow opened
0.99	0.01	under 18Kts	Bow closed

A2:

no water	flooding	H1	F2
0.05	0.95	over 18Kts	Bow opened
0.99	0.01	over 18Kts	Bow closed
0.7	0.3	under 18Kts	Bow opened
0.99	0.01	under 18Kts	Bow closed

B:

no Anti FSE	Anti FSE existed
0.99	0.01

C1:

reach CP	under CP	G1
0.8	0.2	unstable
0.2	0.8	stable

C2:

reach CP	under CP	G2
0.8	0.2	stable
0.2	0.8	unstable

D:

TBH 80cm	non TBH	E2	E3	J
0.05	0.95	deficient	E D loading	empty in 2 hrs
0.9	0.1	deficient	E D loading	more than 2 hrs
0.01	0.99	deficient	no E D OP	empty in 2 hrs
0.1	0.9	deficient	no E D OP	more than 2 hrs
0.05	0.95	sufficient	E D loading	empty in 2 hrs
0.1	0.9	sufficient	E D loading	more than 2 hrs
0.01	0.99	sufficient	no E D OP	empty in 2 hrs
0.01	0.99	sufficient	no E D OP	more than 2 hrs

E2:

deficient	sufficient
0.9	0.1

E3:

E D loading	no E D OP
0.8	0.2

F1:

Bow opened	Bow closed	K1	M1
0.01	0.99	No D Check	AssB presented
0.99	0.01	No D Check	AssB absented
0.001	0.999	recheck	AssB presented
0.1	0.9	recheck	AssB absented

F2:

Bow opened	Bow closed	K2	M2
0.01	0.99	No D Check	AssB presented
0.99	0.01	No D Check	AssB absented
0.001	0.999	recheck	AssB presented
0.1	0.9	recheck	AssB absented

G1:

unstable	stable	N1	D
0.95	0.05	overloaded	TBH 80cm
0.2	0.8	overloaded	non TBH
0.1	0.9	not overloaded	TBH 80cm
0.05	0.95	not overloaded	non TBH

G2:

stable	unstable	N2	D
0.95	0.05	overloaded	TBH 80cm
0.2	0.8	overloaded	non TBH
0.1	0.9	not overloaded	TBH 80cm
0.05	0.95	not overloaded	non TBH

H1:

over 18Kts	under 18Kts
0.9	0.1

H2:

no DI fitted	DI fitted
0.99	0.01

J:

empty in 2 hrs	more than 2 hrs	O
0.1	0.9	no BHCP
0.9	0.1	BHCP installed

K1:

No D Check	recheck	P
0.05	0.95	BD indicator
0.9	0.1	no indicator

K2:

No D Check	recheck	Q	R
0.1	0.9	M aware	NR is FTG
0.5	0.5	M aware	NR is STOP
0.99	0.01	M unknow	NR is FTG
0.5	0.5	M unknow	NR is STOP

L3:

shortOf MP	MP sufficient
0.9	0.1

L4:

not account	accounted
0.9	0.1

L5:

safe	unsafe
0.75	0.25

L6:

TP Yes	TP No
0.9	0.1

L7:

satisfy	concerned
0.8	0.2

L8:

good mngmt	poor mngmt
0.2	0.8

M1:

AssB presented	AssB absented	T1
0.2	0.8	CO left early
0.99	0.01	stayAt BD

M2:

AssB presented	AssB absented	T2
0.2	0.8	CO left early
0.99	0.01	stayAt BD

N1:

overloaded	not overloaded	H2	L4
0.9	0.1	no DI fitted	not account
0.1	0.9	no DI fitted	accounted
0.2	0.8	DI fitted	not account
0.05	0.95	DI fitted	accounted

N2:

overloaded	not overloaded	H2	L5
0.1	0.9	no DI fitted	safe
0.9	0.1	no DI fitted	unsafe
0.05	0.95	DI fitted	safe
0.2	0.8	DI fitted	unsafe

O:

no BHCP	BHCP installed	L8
0.1	0.9	good mngmt
0.99	0.01	poor mngmt

P:

BD indicator	no indicator	L8
0.95	0.05	good mngmt
0.05	0.95	poor mngmt

Q:

M aware	M unknow	L8
0.99	0.01	good mngmt
0.01	0.99	poor mngmt

R:

NR is FTG	NR is STOP	U
0.99	0.01	poor SSO
0.1	0.9	good SSO

T1:

CO left early	stayAt BD	L3
0.95	0.05	shortOf MP
0.1	0.9	MP sufficient

T2:

CO left early	stayAt BD	V	U
0.95	0.05	earlier HSO	poor SSO
0.1	0.9	earlier HSO	good SSO
0.1	0.9	normal	poor SSO
0.05	0.95	normal	good SSO

U:

poor SSO	good SSO	W	L7
0.1	0.9	clear	satisfy
0.05	0.95	clear	concerned
0.95	0.05	vague	satisfy
0.2	0.8	vague	concerned

V:

earlier HSO	normal	L6
0.9	0.1	TP Yes
0.1	0.9	TP No

W:

clear	vague	L8
0.95	0.05	good mngmt
0.05	0.95	poor mngmt

Appendix C – The specifications of sensitivity finding reports in Netica

SENSITIVITY TO FINDINGS

A report will be displayed to show how much the beliefs, mean value, etc. of the target node could be influenced by a single finding at each of the other nodes in the net (each is called a "findings node"). The first part of the report has a section for each findings node, showing how much it can effect the target node using several different sensitivity measures. The second part is a summary table which compares the sensitivities for each of the findings nodes. ... Use the summary list of sensitivities at the end of the report generated to identify possible findings nodes which will provide the most information about the target node. If you want more detailed information of how these findings nodes can effect the target node, look up each of them in the first part of the report.

Below are descriptions of each of the utility-free sensitivity measures that Netica calculates. First are some notes for interpreting the descriptions.

Key / Notes

Definition:	In the definitions, "belief" means posterior probability (i.e. conditioned on all findings currently entered). In the names of the various measures "real" refers to the expected value of continuous nodes, or discrete nodes which have a real numeric value associated with each state. "expected value" means to take the expectation over a quantity (as described in the onscreen help).
Range:	The minimum and maximum values that this measure can take on.
Compare:	A quantity which is useful to compare the value of this measure against (perhaps to express this measure as a percentage).
Equation:	Note that all the conditionals should include all findings already entered into the network, so P(q) is really P(q|E), P(q|f) is really P(q|f,E), etc.

Notation:

Q	is the query variable
F	is the varying variable
q	is a state of the query variable
f	is a state of the varying variable
Xq	is the numeric real value corresponding to state q
SUM~q	means the sum over all states q of Q. It applies to the whole expression following.
MIN~q MAX~q	are similar to SUM~q
E(Q)	is the expected real value of Q before any new findings
E(Q|f)	is the expected real value of Q after new finding f for node F
V(Q)	is the variance of the real value of Q before any new findings
H(Q)	is the entropy of Q before any new findings

RMS	is "root mean square", which is the square root of the average of the values squared.

Minimum Belief

Definition:	Minimum belief that each state q of Q can take due to a finding at F. This provides a value for each state.
Range:	[0, P(q)] P(q) if Q is independent of F
Compare:	P(q)
Equation:	Pmin(q) = MIN~f P(q|f)

Maximum Belief

Definition:	Maximum belief that each state q of Q can take due to a finding at F. This provides a value for each state.
Range:	[P(q), 1] P(q) if Q is independent of F
Compare:	P(q)
Equation:	Pmax(q) = MAX~f P(q|f)

RMS Change of Belief

Definition:	The square root of the expected change squared of the belief of state q of Q, due to a finding at F. This provides a value for each state. This is the standard deviation of P(q|f) about P(q) due to a finding at F, with the finding at F distributed by P(f).
Reference:	Spiegelhalter89 & Neapolitan90,p394. They call the square of this quantity simply "variance".
Range:	[0, 1] 0 if Q is independent of F
Compare:	P(q)
Equation:	sp(q) = sqrt (Vp(q)) Vp(q) = SUM~f P(f) [P(q|f) - P(q)] ^ 2

Entropy Reduction (Mutual Information)

Definition:	The mutual information between Q and F (measured in bits). The expected reduction in entropy of Q (measured in bits) due to a finding at F.
Range:	[0, H(Q)] 0 if Q is independent of F
Reference:	Pearl88,p321. He has sign of I(T,X) backwards. Var mapping: T->Q, X->F, I(T,X)->I
Compare:	H(Q)
Equation:	I = H(Q) - H(Q|F) = SUM~q SUM~f P(q,f) log (P(q,f) / [P(q) P(f)])

Note that the log is base 2, which is traditional for entropy and mutual information, so that the units of the results will be "bits".

More complete documentation will be available at Norsys website: www.norsys.com