Quantitative Human Reliability Assessment in Marine Engineering Operations

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THE FOLLOWING PUBLICATIONS, FIGURES, PLATES AND TABLES HAVE BEEN EXCLUDED ON INSTRUCTION FROM THE UNIVERSITY.

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Abstract

Marine engineering operations rely substantially on high degrees of automation and supervisory control. This brings new opportunities as well as the threat of erroneous human actions, which account for 80-90% of marine incidents and accidents. In this respect, shipping environments are extremely vulnerable. As a result, decision makers and stakeholders have zero tolerance for accidents and environmental damage, and require high transparency on safety issues.

The aim of this research is to develop a novel quantitative Human Reliability Assessment (HRA) methodology using the Cognitive Reliability and Error Analysis Method (CREAM) in the maritime industry. This work will facilitate risk assessment of human action and its applications in marine engineering operations. The CREAM model demonstrates the dynamic impact of a context on human performance reliability through Contextual Control Model controlling modes (COCOM-CMs). CREAM human action analysis can be carried out through the core functionality of a method, a classification scheme and a cognitive model. However, CREAM has exposed certain practical limitations in its applications especially in the maritime industry, including the large interval presentation of Human Failure Probability (HFP) values and the lack of organisational factors in its classification scheme. All of these limitations stimulate the development of advanced techniques in CREAM as well as illustrate the significant gap between industrial needs and academic research.

To address the above need, four phases of research study are proposed. In the first phase, the adequacy of organisation, one of the key Common Performance Conditions (CPCs) in CREAM, is expanded by identifying the associated Performance Influencing Factors (PIFs) and sub-PIFs in a Bayesian Network (BN) for realising the rational quantification of its assessment. In the second phase, the uncertainty treatment methods' BN, Fuzzy Rule Base (FRB), Fuzzy Set (FS) theory are used to develop new models and techniques that enable users to quantify HFP and facilitate the identification of possible initiating events or root causes of erroneous human action in marine engineering operations. In the third phase, the uncertainty treatment method's Evidential Reasoning (ER) is used in correlation with the second phase's developed new models and techniques to produce the solutions to conducting quantitative HRA in conditions in which data is unavailable, incomplete or ill-defined. In the fourth phase, the CREAM's prospective assessment and retrospective analysis models are integrated by using the established Multiple Criteria Decision Making (MCDM) method based on the combination of Analytical Hierarchical Process (AHP), entropy analysis and Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS). These enable Decision Makers (DMs) to select the best developed Risk Control Option (RCO) in reducing HFP values.

The developed methodology addresses human actions in marine engineering operations with the significant potential of reducing HFP, promoting safety culture and facilitating the current Safety Management System (SMS) and maritime regulative frameworks. Consequently, the resilience of marine engineering operations can be further strengthened and appreciated by industrial stakeholders through addressing the requirements of more safety management attention at all levels. Finally, several real case studies are investigated to show end users tangible benefits of the developed models, such as the reduction of the HFPs and optimisation of risk control resources, while validating the algorithms, models, and methods developed in this thesis.

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The author would also like to dedicate this work specifically to the Libyan martyrs, who have sacrificed their spirits for the sake of freedom, dignity and justice for the Libyan people.

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List of Abbreviations

ABS	American Bureau of Shipping
AHP	Analytical Hierarchical Process
AI	Artificial Intelligence
APOA	Assessed Proportion of Affect
ATHEANA	A Technique for Human Error Analysis
A-TOPSIS	Adjusted Technique for Order Preference by Similarity to the Ideal Solution
ATSB	Australian Transportation Safety Bureau
BNs	Bayesian Networks
BOP	Blow Out Preventer
BREAM	Bridge Reliability and Error Analysis Method
CBDT	Cause-Based Decision Tree
CFFs	Cognitive Failure Functions
CFPs	Cognitive Failures Probabilities
COCOM	Contextual Control Model
COCOM-CMs	Contextual Control Model Controlling Modes
CPCs	Common Performance Conditions
CPs	Cognitive Processes
CPTs	Conditional Probabilities Tables
CREAM	Cognitive Reliability and Error Analysis Method
DAG	Directed Acyclic Graph
DMs	Decision Makers
DNV	Det Norske Veritas
DREAM	Driving Reliability and Error Analysis Method
DTs	Decision Trees
EDF	Electricité de France
EFCs	Error Forcing Conditions
EPCs	Error Producing Conditions
ER	Evidential Reasoning
FES	Fuzzy expert system
FFs	Fuzzy Functions
FL	Fuzzy Logic

FRB	Fuzzy Rule Base
FS	Fuzzy Set
FSA	Formal Safety Assessment
FTA	Fault Tree Analysis
GTTs	Generic Task Types
HDT	Holistic Decision Tree
HEART	Human Error Assessment and Reduction Technique
HEP	Human Error Probability
HFEs	Human Failure Events
HFP	Human Failure Probability
HOFs	Human and Organisational Factors
HPLV	Human Performance Limit Value
HRA	Human Reliability Assessment
IACS	International Association of Classification Society
IDS	intelligent decision system
IFs	Influence Factors
ILO	International Labour Organization
IMO	International Maritime Organization
INS	Integrated Navigation System
ISM Code	International Safety Management Code
LR	Lloyds Register
M- TOPSIS	Modified Technique for Order Preference by Similarity to the Ideal Solution
MAIB	Marine Accident Investigation Board
MAUD	Multi Attribute Utility Decomposition
MAVT	Multi-Attribute Value Theory
MBI	Marine Board Investigation
MCDM	Multiple Criteria Decision Making
MERMOS	Methode d' Evaluation de la Realisation des Missions Operateur pour la Surete (where a possible translation of the acronym might be "evaluation method to understand operators' safety mission")
MMI	Man Machine Interaction
MODM	Multiple Objective Decision Making
NARA	Nuclear Action Reliability Assessment

NIS	Negative Ideal Solution
NPP	Nuclear Power Plant
NTSB	National Transport Safety Board
OWA	Ordered Weighted Averaging
PIFs	Performance Influencing Factors
PIS	Positive Ideal Solution
PRA	Probabilistic Risk Assessment
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
PSA	Probabilistic Safety Assessment
PSC	Port State Control
PSF	Performance Shaping Factor
QFs	Quality Factors
RCO	Risk Control Option
RINA	Registro Italiano Navale
RMS	Risk Management System
SAW	Simple Additive Weighting
SLIM	Success Likelihood Index Method
SMS	Safety Management System
SOLAS	Safety of Life at Sea
SPAR-H	Standardized Plant Analysis Risk-Human Reliability
SRK	Skill, Rule and Knowledge
TCC	Technical Cooperation Committee
THERP	Technique for Human Error Rate Prediction
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution
TRC	Time Reliability Curve
TSB-C	Canadian Transportation Safety Board
USCG-MSMS	United States Coast Guard Marine Safety Management System
USNRC	United States Nuclear Regulatory Commission
VDR	Voyage Data Recorder
VFT	Value Focused Thinking
VMSAS	Voluntary Member States Audit Scheme

Definitions

Human action: It is the act through which human is in a direct interface with a process or with equipment (Pyy, 2000).

Human error: It is the fallacy causal relation of human action or performance characteristic to an observed outcome (Hollnagel, 1998a).

Error: It is an action gone wrong in the sense that the outcome was not the expected or desired one (Hollnagel, 1998a).

Cognitive errors: They are all actions involving a modicum of cognition. As a result all errors must also be cognitive (Hollnagel, 1998a).

Erroneous human action: It is the observable and verifiable human action that exceeds some limit of acceptability resulting of cognition, technology and of organisation. In other words, it is any member of a set of responses that exceeds some limit of acceptability. It is an out-of-tolerance action where the limits of performance are defined by the system (Hollnagel, 1998a).

Human failure probability: It is the failure probability of a defined human action in a HRA model. There may be many reasons for failure (compare to human error). A human failure affects components (faults) and processes (disturbances). If the effect is significant (critical), a recovery or repair has to take place (Pyy, 2000).

Latent failure conditions: They are the latent conditions in a system that may become contributing causes for an accident. Latent failure conditions are thus seen in contrast to active failures, i.e., failures of technological functions or human actions, which become the local triggering events that afterwards are identified as the immediate causes of an accident (Hollnagel, 1998a).

Human reliability: It is the probability that a person will perform according to the requirements of the task for a specified period of time, to that is sometimes added that the person shall not perform any extraneous activity which can degrade the system (Swain & Guttmann, 1983).

Probabilistic safety assessment: It is a probabilistic model usually based on HRA method, to identify and classify those elements where improper operation of can result in a contingency. The outcome of a PSA can be a quantitative estimate of the risk in one of the following (Dougherty and Fragola, 1988): A description of equipment failures, human failures, and process events whose combination must occur before a specified hazard can occur (Hollnagel, 1998a).

Error of omission: It is the failure to carry out some of the actions/ sub goals necessary to achieve a desired goal (Hollnagel, 2000a).

Error of commission: It is carrying out an unrelated action/ sub goals, which prevents the achievement of the goal (Hollnagel, 2000a).

Chapter 1
Introduction

Summary

This chapter highlights the restricted potential of the maritime regulative framework, which has been used to describe the safety standard of a vessel. It encourages the use of HRA methods and probabilistic calculus to assess human performance reliability in marine engineering operations and helps to define ways of how the human reliability can be improved. It also describes the statement of problem and outlines the research aim and objectives, which is followed by an overview of the research methodology as well as the scope and structure of the thesis.

1.1. Background

Seaworthiness and compliance are terms that have historically been used as reference parameters to describe the safety standard of a vessel in the maritime industry. Observably, these parameters have restricted potential in incidents' and accidents' prevention, owing to the complexity of many factors, of which the likelihood of erroneous human actions accounts for 80-90% (Baker and Seah, 2004; Jalonen and Salmi, 2009). Currently, the maritime industry is regulated by a complex international legal framework. The international nature of the shipping industry has made the enforcement of the legislative framework difficult. Although efforts have been made to change the enforcement process, preventive actions are still uncommon. The creation or amendment of legislation often occurs reactively, typically following a major disaster. Nevertheless, within this legal framework significant improvement has been achieved during the last few decades, which can be clearly observed by an average 2 - 3% annual reduction in the total loss ratio of ships (Lancaster, 1996; Soma, 2003; Pomeroy, 2006). Despite this fact, the current increasing trend of marine engineering system design complexity and the substantial reliance on a high degree of automation and supervisory control in its operation bring new opportunities as well as threats (Hollnagel, 2000b). In fact the advance in technology has increased operating system reliability and reduced its maintenance requirement. In the meantime familiarity with the system has been reduced by the reduction in routine intervention. Considering the effect of the advance of technologies on the gained knowledge and skill of successive supervisory and operational crews, the current problem is about how the reduction in this routine intervention will affect the safe operation of the ship during its service lifetime

(Pomeroy, 2006). Hollnagel (2008a, b) stated that safety cannot genuinely be improved only by looking to the past and taking precautions against the accidents that have happened. These facts make it necessary that the safety performance of supervisory and operating personnel should be assessed proactively; accordingly, resources available to enable the safe performance could purposefully be planned. In this respect, HRA methods and Probabilistic Safety Assessment (PSA) or Probabilistic Risk Assessment (PRA) models which have been used effectively to improve the Safety Management System (SMS) in the nuclear, aviation and chemical ergonomics are available to provide best proactive approaches to safety practices. These can be easily applied to mitigate the erroneous human actions contribution in incidents and accident of the maritime industry (NRC, 1994; Amrozowicz et al., 1997) irrespective of regulative requirements.

HRA is a practical tool to define and formulate the overall human performance reliability. It enables users to implement the necessary changes that ensure standards of SMS on board and ashore. HRA can be a helpful tool to assess and analyse human performance and maintain this assessment and analysis in the long term. Through HRA the challenge is to improve human performance in relation to safety issues, resulting in changes to safety culture; this would produce significant operational improvements and savings. By improving human performance and safety culture throughout the organisation, there is a huge potential for cost saving and to build a reputation as a competitive advantage. Throughout HRA several achievements could be observed. These include but not limited to improved SMS performance, improved crew safety performance, improved incidents, accidents and resulting claims' statistics and improved organisation uniformity. These will also clearly demonstrate that the fundamental requirement for improvements to human safety performance, with reduced frequency of incidents and accidents, can be achieved through a structured approach addressing working context, human behaviour and working culture.

1.2. The statement of problem

First generation HRA methods have been widely used to account for human performance reliability. Their wide applications have been documented in many studies (e.g. Swain and Guttman,1983; Williams, 1988; Swain, 1990; Hollnagel, 1993; Kirwan, 1996; Kirwan 1997a, b; Hollnagel, 1998a; Pyy, 2000; Hallbert et al., 2004; Kirwan et al., 2005; Chander et al., 2006; Forester et al., 2006; Yang et al., 2007; Reer, 2008a, b; Bell and Holyroyd, 2009; Adhikari et al., 2009; Boring et al., 2010b; Spurgin, 2010;

Licao et al., 2011). For example, the Technique for Human Error Rate Prediction (THERP) method developed by Swain and Guttman (1983) was used by Amrozowicz et al. (1997) as a benchmark specifically to assess the Human Error Probability (HEP) of the marine tanker system, which has been identified as a source of high risk and has a high potential for improvement. This methodology had allowed the production of possible human task activities and their corresponding HEPs. Martins and Maturana (2010) had also presented a methodology emphasizing the use of the THERP method to reach the Formal Safety Assessment (FSA) objectives. Basically, HEPs are the origin of the greatest uncertainty when FSA is performed. The use of the THERP method in association with the FSA has helped to identify the implications of erroneous human actions in specific areas of potential risk reduction and offered a possibility to infer means for its reduction. However, due to the complexity of the studied system, THERP could not be used to consider all hypotheses that brought hazards to the ships.

Although first generation HRA methods are well documented, they are still revealing some applicable problems (Hollnagel, 1998a; Zio et al., 2009; Martins and Maturana, 2010; Spurgin, 2010). In fact, first generation HRA methods are:

- Very much an engineering approach to the human error modelling. Its methodologies are referred to as decomposition methods (Hollnagel, 1993; Spurgin, 2010), in which a human operator is essentially treated as a component in a system, so an operator failing to respond to an event is termed errors of omission, while unintended human action is labelled errors of commission.
- Limited in consideration of human behaviour and human decision making factors that cannot be categorised simply as omissions or commissions. Human failure is far more complex than the failure of a system component (Doughty, 1990).
- Largely failing to consider the context in which erroneous human actions are made. In addition, they are heavily focused on errors of omission and less on consideration of errors of commission (Hollnagel, 1998a; Spurgin, 2010).
- Practically limited in task dependency assessment (Podofillini et al., 2010). For example, the most widely used dependence assessment method of THERP introduces five levels of dependence (zero, low, moderate, high, complete) corresponding to different values of conditional HEPs. In THERP the task dependency is modelled through a few general guidelines specifying some of the factors that may influence the dependence level. Guidelines give only generic tendencies of the impact of

factors on the dependence level, and a lot of room is left for interpretation. The assessment therefore requires a considerable amount of expert judgment, which may lack transparency and traceability (Zio et al., 2009). Hollnagel (1998a), Cepin (2006), Zio et al. (2009) and Podofillini et al. (2010) also highlighted the consequential need for a new, explicit and transparent dependence assessment method.

During the 1990s many issues related to HRA were raised by Reason (1990a, b) and others, e.g. Roberts (1990) and Hollnagel (1993). These issues drove the revision of HRA methodologies and the adoption of more sophisticated models and understandings of erroneous human action. Therefore, second generation HRA developers have put forward cognitive effect and context impact in their developed methodologies. For example, Cognitive Reliability and Error Analysis Method (CREAM) provides a strong argument for considering the use of cognitive factors' effect and context impact (Hollnagel, 1998a) and considers the context under which an action takes place to determine Human Failure Probability (HFP) (Hollnagel, 1998a; Spurgin, 2010).

CREAM is well documented for a retrospective as well as a prospective approach to the formulation of HRA. Prospectively, it is developed in two versions. One is the simplified view of the Contextual Control Model Controlling Modes (COCOM-CMs) (strategic, tactical, opportunistic and scrambled) as the candidate model of cognition, which ends by determining the probable control mode and the generic action failure probability, based on the assessment of nine Common Performance Condition (CPC) primary effects. The other version is extended to a more detailed view of erroneous human actions. It is based on two concepts: the 13 generalized Cognitive Failure Functions (CFFs) and the nine CPCs called functional modifiers. These CPCs determine the context under which the crew or personnel operates. Consequently, the CREAM is a context driven method with a more psychological view of HRA. The context is considered to affect some aspects of the operators' cognitive processing. Over a range of accidents, the context can vary from reduced, satisfactory and improved impacts, depending on the amount of attention given to each context element by a designer or operator (Hollnagel, 1998a; Boring, 2007; Spurgin, 2010). This can lead to a functional failure, which in turn leads to an error. The general concepts are very much in line with current thinking about how erroneous human actions are caused.

Retrospectively, CREAM is carried out recursively through the core functionality of a method, a classification scheme and a cognitive model to identify possible initiating events or root causes of erroneous human action. However, the drawbacks of CREAM are:

- The basic method application ends by determining the probable control mode and the generic action failure probability. This approach considers only the improved and reduced effect levels of each CPC and ignores the satisfactory effect level, which is supposed to be the marginal and transient condition of context-CPCs that might affect existing task scenarios.
- The 13 extended method CFFs, practically, are quite high level descriptions of potential cognitive errors possibly associated with a task (Hollnagel, 1998a; Boring, 2010a; Spurgin, 2010). Therefore, it would be difficult to differentiate CFFs in practice, because the human action controlling influence is a procedure conditioned by training and MMI design and layout.
- In evaluating a situation using extended CREAM, the evaluator has to select the CFF and also determine which CPCs are involved and to what degree (Hollnagel, 1998a; Spurgin, 2010). This is a quite high level task in performance assessment.
  Data used to demonstrate Cognitive Failures Probabilities (CFP) corresponding to the 13 CFFs associated with a task has been selected from a variety of sources, such as Beare et al.'s (1983) study, THERP (Swain and Guttman, 1983), Human Error Assessment and Reduction Technique (HEART) (Williams, 1988), and Gertman and Blackman's (1994) human reliability and safety analysis data handbook (Spurgin (2010). Therefore, the use of this data is to provide a demonstration of the method, and not a justification of its accuracy (Spurgin, 2010).
- There is a need to better qualify terms like adequacy of organisation in retrospective applications. Also, some of the words used in the classification scheme tables can be better defined (Hollnagel, 1998a; Spurgin, 2010).

There have been several research studies to improve and further develop the CREAM basic method for determining the numerical values of COCOM-CMs' probabilities. The following are examples of those studies:

- Fujita and Hollnagel (2004) have provided an improvement to the basic screening method of CREAM, in which the equations calculate a mean failure rate in response to a change of the CPCs score directly without invoking the notion of human action control modes. In the derivation of these equations it is assumed that the numbers of improved CPCs is equal to the numbers of reduced CPCs. According to the dependency of CPCs described by CREAM model, the assumption may not hold. For instance, in the example taken from the original CREAM, there are 7 improved CPCs and 9 reduced CPCs: This requires caution in the use of the provided equations to calculate a mean failure rate.

- Konstandinidou et al. (2006) have used Fuzzy Logic (FL) to map CREAM CPCs' logical relation rules as a base to enable calculating the numerical values of action failure probabilities. However, their study has been exposed as having some practical problems, such as the ignorance of different effects/importance on human performance that CPCs may have in the practical HRA applications; the logicality of using multiple-input single-output rule base to model the relations between the control modes and CPCs; the loss of useful information in fuzzy Max-Min inference operation; and the lack of adequacy of modelling CPC dependencies and of instant human failure probability estimation. Although different weights have been assigned to CPCs in the studies by Marseguerra et al., 2006 and Marseguerra et al., 2007, the other concerns stated above have not been well addressed (Yang et al., 2010).
- Kim et al. (2006) have proposed a Bayesian Network (BN) probabilistic model for determining COCOM-CMs' probabilities. This BN probabilistic model has been developed to deal with the limitations of the CREAM basic method, which can only determine the probable control mode and a generic action failure probability for many possible different kinds of context scenarios separately, in the worst case, for 31,104 context scenario end results. Although a divorcing concept is applied in the construction of the BN model to reduce the number of possible combinations of the nine CPCs' positive and negative deterministic effect levels, assigning conditional probabilities deterministically is still complex. For instance, there are 45,000 deterministic conditional probabilities needed to determine the Conditional Probability Table (CPT) corresponding to the COCOM-CMs' node.
- He et al. (2008) have presented a simplified CREAM prospective quantification process, which uses a similar quantification equation for both basic and extended methods. To differentiate between the basic and the extended methods in application, their study suggested values for some parameters, such as context influence index and performance influencing index, to be used in a similar quantification equation.

With use of this methodology, the quantification process considers the task as a whole; also, it is not easy to tell which control mode is really right for the continuous and gradual change from one control mode to another, specifically during the potential overlaps that exist between the adjacent modes.

- Yang et al. (2010) have used a fuzzy Bayesian reasoning approach to facilitate the quantification of CREAM in maritime human reliability analysis. Their developed generic methodology incorporated FL, Evidential Reasoning (ER) and Bayesian inference. The kernels of the proposed methodology framework are to use ER to establish fuzzy IF-THEN rule bases with belief structures, and to employ a Bayesian inference mechanism to aggregate all the rules associated with a seafarer's task for estimating his/her failure probability. The presented methodological framework has dealt with CPCs' dependency effect within each scenario's fuzzy rule. The used scenarios revealed a limited number of CPC effect levels. However, in situations where the nine CPCs have effect levels, which will necessitate a maximum of 46,656 rules to be assessed, these will constrain the extent of using the proposed framework in the application domain.

For retrospective accident analysis, a specified marine domain version of CREAM called Bridge Reliability and Error Analysis Method (BREAM) has been developed (Nygren, 2006). In addition, it has also been adapted to road traffic as Driving Reliability and Error Analysis Method (DREAM) (Warner and Sandin, 2010). Serwy and Rantanen (2007) have stated that the CREAM performance analysis model is very tedious to apply manually and not yet in widespread use, and is, therefore, largely untested. Therefore, to allow for rapid and systematic evaluation of the CREAM performance analysis method, they developed a software tool for its application. The simplicity of the software allows the user to analyse events in much more detail but also reveals some critical shortcomings in identifying the specific/general root cause directly related to organisational issues in both the method and consequently the software tool (Serwy and Rantanen, 2007).

HRA in oil tankers' operations has been presented by Subramaniam (2010), where a specific oil tanker accident was analysed by utilising several developed novel mathematical model approaches such as Decision Making Trail and Evaluation Laboratory (DEMERTEL) and discrete Fuzzy Sets (FSs), etc.

- Lee et al. (2011) have developed a methodology based retrospective analysis of the CREAM method. The methodology focuses on the root cause of communication errors and assessing the type of communication errors which could happen in Nuclear Power Plants (NPPs). The antecedent consequent links of influential factors related to communication errors in the CREAM classification scheme have been developed. A quantitative analysis method focusing on estimating the probability of communication errors is suggested. Finally, methodology validation results have shown that it is possible to foresee the effects of given plant conditions on communication errors and reduce the error occurrences.

The above stated drawbacks have highlighted the need for new, simple and consistent models. These models will enable users to obtain consistent values for CREAM COCOM-CMs' probabilities and the analogous crisp values of HFP. In addition, models will also better qualify terms like adequacy of organisation in retrospective and prospective applications. Such models will also be integrated with a newly developed Multiple Criteria Decision Making (MCDM) method so as to enable Decision Makers (DMs) to select the best developed Risk Control Option (RCO) in reducing HFP.

1.3. Research objectives

The aim of this research is to develop a methodology for HRA in an uncertain environment in marine engineering operations. Formulating such a methodology will enable users to assess and analyse human reliability and to identify ways of reducing HFP. As a result, decision makers and stakeholders will be able to manage and control marine engineering operations' vulnerability even given the uncertainty of human, technological and organisational factors. To achieve this aim, the following research objectives are formulated to:

- Identify human, technological and organisational factors which influence human reliability.
- Identify the relevant HRA methods that could be used to describe, assess and analyse marine engineering operations' contexts.
- Develop advanced uncertainty treatment modelling to facilitate the quantification of CREAM CPC adequacy of organisation.
- Develop advanced uncertainty treatment modelling to facilitate the quantification of HRA in marine engineering operations.

- Develop RCOs to improve human performance reliability.
- Develop a MCDM method to select the best RCO.
- Validate the developed models throughout the formulation of the research methodology.

1.4. Research methodology and scope of the thesis

Basically, research methodology formulates the way in which the research problem is systematically and rationally solved. Therefore, various methods and techniques to be used throughout the implementation of the methodology are consistently considered. The research methodology's detailed formulations are to:

- Identify the research problem in view of HRA's potential capability to assess and analyse human performance implications in marine incidents and accidents.
- Conduct a literature review. This will review the trend of marine engineering systems' technology development and its effect on crew skill and competence, the profile of the maritime legislative framework and its consequent drawbacks, the statistical analysis of marine incidents and accidents, the human performance implication in marine incidents and accidents, the development of HRA methods and characteristics, and the viability of probabilistic techniques in solving the research problem.
- Develop a new HRA methodology using CREAM features and generate new HRA models to quantify human performance reliability.
- Develop a new adequacy of organisation reliability assessment methodology based on the hierarchical process of the identified human, technological and organisational factors.
- Develop a new decision making model for preference-ranking RCOs that have been developed to reduce assessed HFP.
- Validate the developed methodology and the supporting models using various case studies.
- Conclude the research contributions with the presentation of possible future work.

The scope of the research is defined within the ship system's socio-technical components, such as human, technological and organisational factors. These factors determine the contribution of erroneous human actions in ship operations. In this context, the primary scope of this thesis is to assess the identified human, technological and organisational factors affecting the adequacy of organisational reliability; secondly, to quantify human performance reliability in ship operations; thirdly, to enhance the quantification of human performance reliability assessment; fourthly, to analyse the assessed human performance reliability with the aim of identifying their initiating events or root causes and finally to improve human performance through the selection of the best RCO in an effective decision making method. This scope will provide an integrated HRA approach to the safety of marine engineering operations.

1.5. Structure of the thesis

There are seven chapters in this thesis, including this introduction. Figure 1.1 highlights the visual model of the thesis structure that leads the reader to the stated aim and objectives in Section 1.3. The arrows present in the figure denote input of each phase of the work. Below also follows brief description of each chapter presented in the thesis.

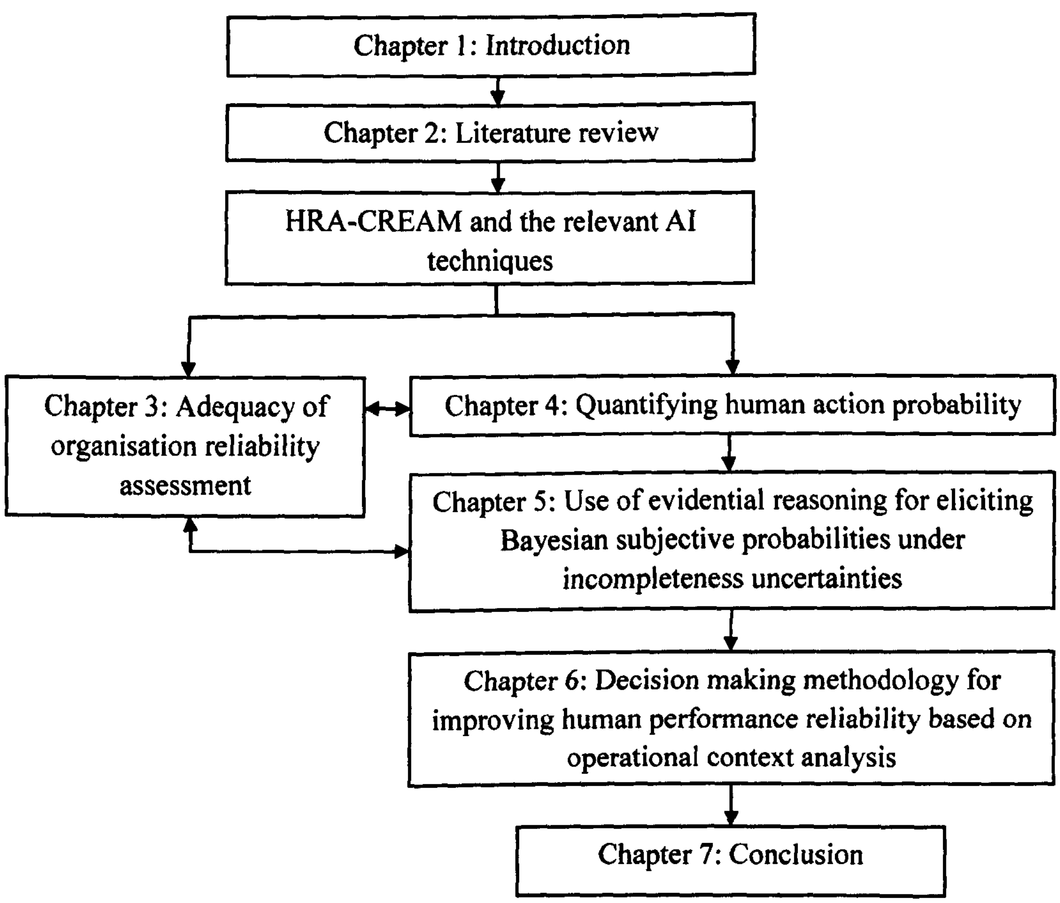


Figure 1.1: Thesis visual representation

Chapter 2 reviews the relevant literature that defines the subjects of this research. It provides information about the trend of marine engineering systems' technological development and the effect on crew skill and competence. It instantiates both the profile of maritime legislative framework and its current state of implementation, and explicates the statistical analysis of marine incidents and accidents to define human performance implications. It reviews HRA methods' development and characteristics, as well as verifies probabilistic models of relevance to the research problem. It differentiates the reviewed HRA methods' characteristics. These provide the basis of identifying the research statement of problem, aim and related objectives, and formulating the research methodology.

In Chapter 3, a new BN model is developed to evaluate the adequacy of shipping organisations. It first reviews the relevant literature related to the adequacy of organisation and defines its expanded Performance Influencing Factors (PIFs) and sub PIFs. The discrete effect's levels/ descriptors of PIFs and sub PIFs are defined to the interest of adequacy of organisation reliability assessment. A hierarchical process features PIFs and sub PIFs' logical relation is designed. BN essential development characteristics are reviewed. A generic methodology for establishing the BN model of the adequacy of the organisation reliability assessment is developed. In Netica software, the assigned CPTs and BN qualitative characteristics are used to develop a computerised tool of evaluating the adequacy of organisation. The 'M.V. HANJIN DAMPIER' grounding accident is analysed as a case study to validate the established BN model. Finally, a sensitivity analysis of the model is carried out to verify the outcome of the work in the conclusion.

In Chapter 4, CREAM bi-directional approaches to the assessment and analysis of human performance are discussed. A generic methodology to establish CREAM BN model for COCOM-CMs' reliability assessment is developed. In formulation of this methodology, the following sections are analysed: first, CREAM's nine CPCs' dependency characteristics are modelled in four convergent connections of a BN with the use of Netica software. The CPTs of the CPCs which are adjusted according to their interdependence are assigned deterministically. Secondly, new attribute and sub attribute nodes are introduced to simplify the assignment of CPT of the COCOM-CMs' node. Thirdly, the nine original CPCs of CREAM, including dependency adjusted ones, are modelled in convergent connections of BN. Such connections match the d-separation characteristic and the cause-effect relationship in BN, thus affecting the newly introduced attributes and sub attribute nodes and the COCOM-CMs node marginal probabilities. Sub attribute nodes' CPTs are assigned uniformly, while Fuzzy Rule Base (FRB) is also used to simplify the subjective elicitation of CPT of COCOM-CMs' node by experts. FSs theory is used to transform COCOM-CMs' probability to a crisp value of HFP. Fourthly, the heeling accident on M/V *Crown Princess* is used as a case study to validate the established generic CREAM-BN model. Fifthly, the BN model's final inference and aggregation of COCOM-CMs posterior probabilities is transformed with the use of FSs to a crisp value of HFP. Finally, model sensitivity is verified, and the outcome of the work is concluded.

Chapter 5 describes the heuristic tools that have been used to enhance BN characteristics. A new generic methodology is developed to enhance the capability of the developed CREAM BN model for assessment of the reliability of COCOM-CMs. The developed model is enhanced to consistently deal with incomplete or ill-defined context data. In this respect, ER technique is used effectively to synthesis the partial degrees of belief elicited by experts and to define the unknown probability mass. ER is also used effectively to aggregate the probability of factors that symmetrically affect CPCs. The unknown probability masses are used to develop two sets of CPTs in the worst and best scenarios respectively. These CPTs are used in two developed BNs. BNs' final inference and aggregation of COCOM-CMs' posterior probabilities are transformed to a crisp value of HFP with the use of FSs theory. Both BN-derived HFPs provide the boundaries of a HFP range. This range is averaged to a crisp value of HFP. The *Transocean's Deepwater Horizon* accident is used as case study to validate the established models. Finally, the models' sensitivity analyses are verified, and the outcome of the work is concluded.

In Chapter 6, a new human reliability based decision making method is developed. It first reviews the characteristics and limitations of the decision making methods and models, followed by the some solutions to overcoming the limitations of the reviewed methods and models in different applications. The CREAM retrospective approach to human performance analysis is analysed in detail. This is to provide the basis for specifying a CREAM classification scheme in maritime ergonomics. The generic decision making methodology is developed through combining Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), Analytical Hierarchical

Process (AHP), and Entropy calculation. To validate the developed methodology, the CREAM classification scheme is used to identify the phenotype initiating events and the genotype root causes of crew performance during the heeling accident on M/V *Crown Princess*. Consequently, alternatives of RCOs are developed, and RCO evaluation criteria are chosen. AHP together with some linguistic terms and their associated numerical scales is referred to experts to evaluate the importance of the chosen criteria. An entropy algorithm is used to calculate the objective weights of the criteria. After the combination of both subjective and objective weights of the criteria, TOPSIS is used to prioritise the RCO alternatives.

Chapter 7 summarises the main concepts that are recognized throughout the implementation of the research methodology. It concludes the research achievements and how they are progressed to obtain the research aim. Additionally, it presents the limitations of this research and highlights the possible future work that could be further developed to tackle the limitations.

Chapter 2

Literature review

Summary

This chapter reviews the fundamental elements that make a valuable contribution to every step of the research pathway. It commences by highlighting the current trend in the marine engineering system's technological development and its effect on crews training and competencies, followed by screening of maritime safety effectiveness and understanding of the contribution of erroneous human actions to marine incidents and accidents. The most common HRA methods and their associated probabilistic models are also reviewed. These fundamentals inevitably help to conceptualise clearly and precisely the research problem. They also help to understand the relationship between the research problem and the body of knowledge in HRA methods and the associated probabilistic models. By describing which methods, models and procedures have been used in other industry ergonomics, as well as their strengths and weaknesses, including which has worked well, and what problems have been met, the researcher will be better positioned to formulate a methodology that is capable of providing valid answers to the research objectives. Moreover, this chapter also explains how the findings of this study would fit into the existing body of knowledge, and how the answers from the research objectives compare with what others have found. Finally, it will place the findings of this research into the context of maritime safety.

2.1. Introduction

The trend in marine engineering systems design over recent years has been towards increasing complexity in shipboard systems. Modern vessels nowadays rely on a high degree of automation and supervisory control. The advance in automation technology increases the use of programmable electronic systems in place of traditional hard-wired or pneumatic controls. This advance provides an opportunity for reducing both the initial investment cost and the following operational costs. Moreover, with this technology, things can now be done that previously would have been impossible. For example, it was once impossible to build an engine that did not require a camshaft and to enhance the overall fuel efficiency on a continuous basis through a sophisticated power management system; however, this is possible nowadays. The possibility of increasing the level of functionality encourages the design and construction of more complex automation and supervisory control systems. This advance offers ship owners more options. The downside of this trend is that the owners are left with systems that may not be necessarily understood, or, in extreme cases, that even have unknown properties. The result may well be a system beyond the understanding of average seafarers. Hence, the possible interactions and dependencies are no longer obvious, unlike with older, simple systems. In reality, the systems are usually not considered in their full contexts, in which they are a collection of individual components configured into higher-level systems, operated by a range of seafarers in the marine environment. To consider any single element in isolation is likely to provide an incomplete picture (Bailey, 2005; Pomeroy, 2006).

Fundamentally, it is known that the introduction of new technologies brings both opportunity and threats associated with the changes to the systems (Hollnagel, 2000b), as the environment in which the experience for dealing competently with all manner of abnormal situations exists has been changed. On the other hand, the advance in technology has increased operational system reliability and reduced its maintenance requirement. In the meantime, familiarity with the system has been reduced by the reduction in routine intervention.

Much incidents' analysis has shown that human behaviour underlies many marine accidents, and that there is an over-reliance on the last-line of defence risk control measures (Hollnagel, 1998a; Pomeroy, 2006; Bijwaard and Knapp, 2009). Consequently, the management of marine risks represents a challenge to the industry and requires some changes in the way that engineering systems are designed, configured, maintained and operated, particularly by taking greater account of human behaviour. The maritime industry is receptive to efforts of improving safety through better management of the human element. Humans certainly have to understand the perception of risk. This perception will develop the behavioural changes towards the safe operation of complex ship systems (Pomeroy, 2006). However, HRA methods developed in the nuclear and aviation ergonomics could be used in the evaluation and development of human behavioural changes (NRC, 1994). Firstly, foretelling human performance reliability enables the perception that those human-contributed risks might develop while operating these systems. Secondly, analysing the context of assessed human performance enables identification of the possible phenotype initiating events or genotype root causes that are needed to develop the effective corrective actions. This could certainly help to plan available resources effectively to maintain safe human performance over an appropriate timescale.

In maritime ergonomics, the ship system is characterised as a physical entity embedded within complex socio-technical system components, which feature the combined quality of physical system performance, people performance, organisation decision and environmental effects. These components determine the risks of the ship system. As delineated in Figure 2.1, the innermost layer is called the Man Machine Interaction (MMI) methods, representing the interface between the physical system and its operators. Basically, the performance and safety of the physical system is influenced by the design, as well as by human factors. Moving outwards from the centre, the personnel sub-system is shown to operate in an organisational environment, representing the result of management decisions corresponding to the organisational/management infrastructure. These components are in turn controlled by the environmental context, which is governed by economics, politics and social issues. Understanding the interaction of the socio-technical system components offers an integrative perception of ship system reliability assessment. Moreover, the discrepancies in socio-technical system components vary appreciably between shipping regions. These are potential risks that might cause human behaviour related problems.

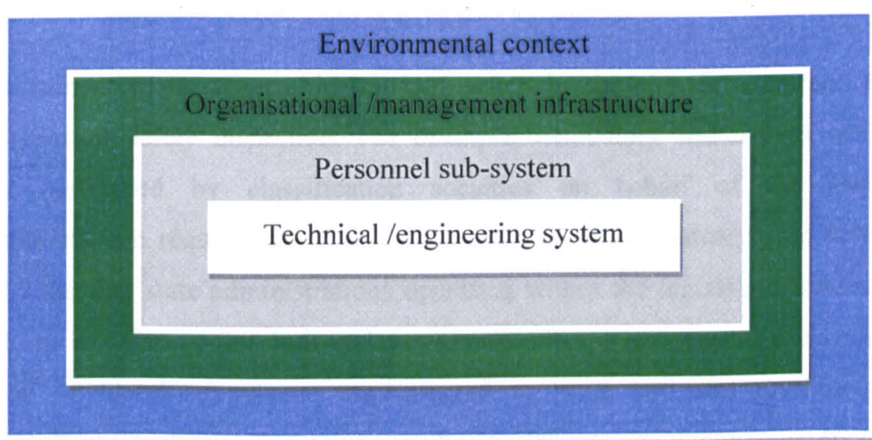


Figure 2.1: Components of the socio-technical system adapted from Hollnagel (2010)

2.2. Overview of shipping related safety

According to the UNCTAD (2011), over 80% of the volume of world merchandise trade was carried by sea for the year 2010; this was translated to 8.4 billion tons of cargo and around 32.7 trillion ton-miles. Due to the increased world trade, the number of vessels has grown by approximately 16% over the last ten years (Lloyd's Register Fairplay, 2008). In this context, Bijwaard and Knapp's (2009) study revealed that the incident rate of ship accidents was relatively low. In contrast, the hull and machinery insurance portfolio for the year (2008) showed an increase in the frequency of the number of claims, compared to the last 10-15 year period, where it has been reported to be flat or have a reduced frequency (Nomis, 2008). Claims' frequency reported per 4th quarter of 2008 was 15% higher than for the same period in 2007(Nomis, 2008). Earlier analysis of root cause of increased claims frequency was attributed to the lack of experienced seafarers, especially for nautical claims in both the 2007 and 2008 figures (Nomis, 2008).

The shipping industry is regulated by a complicated international legal framework. Basically, it is based on the recommendations and guidelines of more than 50 conventions with numerous protocols and amendments (Knapp and Velden, 2010). These conventions are developed by the International Maritime Organization (IMO) and the International Labour Organization (ILO) with the support of various regional bodies. However, there are still some loopholes in their enforcement system, which can lead to incidents. Shipping incidents tend to carry very high economic costs, due to the large asset values and the high operational risks involved in shipping (Knapp and Velden, 2009; Knapp and Velden, 2010; Knapp et al., 2011).

The enforcement of an acceptable level of safety in shipping is attempted through various types of safety inspection. For example, mandatory inspections, which are normally performed by classification societies on behalf of the flag state administrations, are required in order to issue and maintain statuary ship certificates needed by the flag state administrations operating within the legislative framework of the IMO. In addition, ships' hull and machinery surveys are normally performed in respect of an identified scheme implemented to issue hull and machinery class certificates. Non-mandatory inspections can be divided into those performed by industry and those performed by Port State Control (PSC). Industry inspections are performed by vetting inspection regimes, to enable a vessel to obtain an acceptable vetting inspection report, in order to load and ship cargo. PSC is a right that allows port states to inspect a vessel calling at a port under its jurisdiction. There are currently ten PSC regimes, which are grouped by regions. If a PSC inspection detects violations from minimum safety standards, the vessel can be detained and deficiencies will need to be rectified before it can proceed (Knapp et al., 2011).

The international nature of the shipping industry has made it complex and difficult to enforce the legislative framework developed by IMO's member states. Despite efforts being made by IMO's member states to change this process, preventive actions are still uncommon, resulting in the creation or amendment of legislation being reactive and typically following the outcome of a major disaster (Knapp and Velden, 2009; Knapp and Franses, 2009b).

In 1993, the IMO adopted the International Safety Management (ISM) Code as a challenge to provide a proactive qualitative tool for maintaining ship safety at an operational level. The ISM Code came into force in July 1998 for passenger vessels, tankers and dry bulk carriers, and in July 2002 for all other ship types. The ISM Code introduced the concept of SMS and Risk Management System (RMS) at an individual ship level, as well as at shipping organisations (Knapp and Velden, 2010). Although the ISM was seen to involve commitment from the top, verification of positive attitudes and competence, clear placement of responsibility, quality control of work, and promotion of a safety culture, and as a vehicle for continuous improvement by introducing a human factor into the SMS, it was not easy to measure those factors that could produce tangible and specific answers from administrations about its effectiveness (IMO, 2005).

In the years 2001 and 2002, the IMO approved guidelines for the application of Formal Safety System (FSA) for use in the IMO rule-making process. FSA is a rational and systematic process for assessing risks relating to maritime safety and marine environment protection, and for evaluating the costs and benefits of IMO's options for reducing these risks (IMO, 2007). Some of the major drawbacks of FSA studies are the lack of adequate data for the proper analysis of risk factors and different applications of the guidelines. Additionally, in FSA, the erroneous human actions generating hazards and the likely risk factors could only be quantified by making use of HRA-PSA techniques (Fang et al., 2005). To address the lack of FSA enforcement, the IMO provides training and support to its member states through its Technical Cooperation Committee (TCC). In this respect, the IMO also developed the Voluntary Member States Audit Scheme (VMSAS), which should provide a better mechanism to encourage compliance from member states (Knapp and Franses, 2009a).

Finally, the effectiveness of safety inspections in the shipping industry has been analysed in the literature from various aspects and by many researchers (for example, Payoyo, 1994; Knapp and Franses, 2007a, b, c; Carriou et al., 2008; and Knapp and Franses, 2009a). Until now, research in this area has been focused on the determination of relevant risk factors and on the estimation of incident probability reduction (Knapp et al., 2011). Little has been done in the area of HRA in the shipping industry. This reveals that there is an obvious gap between industrial need and academic research. Therefore, the effectiveness of safety inspection in shipping needs to be extended to cover HRA (NRC, 1994).

2.3. Marine accidents' statistical analysis

The effort of allocating various forms of erroneous human actions to verified accident causes is surely not a simple task. Its difficulty is augmented in the case of maritime transport, because accident monitoring and documentation is not usually very adequate or of a high standard. Nonetheless, a review of available databases of marine accidents was undertaken by the ABS in 2004, to better understand the role of humans in incident/accident causation and their consequent mitigation (Baker and Seah, 2004). The analysis included accidents associated with commercial passenger vessels, freighters, tankers, tugboats, and offshore supply vessels. Accident data from the UK, Canada, and Australia were reviewed and analysed. Accidents cited in the United States Coast Guard Marine Safety Management System (USCG-MSMS) database were also reviewed and analysed. The finding of these reviews revealed that erroneous human action continued to be the dominant factor leading to maritime incidents and accidents. In its domination it takes the form of failures of situation awareness and situation assessment. Basically, erroneous human action refers to an observable and verifiable act (Hollnagel, 1998a). The American Bureau of Shipping (ABS) analysis showed that 50% of maritime accidents were initiated by observable erroneous human action, while another 30% of maritime accidents occurred due to failures of verifiable human actions to avoid an accident (Jones, 2002; Baker and Seah, 2004).

As shown in Figure 2.2, the trend of marine accidents over the years 1990-2000 was steadily downwards. Marine accidents often lead to a loss of property, life, and environmental damage. However, the magnitude of damage inflicted by a major shipping accident increases virtually with the public attention paid to those accidents and their negative influence on the perceived safety of shipping. For example, in the past several decades, accidents such as the Herald of Free Enterprise, Estonia, Erica, Exxon Valdez, Prestige, Amoco Cadiz, Braer and Sea Empress have repeatedly attracted public attention and facilitated the development of new laws or amendments to the international conventions.

Figure 2.2: The trend of shipping accidents over the past decade, adapted from Baker and Seah (2004)

The analysis carried out by ABS included, firstly 150 accident reports collected from the Australian Transportation Safety Bureau (ATSB), 100 accident reports collected from the Canadian Transportation Safety Board (TSB-C), and 100 accident reports acquired from the United Kingdom Marine Accident Investigation Board (MAIB). The qualitative grouping of the causal factors identified as the primary contributing root causes of each accident is shown respectively in Table 2.1. The sources of collected accidents and their causation groupings' percentage are also shown in Figure 2.3.

Table 2.1: MAIB, TSB-C and ATSB shipping accident reports' causal factors and their qualitative groupings. Source: Baker and Seah (2004)

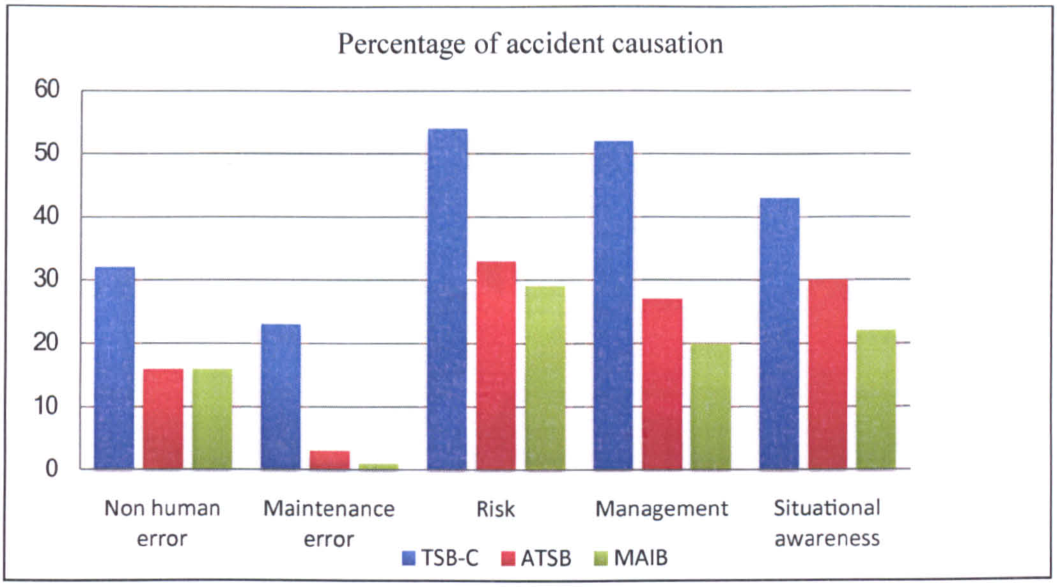


Figure 2.3: The percentage of accident causation based on qualitative grouping of MAIB, TSB-C and ATSB. Data adapted from Baker and Seah (2004)

Secondly, 71,470 accidents were cited in the USCG-MSMS database over the period 1991 to 2001. The top-level accident causations of analysed accidents are shown in Figure 2.4; and the top-level breakdown of root causes related to human factors is shown in Figure 2.5.

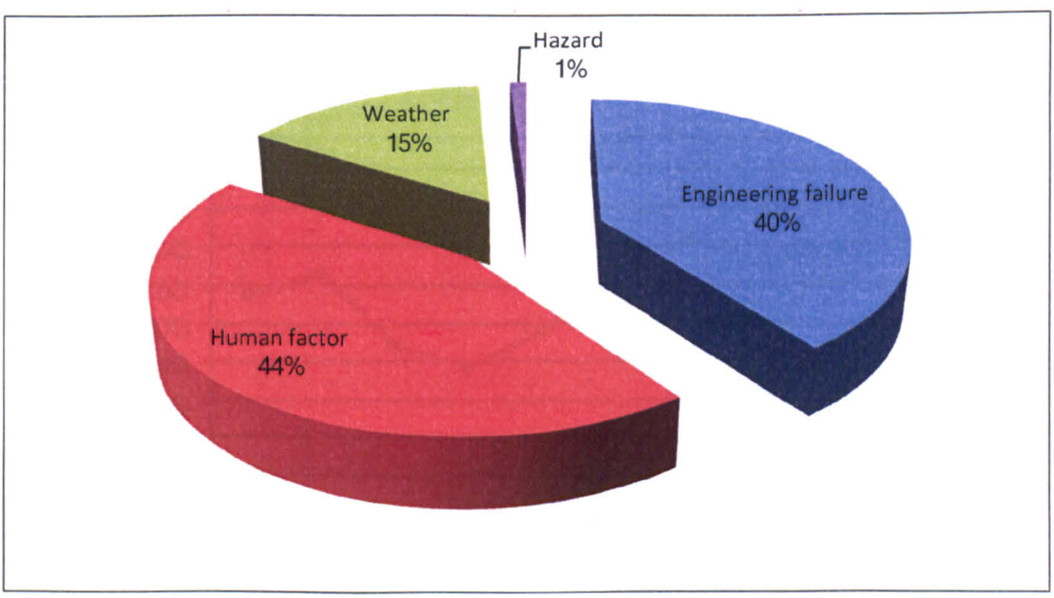


Figure 2.4:Top-level accident causation cited in the USCG MSMS database, adapted from Baker and Seah (2004)

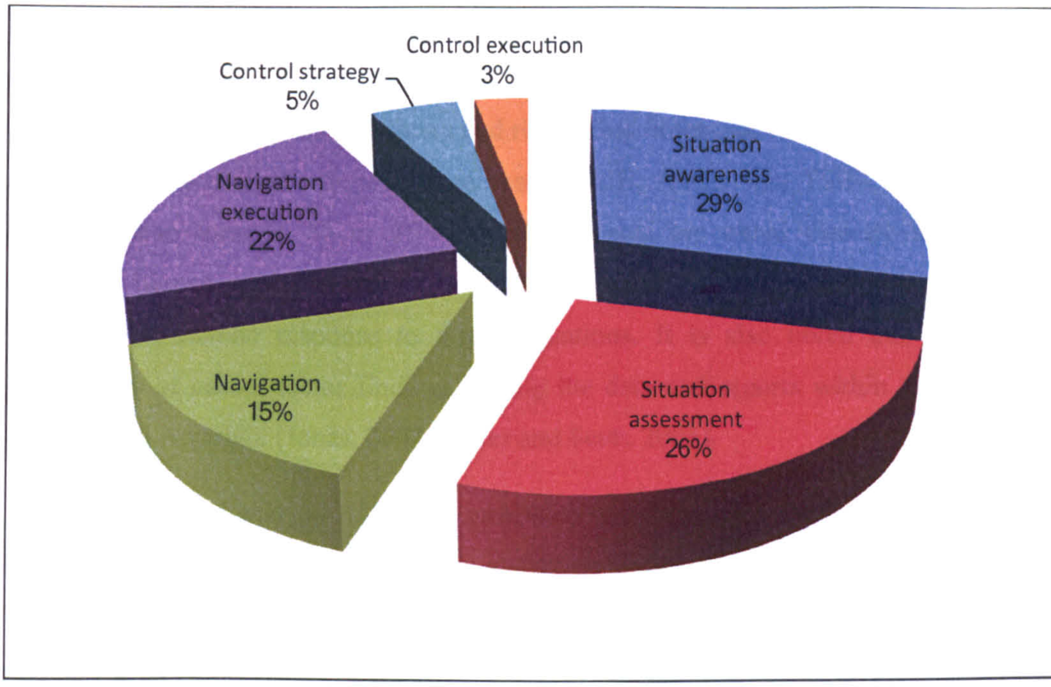


Figure 2.5: Top-level breakdown of root causes related to human factors, adapted from Baker and Seah (2004)

Figure 2.6 shows the trend of accidents cited in the USCG-MSMS database over the period 1991 to 2001.Though the results suggest a slight increase in the number of accidents; they also show that the trend was unstable. Generally, over the 1990s, the human element has received much scrutiny by the maritime industry.

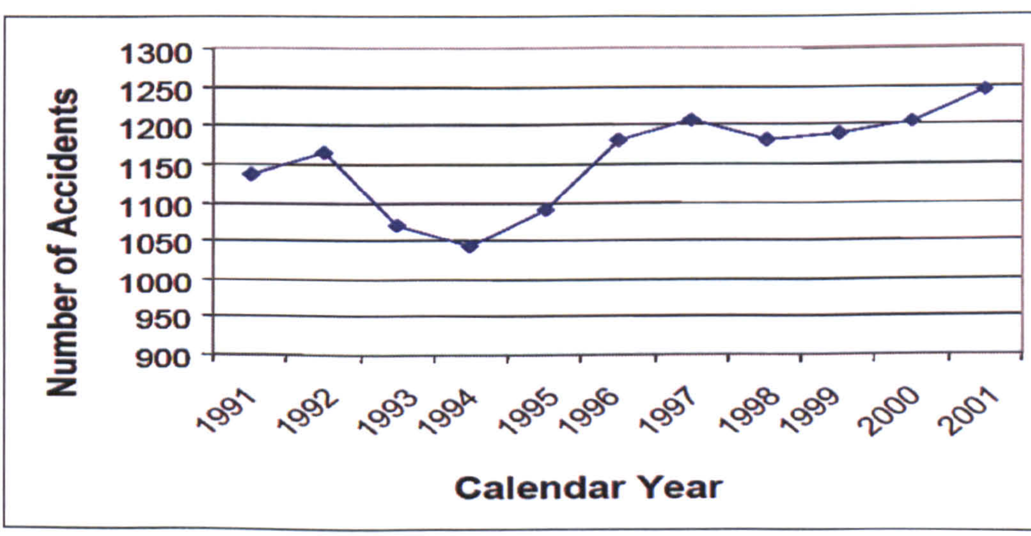


Figure 2.6: The trend of shipping accidents cited in the USCG-MSMS database over the period 1991 to 2001, adapted from Baker and Seah (2004)

The review of accident data from MAIB, ATSB, and TSB-C shown in Table 2.1 revealed some interesting consistencies. Firstly, each of the groups of management practices, situation awareness failures and risk taking /tolerance represents about 25% of accident causation in the respective source - MAIB, ATSB, and TSB-C. Secondly, in each of these sources, 80 to 85% of all accidents are either directly initiated by erroneous human action or are associated with erroneous human action by means of inappropriate human response to threat situations. It is also noted that there is a consistency of causal factor findings among the data and reports within the US, UK, Canada, and Australia (Jones, 2002; Baker and Seah, 2004).

A recent statistical analysis of serious casualties' data involving the human element has been provided by Mandryk (2011). This analysis shows the trend of serious casualties by vessel type during the period 2006-2010, as shown in Figure 2.7. The analysis profile included 21,000 casualties' reports of commercial vessels >100GT excluding fishing vessels.

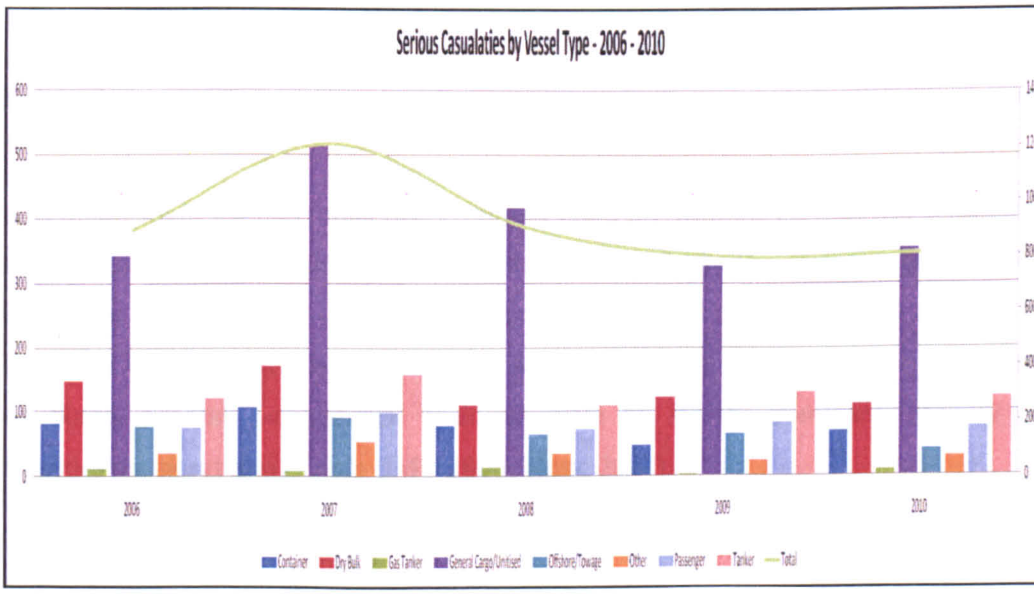


Figure 2.7: Analysis of serious casualties by vessel type-2006-2010 adapted from (Mandryk, 2011). The left side vertical axis represents the number of vessels per type, and the right side vertical axis represents the total number of vessels of all types.

2.3.1. Individual risk and total loss of ship analysis

A comprehensive analysis of Lloyd's casualty database was conducted by Det Norske Veritas (DNV) and submitted by the International Association of Classification

Societies (IACS) to the IMO (2006). The analysis reflected the annual accident frequency distribution on accident event, as shown in Figures 2.8; and individual risk distribution on accident event, as shown in Figure 2.9. This analysis was based on accident data for the period 1990-2003. It included 16 generic ship types that were built in 1980 and later.

Figure 2.8: Total loss frequency/year for different ship types, distribution by accident event. Source: IMO (2006)

A comparison of the individual risk given in Figure 2.9 with the general risk acceptance criteria given in IMO (2000) is presented in Figure 2.10. The statistics gave a clear indication of two critical observations: first, it was noted that the general cargo ships showed a high risk level both in terms of total loss of ship and fatalities to individuals on board. Second, occupational accidents were by far the dominant category for fatalities on most types of ship (IMO 2006; Huss, 2007).

Figure 2.9: Individual risk on different ship types, distribution by accident event breakdown. Source: IMO (2006)

Figure 2.10: Individual risk on different ship types developed by DNV. Source: IMO (2006)

2.4. Human reliability analysis

Human reliability means the probability of a person correctly performing an action demanded by a system in a specific time without performing any extraneous activity that can degrade the system's performance (Swain and Guttmann, 1983). Swain (1990) also stated that any method by which human reliability is assessed may also be called a HRA. For instance, in risk assessment HRA is defined as the use of systems engineering and human behavioural science methods in order to render a complete description of human contribution to a risk. HRA includes a series of methods to identify sources of erroneous human actions and to assess the likelihood of their occurrence (Boring, 2008). There are other related qualitative definitions of HRA. For instance, it is the certainty that human ability can adapt to changing conditions in specific situations (Pyy, 2000). Usually, HRA relates to methodologies for anticipating and assessing the effect of failures that are related to erroneous human actions and not the failure of some physical components. It is worth noting that erroneous human action is a major contributor to the risk and reliability of many engineering systems. For example, over 90% of nuclear industry accidents (Reason, 1990a), over 80% of chemical and petro-chemical industries accidents (Kariuki and Lowe, 2007), over 80% of marine casualties (Ren et al., 2008), and over 70% of aviation accidents (Helmreich, 2000) are initiated or caused by erroneous human actions. However, the differences in erroneous human actions are attributed to the degrees of coupling between human action and operational context, which may vary due to different designs, definitions, training and analysis practices (Pyy, 2000).

The real importance of HRA is to find credible ways of helping designers, managers, operators, and authorities to be able to increase the safety and profitability of technological systems. These could be achieved by maintaining a risk level as low as reasonably acceptable in a working environment. For these reasons the HRA approaches are coupled with PSA or PRA. They introduce people to a thought process to perceive operating risks and help to define ways in which the risks can be reduced. Having identified the risks and their probabilities, the next step can be to decide what, how, and when changes should be made, in potential conditions that might lead to a loss of output as well as an unsafe systems' state. HRA approaches directly affect the operating cost of running system equipment. Basically, reliability is tied to a cost or a failure to provide service when required. As a result, loss is usually tied to a loss of reliability (Spurgin, 2010). Thus, an increase of system reliability could benefit an organisation's profitability.

Certainly human actions are an essential part in engineering systems' operation and maintenance during normal and abnormal conditions. The safe and economic operation of such systems can be ensured by proactive measures that may also be complemented by a reactive performance analysis to identify causes of specific disturbances. Thus, one of the HRA objectives is to concentrate on human actions that are important to system safety, such as actions causing system disturbances (initiating events), actions causing latent failures in safety-related systems (imperfect intervention), and actions taking place during the mitigation of disturbances (controlling actions after initiating events). In all respects, human actions can have both positive and negative impacts on safety. Consequently, technological, organisational and individual factors that shape human actions often appear as PSF embedded in the HRA models (Pyy, 2000).

2.4.1. Development of HRA

HRA is a fairly new interdisciplinary research area, developed after the Second World War to accelerate the technical development of military equipment. The first probabilistic human reliability study was carried out in 1952 for weapon system feasibility studies (Swain, 1990). One of the results of this study was that it was applied to different ergonomics, reliability, operability and maintainability. As a result, in the 1960s HRA was transferred to civil applications mainly in NPP control rooms' MMI system design. The development of HRA was associated with an increased use of probabilistic safety and availability analysis methods (Spurgin, 2010). The first probabilistic study for a NPP safety was presented in the 1960s (Farmer, 1967). In the middle of the 1970s, a large PSA was published (NRC, 1975). Since then HRA has seemed to be tied to PSA/PRA, presumably to meet mandatory safety goal regulations, which have focused on the NPP specific reliability characteristic (Hollnagel, 1998a).

One approach that has been used to narrate the chronological development of HRA methodologies from the 1960s to the present day is the so-called first, second, and emerging third generation HRA methodologies. However, these methodologies are still being developed, and contain elements of controversy in terms of the appropriate representation of HFP (Hallbert et al., 2004; Forester et al., 2006; Boring, 2010a; Spurgin, 2010). Moreover, the idea that human error is a random event is no longer acceptable; and the concept that humans can be set up to fail due to the context under which they are operating is gaining credibility (Reason, 1990b, c; Roberts, 1990; Hollnagel, 1998a). This concept means, in effect, that people can do something to avoid erroneous human actions. Hence, it is believed that these methodologies still need to incorporate more sophisticated understanding of human behaviour, given the many developments that have occurred in behavioural, cognitive and organisational sciences. These developments could be achieved by extending methodologies underlying concepts, models and applicability.

First generation HRA methods sum the probability of an erroneous human action via a simple fault or event tree analysis, which could lead to the ultimate success or failure of the operator in achieving his/her desired goal. The first generation HRA methodologies are generally referred to as decomposition methods (Hollnagel, 1993). Their fault or event tree binary analysis essentially treats the human operator as a component in a system. The operator failing to respond to events is termed errors of omission, while unintended human action is labelled errors of commission. However, evolutionary research in the fields of human behaviour has revealed that operator decision making and behaviour cannot be categorised simply as omissions or commissions. Human failure is far more complex than the failure of a system component (Doughty, 1990). For instance, Reason (1990c) has formed system failure involving erroneous human actions in a model of Swiss cheese slices sliding relative to each other. The system does not fail because of a single slice failure; it continues to slide until a series of holes align, which forms the failure of several elements almost simultaneously. Basically a system is designed with a number of independent safety barriers. Nevertheless, human behaviour can link the risks of two or more barriers failing, provided that the system is influenced by external events leading to a common cause that may simultaneously disrupt several safety barriers.

The field of psychology has thrown some light on the responses of crews during accidents and during normal proceedings. For example, Reason (1990a) has covered the separate actions of slips and mistakes. Additionally, Rasmussen (1987) and Reason (1990a) have described the classification system known as the Skill, Rule and Knowledge (SRK) error modes, in which they have advocated that a skill-based error mode is an inattention involving slips and lapses in human attention or concentration. Skill-based errors are committed while performing common activities in routine situations. Generally, skill-based performance mode failure probability is typically less than 0.0001. Studies in the nuclear industry have shown that roughly 25% of all performance mode failures are attributable to skill-based errors (Summers, 2007). On the other hand rule-based behaviour is based on selection of stored rules in logic recognition. Its prevalent error mode is misinterpretation. Therefore, the greater the familiarity with the task achievement, the less likely that perceived risk will match an actual risk. Rule-based errors are committed due to misapplication of stored rules accumulated through experience and training. Rule-based and knowledge-based performance modes involve making choices. Generally, rule-based behaviour failure probability would roughly be 0.001 when people make choices or decisions. Studies in the nuclear industry have shown that approximately 60% of all errors are attributable to the rule-based contribution (Summers, 2007). Furthermore, knowledge-based behaviour is a pattern recognizable to the individual and requires diagnosis and problem-solving in response to a totally unfamiliar situation without the application of skill- or rule-based behaviour. Most decisions are made with limited information and assumptions. Consequently, the prevalent error mode is an inaccurate mental model of the system, process, or status. Generally, under such circumstances the likelihood of failure is particularly high, approximately 0.5. Studies in the nuclear industry have shown that roughly 15% of all errors are knowledge-based (Summers, 2007).

During the 1990s many issues related to HRA were raised by Reason (1990a, b) and others (e.g. Roberts, 1990; Hollnagel, 1993). These issues drove the revision of HRA methodologies and the adoption of more sophisticated models and understandings of erroneous human actions. Thus, recently, second generation HRA methodologies have attempted to develop more sophisticated approaches to human reliability, particularly the ability of humans to recover and prevent some or all of the consequences of the threat of impending system failures (Doughty, 1990). Second generation HRA developers have put forward cognitive effect and context impact in their developed methodologies. For example, CREAM HRA provides a strong argument for considering the use of cognitive factors' effect and context impact on human performance reliability (Hollnagel, 1998a). More modern second generation HRA methods, such as the Methode d' Evaluation de la Realisation des Missions Operateur pour la Surete (where a possible translation of the acronym might be "evaluation method to understand operators' safety mission") (MERMOS) (Le Bot et al., 1999; Pesme et al., 2007) and A

Technique for Human Error Analysis (ATHEANA) methods (Cooper et al., 1996; Forester et al., 2004; Forester et al., 2007) explicitly consider and model the contextual factors in an extensive way. First generation methods largely failed to consider the context in which erroneous human actions are made, while the second generation methods consider and model the influences of context on erroneous human actions. Other distinctions have been drawn based on the consideration of errors of commission in the second generation methods, as opposed to a heavy focus on errors of omission in the first generation methods. Obviously, the HRA community has been inclined to refer to the HRA generational gap simply in terms of chronology. The first developed HRA methods are considered the first generation methods, while the subsequent developed HRA methods are considered second generation methods. The latter tend to be easier to use and have broader coverage than the former. Thus, the actual defining characteristics of the second generation methods are the methods' relative novelty, simplicity, and comprehensiveness (Boring, 2007).

In emerging third generation methodologies, a modelling and simulation system of a range of human behaviours is used to recover and prevent failure (Chandler et al., 2006). The importance of simulation and modelling of human performance for the field of HRA has been outlined by Cacciabue (1998). It is specifically to address the dynamic nature of human performance in a way that has not been found in most HRA methods. Several researchers e.g., Jae and Park (1994) and Sträter (2000) have hypothesized the need for a dynamic HRA, and have begun developing new HRA methods or modifying existing HRA methods to account for the dynamic progression of human behaviour leading to HEPs, and following up Human Failure Events (HFEs). There has been an interest in combining simulation and modelling in HRA (Mosleh and Chang, 2004; Reer et al., 2004; Sträter, 2005; Boring, 2006; Trucco et al., 2006). The simulation may be used to produce estimates of PSFs, which can be quantified to produce HEPs based on specific HRA methods. The challenge of such an approach is to find a mapping of available performance measures from the simulation to the specific Performance Influencing Factors (PSFs) required by a HRA method. Having categorised HRA methods according to the chronology of their first development, it is perhaps better to characterise the different methodologies according to their characteristics (Pyy, 2000; Boring, 2007; Spurgin, 2010).

2.4.2. HRA models' characterization

Various HRA models or techniques are available, and each features its own characteristics. Based upon their use, a number of approaches have been singled out (Salmon et al., 2003; Lyons et al., 2005; Everdij and Blom, 2010; Spurgin, 2010). The problem with HRA methods is that they have no common underlying model or philosophy, due to the differences among the approaches with respect to their development. As a result, they are characterised according to the following concepts: task-related models, groups of sub-tasks models, time reliability models, context-related models, and context task-related models. A separate group of applications uses only expert judgment (Pyy, 2000; Forester, 2006; Boring, 2007; Spurgin, 2010). However, the utility of a particular HRA method is a relative function of a number of components, not just the absolute value of a method. For example, if the researcher is undertaking a completely new application, appropriate data that could be used may be limited. In this situation, a method may have to be selected by using generic data. Equally, if selecting a method to embody many years of operational data, the researcher is unlikely to select a method based upon generic data. For cases where data and experience are available, there are a number of approaches that could be used, including expert judgment (Boring, 2007; Spurgin, 2010).

Expert judgment is an integral part of HRA, and it is difficult to proceed in the process of HRA without some recourse to its use. Expert judgment is not a model but a process of capturing information about human actions based upon the use of the knowledge and understanding of persons who are either directly involved in the operation of a system or who observe the actions of others. Expert judgment has been used to provide HEPs for given actions or estimate the impact of sub-tasks or environments on HEPs. The correct use of expert judgment is critical to the HRA process (Comer et al., 1984; Boring, 2007; Spurgin, 2010). Figure 2.11 depicts a set of models that are dominated by one or other of the above-stated characteristics.

Figure 2.11: Various human reliability assessment models reviewed and grouped by characteristics. Adapted from Pyy (2000) and Spurgin (2010)

2.4.2.1. Task-related HRA models

Task-related HRA models are considered in two groups. The first group includes the THERP, and a derivative of the THERP, called the Cause-Based Decision Tree (CBDT) approach. The second group includes the HEART, the Nuclear Action Reliability Assessment (NARA), and the Standardized Plant Analysis Risk-Human Reliability (SPAR-H). SPAR-H appears to fall into both the task group and the context group. This is because of the strong contextual influence of SPAR-H PSFs involved in deriving the HEP (Gertman et al., 2005; Spurgin, 2010).

- **The THERP**

The THERP approach developed by Swain and Guttman (1983) is based on the results of a task analysis, which breaks a task into a number of sub-tasks, and arranges it into an assembly of discrete HRA sub-tasks, to form a HRA event tree. To quantify this event tree, each of the sub-tasks depicted in a human reliability event tree is allocated an estimate of HEP value based on its identifying description in a series of look-up tables in the THERP handbook (Swain and Guttman, 1983). The total HEPs in the tree are summed to give an overall HEP. To account for human capability to correct an error, the THERP approach also introduced the possibility of an operator recovering from an error during the event tree by means of a return path that diminishes the effective failure probability. In THERP the task dependency is modelled through a few general guidelines specifying some of the factors that may influence the dependence level. Guidelines give only generic tendencies of the impact of factors on the dependence level, and a lot of room is left for interpretation. The assessment therefore requires a considerable amount of expert judgment, which may lack transparency and traceability (Zio et al., 2009).The THERP approach is very much an engineering approach to the human error modelling problem, as it specifically considers the human action omission (Hollnagel, 1993; Kirwan, 1996; Kirwan, 1997a, b; Hollnagel, 1998a; Adhikari et al., 2009; Spurgin, 2010; Licao et al., 2011).

Although the PSF concept has been introduced in the THERP method to differentiate between tasks being performed in different conditions, the assessment result of similar tasks being performed in different applications of the THERP method has shown less distinction (Spurgin, 2010). This was attributed to the dominant attitude towards the use of similar task procedures and rules for human system interfaces. Considering the effect of training on different crews' performance, it would seem that the task is just a part of a different set of conditions. Moreover, the THERP PRA model's (event tree) final HEP value is based on the results of a task analysis. However, the most essential part behind the skill of using THERP to sum up HEP is the selection of the key sub-tasks to model (Spurgin, 2010).

The significance of THERP is that it is relatively easy to apply. It can be used for the tasks similar to the original applications and mostly it is well documented. The weakness of THERP is that it might be difficult to define the number of key sub-tasks in a real application and to determine their HFPs. This would affect the task significance in defining the overall HEP (Humphreys, 1995; Kirwan, 1996; Kirwan, 1997a, b; Yang et al., 2007; Adhikari et al., 2009; Bell and Holyroyd, 2009; Spurgin, 2010).

- **CBDT**

The CBDT approach is a derivative of THERP developed by Beare et al. (1990). It is a set of sub-tasks placed in a decision tree or event tree format model. The effective overall HEP is obtained by summing the individual sub-tasks' HEP values from the output of each separate decision tree. In this respect, CBDT defines the specific areas that can lead to failure probabilities. Utilising the CBDT model in the application of the

HRA concept demands a high level of experience as to how control tasks are performed (Kohlhepp, 2005; Spurgin, 2010).

The concept of the PSF is a key element in a number of HRA methods. With the use of this concept various tasks at different plants can be modelled, and accordingly their HEP values can be modified. The main idea of this approach is to capture the essence of a situation in which a task is being performed. Purely quantifying a task and subsequently adjusting its basic reliability by the use of PSFs makes the topic of human reliability very compatible with engineering equipment reliability. As a result, this will ignore the understanding of the real impact of the context in which a human is performing his/her actions (Hollnagel, 1998a; Adhikari et al., 2009; Spurgin, 2010).

Most of the strength of THERP applies to CBDT, while CBDT is easier to apply than THERP is. The THERP HRA big event tree is replaced by DTs, which makes the HRA tree's structure much easier to follow. This would make the definition of sub-tasks much easier. The sum of Decision Trees' (DTs) end states is the overall HEP. CBDT is generally well documented. The weaknesses of CBDT raised by some users include the selection of pathways and limited end states. In addition, the source of the built-in data is questionable. CBDT tends to isolate the analysts from the real plant experience. This would weaken the meaning of the headings in the decision trees and affect the overall HEP (Forester et al., 2006; Spurgin, 2010).

- **HEART**

HEART represents a step forward in the development of task-related methods to deal with some limitations of THERP in combining the sub-tasks and their quantification process. This development was approached by quantifying the whole task rather than building the complete task from the sum of the sub-tasks. Such an approach enables the modelling of HRA in operations to be more holistically (Williams, 1988). HEART provides a large amount of experience from different industries to the human factor effects. It has defined a number of different PSFs, a number of weighting factors (composed of Error Producing Conditions (EPCs) and Assessed Proportion of Affect (APOA)) to cover the potential influences of different PSFs, and a method to modify the basic task with each of these PSFs. The key elements of HEART are to list a number of tasks in tabular form along with an associated mean HEP in a range of values to cover uncertainties in the estimates. HEART uses the task dependency assessment approach in

THERP, which is approximately the case in a number of HRA developments such as SPAR-H (Kirwan, 1996; Kirwan, 1997a, b; Yang et al., 2007; Adhikari et al., 2009; Spurgin, 2010).

The strength of the HEART model is appreciated by users, because it is relatively easy to apply. It provides the experience gained during a number of PRAs. In addition, it is reasonably documented. The weakness of the HEART model is that it is not easy to select the key tasks, and the tasks' description is very vague, which would affect the tasks' significance in defining HEP. Data for HEPs are of a very questionable derivation. HEART's 38 EPC may have some meaning for general human reliability, but not in specific HRA/PRA. HEART demands a high level of expert judgment in selecting the appropriate Generic Task Types (GTTs), EPCs and APOA (Adhikari et al., 2009; Bell and Holyroyd, 2009; Spurgin, 2010; Chadwick and Fallon, 2011).

- **NARA**

NARA was developed by Kirwan et al. (2005) to improve some of the characteristics of HEART. This has been undertaken by modifying some of the shortcomings identified in HEART. The changes to HEART include replacement of tasks that are considered new in NARA now, changes in the value of EPCs, and the HEPs distribution. These values are from a new database called CORE-DATA, developed by Gibson et al. (1997) and Gibson and Megaw (1999). The NARA tasks are broken down into four groups: task execution, plant status and availability of plant resources, alarm/indication response, and communications. NARA defines 18 EPCs, as opposed to the 38 in HEART. As there is a possibility of repeated terms being multiplied together in the process of implementation, leading to very low and unrealistic HEP values, NARA introduced the process of Human Performance Limit Value (HPLV) to ensure that the calculated HEP does not fall below HPLV (Spurgin, 2010).

The general mathematical approach taken in NARA is essentially the same as in HEART, and it is based on the same idea of a series of task reliabilities modified by EPCs. The proportion of EPCs is changed by experts. NARA is currently in the process of evaluation, with the possibility of replacing HEART as the HRA method for the PRAs. NARA has been reviewed by an international group of HRA experts, which is a valuable step in the process of acceptance (Umbers et al., 2008; Spurgin, 2010).

The updated version of NARA shows superiority to HEART. It is relatively easy to apply and can be applied to a situation with limited data. In addition, it is reasonably documented and reviewed by an international group of HRA experts. The weakness of the NARA model is that it is not easy to select tasks, although the task descriptions are more appropriate than those in HEART. This would affect the task significance in defining HEPs. NARA uses a questionable CORE-DATA, even though it is considered better than HEART data. Furthermore, NARA needs a high level of expert judgments (Everdij and Blom, 2010; Spurgin, 2010).

2.4.2.2. Time-related HRA models

- **Time Reliability Curve (TRC)**

The concept behind TRC is that a crew will eventually respond to an accident if he is given enough time. Therefore the estimated HEP decrease depending on the time available before an accident reaches an irreversible point. The TRC is an attempt to respond to the criticism of THERP in that it did not cover cognitive actions. THERP-TRC is approached by incorporating two sets of TRCs, one for screening and the other for final evaluation purposes (Swain and Guttman, 1983). The TRCs are used to assess the HEP median value and distribution as a function of time. THERP suggested the use of PSFs to modify its TRCs. THERP-TRC represented non-success rather than the no response curves given in the other TRCs (Kozinsky et al., 1983). The developing interest in TRCs stemmed from the simulator data collection work. Simulation was focused more on non-success to capture failures and later recoveries rather than no response to successful operations (Bareith, 1996). The basic TRC scaling was conceptualized by using a task mean time. It was further modified by Rasmussen (1979) SRK model regarding whether the task was considered to be skill, rule, or knowledge based.

The strength of the TRC models relates more to the information gained from the simulation derived by the TRCs than to generic information (Parry et al., 1992). Actual TRCs based on valuable information yield relative confirmation of accuracy and reliability of crews' actions in similar tasks at different plants (Spurgin et al., 1990). The TRC represents a random variation of crews' general responses in different plants. TRC comparisons indicate the importance of training, procedures, and MMIs. TRCs also can be of assistance to the domain experts in their assessment (Spurgin, 2010).

The weaknesses of TRC models include the fact that they cannot be used to support the definition of HEP for tasks performed over a large available time. Operator reliability can be high even for short task times. The use of time as the main variable defining crew HEP values is not proven, although the quality of the procedure, MMI, and training is more indicative of human error potential. TRCs used in HRA are more related to simulator-developed data and the insights gained from these developed data in carrying out PRA/HRA studies (Spurgin, 2010).

2.4.2.3. Context-Related HRA Models

Context-related HRA models consider the context under which an action takes place in order to determine HEP (Hollnagel, 1998a; Spurgin, 2010). Though a context is directly related to a task, a HEP is determined by each of the influential context elements. Clearly, some of these are the quality of training of the crew, the quality of the procedures, the quality of the MMI, and the quality of the communication standards, etc. The important context elements depend on the situation being considered, where the quality of any context element can vary from reduced, satisfactory and improved. Over a range of accidents, the context can vary depending on the amount of attention given to each context element by a model designer or operator (Hollnagel, 1998a; Boring, 2007; Spurgin, 2010).

- **Holistic Decision Tree (HDT)**

HDT model is a context method developed by Spurgin et al. (1990). It was based on observation of control room crews' responses to an accident scenario on simulators. The simulation results indicated that the operators were more influenced by context rather than vague task concepts while responding to accidents. The HDT method was developed further by Bareith (1996) and subsequently by Spurgin, (1999, 2000) through the analysis of the results of simulator sessions carried out with a full complement of control room crews. In the HDT method the use of Influence Factors (IFs) is similar to the use of PSFs of other methods. Each IF has a range of different Quality Factors (QFs), similar to EPCs associated with HEART and NARA; QFs are described in detail and based upon the associated technology to cover the potential of IFs (Spurgin, 2010).

The strength of the HDT method includes its capacity in dealing with the whole response by a crew to an accident, and focusing on the context of an accident. The method is also easy to understand. It indicates clearly which parameters can be changed in order to improve crew reliability (Spurgin, 2010).

The weakness of the HDT method is that expert judgment is needed to ascertain the quality impact of procedures, and training, etc. The HDT method does not explain detailed failures associated with tasks and sub-tasks and does not feature various context conditions that need to be defined. The range of HEPs for a given accident situation need to be fixed by expert judgment, and this offsets the possible HEP accuracy (Spurgin, 2010).

- **CREAM**

CREAM was developed by Hollnagel (1998a). CREAM COCOM-CMs feature human competence control in structuring one's actions. CREAM determines the context through nine defined CPCs. The CPCs describe the context common conditions, rather than task identification. The method also concentrates upon cognitive characteristics associated with a task (Hollnagel, 1998a). CREAM is more associated with context-related methods like HDT than task-related methods like NARA (Spurgin, 2010). Clearly, it is a second-generation HRA model. It is an approach of modelling the cognitive effect and context impact of human actions. It is a context driven method with a more psychological view of HRA. The context is considered to affect some aspects of the operators' cognitive processing. This leads to functional failure, which in turn leads to an error. The general concepts are very much in line with current thinking about how errors are caused (Hollnagel, 1998a; Yang et al., 2007; Reer, 2008 a, b; Bell and Holyroyd, 2009; Adhikari, et al., 2009; Boring, 2010a; Spurgin, 2010).

Spurgin (2010) said that CREAM data has been selected from a variety of sources (for example, Beare et al., 1983; Swain and Guttman, 1983; Williams, 1988; Gertman and Blackman, 1994). This was used to demonstrate error probabilities corresponding to the 13 CFFs associated with a task. However, in evaluating a situation using CREAM, the evaluator has then to select the CFF and also determine which CPCs are involved, to what degree if involved and which is a high level task (Hollnagel, 1998a; Spurgin, 2010).

CREAM Extended in application is somewhat similar to the high level concepts of both HEART and NARA, in that they consider a basic value of HEP corresponding to a task or CFP and then change the value by a set of modifiers to account for specific performance conditions. In the case of CREAM, these are called CPCs, which are weighting factors equivalent to the combination of EPCs and APOA for HEART and NARA. In CREAM, the CPCs are double-sided, with a possible positive or negative effect on human reliability. The weighting factors, i.e., CPCs, can either decrease or increase a CFP. In extreme cases of applying CREAM Extended, it is possible that the value of the adjusted CFP becomes larger than one. This is a consequence of the way in which the adjustments are made, and the problem can be found in other HRA approaches that use the same principle, e.g. HEART. The simple solution to this problem is to treat all values greater than one as equal to one, since a probability by definition cannot be greater than one.

CREAM is a very well documented method. The database for cognitive failures represents a cross-section of the available data. CREAM data are used to provide a demonstration of the method, and not a justification of its accuracy (Spurgin, 2010). CREAM defines 13 CFFs for human actions of observation, interpretation, planning, and execution. The relationship between CPCs and CFFs- Cognitive Processes (CPs) is tabulated, which allows assessment of the influence of CPCs on CPs (Yang et al., 2007; Reer, 2008 a, b; Bell and Holyroyd, 2009; Adhikari et al., 2009; Spurgin, 2010).

The weakness of CREAM is that it is difficult to differentiate between CFFs in practice, because the controlling influence is procedure-following, conditioned by training and MMI design and layout. The definition of CPCs should better focus on systematic influences rather than individual influences (Spurgin, 2010). The tabulated relationship between CPC and CPs may be modified by the characteristics of a particular accident. There is a need to better qualify terms like adequacy of organisation in retrospective applications. Also, some of the words used in the classification scheme tables could be better defined (Yang et al., 2007; Reer, 2008 a, b; Bell and Holyroyd, 2009; Adhikari et al. 2009; Spurgin, 2010).

- **SPAR-H**

The SPAR-H model was built based on the experience of Gertman et al. (2005) in human factors and HRA. The underlying psychological basis for the SPAR-H construct is the informational model of human factors. The model conceptualised the diagnosis and action of crews' responses to accident conditions. It consists of probabilities associated with diagnosis and action. They take the HEP values as 0.01 for diagnoses and 0.001 for actions. The effective HEP is made up of these elements along with a set of PSFs stemming from the context and selected by experts. The method can be applied to retrospective as well as prospective scenarios (Gertman et al., 2005).

The strengths of the SPAR-H method include: it is a well-documented HRA method; the limited probabilities of diagnosis and action of crews' responses to accident conditions facilitate its field applications and it is well designed for intended use and provides guidance for PSFs' selection (Forester et al., 2006; Bell, and Holyroyd, 2009; Spurgin, 2010).

The weaknesses of the SPAR-H method include: it is limited in applications because of the simplified human performance approach; and the method also needs specific domain expertise in using its PSFs' tables (Forester et al., 2006; Bell and Holyroyd, 2009; Spurgin, 2010).

- **ATHEANA**

The ATHENA method was developed by Cooper et al. (1996), using the HEP values associated with HEART. Forester et al. (2004) and Forester et al. (2007) have used domain experts' elicitation of HEPs in the ATHEANA methodology. Expert judgment was used to meet the criticism of the HEART database and its justification. ATHEANA methodology can be broken down into two parts: identification of human errors within an event sequence and quantification of these human errors. ATHEANA has a searching method to identify existing Error Forcing Conditions (EFCs) that can lead to errors. This type of process is very useful in the case of accident analysis in order to ensure that all sources of errors are identified. It is helpful to have such EFC taxonomy for future applications.

The advantage of the ATHEANA method is that it provides taxonomy for considering EFCs. It is of a more systematic process in application than other Context-Related HRA. It uses an expert judgment elicitation method rather than HEART data. The current and future development of the method approach is supported by the United States Nuclear Regulatory Commission (USNRC) (Forester et al., 2006; Reer, 2008a, b; Adhikari et al., 2009; Bell and Holyroyd, 2009; Spurgin, 2010).

One of the weaknesses of the ATHEANA method is that more experience in its application is needed. The method needs to integrate simulation results to replace the expert elicitation approach. The method is in need of an approach to simplify its problem as to how to identify the more effective EFCs (Forester et al., 2006; Reer, 2008 a, b; Adhikari et al., 2009; Bell and Holyroyd, 2009; Spurgin, 2010).

- **MERMOS**

MERMOS has been under development for some time to support "Electricité de France" EDF activity during NPP accidents (Villemeur et al., 1986; Le Bot et al., 1999). The MERMOS method has been centred on the use of simulator information and data collected by observers noting the actions of the crew when they are responding to a simulated accident. The method makes use of simulator sessions to extract data and insights and appears to have a lot of possibilities that can be used as the basis of inputs into a PSA. EDF believes that there is a minimum error rate below which one cannot go to define HEPs.

The MERMOS method defines a number of ideas and descriptions relative to HRA, with some different terminologies to other HRA methods. One of the clearest expositions of MERMOS is presented in the works by Pesme et al. (2007) and LeBot et al. (2008). Three noteworthy points are the idea of the human reliability mission; the consideration of the set of circumstances effect as a result of an initiating event; and the failure of humans or equipment and their interactions. The breakdown of an accident sequence into a number of branches is the HRA task. Insights into the breakdown are led by EDFs' extensive experience stemming from their years of observation of simulator sessions. In addition, the simulator experience has yielded the possibility of actual data, as a large number of EDFs' power plants are nearly identical; and these sessions can be used to train experts to make more informed estimates of the crew HEPs.

MERMOS is a significant piece of work that has been undertaken by EDF. The method had to answer questions resulting from a different relationship between man and machine. To really understand everything, a much better understanding of the parts and the underlying philosophy of the method is needed.

The strengths of the MERMOS method are: 1) the use of simulated accident scenarios helps to identify the alternative pathways that operators might take; 2) simulator data can be used to identify performance-related effects; 3) the available simulator-related information and database of operator actions enables analysts to better understand operator actions associated with given accidents; 4) lower limits for HEP are defined by virtue of simulator; and 5) the MERMOS data can be used to confirm or refute the capability of the EDF operators in effectively dealing with accidents. This information can be used to help station managers and safety authorities to identify the need for changes to operator training, procedures and instrumentation/ displays in order to enhance plant safety (Forester et al., 2006; Reer, 2008a, b; Bell and Holyroyd, 2009; Spurgin, 2010).

The weaknesses of the MERMOS method are that: 1) information and database are of EDF propriety; 2) information and database are not transparent to outside persons; and 3) it is difficult to form a clear picture of the method from published papers - this limits insights gained from MERMOS for outside experts performing HRA studies (Reer, 2008a, b; Bell, and Holyroyd, 2009; Spurgin, 2010).

- **Success Likelihood Index Method (SLIM)**

The SLIM method was developed by Embrey et al. (1984). SLIM provides a set of PSFs and their anchor (reference) values. In assessment of HFP, the SLIM makes use of expert judgment to select a number of PSFs and weigh them according to their perceived contribution in a given accident. These weighted values are then used to derive a modified HEP, using anchor values. SLIM makes use of PSFs to measure the influence of the context; therefore, the method relates context to human error. This is not the same meaning of PSF as used in THERP. A test of SLIM- "Multi Attribute" Utility Decomposition (MAUD) indicated that unless the expert elicitation process is carried out with care, consistent results will not be obtained.

The strength of SLIM is that it is the first HRA method based on the HEPs derived from context. The method is fairly easy to apply. It should yield plant-specific HEPs rather than generic HEPs by using NPP expert domain judgments (Forester et al., 2006; Adhikari et al., 2009; Spurgin, 2010).

The weakness of SLIM is that it lacks the guidance in selecting PSFs that basically need to be defined systematically. It demands more effort to determine the relative importance of PSFs. The appropriate domain experts in applications of SLIM are rare. The appropriate anchor values that are needed to weigh PSFs of SLIM are difficult to select (Forester et al., 2006; Adhikari et al. 2009; Spurgin, 2010).

2.4.3. Deferential assessment of HRA methods

The field of HRA aims to identify the causes and sources of erroneous human actions. In achieving these aims HRA typically includes defined phases, which range from identifying error sources, to modelling these errors as part of a systemic analysis, to quantifying HEPs (Boring, 2008). The broad range of HRA methods is therefore used mainly for either analysis or assessment of erroneous human actions, or to encompass the complete spectrum of HRA (Gertman et al., 2005). Each HRA method is designed for specific purposes, and the lack of complete coverage of qualitative analysis and quantitative assessment phases by many methods should not necessarily be viewed as a shortcoming on behalf of those methods (Boring, 2010a). In the meantime, the current HRA practice for dependence assessment has a number of limitations (Podofillini et al. (2010). Hollnagel (1998a) and Zio et al. (2009) highlighted the consequential need for a new, explicit and transparent dependence assessment method. The THERP dependence assessment method is the most widely used, although it may lack traceability and repeatability (Zio et al., 2009; Podofillini et al., 2010).

The broad range of PSFs included in HRA methods vary from small to large sets of PSFs. Although each HRA method brings with it a slightly different emphasis and slightly different set of PSFs, there is considerable overlap in the PSFs' description. This variability in PSFs is a reflection of the vastness of factors that can influence human performance; the different approaches used to distil these into a usable set of factors; and the different applications for which HRA methods were originally designed (Boring, 2010a). Galyean, (2006) has suggested that the need to drill down into the degrees of human performance by using an ever-increasing list of PSFs is misguided. The advantage of constructing a short list of PSFs, apart from simplifying the amount of effort required for an analysis, is that the PSFs could actually be non-overlapping, omitting the possibility of double-counting effects, which can have false effects on the HEP calculation.

In structuring HRA-PSA models to sum the overall HEPs of tasks, models are classified into holistic and decomposed. The holistic model aims at assessing the human task as a whole, whereas the decomposed model aims at dividing the task into small sub-tasks. The reason for decomposition is sometimes related to the availability of data and sometimes to the risk management viability. Data may be either available on the human task as a whole or about different decomposed sub-tasks. In this context, if the model structure is too deep, it might be impossible to collect data and include all dependencies. There is also evidence that too decomposed a model may lead to optimistic probabilistic results due to, for example, not all the dependencies being taken into account (Poucet, 1988; Pyy, 2000).

FAA/EUROCONTROL (2007) proposed a generic safety assessment process including seven safety assessment stages, as shown in Figure 2.12. Considering the preceding HRA-related extract, Table 2.2 lists **the broad range of HRA methods'** characteristic that can be used further to differentiate between all HRA methods that were reviewed in the preceding sections. It also can be used as a guide to extend the scope of applications of the chosen method in the safety assessment process. Such characteristics are listed according to the following heading and abbreviations:

- Method name acronym.
- Type: Specifying whether a human performance analysis method is a specific technique denoted by (S), or an integrated method (of more than one technique) denoted by (I).
- Safety assessment stages: Denoting the generic safety assessment process stages in which the reviewed HRA methods could be of use. These stages are: 1) scope of the safety assessment; 2) learning the nominal operation as it should work or function; 3) identify hazards; 4) combine hazards into risk framework; 5) evaluate risk; 6) identify potential mitigating measure to reduce risk; 7) safety monitoring and verification; 8) learning from safety feedback.
- Domains: Denoting the industrial ergonomics in which the reviewed HRA methods have been used.
- Application: Denoting the hardware (HW), human (HU), and procedures (PR) in which the reviewed HRA methods have been applied

Figure 2.12: A generalized seven-stage safety assessment process. Source: FAA/ EUROCONTROL (2007)

Table 2.2: The broad range of HRA methods' characteristics

Method name acronym	Type	Safety assessment stages								Domains	Application		
		1	2	3	4	5	6	7	8		HW	HU	PR
THERP	S					X				Nuclear/Defence/ Marine	X	X	X
CBDT	S					X				Nuclear		X	
HEART	S					X				Nuclear/ Chemical/Defence		X	
NARA	S					X				Nuclear		X	
TRC	S					X				Nuclear		X	
HDT	S					X				Nuclear		X	
CREAM	I					X				Nuclear/Space/Marine		X	
SPAR-H	S					X				Aviation		X	
ATHEANA	S								X	Nuclear		X	
MERMOS	I				X					Electrical/ nuclear		X	
SLIM	S					X				Nuclear/Chemical		X	

Although some of the first generation methods have a consistent approach to the HRA, context is certainly modelled to some extent. Context and cognition are the two features that second generation methods are supposed to contain. Emerging third generation methods based on more dynamic simulation are still under investigation. Overall, the result shows that the second generation HRA methods like CREAM, MERMOS and ATHEANA are still at the development stage and their application is limited compared to the well established methods like THERP and HEART. However, the ability of CREAM, MERMOS and ATHEANA to provide relatively precise qualitative and quantitative results, and with better understanding of human performance under his/her cognition effect and specific contexts' impact, distinguishes them as the next generation of HRA.

2.5. Review of uncertainty treatment technique

Predominantly, all knowledge in the real world is accompanied by a certain amount of uncertainty. Historically, human beings have proved the ability to use this uncertain knowledge effectively, to shape their model of reality in taking decisions and performing actions. How this was done has been an intriguing concern of knowledge science enquiry for centuries, as it has the very nature of uncertainty itself. Inevitably, Artificial Intelligence (AI) is an approach to dealing with uncertainty. The aim of AI is to identify the many facets of uncertainty and to represent them so that the knowledge they embody can be used effectively. The first step in setting AI to cope with uncertainty lies in understanding what uncertainty really is, and in establishing techniques to formalise and use uncertainty in cognitive processes.

When uncertainty is to be dealt with, the possible solutions are as many and various as its interpretations are. Many of these solutions share the attitude of viewing the knowledge and the uncertainty as two independent entities, and thus treating them by means of two distinct loosely-coupled processes. The reasoning process handles knowledge as if it were exact, while a parallel uncertainty inference process accompanies it, computing the uncertainty affecting each newly derived fact. This uncertainty is in its turn usually based on the uncertainty affecting the facts used to derive the new fact. The way in which uncertainty is represented and processed by the parallel uncertainty inference process is a distinguishing characteristic of the different available techniques (Saffiotti, 1987).

There are many different uncertainty management techniques, which are in need of a common framework in which they can be formalized. Thompson (1985) has proposed a clean general paradigm in which uncertainty management techniques would be formalized. This is structured into four parts:

- The base elements on which the theory is defined: they would typically consist of an algebra of statements describing the object domain, and some certainty and utility functions defined over this algebra;
- The observation reports, that is, how the new evidence is represented in the theory;

- The updating mechanism, defining how the transitions from one state of certainty to another are performed;
- The decision mechanism, which reaches a decision based on the state of certainty.

Granted the above structure for formalizing uncertainty management techniques, the updating mechanism of any probability calculus theory is essential to implement what Domotor (1985) called the probability kinematics, that is, the movements of the probability masses among the statements of algebra. Probability calculus, which takes into account both partial knowledge and partial ignorance, virtually became the key concept of sciences' development. It is the effective tool necessary to use to formalize a progressive approach to the HRA reality.

Probability calculus needs a precise definition of its foundations, in particular, the concept of uncertainty. Accordingly, the most fitting probability calculi of AI techniques that are of relevance to the research objectives hypothesis will be presented under the following heading:

- **Bayes' theorem**

Bayes' theorem stands on how probabilities attached to a set of (exhaustive and mutually exclusive) hypotheses $A = \{A_1; \ldots, A_n\}$ are to be revised in light of new evidence E. In its most popular form, it states that

$$P(A_n|E,H) = \frac{P(A_n|H) \times P(E|A_n,H)}{P(E|H)}$$

where,

$P(A_n|E,H)$, is the revised posterior probability of A_n in light of new evidence E,H.

$P(A_n|H)$, is the is the prior probability of A_n in light of information H.

$P(E|A_n,H)$, is the likelihood probability of the evidence E given A_n, H.

$P(E|H)$, is the marginal probability of E given H.

where all the probabilities are conditioned by some former information H. H could consist of the simple hypotheses of the problem, but usually it consists of the evidence $\{ E_1, \ldots . E_m\}$ currently obtained.

The importance of this theorem lies in its expressing a measurable proportionality (the likelihood $P(E|A_n, H)$) between the probability of A_n before and after the acquisition of the new evidence E. From a knowledge science point of view this means formalizing an inductive behaviour. For the purposes of this research it is sufficient to notice that

Bayes' theorem is a good candidate for the updating mechanism of an uncertain reasoning system. In applications, Bayes' theorem is the kernel of BNs inference mechanism about the real world knowledge and the coupled uncertainty (Saffiotti, 1987). However, the applications of BN will be dealt with in the literature review of the related chapter.

- **ER**

The theory of ER came into being in the 1960s from the work of Arthur Dempster (1968), and was then put into a suitable form for finite domains by a student of his, Glen Shafer (1976); it is often referred to as the Dempster-Shafer theory of evidence or D-S theory. It can be applied successively to combine any number of bodies of evidence that are in symmetric positions; as a result there is no distinction between prior probabilities and likelihood functions, as there is in the Bayes theory. Bayesian approaches work well only if prior and conditional probabilities are well defined. This might not always be the case in most real-world scenarios. However, a more informative approach would be to assign the probability belief to the combined bodies of evidence, which can be determined by using further information. This representation of uncertainty is difficult using Bayes' theory. An extension of the Bayes theory, the Dempster-Shafer evidence theory (Shafer, 1976), uses belief and plausibility values to represent the evidence and corresponding uncertainty. These values can represent how the uncertainty of a hypothesis increases or diminishes as more and more evidence is available to the system. The advantage of this approach is that it allows the researcher to work with incomplete, ambiguous or conflicting evidence (Srinath and Otman, 2010).

The application of the Bayes theorem leaves little room for representation of ignorance and vagueness in quantitative estimates. Adhering to the classical probability calculus, the Bayesian approach can only replace ignorance with indifference. Shafer's belief functions are different in this respect. Free from the additively requirement of classical probabilities, they preserve the vagueness of subjective beliefs. Together with Dempster's combination rule, the belief functions offer an alternative to the Bayesian updating of probability estimates.

Over the past two decades, considerable research has been conducted on integrating techniques from AI and operational research for handling uncertain information (Yager, 1987; Yager, 1995; Yen, 1990; Zimmermann, 1990). Following this line of research, an

ER approach has been developed for Multiple Attribute Decision Analysis (MADA) under uncertainty (Yang and Singh, 1994; Yang, 2001; Yang and Xu, 2002). This approach is based on an evaluation analysis model (Zhang et al., 1989) and the D-S theory of evidence (Lopez de Mantaras, 1990). In recent years, the ER approach has been applied to decision problems in engineering design, safety and risk assessment, organisational self-assessment, and supplier assessment - e.g., motorcycle assessment (Yang and Singh, 1994); general cargo ship design (Sen and Yang, 1995); marine system safety analysis and synthesis (Wang et al., 1995 and 1996); software safety synthesis (Wang, 1997; Wang and Yang, 2001); retrofit ferry design (Yang and Sen, 1997); executive car assessment (Yang and Xu, 1998); organisational self-assessment (Yang et al., 2001); and detection of faults in various mechanical devices (Basir and Yuan, 2007).

- **Fuzzy expert system (FES)**

FES is an AI technique designed to mimic how experts solve problems. With this technique the decision making process must be explicitly modelled and the relevant ambiguities and uncertainties must also be properly taken into consideration. For the uncertainties, overlapping Fuzzy Functions (FFs) can be used to quantitatively represent the input and output values. For the relevant ambiguities, fuzzy rules can be used to constitute the knowledge base clarifying the decision making process. Such expert system framework is called FES. Different interpretations of the fuzzy rules are used, thus, different procedures for the association of an output conclusion to a given input fact can be considered for expert system modelling. As well as this, different methods have been applied for the defuzzification of an output fuzzy conclusion to crisp value (Dubois and Prade, 1996).

A fundamental characteristic of a FES is that it must be able to generate an explanation of its conclusions by allowing the researcher to systematically trace the steps of its reasoning. To assist this aim, the expert system is equipped with an explanatory interface that facilitates communication between the user and the expert system. This should enable the user to know how the expert system obtained the final conclusion or why specific information is being requested from the user. This capability is crucial for building user confidence in the expert system. It is also very important for the identification of errors, omissions, and inconsistencies in the developed model (Klir and Yuan, 1995; Zio et al., 2009)

HRA is a fundamental element in the PSA of any techno-logical system. Within HRA the assessment of dependence among human failure events is an important activity. Current HRA practice for dependence assessment has a number of limitations (Hollnagel, 1998a; Zio et al., 2009; Podofillini et al., 2010). To overcome these limitations, Zio et al. (2009) and Podofillini et al. (2010) proposed FES to overcome some of the above limitations. The capability of the FES is a major added value of the proposed procedure. Terano (1983) and Richei (2001) have applied the modelling paradigm of FS theory (Zadeh, 1965) to HRA. The vast majority of these applications exploit FL for its capability to formally represent qualitative and ambiguous statements, rather than to build a FES-capturing expert knowledge. An early approach to applying FS theory in HRA focuses on the description of human behaviour in FL terms (Terano, 1983; Onisawa, 1988). The models thereby derived lead to the evaluation of a subjective reliability measure, quantitatively represented by a FS, and which can be directly incorporated into a fuzzy fault tree analysis (Onisawa, 1988; Onisawa, 1996; Suresh et al., 1996, Huang, 2001). In principle, this allows evaluation of the system failure probability while propagating both the uncertainty of the failure rates of the hardware components and the ambiguity of the reliability of the human actions. More recently, rule-based FESs have been developed to account for the vagueness of the linguistic statements associated with the evaluation of the context (Huang, 2001), and eliciting expert knowledge to complete classical HRA methods. For example, in Konstandinidou (2006), Marseguerra (2006) and Yang et al. (2010) rule-based FES is applied to compute human error probabilities via the CREAM (Hollnagel, 1998a), by converting the characterization of the CPCs into fuzzy numbers.

- **AHP**

The AHP is a decision aiding method developed by Saaty (1980). It aims to quantify the relative importance of a given set of alternatives on a ratio scale, based on the judgment of the decision maker. It also stresses the importance of the intuitive judgments of a decision maker and the consistency of the comparison of alternatives in the decision making process (Saaty, 1980). Since a decision maker intuitively bases his/her judgments on knowledge and experience in making decisions, the AHP approach agrees well with the behaviour of a decision maker. The strength of this approach is that it organizes tangible and intangible factors in a systematic way, and provides a structured yet relatively simple solution to the decision making problems (Skibniewski and Chao, 1992). In AHP, a hierarchical system is used to analyse a problem in a descending order from large to smaller criteria, and it would be possible to connect, through simple paired comparison judgments, the small to the large (Kamal, et al. (2001).

The use of pair-wise comparisons and the hierarchical formulation of criteria is a major feature of AHP. One of AHP's strengths is the possibility of evaluating criteria and alternatives qualitatively and quantitatively on the same preference scale. These can be numerical, verbal or graphical. The use of verbal responses is intuitively appealing, user-friendly and more common in our everyday lives than numbers. It may also allow some ambiguity in non-trivial comparisons (Ishizaka and Labib, 2011).

- **Entropy**

Entropy is an inherent characteristic of a data sample. In information theory, entropy can be used as a measurement for an event knowledge uncertainty, which would decline by the increase in the amount of information, as the structure of a system becomes more regular, or the function of a system becomes more comprehensive. As a result, entropy could be used as an objective measurement of disorder in order to evaluate the implicit uncertainty of each attribute based on probability theory. Therefore, the implicit information disorder of each attribute can be indicated by its entropy value (Zhang et al., 2007).

- **TOPSIS**

TOPSIS is a MCDM model usually developed by DMs to organize the problems to be solved. It includes a set of developed decision alternatives and a set of evaluation criteria. DMs carry out analysis and comparisons, and use TOPSIS algorithms to preference rank the developed decision alternatives. Accordingly, the selection of a suitable decision alternative(s) can be made. The base of TOPSIS is rather straightforward. It originates from the concept of a displaced ideal point from which the compromise solution has the shortest distance (Belenson and Kapur, 1973; Zeleny, 1974). Hwang and Yoon (1981) have further proposed that the ranking of alternatives should be based on the shortest distance from the Positive Ideal Solution (PIS) and the farthest from the Negative Ideal Solution (NIS). The ideal solution that maximizes the benefit criteria and minimizes the cost criteria is also called PIS; whereas the NIS is also called an anti-ideal solution that maximizes the cost criteria and minimizes the benefit criteria. The so-called benefit criteria are those for maximization, while the cost criteria are those for minimization (Ziya Ulukan and Kop, 2009). TOPSIS simultaneously considers the distances to both PIS and NIS, and a combined measure of these two distance is used to preference order the decision alternatives according to their relative closeness (Shih et al., 2007).

2.6. Conclusions

HRA methods and models are critically investigated to structure a concept for selecting an appropriate HRA method. This method is inevitably needed to mitigate the contribution of erroneous human actions to the drawbacks of maritime safety. The preceding review of HRA methods and models has touched upon their strengths and weaknesses. However, a common problem with task-related methods is the difficulty of selecting a task within the list of tasks that compares closely with the actual task being analysed. This could lead to difficulties in selecting the relevant HEPs. Additionally, there are a number of different data sources of HEPs and PSFs used within these HRA models. While some are free-standing and have been used by some investigators, others draw upon the use of expert judgment from a known domain expertise to provide a HEP estimate. Another interesting source of data is from simulator records, however there are some limits to its use.

Context-related methods are based upon knowledge of how the context sets up the probability of erroneous human actions. These methods also rely on the same sources of data stated above. Though there are questions raised about the appropriateness of this data, it seems that there is a need not only for a HRA model to be developed, but also for the inclusion of an associated database as part of its work. In this respect, one thing that can be done is to accept the model or method but not the data, because it is clear that if the original database was constructed from another industry, it cannot be fully defended in maritime operations. In fact, the concept of consistency of the used model seems to be more important than the accuracy of data, because the latter could lead to a situation in which all are unsafe systems to some degree or in some situations. Given that expert judgment has been used during the earlier studies of HRA applications and in a progressive manner to satisfy an immediate need to estimate the impact of a PSF on an HEP, expert judgment could also be used to estimate HEPs for given human performance situations in incident/accident scenarios. This data could be collected and stored for successive use in model validation.

HRA methods could be used to improve human actions and promote safety culture in maritime operations. Given that, the preceding review and the differential assessments of HRA methods are developed to guide the selection of the appropriate HRA method. CREAM is seen as the appropriate HRA method, due to its relative novelty, consistency, simplicity, and comprehensiveness. CREAM COCOM-CMs and CPCs effect levels could be used to derive a probability value for erroneous human actions. CREAM also includes a consistent human performance analysis model that could be used to identify the well thought-out initiating events or root causes of incident and accident.

To establish CREAM models for human performance reliability assessment, AI technique characteristics can be used to define and update the knowledge and uncertainties of human performance in marine engineering operations. Some typical uncertainty treatment methods used in this study are reviewed and critically analysed.

The CREAM HRA method in association with probabilistic models can be developed to achieve the aim of this study. As evaluating human action in terms of cognition functions' failure in observation, identification, planning and execution in maritime operations is difficult to verify, less reliance will be put on the selected method associated with database and more reliance will be placed on judgment from a known domain expertise to provide estimates of discrete probabilities. Through the comprehensive review, it is realised that the application of CREAM needs the support of many new models dealing with its inherent shortcomings exposed in the other applications, including modelling the interdependencies of CPCs, elicitation of subjective data and consideration of multiple criteria in RCO selection to improve HFPs etc. Next, such problems will be analysed and addressed in the following chapters.

Chapter 3
Adequacy of organisation

Summary

In this chapter, the human, organisational and technological PIFs and sub PIFs affecting the adequacy of organisation reliability are identified. A hierarchical process is developed, in which PIFs and sub PIFs are grouped horizontally according to their cause/effect relationships, and categorised vertically according to their functioning levels. This process underlies the first step of the developed methodology, to establish a BN model for the adequacy of organisation reliability assessment in maritime operations. Throughout the methodology development, BN's qualitative and quantitative characteristics are dealt with, to enable the establishment of a BN model. A case study is investigated to validate the established adequacy of organisation BN model. BN model sensitivity analysis is also conducted. Finally, the developed technical work achievements in this chapter are concluded.

3.1. Introduction

Focusing on the human contribution to accident sequences, a well known theoretical framework distinguishes between erroneous human actions made at different levels of the organisation (Reason, 1987; Reason, 1990c). This framework hypothesises that the generation and evolution of an accident depends on the level of the organisation at which errors are made: errors made at the highest level of the organisation do not necessarily become immediately visible, but remain in a latent state. They propagate and expand throughout the organisation, affecting a large number of subsequent decisions and then become apparent at the level of active plant operation and control (Maurino et al., 1995). In these contexts, adequacy of organisation - one of the nine (in CREAM) CPCs - is considered as a major source and cause, affecting human behaviour in the active control of marine engineering operations.

Adequacy of organisation is a backbone CPC in CREAM COCOM-CMs' reliability assessment (Hollnagel, 1998a). There is little quantitative research associated with its assessment and in the literature, specifically in maritime ergonomics. As a concept, adequacy of organisation means the ability to safely and reasonably assure the organisational requirement for sequential or special configured marine engineering operations. In this context, usually systems and equipment utility, operational and reference data, and crew and supervisor competence control, are carefully coupled, structured and arranged. Therefore, the effect of adequacy of organisation on supervisors and operators needs to be further expanded to identify the relevant PIFs and sub PIFs, which affect operators' ability to perform an action in the context of marine engineering operations. This includes the operational core and the administrative support, containing a body of cognitive knowledge characterised by uncertainty. However, to acquire a new inferred quantitative knowledge regarding the organisational certainty of system operation demands a method that is able to probabilistically reason the effect of identified PIFs and sub PIFs. In this respect, probabilistic theory is the prevailing method for dealing with uncertainty, leading to the underlying concept of BNs (Tensen and Nielsen, 2007; Kjaerulff and Madsen, 2008).

The probability assessment of adequacy of organisation as an effect of its influencing factors is carried out with respect to four discrete ***states***. These are ***very efficient***, ***efficient***, ***inefficient***, and ***deficient***. Adequacy of organisation is directly influenced by the discrete state levels of variables' operational processes, organisation culture and resources management.

In this technical chapter, Section 3.1 provides the introduction. Section 3.2 provides the literature review, including BN's background, fundamental principles of Bayesian probabilities, and identification of PIFs and sub PIFs of expanded adequacy of organisation in maritime operations. Section 3.3 provides the methodology for establishing a BN generic model for the adequacy of organisation reliability assessments. Section 3.4 presents a specific case study to validate the established BN generic model. Section 3.5 discusses the conclusion regarding the use of a BN probabilistic model for adequacy of organisation reliability assessment.

3.2. Literature review

3.2.1. BN's background

BN modelling technique plays an important role in the research of knowledge and coupled uncertainty. BN has been successfully applied to different fields due to the flexible nature of its network modelling. BN is a high level representation of a probability distribution over a set of variables that are used for building models of specific problem domains such as adequacy of organisation. BN is represented by a graphical model where nodes represent the variables and arcs represent the statistical dependence among the variables (see Figure 3.2). The flexibility of choosing variables and of modelling relationships among them based on domain specific nature and strong statistical support leads to a high and reliable performance of the BN. This offers a convenient way to tackle a multitude of problems in which a researcher wants to come to conclusions probabilistically. BN shows the dependence-independence relations in a comprehensible form that eases the tasks of decomposition, feature selection, or transformation, besides providing a sound inference mechanism (Mittal and Kassim, 2007). The benefits of using BN representation in this study lie in the way that the structure can be used as a compact representation for naturally occurring and complex PIFs and sub PIFs affecting, e.g., adequacy of organisation in maritime operations.

Though BN technique is an effective way of capturing uncertainties, the required knowledge and engineering efforts needed to create conditional probability values per each given variable in a network are quite high. Additionally, current algorithms that can be used to learn prior and conditional probabilities from data are often complex and cumbersome to employ and data is not always available. Even though prior probabilities can be elicited from experts, they sometimes raise the problem of accuracy in values. However, translating experts' qualitative knowledge into numerical probabilistic values is a daunting and often complex task.

BN explicitly represents uncertainty in a way that can be clearly understood. Although it can be used to do so, BN is not ideally suited to situations where it is necessary to represent complexity in great detail or where concepts of cause and effect are not enough to capture ideas of how the model functions. Moreover, in BN the representation of uncertainty requires information on what that uncertainty might be. This needs an increase in the amount of information that has to be put into the model. Therefore, it is unavoidable to have information associated risks assessed.

3.2.2. Fundamental principles of Bayesian probabilities

BNs as graphical models provide a natural way of dealing with two major problems, uncertainty and complexity. In addition, they provide intuitive ways in which both humans and machines can model a highly interactive set of random variables, as well as complex data structures, to enable them to make logical, useful, and valid inferences from data. Basically, in mathematical notation, a graph (G) is simply a collection of vertices (V) and edges (E), that is, $G = (V, E)$ and a typical graph (G) is associated with a set of variables (nodes) $N = \{ X_1, X_2 \dots X_n\}$ and by establishing one to one relationships among the variables in (N), each edge in a graph can be either directed or undirected.

Directed graphs in particular consist only of directed edges. Directed Acyclic Graph (DAGs) are special kinds of directed graphs that do not include cycles. One of the advantages of directed graphs over undirected graphs is that DAGs can be used to represents causal relationships among two or more variables, for example, an arc from (*A*) to (*B*) indicates that (*A*) causes (*B*). Such a feature can be used to construct a complex graph with many variables. Additionally, directed graphs can encode deterministic as well as probabilistic relationships among variables. BNs are an example of DAGs, where nodes represent random variables and the arcs represent direct probabilistic dependences among the variables (Pearl, 1988).

Building on graph theory and conditional probability, Bayesian modelling is the process of using initial knowledge and updating such belief using Bayes' theorem in relation to the probabilistic theory, resulting in BNs (belief networks, causal probabilistic networks, or causal networks). Bayesian interpretation of probability is based on the principles of conditional probability theory. In Bayesian statistics, conditional probabilities are used with partial knowledge about an outcome of an experiment (Daniel et al., 2005). For example, such knowledge is conditional on relationships between two related events (*A*) and (*B*), such that the occurrence of one will affect the occurrence of the other. Suppose event (*B*) is true, that is, it has occurred, and then the probability that (*A*) is true given the knowledge about (*B*) is expressed as $P(A|B)$. This notation suggests the following two assumptions:

1. Two events (*A*) and (*B*) are independent of each other if $P(A) = P(A|B)$
2. Two events (*A*) and (*B*) are conditionally independent of each other given *C* if $P(A|C) = P(A|B, C)$

From the above two assumptions, Bayes' theorem swaps the order of dependence between events. For instance:

3. $P(A|B) = \frac{P(A,B)P(A)}{P(B)}$

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

$$P(A|B) = \frac{P(B|A)P(A)}{\sum_j P(B|A_j)P(A_j)}$$

where j indicates all possible states of (A);

- $P(A|B)$ is posterior probability given evidence (B).
- $P(A)$ is the prior probability of (A).
- $P(B|A)$ is the likelihood probability of the evidence given (A).
- $P(B)$ is the marginal probability of (B).

3.2.3. Identification of PIFs and sub PIFs of expanded adequacy of organisation in maritime operations

3.2.3.1. The hierarchical process of PIFs and sub PIFs

The hierarchical process of expanded adequacy of organisation categorises the identified PIFs and sub PIFs vertically into four categories. They are designated from top down respectively as root cause, sub-condition, condition and functional PIFs. Horizontally, the PIFs and sub PIFs are classified into three groups, specified from left to right as process, culture, and resources (see Table 3.1). PIFs and sub PIFs' relationship as children-parents, descendents-ancestors, can be identified intuitively from the following sections definitions and the mapping of adequacy of organisational BN shown in Figure 3.2.

The PIFs and sub PIFs' relationships are structurally based on their compatibility to the real world of maritime ergonomics. Their relationships are identified in connection with their definitions. To simplify and eliminate the uncertainty associated with PIFs and sub PIFs' subjective assessment approach, their assessment is carried out on two discrete state levels. However, the adequacy of organisation is assessed on four discrete state levels, in order to qualify and agree the proposed model assessment results with CREAM - one of the nine CPCs' discrete state levels - in quantifying COCOM-CMs' reliability.

The identification of PIFs and sub PIFs in maritime ergonomics is carried out with reference to the literature available on the research of HRA from the leading nuclear, aviation, health, and chemical industries. To adapt PIFs and sub PIFs in maritime operations, a corporate management generic structure is followed. The generic structure is derived from the literature references stated in association with the definition of each PIF and sub PIF. Thus, a hierarchical process is developed to arrange the identified PIFs and sub PIFs (see Table 3.1). This process underlies the first step of the developed methodology, to establish a BN model for the adequacy of organisation reliability assessment.

Table 3.1: Adequacy of organisation extended PIFs and sub PIFs hierarchical process

PIFs groups / PIFs categories	Process	Culture	Resources
Root cause	Management commitment. Crew involvement. Proactive control measures. Reactive control measure. Standards. Policy. Communication. Strategy and objectives. Maintenance procedures. Contingency procedures. Operational procedures.	Management commitment. Crew involvement.	Proactive control measures. Reactive control measure. Availability of equipments and records. Quality of equipments and records. Availability of condition monitoring and controls. Trust of condition monitoring and controls. Skill of human resources. Knowledge of human resources. Motivation of human resources.
Sub-condition	Controls. Safety culture. Norm.		Controls.
Condition	Human resources. Organisational culture. Management quality. Organisational structure. Safety management system.	Safety culture. Norm. Organisational structure. Operational processes.	Operational processes. Organisational structure. Safety management system. Equipments and records. Condition monitoring and performance control. Human resources.
Functional	Operational processes	Organisational culture	Resources management
End point effect		Adequacy of organisation	

3.2.3.2. Operational processes

Operational processes involve a dynamic set of human actions. In these processes the competences of operators or supervisors in controlling marine engineering operations are affected by working contexts. Operational processes constitute the core functions of an effective and efficient system operation (Mullins, 2005; Kondalker, 2007). The probability assessment of operational processes is based on two state levels, these are *effective* and *ineffective*. Organisationally, the operational process effect is directly influenced by the discrete state levels of variables' SMS, organisational structure, and management quality.

3.2.3.3. Management quality

Management quality reflects the follow up and support of managerial process tools such as standards, polices, and controls used to govern the effectiveness and efficiency of the operational process in correlation with the SMS and organisational structure (Schein, 1985; Mullins, 2005; Kondalker, 2007). The probability assessment of management quality is based on two state levels, ***high*** and ***low***. Management quality effect is directly influenced by the discrete state levels of variables' standards deployed, policy followed, and proactive and reactive control measures implemented.

3.2.3.4. Standards

Standards are the acknowledged measure of comparison in a form of rules, regulations and guidelines established by recognised bodies such as classification societies, legislative organisation and system manufacturers (Schein, 1985; Mullins, 2005; Kondalker, 2007). Their probability is assessed with respect to two state levels, ***adapted*** and ***not adapted***.

3.2.3.5. Policies

Policies are mandatory general guidelines adapted from standards to be implemented. Policies are required to be considered by operators and supervisors while performing their managerial, operational, maintenance, and contingency tasks. As guidelines, they are changeable, considering the situation at a particular time. For example, policies lay down broad parameters under which the job is undertaken by individuals to attain the overall organisational goals (Schein, 1985; Mullins, 2005; Kondalker, 2007). Their probability is assessed using two state levels, ***clear*** and ***unclear***.

3.2.3.6. Controls

Controls are a set of proactive and reactive measures and procedures performed by required control bodies. They are in place to assure that a human is safely performing the effective and efficient operational process with respect to the operational standards (Schein, 1985; Mullins, 2005; Kondalker, 2007). The probability assessment of controls is based on two state levels, ***effective*** and ***ineffective***. Controls effect is directly influenced by the discrete state levels of variables' proactive control measures and reactive controls measures.

3.2.3.7. The proactive and reactive control measures

Proactive control measures are dedicated to prevent, detect, protect, recover and contain the events that may combine to initiate an accident; while reactive control measures are used to learn the lessons of past experience and to develop appropriate feedback mechanisms. Reactive control measures deductively investigate accidents' initiating events, and analyse their root causes. Proactive control measures cover a wide spectrum of applications comprising both safety assessment and design approaches. In particular, they are exploited for PSA, safety analysis of maximum credible accidents, design of standard and emergency procedures, design of decision support tools, and operator training (Maurino et al., 1995).

Proactive controls are measures that can be used before an event occurs to assess the safety level of the system as a whole (Reason, 2002; Vervloesem, 2000). Their probability can be assigned on two discrete states, ***good*** and ***poor***.

Reactive controls are measures which can be applied in context disturbances and after the occurrence of an event (Reason, 2002; Vervloesem, 2000). Their probability is assessed based on two discrete states ***good*** and ***poor***.

3.2.3.8. Organisational structure

Organisational structure is the mapping of the formal and informal consistency of operational processes. Formal consistency has well defined lines of command and control, delegation of authority, and a system where effective coordination can be carried out; it lays down detailed policies, procedures, and standing orders, so that everybody is aware of his/her duties and obligations towards the effective and ineffective operational processes. In other words, organisational goals are set and individual tasks are assigned, and supervision and control strictly exercised. An informal organisational structure is developed in the shadow of the formal organisational structure in a form of organisational culture. Informal organisation has group goals, social roles to play, leader-follower relationship, unwritten behaviour patterns, and a code of conduct. It enhances the effectiveness of organisational communication channels. The informal organisational structure is a powerful instrument and runs parallel to the formal organisational structure. The leaders of the informal organisation train subordinates and assist them when necessary, in order to ensure welfare, promotional, financial and social obligations are fulfilled by the management. The power of the informal organisations is immense: sometimes it means a failure or a success for an organisation, which must be understood by the management (Schein, 1985; Mullins, 2005; Kondalker, 2007).

Two state levels, ***effective*** and ***ineffective*** are developed to assess the conditioned probability of an organisational structure of a maritime entity on the level of ship owners/management as well as onboard ships. The organisational structure of a maritime entity is directly influenced by communication, strategy and objective, management quality, and organisational culture.

3.2.3.9. Objectives

The success of a maritime organisation is measured by the progress of its employees towards goals set. Management has a responsibility to clarify organisational goals and to attempt to integrate personal competence goals with the overall objectives of an organisation. The degree of integration can be improved by directing individuals' efforts towards the success of an organisation in an effective operational process (Schein, 1985; Mullins, 2005; Kondalker, 2007). An organisation's goals may be pursued in accordance with organisational principles, which are based on employee beliefs, values and attitudes. Organisational principle determines the culture of an organisation and provides a set of standards that govern the overall conduct of an organisation (Brown, 1992).

Clearly defined and agreed objectives are the first stage in the design of an organisation's structure. They help to facilitate systems of communication between different parts of the organisation. The ability to communicate corporate objectives to those responsible for seeing that those objectives are achieved is also an essential characteristic of an effective incentive payment scheme for all the organisation's employees (Richardson and Thompson, 1994).

The choice of objectives is an essential part of a decision-making process involving future courses of action. Objectives may be set out either in general terms or in more specific terms. General objectives are determined by top management. Specific objectives are formulated within the scope of general objectives and usually have more defined areas of application, and time limits.

Although objectives may sometimes be implicit, however, the formal explicit definition of objectives will help to highlight the activities that an organisation needs to undertake and the comparative importance of its various functions. An explicit statement of objectives may assist communication and reduce misunderstandings, and provide more meaningful criteria for evaluating organisational performance. Objectives should not be stated in such a way that they detract from recognition of possible new opportunities, potentially dangerous areas, and the initiative of staff or the need for innovation or change. Objectives can be measured through assigning probabilities on two discrete states, ***clear*** and ***unclear***.

3.2.3.10. Strategy

An explicit strategy is necessary for the operational process due to the following reasons. First, there is a need for individuals to co-operate in order to achieve the benefits of their mutual reinforcement. Secondly, there is a need to consider the effects of changing ergonomic conditions. The absence of an explicit concept of strategy may result in members of the organisation working at cross-purposes. The intentions of top management may not be communicated clearly to those who are expected to implement these intentions. Obsolete patterns of behaviour become very difficult to modify. Changes will become increasingly unreliable as subjective or intuitive assessment increases. To develop a successful statement of strategy demands a creative effort. This may require different methods of behaviour and often a fundamental change in the nature of interactions among managers. Effective strategic management creates a productive alliance between an organisation's culture and the resources it has at its disposal (Richardson and Thompson, 1994; Tilles, 1969). Hence, if the operational processes are to be successful then the organisation's structure must be related to its objectives and strategy. The structure should be appropriately designed to suit environmental influences, continuing development, and management of opportunities and risks. Strategy probability can be assessed using two discrete state levels, ***clear*** and ***unclear***.

3.2.3.11. Communication

Communication is the most vital element of any organisation. Without communication an organisation would only be an inoperative assembly of people, objects and processes. Organisational effectiveness depends on the quality of communication, which gives life to organisational structure. Communication holds operational processes and organisational structure together. If communication stops, the organisation will cease to exist. Communication is a dynamic force that shapes an organizational behaviour. The strength and weakness of this force are highly dependent on the effective downstream' and upstream' patterns of communication. Communication is vital for the very existence of ergonomics as there is a need to communicate with external organisations and agencies, and incorporate various inputs for survival and growth. Communication shifts information of value acquired from the environment to various departments, crew and individuals. Effective communication is an essence of successful managers, supervisors and operators. Effective management is an output of successful communication. Poor communication or ineffective communication is a source of frustration, interpersonal conflict and stress. Effective communication is essential for management to successfully perform its functions. It is an essential ingredient in managing employee relationships. The operational processes are meaningless unless everyone is willing to put in an effort together to achieve its objectives. Communication is essential to keep the entire organisation functioning at an optimum level, enabling management personnel to achieve their highest effectiveness. Yet management needs to confide in employees and make them aware of organisational policies, problems and vision, and this is where communication plays an essential role (Mullins, 2005).To measure communication, two discrete state levels, ***effective*** and ***ineffective*** are proposed.

3.2.3.12. SMS

SMS forms an actual management attitude for occupational safety and environmental protection. SMS is a comprehensive control of safety and includes the management of methods, procedures and people. Safety management comprises both preventive and corrective actions that aim to improve the working environment. It emphasises the role of management as a body that controls and takes charge of safety. The management is responsible for setting goals, providing resources and supervising implementation (Kuusisto, 2000; Hale et al., 1997; Hale and Baram, 1998; EPSC, 1996; HSE, 1997).

While SMSs may vary considerably in their practical implementation, they are all used to control the following fields:

- Safety policies and plans (including the definition and prioritisation of safety objectives, and the development of their implementation programmes).
- Organisation structure and communication effectiveness (definition of responsibilities and creation of communication channels).
- Risk management (identification and assessment of risks, and risk control methods).
- Auditing and assessment (conducting proactive and reactive control measures) (Booth and Lee, 1995).

SMS suffers from the problems of massive management systems and documentation of information. In practice, the focus of SMS audits and inspections is easily drawn to the organisational structures and processes instead of their contents (B.S. 8800, 2004; Reason and Hobbs, 2003). Therefore, it can only be used to aim at ensuring safety.

SMS can be measured using two state levels, ***effective*** and ***ineffective***. SMS of a maritime organisation at the levels of ship owners/management as well as onboard ships is directly influenced by management quality and procedures.

3.2.3.13. Procedures

Procedures are written instructions as to how tasks are to be done, what they involve, and the sequence to be undertaken. An organisation's SMS lays down operational, maintenance, and contingency procedures. Considering the occupational culture, it is worth noting that standing orders, policies, rules and procedures should be carefully drafted. It would be desirable if procedures are provided in a shortened form to the crews and supervisions, preferably in an understandable language. This will assist in simplifying the functioning of the whole organisation. Too many instructions in the form of standing orders, policies, rules and procedures may lead to false perceptions by operators and supervisors (Mullins, 2005; Vervloesem, 2000). Procedures are usually not considered to be a tool that operators can use to control the process; instead, they are thought of as something that controls the operators (Schulman, 1996). Procedures are typically designed in accordance with the constraints and characteristics of the operational process to be controlled, instead of taking into consideration the characteristics of the users (Dien, 1998). Procedures can be assessed using two state levels, ***performed*** and ***not performed***.

3.2.3.14. Organisational culture

Organisational culture consists of norms, values and unwritten rules of conduct as well as management styles, priorities, beliefs and interpersonal behaviours that prevail. Together they create the climate that influences the issue as to how well people can communicate, plan and make decisions (Sinn and Larry, 1991; Kondalker, 2007). In other words, organisational culture consists of (Schein, 1985):

- Practices (e.g. work order procedure, incident reporting system).
- Norms (if one is not sure about how to carry out task, then ask for assistance).
- Values (occupational safety, efficiency, skills).
- Conceptions (one becomes a professional by doing, not by reading)
- Assumptions (if there is an event, someone has made an error. Technology is more reliable than human beings).

The main functions of organisational culture (Mullins, 2005):

- It gives members an organisational identity (i.e., sharing norms, values and perceptions), and gives people a sense of togetherness that helps promote a feeling of common purpose. Culture provides a shared pattern of cognitive perceptions or understanding about the values or beliefs held by the organisation. This enables the members in the organisation to think and behave as they are expected to.
- It facilitates organisational members' cooperative commitment. The common purpose that grows out of shared culture tends to elicit strong commitment from all those who accept the culture as their own. It provides the organisational members with a shared pattern of feeling in terms of value and belief.
- It promotes system stability. By encouraging a shared sense of identity and commitment, culture encourages lasting integration and cooperation among the members of an organisation. It enhances social stability by holding the organisational members together and providing appropriate standards for which they should stand.
- It shapes behaviour by increasing members' awareness of their surroundings. An organisational culture serves as a source of shared meaning that explains why things occur in the way they do. Organisational culture is not fully visible but is able to be felt. At a less visible level, culture reflects the value shared by organisational members.

- It provides a boundary. Culture creates distinction between one organisation and the other. Such a boundary definition helps identify members and non-members of the organisation. Culture serves as a control mechanism that guides and shapes the attitude and behaviour of organisational members.
- It helps organisational members stick to conformity and an expected mode of behaviour. Culture ensures that everyone thinks and behaves in a prescribed manner.

Organisational culture assessment is carried out based on two state levels, ***acquired*** and ***not acquired***. Organisational culture of a maritime organisation on the levels of ship owners/management and onboard ships is directly influenced by safety culture and norm.

3.2.3.15. Safety culture

The concept of safety culture aims at drawing attention to the principles underlying safe operations that guide daily activities, and its associated decision-making. It is closely related to the notion of organisational culture. Safety culture is used to study organisational activities of safety in a normative concept. It is also used to assess an organisation's performance in terms of safety. It also sets requirements for the organisation (Harvey et al., 2002).

The safety culture of an organisation is the product of individual and group values, attitudes, perceptions, competencies, and patterns of behaviour that determine the commitment to, and the style and proficiency of, an organisation's health and safety management. Organisations with a positive safety culture are characterised by communications founded on mutual trust, by shared perceptions of the importance of safety, and by confidence in the efficiency of preventive measures (HSE, 1997). As indicated by its definition, safety culture is an evaluative concept that includes criteria for the operation of good safety critical systems. These include: the positive attitude of crew and supervisors towards safety rules; management opinion prioritised on safety issues must always be based on risk assessment over economy; and the disclosure of safety investigation results from which preventive measures can be learned. Safety culture has also been assessed using different kinds of indicators for the performance of organisations. Such indicators include accidents, and events reported to the authorities, as well as crew and supervisors' participation in safety training (Schein, 1985; Booth, and Lee, 1995; Kuusisto, 2000; Clarke, 2003; Kondalker, 2007; Lee and Harrison, 2000).

To assess safety culture two discrete state levels, ***acquired*** and ***not acquired*** are developed. Safety culture of a maritime organisation at the levels of ship owners/management and onboard ships are directly influenced by crew involvement and management commitment.

3.2.3.16. Norm

Norm is acceptable standards of behaviour that are shared by a group of members (Schein, 1985; Mullins, 2005). When agreed to and accepted by the group, norms act as a means of influencing the behaviour of its members with a minimum of external control. Group norms that are favourable to the organisation are associated with organisational pride, team work, honesty, security planning, and relationship. The behaviour of an individual as a group member must be acceptable to all the other members; this will give an individual good standing and recognition in the group. If norms are violated by an individual, corrective measures should be applied.

The following norms are generally found and practised by all organisations:

- Performance norms are the standards set by the individual worker and approved by the superiors.
- Appearance norms are related to dress code and code of conduct in the organisation. These norms are built into the organisational culture. With regards to code of conduct, an individual is expected to be loyal and display total dedication to the organisation he/she serves. Group norms are a very powerful tool for high productivity and maintenance of peaceful relationships among crew members.
- Behavioural norms are guidelines for general behaviour issued by the management so that all the employees display behaviour in an accepted manner. These norms eventually take the form of organisational culture and are very useful for bringing down conflict or stress level among the group members. Norms are developed over a long period of time. It may take sufficient time for them to be formalized and understood as norms that will not be violated by group members (Kondalker, 2007).

Norm can be estimated using two state levels, ***committed*** and ***not committed***. The norm of a maritime organisation at the levels of ship owners/management and onboard ships is directly influenced by crew involvement and management commitment.

3.2.3.17. Management commitment and crew involvement

Management commitment and crew involvement are crucial for obtaining an efficient organisational culture. Organisations with positive cultural alignment demonstration are generally more resistant to the unsafe conditions and hazards that may occur when a system fails. A positive safety culture does not guarantee accident-free operations, but rather illustrates an organisation committed to proactive and collaborative solutions in the continual battle against system error. Key indicators of safety culture include organisational commitment to safety, operational interactions, formal safety indicators, and commitments to norms.

Organisational commitment to safety refers to the degree to which an organisation's management prioritises safety in decision making, and allocates adequate resources to safety management. In particular, an organisation's commitment to safety is reflected in three sub- factors, including (Thaden and Gibbons, 2008):

- Safety values: These are expressed in words and actions by leadership. This reflects the commitment to safety at the top level of the organisation. Safety performance should be actively managed and monitored with the same systematic effort and attention given to the goals of company finances.
- Safety fundamentals: This means compliance with regulated aspects of safety such as training requirements, manuals and procedures, equipment maintenance, and coordination of activity within and between supervisors and crew. At this level, the organisation should encourage safe practices as a way of operating systems and provide a solid framework to meet those safety requirements.
- Going beyond compliance: This is the priority to allocate company resources with regard to safety (e.g., equipment and personnel time) even though they are not required by regulations. This may be reflected in areas such as human resources management, scheduling of shift work and rest time, providing advanced technology when essential, fatigue management programmes, and other scientifically based risk management systems.

Distinctive relationships between crew supervisors, middle management, and other operational personnel who take safety into account during their work reflect typical operational interactions. This refers to the degree to which those directly involved in supporting work or the supervision of crews are actually committed to safety and reinforce the safety values espoused by upper management, when these values are positive. They include (Thaden and Gibbons, 2008):

- The safety concerns and involvements of senior officers, superintendent engineers, and designated persons ashore on the part of maritime organisation responsibility, particularly their proactive concern for crew and system safety, and their ability to ensure a safe environment.
- The extent to which those who offer and provide safety training are deemed effective, and deal with the actual risk issues associated with particular system operations in the marine domain. In other words, is safety training integrated across all operational personnel? Are the personnel trained to the best industry practice standards?
- Effectively managing, maintaining, and inspecting the safety integrity of the equipment, tools, and procedures, etc., and conveying information through conducting safety briefings.

Management commitment and crew involvement being influencing variables in the adequacy of the organisation model can be measured using two state levels, ***high*** and ***low***.

3.2.3.18. Resource management

Resource management is related to the efficient and effective deployment of an organisation's resources when they are needed. Such resources may include human skills, knowledge and motivation, availability and trust of condition monitoring and performance control technology utilized in system operational processes, and quality and availability of equipment and records' inventory (Kelly, 2006).

Resource management can be estimated by two state levels, ***effective*** and ***ineffective***. Resource management of a maritime organisation on the levels of ship owners/management and onboard ships is directly influenced by system condition monitoring and performance control, equipment and records, and human resources.

3.2.3.19. Condition monitoring and performance control

Condition monitoring and performance control are sophisticated automation systems. They are becoming apparent everywhere in marine engineering operations; they are as diverse as process control and information retrieval application. Automation is technology that actively selects data, transforms information, makes decisions, or controls processes. Such technology exhibits tremendous potential to extend human performance and improve safety. However, recent disasters indicate that automation is not uniformly beneficial. On one hand, people may trust automation even when it is not appropriate, thus failing to intervene and take manual control action when necessary (Lee and Sanquist, 2000). On the other hand, people are not always willing to put sufficient trust in automation, thus undermining its potential benefits. As automation becomes more prevalent, poor partnerships between people and automation will become increasingly costly and catastrophic. Such flawed partnerships can be described in terms of misuse and disuse of automation (Parasuraman and Riley, 1997). Misuse refers to the failures that occur when people inadvertently violate critical assumptions and rely on automation inappropriately; whereas disuse signifies failures that occur when people reject the automation's capabilities. Misuse and disuse are two examples of inappropriate reliance on automation that can compromise safety and profitability. Automation can be a very complex combination of many modes, and reliance is often a more graded process. Automation reliance is not a simple binary process; however, understanding how to mitigate disuse and misuse of automation is a critically important problem with broad ramifications. Recent research suggests that misuse and disuse of automation may depend on certain feelings and attitudes of users' trust-based competence control complemented by automation availability (Lee and See, 2004).

Condition monitoring and performance control in the adequacy of the organisation model can be measured using two state levels, ***reliable*** and ***not reliable.*** Condition monitoring and performance control of marine systems onboard ships is directly influenced by system trust and availability.

3.2.3.20. Trust

Trust, as a social psychological concept seems to be particularly important for understanding human-automation partnerships. Trust can be defined as the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability (Parasuraman and Riley, 1997). This basic definition must be elaborated on in order to consider the appropriateness of trust, the influence of context, the goal-related characteristics of the agent, and the cognitive processes that govern the development and erosion of trust. In this definition, an agent can be an automation or another person that actively interacts with the system's operation on behalf of the operator (Lee and See, 2004). Many studies have demonstrated that trust is a meaningful concept to describe human-automation interaction in both naturalistic (Parasuraman and Riley, 1997) and laboratory settings (Muir and Moray, 1996; Lee and Moray, 1992; Halprin et al., 1973; Lewandowsky et al., 2000). These observations demonstrate that trust is an attitude towards automation that affects reliance and that it can be measured consistently. People tend to rely on automation they trust and reject automation they do not. By guiding reliance, trust helps to overcome the cognitive complexity people face in managing increasingly sophisticated automation. Human-automation trust and reliance depends on characteristics of the automation, the individual, organisational, and cultural context. This context affects initial levels of trust and how people interpret information (Lee and See, 2004).

Trust as a discrete variable in the adequacy of organisation model is assessed based on two state levels, ***high*** and ***low***.

3.2.3.21. Availability

Availability of condition monitoring and performance control systems is determined by reliability (the probability of the system effectively working) and maintainability (the ability to restore the system to service). Availability is the measure of the time at which the system is in an operational state compared to the total life time (Benbow and Broome, 2008).

Availability of condition monitoring and performance control systems in the adequacy of an organisation model is measured on two state levels, ***high*** and ***low***.

3.2.3.22. Human resources

Human resources are the scarcest and most crucially productive resource that creates the largest and longest lasting advantage for an organisation. It resides in the knowledge, skill, and motivation of humans, who are under the right conditions learn and grow better with age and experience, which no other resources can do (Kelly, 2006; McGregor, 1987).

Human resources as a discrete variable in the adequacy of an organisation model can be measured using two state levels, ***sufficient*** and ***insufficient***. Human resource in a maritime organisation is directly influenced by human skill, knowledge and motivation.

3.2.3.23. Knowledge

Knowledge in engineering and science can be defined as a body of justified true beliefs (such as laws, models, objects, concepts, know-how, processes, and principles) acquired by human beings about a system of interest, where the justification condition can be met based on the reliability theory of knowledge. The most basic knowledge category is the cognitive knowledge acquired through human senses. The next level is based on correct reasoning from hypotheses. The third category is belief, denoting intellectual or emotional acceptance of a proposition. In other words, knowledge is based on inference with incomplete or unreliable evidence. These categories constitute the human cognition of knowledge that might be different from a future state of knowledge achieved by an evolutionary process (Ayyub and Klir, 2006). Knowledge can be modelled using two state levels, ***good*** and ***poor***.

3.2.3.24. Skill

Skill is the ability and capacity acquired through deliberate, systematic, and sustained effort to smoothly and adaptively carry out complex activities or job functions involving ideas (cognitive skills), things (technical skills),and/or people (interpersonal skill) (Mullins, 2005; Kondalker, 2007). Skill in the adequacy of an organisation model is estimated using two state levels, ***high*** and ***low***.

3.2.3.25. Motivation

Motivation is the internal and external factors that stimulate desire and energy in humans to be continually interested in and committed to a job, role or subject, and to exert persistent effort in attaining a goal. Motivation is the energizer of behaviour and mother of all action. It results from the interactions among conscious and unconscious factors such as the intensity of desire or need, incentive or reward value of the goal, and expectations of the individual (Schein, 1985; Mullins, 2005; Kondalker, 2007). To use probability to model motivation in the adequacy of an organisation model two state levels, ***high*** and ***low*** are created.

3.2.3.26. Equipment and records

Equipment is the tangible properties characterised by a durable nature which is useful in the operation of systems. Examples of equipment include devices, machines, tools, spares and stores. Records are documents that memorialize and provide objective evidence of activities performed, events occurred, results achieved, or statements made. Records are created/or received by an organisation in respect of technical services related to system operations.

Equipment and records in the adequacy of an organisation model can be probabilistically assessed using two state levels, ***effective*** and ***ineffective***. The equipment and records of a maritime organisation are directly influenced by their quality and availability.

3.2.3.27. Availability

Availability of equipment and records is characteristic of resources that are committable, operable, or usable upon demand to perform their designated or required functions. It is the aggregation of the resources' accessibility, reliability, maintainability, serviceability, secure-ability and readability.

Availability of equipment and records in the adequacy of an organisation model is measured on two state levels, ***high*** and ***low***.

3.2.3.28. Quality

Quality of equipment and records is a measure of fineness or state of being free from defects, deficiencies and significant variations. A standardised definition of quality is described as the totality of features and characteristics of a product or service that bears its ability to satisfy stated or implied needs.

Quality of equipment and records in the adequacy of an organisation model can be measured on two state levels, ***high*** and ***low***.

3.3. Methodology of establishing a BN generic model for adequacy of an organisation reliability assessment

3.3.1. Procedures for building Bayesian models

The construction of BNs consists of several steps (see Figure 3.1). The first step involves identification of the relevant variables constituting the problem to be modelled and its definitions. This step is dealt with in Section 3.2.3. Once the variables are arranged (see Table 3.1), the second step is to determine the relationships among them, i.e., their direction dependent separation (d-separation) properties; and establish the graphical structure of the model (see Figure 3.2). In the third step, variable states are defined (they are detailed in the definitions of each PIF and sub PIF) and their relevant prior probabilities are assigned (Druzdzel and Gaag, 2000). Probability values are normally estimated or appropriated based on certain sources of evidence such as empirical data, expert's belief, literature review, or intuition. The fourth step is to apply Bayesian rules to compute the marginal probability value of each of the variables in the model. This implies the use of a machine learning tool to establish a Bayesian model which shows the evidence that has been added and propagated through the model and the result of posterior probabilities. The fifth stage is to run a sensitivity analysis to assess the performance of the model against its parameters. Sensitivity analysis is a process of model validation. It takes place by further optimising and refining CPTs that comply with assessment objective conditions. The sixth stage of model building requires development of scenarios to train and update the model. The modelling steps are normally conducted to reach a stable computational model (Mittal and Kassim, 2007).

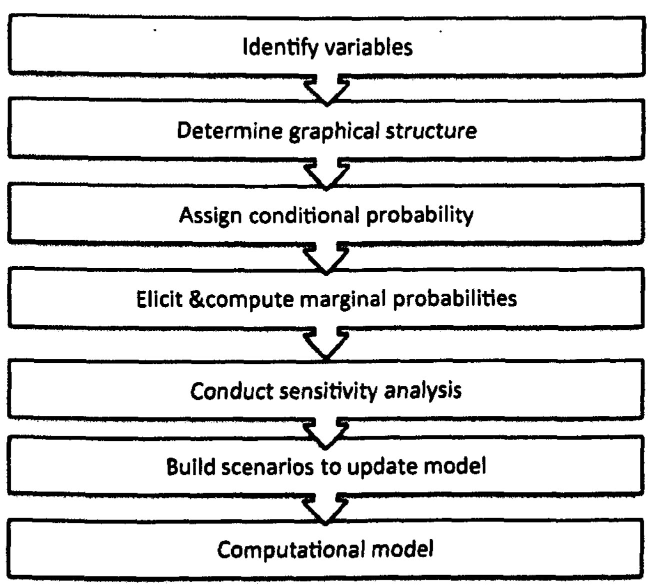


Figure 3.1: The essential steps and procedures in building BN models

3.3.2. The process for obtaining an initial graph

BN is a direct model of a real world environment rather than a model of reasoning (e.g., neural networks) process, carried out in many knowledge representation schemes. After identifying the relevant PIF and sub PIF variables affecting adequacy of organisations and their causal relations, it is possible to start drawing links between them and constructing a qualitative network, which represents all the relevant variables and their dependencies (see Figure 3.2). The knowledge about BN and the intuitive understanding of the various dependencies among variables are then used to construct the causal structure of adequacy of organisation. Here the graphical representation becomes very handy. It permits users to directly express the fundamental qualitative relationships in terms of direct or indirect influence (Yang, 2006).

When deciding how to capture a particular idea, it is important to consider the spatial area characteristics and time period which the constructed BN represents. Consequently, the process for obtaining an initial graph is implemented along the following lines. First, an algorithm of four categories of variables (nodes) is adapted for the graphical structure, which provides a useful starting point to meet BN end point node that effects the adequacy of organisation as a variable. The four categories are root cause variables, sub-condition variables, condition variables, and functional variables. Variables' relationships are structured with respect to the probabilistic causation theory, implying the effect is produced by specified directed or known causes and an unspecified indirect cause such as error and unknown causes (Anderson and Vastag, 2004; Anderson et al., 2004). This idea can be represented by a conditional probability as $p\ (effect \mid cause) = p\ (effect \cap cause) / p\ (cause)$, which forms the basis for Bayesian modelling that can be used directly within the BN to model information elicited from a domain of assessment. This would explicitly develop the idea that the BN represents uncertainty in a way that can be clearly understood. Accordingly, nodes associated with root cause (sub PIF) variables, which are not directly influenced by any other identified variables can be defined as root cause nodes. All the variables (sub PIFs) that are directly influenced by the root cause nodes can be discovered and the nodes associated with them can be defined as sub-condition/condition nodes. A given sub-condition/condition variable node has as its parents all those root cause nodes that directly influence this particular sub-condition/condition node. A set of child-parent links is then drawn, which now serve as edges of the graph. Thereby all variables that are directly influenced by the condition variable nodes can be discovered and the nodes associated with them can be defined as functional nodes. A given functional variable node has as its parents all those condition nodes that directly influence this particular functional node. However, dependency between condition nodes, condition nodes and functional nodes among model variable nodes is allowed for, and their influencing edges are drawn in the graph. Finally, the end point effect node (the objective of the model) has as its parents all those functional nodes that directly influence this particular effect node. A set of child-parent links is then drawn, which now serve as edges of a graph. This process continues until all variables have a place in the graph and all child-parent links are accounted for by edges of the graph.

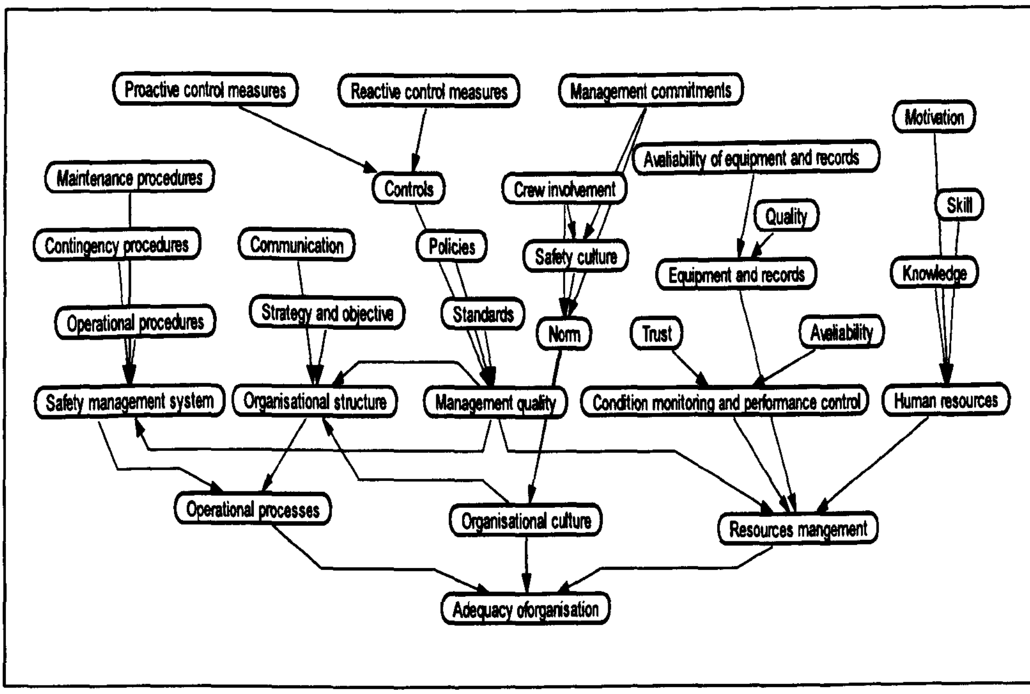


Figure 3.2: BN modelling the adequacy of organisation expanded PIFs and sub PIFs

3.3.3. BN d-separation characteristics' check

In building a BN model, oriented influencing links need to be verified by checking their direction dependent separation (d-separation) characteristics. This is to ensure that the model's integrity is in compliance with BN characteristics, matching a perception of a real world (Jensen, 2001), and showing how mutual information is conditionally propagated among model variables (Jensen, 1996).

A BN structure is useful if its nodes are identical to the set of variables representing the real world. Therefore, the nodes criteria used to learn a BN structure should represent the real world variables criteria, in a way that its compatibility does not distinguish the among BNs nodes (Chickering, 2002).

A major advantage of BNs over many Belief Networks is in the use of a knowledge-based system to represent uncertain knowledge by means of both graphical structure and associated numerical parameters. In a BN, the qualitative component (the graph) represents dependence and independence statements. The absence of some arcs means the existence of certain conditional independence between variables, while the presence of arcs may represent the existence of direct dependence. Learning the structure of a belief network from data using independence-based criteria contributes to the ability to determine parameters' dependencies strength and increase the reliability of the learned structure (Cheng et al., 2002).

Basically, the mutual information between dependent variables, for instance (A) and (B), measures the expected information gained about (B), after observing the value of the variable (A). In BNs, if two nodes are dependent, knowing the value of one node will give some information about the value of the other node. In this context, the mutual information between two nodes can indicate if the two nodes are dependent and if so, how close their relationship is (Cheng et al., 2002).

For any three nodes (X), (Y) and (Z) of a BN structure in the form (X–Y–Z), there are only three possible structures:

(1) $X \rightarrow Y \rightarrow Z$ (serial connection structure).

(2) $X \leftarrow Y \rightarrow Z$ (divergent connection structure).

(3) $X \rightarrow Y \leftarrow Z$ (convergent connection structure).

It is only the third type, convergent connections, that can let information pass from (X) to (Z) when (Y) is observed and active by given evidence. Consequently, only convergent connections can make (X) and (Z) conditional dependent on (Y).

Divergent connections and serial connections can allow information pass from (X) to (Z) when (Y) is hidden (Cheng et al., 2002).

D-separation (conditional independence) is a very important concept in Bayesian probability theory, because it assists in modifying the initial networks towards a more effective model; it also provides the basis of the quantitative computation, as well as combines the probabilities representing uncertainty in a BN. D-separation can be well explained by means of the "Bayes Ball" concept (Shachter, 1988). Two (sets of) node(s) (*A*) and (*B*) are d-separated given a (set of) node(s) (*C*) if and only if there is no way for a ball to get from (*A*) to (*B*) in the graph, where the allowable/unallowable movements of the ball are shown in Figure 3.3. Hidden nodes are nodes whose values are not known, and are depicted as not shaded; observed ones, which are conditioned, are shaded. The dotted arcs indicate the directions of flow of the ball with respect to BN connection characteristic.

To demonstrate the "Bayes Ball" concept, firstly, consider the first column of Figure 3.3, showing the converging connections in a BN, in which two converging arrows from the nodes (*A*) and (*B*) point to the node (*C*). If (*C*) is hidden, then (*A*) and (B) are conditionally independent, and hence the ball does not pass through, which is indicated by the curved arrows. However if (C) is observed, then (*A*) and (*B*) become dependent, and the ball does pass through. Other graphs can also be analysed in a similar way, for instance, in the diverging or serial connections, if (*C*) is observed, all balls cannot get through, which indicates that (*A*) and (*B*) become conditionally independent (Yang, 2006). The use of a d-separation concept to check the accuracy of a qualitative BN in presenting a realistic situation can be demonstrated in the following example.

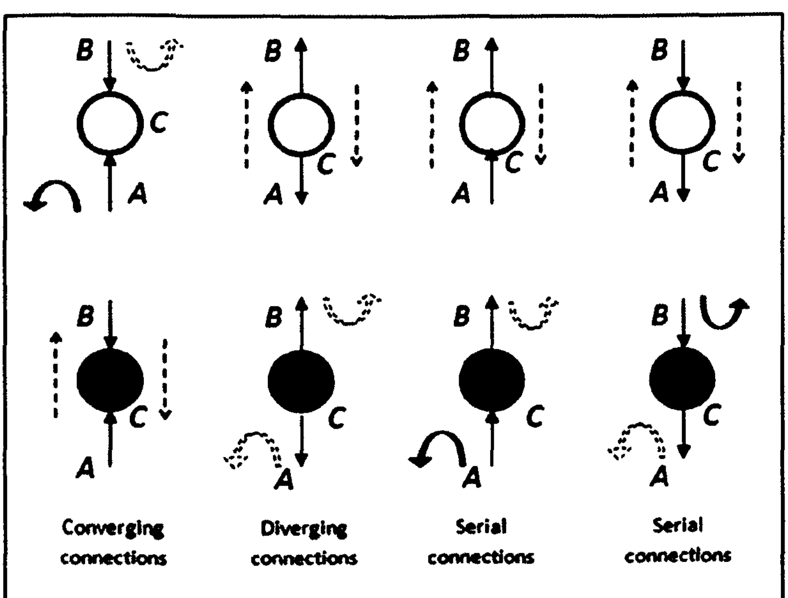


Figure 3.3: BN d-separation concept illustration adapted from Yang (2006)

Suppose the main diesel engine of a ship failed to start during manoeuvring. Engine failure to start was investigated by the engineers on board. Two potential reasons were analysed: ether lack of fuel supply, or the fuel cut-off device was activated by the safety interlock. To disclose the truth, the fuel supply could be checked by diagnosing two parameters, which are the fuel supply pressure reading, and the fuel supply booster pump running condition; simultaneously the fuel cut-off device could be checked for possible activation. For this special case, an initial BN is built up as shown in Figure 3.4a. Now by using the d-separation concept to verify the network, the relationship between node (B_1) fuel cut-off device and node (C_1) lack of fuel supply is first investigated. Provided that node (A_1) engine failed to start is observed and that node (B_1) fuel cut-off device is found with a new piece of evidence of not being activated, then node (C_1) lack of fuel supply will be affected with a higher probability. Therefore, node (B_1) fuel cut-off device and node (C_1) lack of fuel supply are dependent and suit the concept of d-separation. As a result, the links and directions are sound. However, when a similar analysis is employed to investigate the relationship between nodes (D_1) fuel booster pump running condition and (E_1) fuel pressure reading, the result is different. With the evidence of node (C_1) lack of fuel supply, the dependent connection between nodes (D_1) and (E_1) cannot be constructed. Further careful analysis assists in identifying their right family relationship, shown in Figure 3.4b, in which node (C_2) is the parent of node (E_2) because the situation of the fuel supply decides the fuel pressure reading.

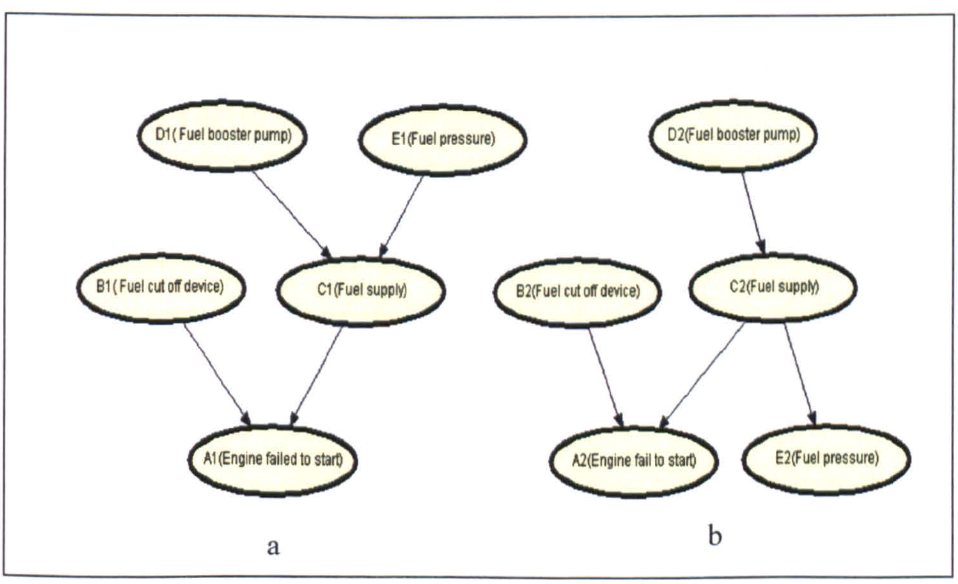


Figure 3.4: An example of using d-separation concept to check BNs qualitatively

To assure that the adequacy of the organisational BN model, encodes the probability density function governing the set of expanded PIFs and sub PIFs, model links d-separation characteristics are verified, as illustrated in the following read.

The root cause nodes of adequacy of organisation model (see Figure 3.2) are the parents of sub-condition/condition nodes. The edges of the graph represent the assertion that variables are conditionally dependent on their parents. For instance, for root cause nodes of management commitment and crew involvement, each is connected in a divergent connection of a BN structure; therefore, their associated influencing edges on safety culture and norm nodes (conditions nodes) need to check their d-separation properties by using the "Bayes Ball" concept. This is approached by giving evidence to the crew involvement root node. Its observation in a BN divergent connection blocks the mutual information between norm and safety culture nodes. Consequently, they become conditionally independent, asserting that the connection structure of crew involvement root node is compatible with the real world equivalent criteria. This process continues until all the connections in the network are verified.

3.3.4. Defining variable states

Special skill and degree of imagination are required to realistically represent the real world in the form of a simple model. Therefore, a network structure, names of the nodes, and names of the states of the nodes are of equal importance in capturing the logic underlying the ideas to be represented.

During the construction of a BN, it is very important to know if all the variables have been included. It may be possible to delete some entirely or combine two or more ideas into one variable. Equally it may be possible to reduce the number of states given to each variable. Therefore, it is important to be sure that all characteristics of a variable are identified and differentiated. However, they should only be included in the BN if they are considered to be a key factor in the functioning of the real world to be modelled. In all respect, states selected should fit within the logic of the BN structure as a whole. In other words, the states given to the children should be logical, as all their parents have appropriate influence on them.

A simple guide to select states for each variable can be described, first to decide on how to describe the variable state at the time of selection, then the state towards which the variable will move under the proposed assessment plan. Finally any intermediate states that are expected to allow the variable to pass through can be described with or without the critical significance to the assessment plan objectives (Cain, 2001). Subsequently, it is imperative to focus on those states that are of interest to the assessment plan objectives. It is also important to remember that the chosen states' assessment must add to a complete unit that a node should take. Nevertheless, focusing strongly on assessment plan needs will help keep the BN to a manageable size. Quantifying the chosen states should not be restricting. It is more important to ensure that the BN is logical and expresses all the necessary vital ideas to a model as it would be possible to adapt it later to help fill in the CPTs (Cain, 2001).

3.3.5.The approach to assigning prior probabilities to model nodes

The prior probabilities of all root, sub-condition, condition, functional, and effect nodes variables states are assigned subjectively due to the lack of objectively measured data. Further investigation could be done to measure states' probability based on empirical data and structured surveys in order to reduce the bids caused by data subjectivity. The unconditional probabilities of all root cause nodes of the generic adequacy of an organisational BN model are equally disrupted on each node stats (see Figure 3.5). Three maritime experts were interviewed to provide their subjective elicitation of conditional probabilities of sub-condition, condition, functional, and end point effect nodes. Elicited conditional probabilities (CPs) are aggregated and normalised by using Equation 3.1 (Klir and Yuan, 1995), to develop the CPTs that are used to establish the generic adequacy of an organisational BN model shown in Figure 3.5.

$$\mathrm{CP} = \frac{\sum_{e=1}^{n} e(x)}{n} \quad \text{.........} \quad (3.1)$$

where, CP is the aggregated and normalised value of conditional probabilities elicited by n experts, $e(x)$ is the conditional probability given by the e^{th} expert.

Verbal Elicitor (VE) developed by Hope et al. (2002) will be used in supports of the qualitative elicitation of unconditional probabilities of leaf nodes, as listed in Table 3.2.

Table 3.2: VE cue words and their associated probabilities

Cue word	Probability
Certain	100%
Probable	90%
Expected	70%
Fifty-fifty	50%
Uncertain	30%
Improbable	15%
Impossible	00%

3.3.6. Technical description of the BN of adequacy of organisation

The BN of adequacy of organisation is composed of following elements: 1) Set of nodes representing the PIFs and sub PIFs as discrete variables; each with a limited set of mutually exclusive states in constituting the domain of adequacy of organisation, and the possible probabilistic values may each take, explain the state of the node. 2) Set of links representing causal relations between nodes. 3) Set of probabilities for each node; specifying the degrees of belief that a node will be in a particular state given states of its parent nodes. These are called CPTs and used to express relationships between nodes.

The above elements create a fully-functioning generic BN (see Figure 3.5). The structure of this BN diagram encodes the perception that adequacy of organisation is affected by the causes of functional nodes operational process, organisational culture, and resources management. These in turn are, affected by the causes of the condition/sub condition nodes depicted in the model. The other relationships represented by the model can be read in a similar way. Underlying each node in the BN (not shown in Figure 3.5) are the CPTs. For example, the Table 3.3 shows the generic CPT, describing the relationships between adequacy of organisation (child node) and operational process, organisational culture and resources management (parent nodes), as well Table 3.4 shows the generic CPT, describing the relationships between operational processes (child node) and safety management system organizational structure and management quality (parent nodes). The remaining generic CPTs for this methodology are provided in Appendix 1. It should be noted that the CPT contains entries for every possible combination of the states of the parents. CPTs are assigned following the approach stated in Section 3.3.5. For example, the adequacy of organisation conditional probability on combination of operational processes' "Effective", Organizational culture' "Acquired" and resources management' "Ineffective" shown in Table 3.3, is aggregated and normalised by the use of Equation 3.1 as follows.

$$\mathrm{CP} = \frac{92 + 90 + 88}{3} = 90$$

In a similar way the remaining CPs are obtained and presented in the perspective CPTs. Once all the CPTs are completed, the BN can be compiled and used for analysis. In general terms, this is performed by altering the states of some nodes while observing the effect this has on the others. As a BN is a network, the impact of changing any variable is transmitted right through the network in accordance with the relationships expressed by the CPTs. Changes in any node simply arise from the combined effect of changes in all the nodes linked to it either directly or indirectly. In formal terms, the BN encodes a joint probability distribution over all the nodes. Every time the state of a node changes, the joint distribution is updated through the iterative application of Bayes' theorem. Changes in the BN are observed as changes in the chance that a node is in a particular state. Due to the uncertainty in the CPTs, it is rare for a node to definitely be in one state or another and it is far more common for probability distributions across all the states of a node to be observed (Cain, 2001).

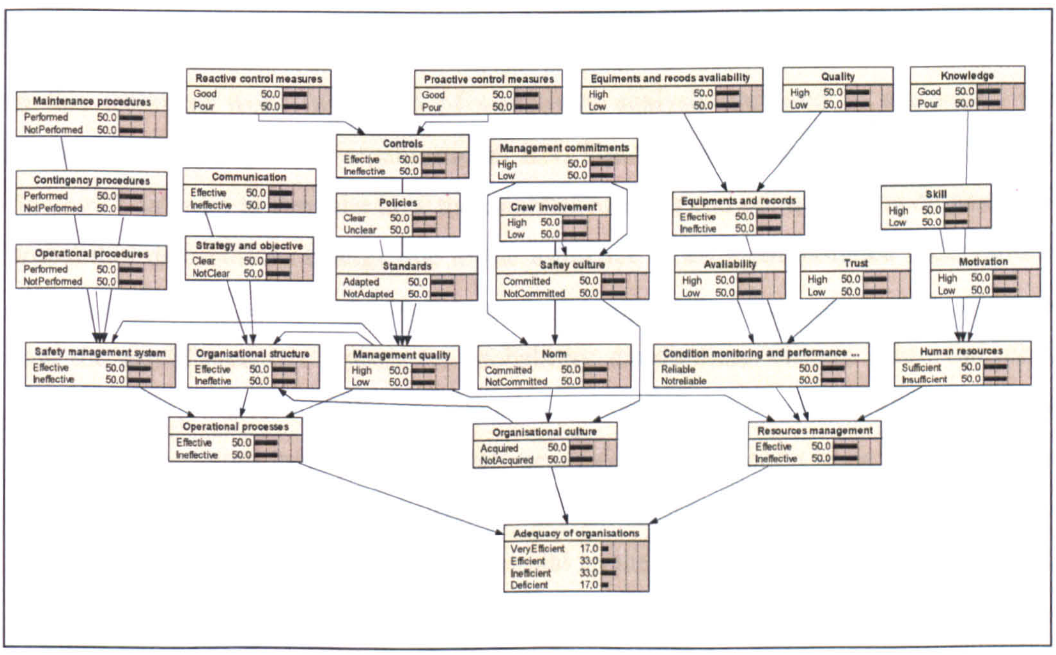


Figure 3.5: Fully-functioning generic BN model of adequacy of organisation

Table 3.3: Adequacy of organisation CPT

Adequacy of organisation C.P.T. (%)								
Operational processes	Effective				Ineffective			
Organizational culture	Acquired		Not acquired		Acquired		Not acquired	
Resources management	Effective	Ineffective	Effective	Ineffective	Effective	Ineffective	Effective	Ineffective
Very efficient	100	10	10	0	0	0	0	0
Efficient	0	90	85	45	55	5	0	0
Inefficient	0	0	5	55	45	85	90	0
Deficient	0	0	0	0	0	10	10	100

Table 3.4: Operational processes CPT

Operational processes C.P.T. (%)								
Safety management system	Effective				Ineffective			
Organizational structure	Effective		Ineffective		Effective		Ineffective	
Management quality	High	Low	High	Low	High	Low	High	Low
Effective	100	80	75	20	80	25	20	0
Ineffective	0	20	25	80	20	75	80	100

3.3.7. Sensitivity analysis

Sensitivity analysis basically examines the relationship between input and output changes of a mathematical model. In the case of a BN model, the input can be observation of prior probabilities of influencing nodes (parents), and the output is belief of posterior marginal probabilities of the influenced nodes (child) or vice versa.

In this technical work two types of sensitivity analysis are used in evaluating the established adequacy of an organisational BN. The first type is termed, ''sensitivity to findings'', in order to consider how the established BN's end point effect node posterior probability distributions change due to the influence of different assigned observations of the leaf nodes. The second type is termed, ''sensitivity to parameters'', and considers how the established BN's posterior probability distributions change when the most influential parameters in a BN are altered. Both sensitivity analysis are needed for a careful and thorough investigation of BN properties (Coupe and Gaage, 2002; Laskey and Mahoney, 2000; Rieman et al., 2001). In this context, sensitivity analysis is used to identify variables, which are highly influential to the target node probabilities change, so that quantification efforts in subsequent model iterations can be well focused.

3.3.8. Sensitivity to findings

Sensitivity to findings (evidence) can use the properties of d-separation to determine whether observations related to one variable may influence belief in a query variable(s) (Korb and Nicholson, 2004). The d-separation occurs when nodes in a causal graph are conditionally independent, given evidence. Using sensitivity to findings, it is possible to rank evidence nodes. This process allows the expert to identify whether a variable is sensitive or insensitive to other variables in given conditions of particular context, which in turn may help to identify errors in either the network structure or the CPTs. Findings information can also be used to provide guidance for collecting further data or to direct expert elicitation and evaluation efforts. Sensitivity to findings can be determined using two types of measures, entropy and mutual information. Both measures are implemented using Netica software (Pollino et al., 2006).

Entropy, H, is commonly used to evaluate the uncertainty or randomness of a variable (X) characterised by a probability distribution $P(x)$ (Korb and Nicholson, 2004; Pearl, 1988).

$$H(X) = -\sum_{x \in X} P(x) \log_2 P(x)$$

Mutual information is used to measure the effect of one variable (X) on another (Y) (Korb and Nicholson, 2004):

$$I(X, Y) = H(X) - H(X|Y)$$

where, $I(X, Y)$ is the mutual information between variables, measuring the expected degree to which the joint probability of (X) and (Y) diverges from what it would be if (X) were independent of (Y) (Korb and Nicholson, 2004). If $I(X, Y)$ is equal to zero, (X) and (Y) are mutually independent (Pearl, 1988). The following are the properties of mutual information:

Intuitively, $I\,(X, Y)$ is the amount of information that (X) and (Y) contain about each other;

- $I\,(X, Y) \geq 0$ and $I\,(X, Y) = I\,(Y, X)$;
- $I\,(X, Y)$ is a measure of the dependence between (X) and (Y):
- $I\,(X, Y) = 0$ if and only if (X) and (Y) are independent;
- $I\,(X, Y)$ grows not only with the dependence of (X) and (Y), but also with $H(X)$ and $H(Y)$;
- $I\,(X, X) = H(X)$; entropy as "self-information".

Mutual information measures a relationship between two random variables that are sampled simultaneously. In particular, it measures how much information is communicated, on average, about one random variable due to the other. The relationship between mutual information and entropy can be visualized using a Venn diagram (see Figure 3.6), which clearly indicates that entropy reduction is equal to the mutual information.

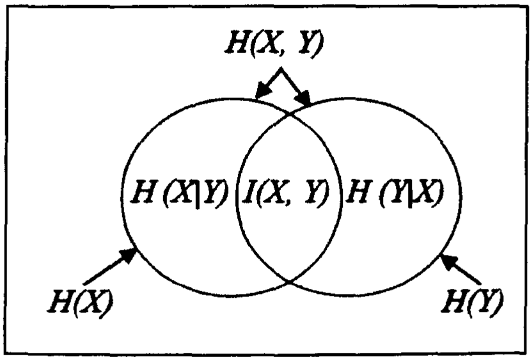


Figure 3.6: Venn diagram indicating entropy reduction is equal to the mutual information.

3.3.9. Sensitivity improvement

The process of building a BN model often includes a number of tasks, one of which is the quantification of the BN, which often requires specifying a huge number of CPTs. Therefore, certain parameters CPT should be specified with a higher degree of precision than the others for the convenience of an assessment. This can be approached by first performing BN sensitivity analysis in order to identify the most important (most critical) parameters, and then further updating those parameters' probabilities to obtain more accurate values. Such process is repeated until refining the probabilities any further does not improve the performance of the BN, or until the cost of further elicitation outweighs the benefits of higher accuracy. Practically, the stopping rules should include: a) satisfactory behaviour of the BN is achieved, and b) higher accuracy can no longer be attained due to lack of knowledge. In this iteratively repeated procedure, the domain experts can focus their attention on parameters' probabilities to which the BN's behaviour shows high sensitivity. Those less influential parameters can be left with crude estimates (Pollino et al., 2006; Wang, 2006).

3.4. A specific case study scenario: The grounding accident of M.V. HANJIN DAMPIER

The main reasons behind the selection of M.V. HANJIN DAMPIER grounding accident as the case study to validate the developed adequacy of organisation BN model are: the direct dependency influence of Master', pilot' and Chief engineer' competence control on vessel safety; the need for an efficient organisational structure and effective SMS to achieve the effective level of crew competence control, and the vital need for an effective communication that would shape the safest departure process. Organisationally the chief engineer failed to communicate the seriousness of the generator problem to the Master and this failure of communication directly contributed to the grounding incident.

3.4.1. The circumstances

At 1032 on 25 August 2002, the Korean flag bulk carrier "HANJIN DAMPIER" departed from the port of Dampier, Western Australia. A pilot was conducting the navigation of the ship, which was loaded with iron ore and had a displacement of 233,158 tonnes with draughts of 17.94 m forward and 18.10 m aft. At 1127, two of the ship's three main generators stopped, leaving only one generator running and connected to the main switchboard. At 1152, the third generator's circuit breaker tripped open. With the total loss of power to the main switchboard the main engine stopped and the ship lost steering. The rudder had stopped at 10° to starboard. As the ship slowed, it started to turn to starboard towards shallow water. The emergency generator failed to start automatically and, as a result, steering was not restored for some four minutes. At 1202, "HANJIN DAMPIER" touched bottom. The ship suffered only minor damage to the bottom shell plating, but the consequences of this incident could have been a lot worse.

3.4.2. The analysis

There would have been no incident if there had been no loss of electrical power on the vessel. Water had entered the port diesel oil storage tank through a broken manhole gasket. This water was then transferred, during a normal fuel transfer operation, to the diesel oil settling tank. However, due to the engineers' use of an incorrect sized gravity disc in the diesel oil purifier, and their incorrect setting of the purifier's fuel outlet line back pressure, the water in the diesel fuel in the diesel oil settling tank was passed to the diesel oil service tank. From here the water reached the three diesel generator engines, leading to the loss of electrical power on the vessel. The emergency generator then failed to start automatically upon the loss of the main source of electrical power, due to a faulty starting battery. Had the emergency generator restored power automatically to the emergency switchboard within the 45 seconds required by the SOLAS regulations, the Australian Transport Safety Bureau (ATSB) concluded that it was likely that the grounding would have been avoided (ATSB, 2003).

The ATSB (2003) report states that numbers one and two generators tripped off the main switchboard, and stopped, at about 1128. At this time the ship was still in the buoyed channel, and being fully laden she had little room for manoeuvre, the open sea still being more than an hour and a quarter away. Given his uncertainty regarding what had caused the first two generators to shut down, and his awareness of the ship's critical navigation situation, the Chief Engineer should have discussed the situation more fully with the Master. This would have given the Master the opportunity to form a contingency plan, in consultation with the pilot, to mitigate the risk to the ship. With number three generator continuing to supply power for a further 24 minutes, there was adequate time at this point in the passage to stop the ship either in the channel or, after it had cleared the channel, in deeper water, and to call for tug assistance. In the event, the Chief Engineer did not communicate the gravity of the generator problem to the Master and this failure of communication directly contributed to the grounding.

The lack of effective communication between the Chief Engineer and the Master meant that the bridge team were unaware of the risk to the vessel after the first two generators had stopped, and thus precluded the possibility that they could take pre-emptive action to reduce the level of risk to the vessel. The ATSB report contained the following statement: "Had there been more effective communication between the Chief Engineer and Master at the critical time after the first two generators had shut down, it is likely that the grounding of Hanjin Dampier could have been averted" (ATSB 2003; Grey, 2005).

3.4.3. The scenario conclusion

Based on the above stated incident analysis, the following facts (observations) could be derived in consistency with BN model root cause variables states. The ineffective communication between the Chief Engineer and the Master had initiated the low crew involvement that led to contingency procedures not being performed. Such an action reasonably could be manifested in low crew skill and knowledge capability, which had affected their motivation and stimulated their low trust in interaction with the functionality of control systems. As a result, the crew was not able to infer the main reasons for the tripping of the main power supply circuit breakers; indeed such uncertainty would reduce the crew competence control in restoring of power supply system high availability; moreover, the situation was aggravated by the failure of the emergency generator starting system, due to a faulty starting battery.

In addition, the duty engineers' failure to drain the settled water in the diesel oil settling and service tanks on a daily bases, and to detect the low performance of purification equipment, are considered as nonconformity with the operational procedures. Furthermore, the wrong installed gravity disc and faulty starting battery for the emergency generator indicated that maintenance procedures were not followed properly. These conditions reasonably reflect the possibility of unclear maintenance policy basically aggravated by low management commitment and low crew involvement.

Maintenance and operational procedures were not followed possibly due to unclear operational and maintenance policies, which are commonly caused by non-adaptable standards, and the lack of proactive control measures. As a result, the performance of the purification system and emergency generator starting system had deteriorated.

Based on these findings, and in association with the model root cause nodes, the prior probability assessment are provided as input observations into the BN generic model shown in Figure 3.5. However, the adequacy of organisational BN generic model revised marginal probabilities (see Figure 3.7) in the light of new evidence reasonably satisfies the qualitative assessment approach. A better model outcome marginal probability could be achieved by updating the model CPTs through optimising the assigned conditional probability of adequacy of organisation node, and subsequently optimising the assigned conditional probability of functional and condition nodes.

The new probable observation probabilities assigned to the prior probabilities of the leaf nodes' crew involvement, availability, contingency procedures, operational procedures, communication, trust, maintenance procedures, skill and knowledge, are based on the probable cue word of VE and its associated probability value given in Section 3.3.5. On the other hand the root cause nodes' management commitments, standards, policies, equipment and records availability, proactive control measures, reactive control measures, quality and motivation are left with their generic prior probabilities, as they are not observed or verified in incident analysis.

Model readout posterior probabilities of the condition, sub-condition, functional nodes, and end point effect node (adequacy of organisation) are conditionally inferred based on their associated CPTs and the prior probabilities of their respective influencing parent nodes and the assigned prior probability of root cause nodes. Consequently, BN model end point effect node (adequacy of organisation) inferred marginal probabilities are

6.33% very efficient, 20.9% efficient, 38.2% inefficient and 34.4% deficient. Accordingly, the model inferred quantitative belief certainty on inefficient and deficient states is compatible to the qualitative finding of the incident analysis. The new beliefs of adequacy of organisation are sensitive to the assigned probable observations of 9 leaf' nodes and the likelihood findings of the other 9 root cause nodes. However, further investigation in context of incident analysis would provide the necessary knowledge needed to clear the uncertainty of the 9 negative root cause nodes.

Deductively, a prognosis scenario as proactive measure to formulate plans for eliminating the possibility of the occurrence of such incidents in future could be developed. It is important to note that some of the assigned observations are not directly based on observed evidence, i.e., verifiable. However, this is a first step to come up with more cases to train and validate the model. This phase of a model development helps experts to examine the model further and refine it based on their domain knowledge. The Bayesian model therefore serves as an interactive tool that enables experts to create a probabilistic model, simulate scenarios, and reflect on the results of the inference.

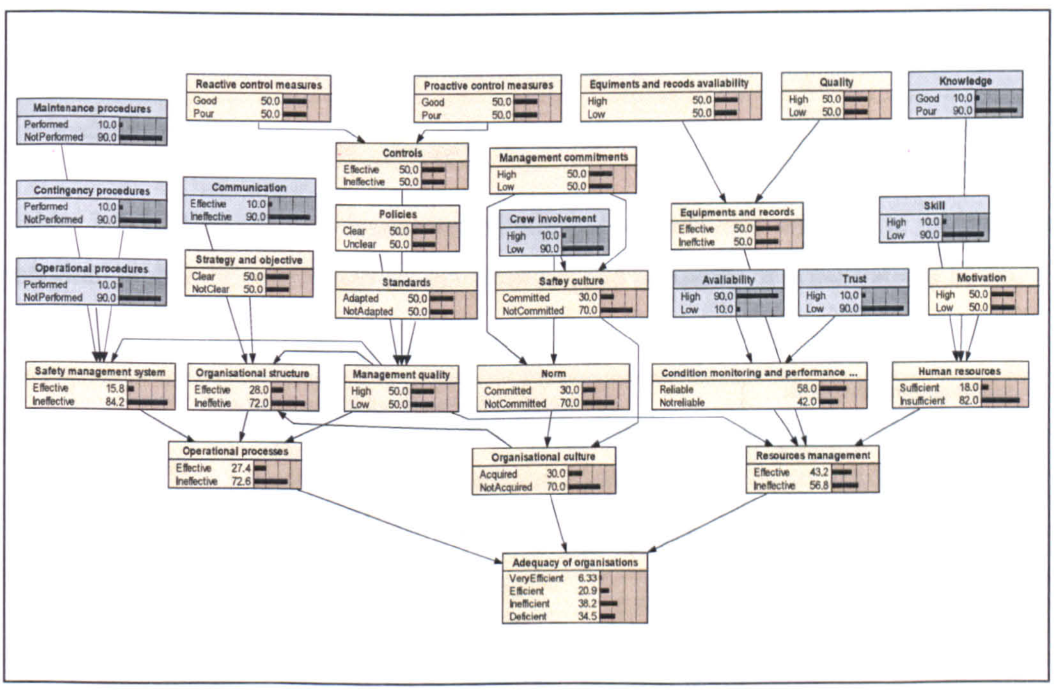


Figure 3.7: The Grounding of "M.V. HANJIN DAMPIER" case analysis based on the BN modelling of adequacy of organisation

3.4.4. Manual computation of marginal probabilities

To demonstrate how the model infers for specific links of the model structure, a manual calculations case is simulated (see Figure 3.7). In this calculation, the concerned nodes' CPTs, and their prior/marginal probability are used. The case computation pathway and the findings are illustrated in Tables 3.5-3.10:

Table 3.5: Condition monitoring and performance control node assigned CPT

Combination	Root cause variables prior probabilities		Condition monitoring and performance control (CM&PC) CPT	
	Availability P (A)	Trust P (T)	Reliable P (CM&PC |A,T)	Not reliable P (CM&PC |A,T)
1	0.9 High	0.1 High	1	0
2	0.9 High	0.9 Low	0.6	0.4
3	0.1 Low	0.1 High	0.4	0.6
4	0.1 Low	0.9 Low	0	1

Table 3.6: Condition monitoring and performance control deduced marginal probabilities

combination	Reliable P (CM&PC |A, T) × P(A) × P(T)	Not reliable P(CM&PC |A,T) × P(A) × P(T)
1	0.090	0
2	0.486	0.324
3	0.004	0.006
4	0.0	0.090
Σ	0.580 (Reliable)	0.420 (Not reliable)

Table 3.7-3.10 show two examples of manual calculations applied to obtain the marginal probabilities of resources management and adequacy of organisations nodes.

Table 3.7: Resources management node assigned CPT

Combinations	Condition variables marginal probabilities				Resources management CPT	
	Human resources *P(HR)*	Condition monitoring and Performance Control *P(CM&PC)*	Equipments and Records *P(E&R)*	Management quality *P(MQ)*	Effective *P(RM |HR,CM&PC ,E&R,MQ)*	Ineffective *P(RM |HR, CM&PC ,E&R,MQ)*
1	0.18 Sufficient	0.58 Reliable	0.50 Effective	0.50 High	1	0
2	0.18 Sufficient	0.58 Reliable	0.50 Effective	0.50 Low	0.85	0.15

Table 3.8: Resources management deduced marginal probabilities

Possible combination	Effective $P(RM \mid HR, CM\&PC, E\&R, MQ) \times P(HR) \times P(CM\&PC) \times P(E\&R) \times P(MQ)$	Ineffective $P(RM \mid HR, CM\&PC, E\&R, MQ) P(HR) \times P(CM\&PC) \times P(E\&R) \times P(MQ)$
1	0.0261	0
2	0.0222	0.0039
....	....	....
Σ	0.432 (Effective)	0.568 (Ineffective)

Table 3.9: Adequacy of organisations node assigned CPT

Combination	Functional variables marginal probabilities			Adequacy of Organisations CPT			
	Operational processes $P(OP)$	Organisational culture $P(OC)$	Resources management $P(RM)$	Very efficient $P(AO \mid OP, OC, RM)$	Efficient $P(AO \mid OP, OC, RM)$	Inefficient $P(AO \mid OP, OC, RM)$	Deficient $P(AO \mid OP, OC, RM)$
1	0.274 Effective	0.30 Acquired	0.432 Effective	1	0	0	0
2	0.274 Effective	0.30 Acquired	0.568 Ineffective	0.1	0.9	0	0

Table 3.10: Adequacy of organisations deduced marginal probabilities

Combination	Very efficient $P(AO \mid OP, OC, RM)$ $P(OP) \times P(OC) \times P(RM)$	Efficient $P(AO \mid OP, OC, RM)$ $P(OP) \times P(OC) \times P(RM)$	Inefficient $P(AO \mid OP, OC, RM)$ $P(OP) \times P(OC) \times P(RM)$	Deficient $P(AO \mid OP, OC, RM)$ $P(OP) \times P(OC) \times P(RM)$
1	0.0355	0	0	0
2	0.0047	0.0420	0	0
....	....	....	....	.....
Σ	0.0633	0.2090	0.3820	0.3450

The manual calculation of the revised marginal probabilities of the end point effect node' adequacy of organisation shows how the Bayes theorem is used in a BN to infer a new belief that would explain the assessment associated uncertainty. The uncertainty of the assessment could be explained further as more information is obtained about the route cause nods that are left with their generic prior probabilities.

3.4.5. BN model sensitivity analysis

The compiled BN model of adequacy of organisation shown in Fig. 3.7 shows the belief bars for each node. These belief bars represent the initial beliefs (presented as probabilities) about the determinants of adequacy of organisation marginal probabilities as evidenced by the data used. In this respect, the performance of the BN model is evaluated in two ways. The first involved calculating the sensitivity of the adequacy of organisation node to findings in all the other nodes of the BN, to identify nodes that have the most influence on adequacy of organisation and the causal relationships of importance using the mutual information values (Korb and Nicholson, 2004). The mutual information, is symmetric between two nodes, and is a measure of the magnitude with which a finding at one node is expected to alter the beliefs at another node (Pearl, 1988; Korb and Nicholson, 2004; Pollino et al., 2006). Netica software is used to display a typical output of sensitivity analysis shown in a bar chart in Figure 3.8 and Table 3.11 (Pollino et al., 2006), in which nodes are ranked according to the degree of influence of their findings on the outcomes of the adequacy of organisation node calculated as a measure of mutual information (entropy reduction). Operational processes PIF is the most influential factor causing the largest entropy reduction of 25.9% in adequacy of organisation reliability. Resources management and organisational culture variables are also showing a strong conclusive influence on adequacy of organisation reliability with 15.2 % and 11.5 % entropy reduction percentage values respectively. These are followed by organisational structure, management quality and norm with 6.35 %, 6.08 % and 5.01 % entropy reduction percentage values respectively. The remaining nodes entropy reduction can be read from Figure 3.8 and Table 3.11 that are showing the knowledge node entropy reduction with the least influential percentage value of 0.0645 %. Nodes mutual information calculation is based on the influence of the new entered observations of the leaf nodes on the prior probabilities of the dependent nodes in the compiled model. The new beliefs that are shown in Figure 3.7 indicate the change of the adequacy of organisation marginal probabilities. The changes reveal the high sensitivity of model measured by the increased inefficient (38.2 %) and deficient (34.5%) stats probability, and reduced efficient (20.9 %) and very efficient (6.33 %) stats probability.

The second way of model performance evaluation involved the root cause nodes of the highest and the lowest mutual information being altered individually and subsequently both together over a defined probability space and changes in the adequacy of organisation are observed. This also intuitively reflects the sensitivity behaviour of every intermediate root cause node of the model.

Model sensitivity to findings is developed in scenarios that are graphically represented in Figures 3.9, 3.10, 3.11 and 3.12. These figures show the patterns of model sensitivity in linear relations; depicting the outcome of the model sensitivity to findings concurs with the assigned observations of both "knowledge" and "management commitments" as specified in each case. Linear relations-derived mathematical characteristics are provided in each figure's associated table. The best fit values (data) define the extent and the direction of model inference, represented in linear relations intersection with the graph axes, as well linear relations slope indicates the rate of change of model outputs in respect of input observations, which can be used to investigate dependent nodes, assigned CPTs. The coefficient of determination (r^2) describes how well the linear relation approximates to the assigned data. It gives the proportion of the variance (fluctuation) of model output beliefs that are predictable from the input observations. It is a measure that allows users to determine how certain they can be in making predictions from a certain model/graph.

Table 3.11: Sensitivity to findings of adequacy of organisation node due to the finding at all nodes, expressed in terms of mutual information/reduction in entropy of the target node belief distribution, due to findings at the varying nodes.

Node	Degree of mutual information/entropy reduction	
Adequacy of organisation	1.78414	100%
Operational processes	0.46246	25.9 %
Resources management	0.27074	15.2 %
Organisational culture	0.19956	11.2 %
Organisational structure	0.11325	6.35 %
Management quality	0.10844	6.08 %
Norm	0.08936	5.01 %
Safety culture	0.08936	5.01 %
Safety management system	0.07458	4.18 %
Management commitments	0.05391	3.02 %
Condition monitoring &Performance control	0.04016	2.25 %
Standards	0.02591	1.45 %
Crew involvement	0.01893	1.06 %
Human resources	0.01388	0.778 %
Equipments and records	0.00974	0.546 %
Controls	0.00925	0.519 %
Policies	0.00925	0.519 %
Availability	0.00525	0.294 %
Equipment & records availability	0.00350	0.196 %
Contingency procedures	0.00300	0.168 %
Operational procedure	0.00294	0.165 %
Communication	0.00281	0.157 %
Trust	0.00241	0.135 %
Proactive control measures	0.00231	0.129 %
Reactive control measures	0.00231	0.129 %
Maintenance procedure	0.00175	0.0979 %
Quality	0.00155	0.0871 %
Skill	0.00148	0.0831 %
Strategy and objectives	0.00141	0.0789 %
Motivation	0.00134	0.0752 %
Knowledge	0.00115	0.0645 %

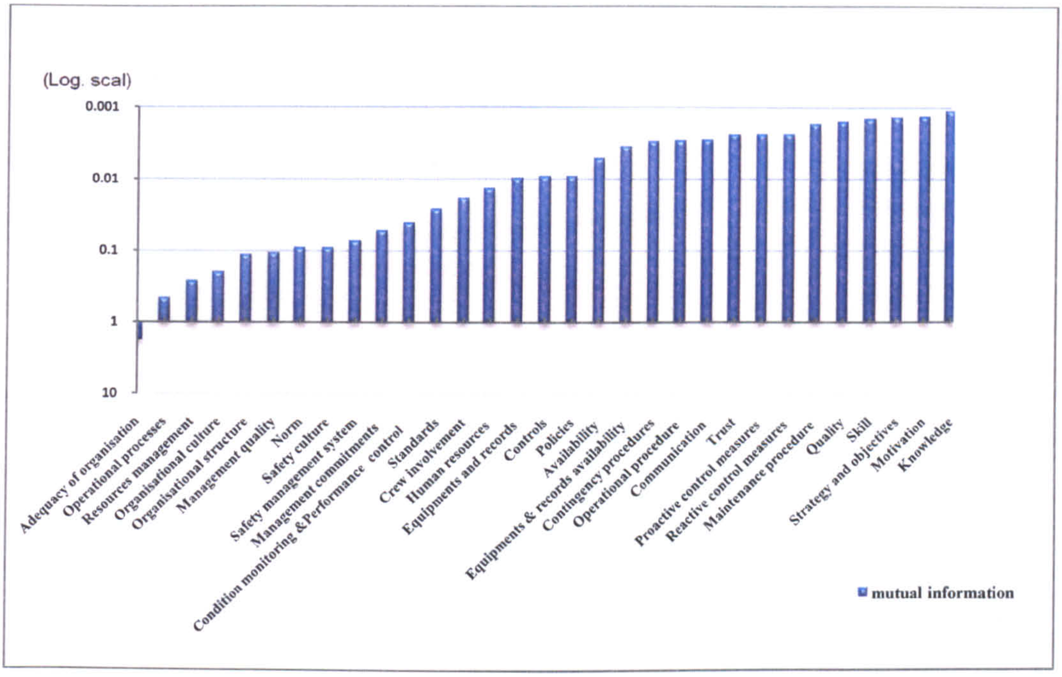
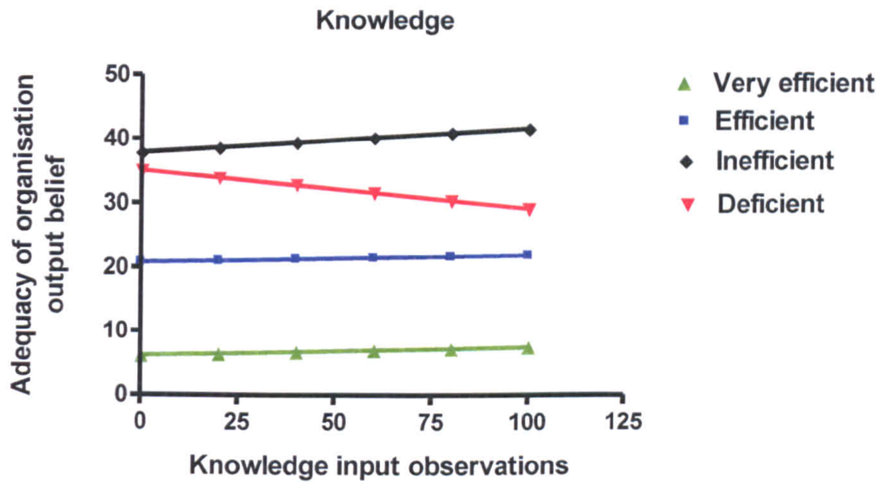


Figure 3.8: Sensitivity to findings of adequacy of organisation node due to the finding at all nodes

3.4.6. Sensitivity to parameter

It can be extremely time-consuming to examine a complex BN's sensitivity to parameter using this type of analysis. Coupe and Gaag (2002) seek to address this limitation by identifying a ''sensitivity set'' of variables, which are defined as being the most influential in BNs. Sensitivity to parameter is done by calculating the output posterior probability of a query node by systematically changing the input parameters of the sensitive set of variables. It is these parameters that are most influential in calculating query node posterior probabilities and it is these parameters on which quantification efforts should be focussed (Coupe et al., 1999). If the graphed sensitivity function does not behave as an expert expects, e.g., its slope rate, and direction, or range of sensitivity is unexpected, this may indicate errors in the network structure or CPTs. For example, Figure 3.13 shows the graphed sensitivity function, depicting its slope rate, direction and ranges, due to model input observation at node "operational processes", which has the highest mutual information with the query node "adequacy of organisation". Such a result is in line with the model objective. Sensitivity to parameters reflects how sensitive the end point node is to the changes of parameter i.e. CPT of the selected node. Such test can be used to debug nodes assigned CPTs in a way that should reflect the real world problem assessment. It is a frequent task intended to tune model assessment with a minimum error rate of the tested cases.

Figure 3.9: Sensitivity results



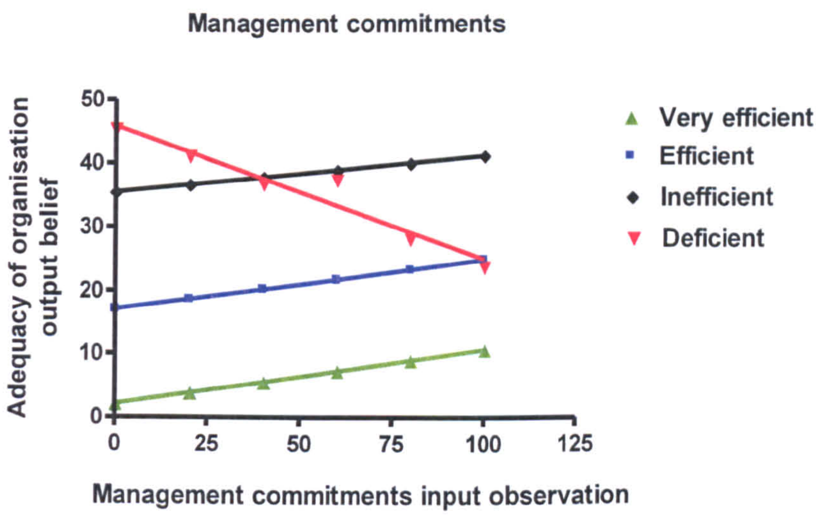
	Very efficient	Efficient	Inefficient	Deficient
Best-fit values				
Slope	0.01269 ± 0.00003869	0.0100 ± 0.000000008324	0.03729 ± 0.0003499	-0.06014 ± 0.0005408
Y-intercept	6.199 ± 0.002343	20.80 ± 0.0000005041	37.89 ± 0.02119	35.12 ± 0.03275
X-intercept	-488.7	-2080	-1016	584.0
1/slope	78.83	100.0	26.82	-16.63
95% Confidence Intervals				
Slope	0.01258 to 0.01279	Perfect line	0.03631 to 0.03826	-0.06164 to -0.05864
Y-intercept when X=0.0	6.193 to 6.206	Perfect line	37.83 to 37.94	35.03 to 35.21
X-intercept when Y=0.0	-493.3 to -484.1	Perfect line	-1045 to -989.0	571.0 to 597.7
Goodness of Fit				
r^2	1.000	1.000	0.9996	0.9997

Sensitivity results due to knowledge node input observations on "Good" state, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states. The provided table states the derived mathematical characteristics of sensitivity results linear relation.

Table 3.12: Sensitivity results due to knowledge node input observations on "Good" state, and adequacy of organisation" node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states.

Knowledge (Good %)	Very efficient	Efficient	Inefficient	Deficient
0	6.20	20.8	37.9	35.1
20	6.45	21.0	38.6	33.9
40	6.71	21.2	39.4	32.8
60	6.96	21.4	40.1	31.5
80	7.21	21.6	40.9	30.3
100	7.47	21.8	41.6	29.1

Figure 3.10: Sensitivity results



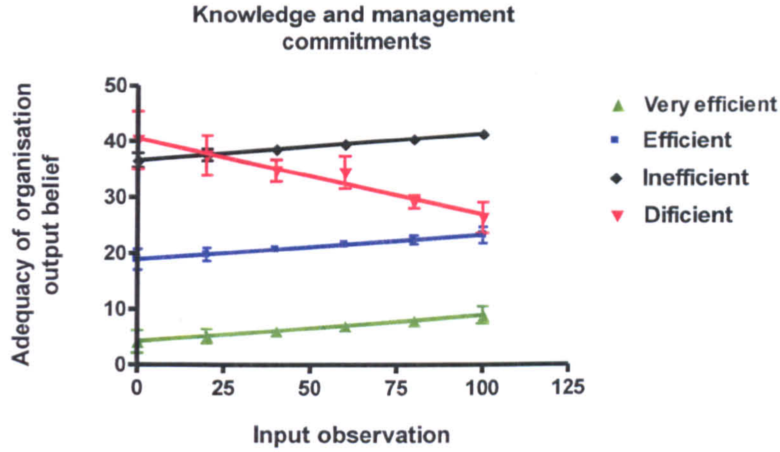
	Very efficient	Efficient	Inefficient	Deficient
Best-fit values				
Slope	0.08403 ± 0.0002757	0.07614 ± 0.0003869	0.05686 ± 0.0003869	-0.2110 ± 0.02681
Y-intercept	2.122 ± 0.01669	17.11 ± 0.02343	35.39 ± 0.02343	45.90 ± 1.624
X-intercept	-25.25	-224.7	-622.4	217.5
1/slope	11.90	13.13	17.59	-4.739
95% Confidence Intervals				
Slope	0.08326 to 0.08479	0.07507 to 0.07722	0.05578 to 0.05793	-0.2854 to -0.1366
Y-intercept when X=0.0	2.076 to 2.168	17.04 to 17.17	35.33 to 35.46	41.39 to 50.41
X-intercept when Y=0.0	-26.01 to -24.51	-228.7 to -220.9	-635.4 to -610.0	172.6 to 310.1
Goodness of Fit				
r^2	1.000	0.9999	0.9998	0.9393

Sensitivity results due to management commitments node input observations on "High" state, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states. The provided table states the derived mathematical characteristics of sensitivity results linear relation.

Table 3.13: Sensitivity results due to management commitments node input observations on "High" state, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states.

Management commitments (High %)	Very efficient	Efficient	Inefficient	Deficient
0	2.11	17.1	35.4	45.4
20	3.8	18.6	36.5	41.1
40	5.48	20.2	37.7	36.7
60	7.20	21.7	38.8	37.3
80	8.85	23.2	39.9	28.0
100	10.5	24.7	41.1	23.6

Figure 3.11: Sensitivity results aggregation



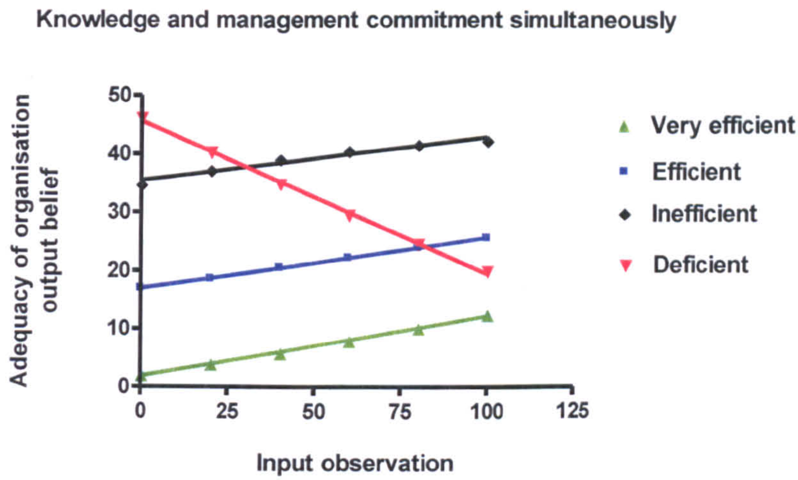
	Very efficint	Efficient	Inefficient	Dificient
Best-fit values				
Slope	0.04836 ± 0.01153	0.04307 ± 0.01061	0.04707 ± 0.007676	-0.1356 ± 0.03061
Y-intercept	4.160 ± 0.6979	18.95 ± 0.6424	36.64 ± 0.4648	40.51 ± 1.853
X-intercept	-86.04	-440.1	-778.4	298.8
1/slope	20.68	23.22	21.24	-7.376
95% Confidence Intervals				
Slope	0.02268 to 0.07404	0.01943 to 0.06671	0.02997 to 0.06417	-0.2038 to -0.06738
Y-intercept when X=0.0	2.606 to 5.715	17.52 to 20.39	35.60 to 37.67	36.38 to 44.64
X-intercept when Y=0.0	-244.5 to -34.40	-1037 to -265.1	-1252 to -557.1	213.2 to 553.0
Goodness of Fit				
r^2	0.6377	0.6224	0.7899	0.6624

Sensitivity results aggregation due to knowledge and management commitments nodes input observations on "Good" and "High" states, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient", and "Deficient" states. The provided table states the derived mathematical characteristics of sensitivity results linear relation.

Table 3.14: Sensitivity results due to knowledge and management commitments nodes input observations on "Good" and "High" state, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states.

Knowledge[1] (Good %) and Management commitments[2] (High %)	Very efficient		Efficient		Inefficient		Deficient	
	1	2	1	2	1	2	1	2
0	6.20	2.11	20.8	17.1	37.9	35.4	35.1	45.4
20	6.45	3.8	21.0	18.6	38.6	36.5	33.9	41.1
40	6.71	5.48	21.2	20.2	39.4	37.7	32.8	36.7
60	6.96	7.20	21.4	21.7	40.1	38.8	31.5	37.3
80	7.21	8.85	21.6	23.2	40.9	39.9	30.3	28.0
100	7.47	10.5	21.8	24.7	41.6	41.1	29.1	23.6

Figure 3.12: Sensitivity results aggregation



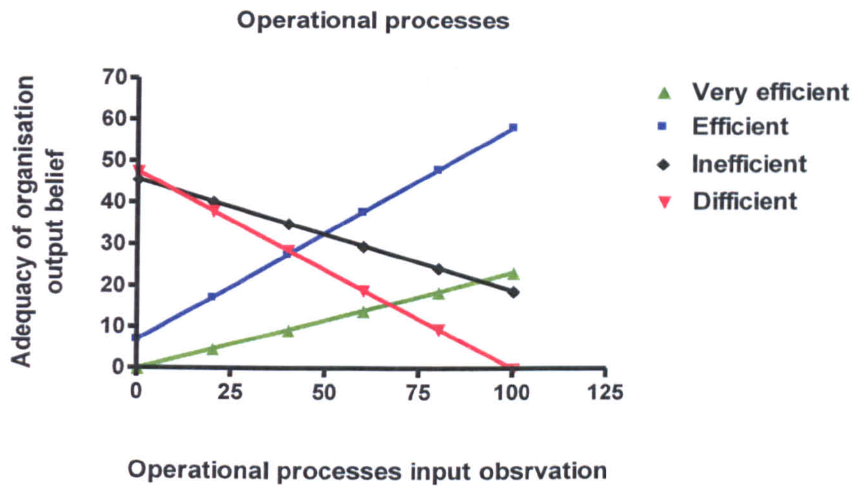
	Very efficint	Efficient	Inefficient	Deficient
Best-fit values				
Slope	0.1034 ± 0.002331	0.08543 ± 0.0006999	0.07443 ± 0.007648	-0.2631 ± 0.005556
Y-intercept	1.856 ± 0.1411	17.03 ± 0.04238	35.43 ± 0.4631	45.69 ± 0.3364
X-intercept	-17.95	-199.3	-476.0	173.6
1/slope	9.673	11.71	13.44	-3.800
95% Confidence Intervals				
Slope	0.09692 to 0.1099	0.08349 to 0.08737	0.05320 to 0.09566	-0.2786 to -0.2477
Y-intercept when X=0.0	1.464 to 2.248	16.91 to 17.15	34.14 to 36.71	44.76 to 46.62
X-intercept when Y=0.0	-22.99 to -13.44	-205.2 to -193.7	-686.2 to -359.0	166.5 to 181.6
Goodness of Fit				
r^2	0.9980	0.9997	0.9595	0.9982

Sensitivity results due to knowledge and management commitments nodes simultaneous input observations on "Good" and "High" states, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient", and "Deficient" states. The provided table states the derived mathematical characteristics of sensitivity results linear relation.

Table 3.15: Sensitivity results due to knowledge and management commitments nodes simultaneous input observations on "Good" and "High" states, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states.

Knowledge and Management commitments (Good and High %)	Very efficient	Efficient	Inefficient	Deficient
0	2.07	17.00	34.7	46.2
20	3.88	18.7	37.1	40.3
40	5.82	20.5	39.0	34.8
60	7.88	22.2	40.4	29.5
80	10.1	23.9	41.5	24.5
100	12.4	25.5	42.2	19.9

Figure 3.13: Sensitivity results aggregation



	Very efficint	Efficient	Inefficient	Difficient
Best-fit values				
Slope	0.2311 ± 0.0002119	0.5118 ± 0.0003977	-0.2670 ± 0.0004364	-0.4750 ± 0.00005017
Y-intercept	0.002857 ± 0.01283	6.896 ± 0.02408	45.53 ± 0.02643	47.50 ± 0.003038
X-intercept	-0.01236	-13.47	170.5	100.0
1/slope	4.326	1.954	-3.745	-2.105
95% Confidence Intervals				
Slope	0.2306 to 0.2317	0.5107 to 0.5129	-0.2682 to -0.2658	-0.4751 to -0.4748
Y-intercept when X=0.0	-0.03276 to 0.03847	6.829 to 6.963	45.46 to 45.61	47.49 to 47.51
X-intercept when Y=0.0	-0.1668 to 0.1414	-13.63 to -13.32	170.0 to 171.1	99.99 to 100.0
Goodness of Fit				
r^2	1.000	1.000	1.000	1.000

Sensitivity results due to operational processes input observations on "Effective" state, and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states. The provided table states the derived mathematical characteristics of sensitivity results linear relation.

Table 3.16: Sensitivity results due to operational processes input observations on "Effective" state and adequacy of organisation node output belief on "Very efficient", "Efficient", "Inefficient" and "Deficient" states.

Operational processes (Effective %)	Very efficient	Efficient	Inefficient	Deficient
0	0.0	6.91	45.5	47.5
20	4.62	17.1	40.2	38.0
40	9.24	27.4	34.9	28.5
60	13.9	37.6	29.5	19.0
80	18.5	47.8	24.2	9.51
100	23.1	58.1	18.8	0.0

3.5. Conclusion

The adequacy of organisation is one of CREAM's nine CPCs. The qualitative definitions of its expanded PIFs and sub PIFs and their cause-effect relationships enabled in this work to structure the hierarchical process needed to develop the qualitative idea of their inevitable effect. As a result, an advanced BN model for proactive assessment of the marginal probability of adequacy of organisation effect levels is developed.

BN is an effective tool helping to model the adequacy of organisation knowledge and associated uncertainty, which may arise in reality due to a variety of causes, for instance, imprecision, complexity and ignorance or volatility of domain knowledge. The established BN model can be used as a tool for identifying and expressing uncertainty; hence, it is also a means for potential reduction of uncertainty. The uncertainty of adequacy of organisation can be identified by including more specific information in the analysis. This could be provided in terms of PIF and PIFs information uncertainty statements and in terms of the model structure itself. BN modelling added flexibility to the probabilistic assessment since it allowed the expression of uncertainty in the format found most appropriate to obtain the objectives of the assessment. The adequacy of organisation CPC is a backbone in the assessment of human Contextual Control Model-controlling mode (COCOM-CMs) of CREAM. Its effect on human action reliability will be investigated further in Chapter 4 and 5.

Chapter 4
Quantifying human action probability

Summary

This chapter presents the methodology for establishing a CREAM BN model of human COCOM-CMs' reliability assessment. Fundamentally, human COCOM-CMs are influenced by the dynamic impact of the effect levels of context-CPCs while the person is performing an action. In the methodology, BN characteristics are used to conceptualise CREAM CPCs' dependency. BN qualitative features such as nodes' cause-effect relationship and d-separation properties are also used to introduce the new attributes and their sub-attribute nodes. These enable the use of a BN divorcing concept to limit the number of possible combinations of influencing nodes of the COCOM-CMs one and to simplify the CPTs assignment of BN nodes. Fuzzy rule bases are used to elicit the CPT of the COCOM-CM node in the BN. The introduction of new attributes to the BN will therefore reduce the number of fuzzy rules required. Fuzzy set theory is used to transform the COCOM-CMs' node marginal probabilities to a crisp HFP value. A case study is investigated to validate the established CREAM BN model. BN model sensitivity analysis is also conducted. Finally, the developed technical work achievements are concluded.

4.1. Introduction

Investigation into the state of HRA has revealed that the main perspective on how technological systems should be designed, built, operated, and maintained has changed dramatically since the middle of the last century. However, technological development had reached a level where the capabilities of unaided human action started to become a limiting factor for the performance of the overall system. Consequently, the human factor was taken into account in the design of systems to ensure that the demands of human performance did not exceed his/her natural capabilities. The concern was initially focused on perception capabilities (Fitts, 1951) but was later expanded to cover the higher order human functions, in particular cognition, as represented by the information processing descriptions of decision making and problem solving. Furthermore, the need to consider the development of the human factor was also motivated by a growing number of major accidents (Kemeny, 1979; Casey, 1993) and by a changed function of technological systems, both of which made the interaction between humans and machines a main issue (Perrow, 1984; Woods et al., 1994; Hollnagel, 1998a).

The growing complexity of technological systems and the dependency of people's ways of life on their proper functioning have clearly revealed that human actions constitute a major source of vulnerability to the integrity of human-technological systems' interaction. In whatever field they are used, incorrect or erroneous human actions are thus a cause of great concern (Hollnagel, 1998a). This view is valid even if the focus of interest shifts to the area of organisations (Reason, 2002).

Human action and context coupling level was first recognised as part of deferent technological systems operational control. Experience has shown that it is equally important in relation to their design and maintenance. Good examples are nuclear power plants, gas and oil production technology, aviation, maritime industry, industrial production processes (see Figure 4.1) and modern hospitals' intensive care units. These systems have often been the focus of considerable concern because of their potential role in any severe accidents that may arise.

Regardless of the domain, somewhere in the range 60-96% of all systems failure seems to be attributable to erroneous human actions (Hollnagel, 1993; Chengi, 1996; Hollnagel, 1998a; Rothblum, 2000; Clifford, 2004; Hetherington et al., 2006). However, for natural reasons, maritime operations have been the lowest widespread user of HRA PSA/PRA in comparison to the above stated technological systems. For example, Figure 4.2 shows the extent to which these assessment tools have played a significant role in controlling the risk of erroneous human action failure to a defined acceptable level (Everdij and Blom, 2008).

Figure 4.1: Human-technology interaction and degree of coupling in deferent contexts (Perrow, 1984).

Figure 4.2: HRA/PSA domains of application (Everdij and Blom, 2008).

Nevertheless, the growing number of cases where erroneous human actions actually are the cause of accidents has been attributed to a combination of human, technological, and organisational factors (see Figure 4.3) (Hollnagel, 1998a, b; Kontogiannis, 1999; Hollnagel, 2002; Kim and Jung, 2002; Hollnagel, 2004; Hollnagel, 2008a, b). In this context the human has become more prone to incorrect actions and erroneous human actions. As a result, the complex changes in system constituents leading to a tighter degree of couplings between context and human action have increased performance demands, thus reducing the operational safety margins. Therefore, it is vital to improve the understanding of the multiplicity of factors that are at play. This requires a conceptual framework that adequately accounts for how actions are shaped by the context in which they take place. This effectively enables the identification of the most important conditions associated with the causes of incorrect actions (Hollnagel, 1998a; Kontogiannis, 1999; Kim and Jung, 2002; Hollnagel, 2002; Hollnagel, 2004).

Figure 4.3: Causes of accidents have been attributed in different ways over the years (Hollnagel, 2002; Hollnagel, 2004)

Deterministic analysis of systems failure in various types of process, known as sufficient detail-working conditions, requires an examination of the links between every possible cause and every possible consequence of component failure. This analysis may practically be difficult to perform, due to incomplete anticipation of the specified links. A common solution is to conduct a probabilistic analysis, with the objectives of reducing the probability that an adverse event occurs and minimising the consequences of uncontrolled developments in accident conditions, such as the potential for injuries and loss of human life, or negative impact on the environment and to the system itself. Therefore, theories, models, and methods that can be applied to solve these problems are in high demand (Hollnagel, 1998a).

4.2. Literature review

Reliability models can be developed for technological systems with relative ease, because they are designed with a specific known set of functions and structure. However, it is extremely difficult to do so for humans, who evolved naturally, as it is difficult to know what basis human actions have in internal, mental or cognitive functions. The second generation HRA methods advocate human performance characteristics in a given context and can be observed and used as a point of reference. Consequently, human reliability modelling cannot be deduced from fundamental psychological principles but must rather start by recognising the inherent variability of human performance in a context and come to terms with the situations where this variability leads to failures rather than successes. Nevertheless, one of the undisputed assumptions in all HRA approaches is that the quality of human performance depends on the conditions under which the tasks or activities are carried out. These conditions have generally been referred to as PSFs. If the reliability model is to serve as the basis for making proactive assessment about likely performance, it must necessarily provide a set of principles for how the PSFs are to be taken into account (Hollnagel, 1998a; Forester, 2007; Reer, 2008 Part1&2; Bell and Holyroyd, 2009).

HRA has been carried out within the shell of PSA to meet mandatory safety goal regulations focused on the plant-specific characteristic. This shell is not capable of modelling characteristics beyond the specified building and operational concept and thus it does not support any larger perspective where humans are involved in the design and construction, operation and maintenance of a system, and in management (Hollnagel and Wreathall, 1996). Human reliability can obviously play a role in every phase of a system's life cycle, although the outcome of action failures in many cases may not be immediately visible. Therefore, it is necessary to develop a comprehensive understanding of human action in context. As it is imperative to account for reliability in relation to cognition rather than manual action, it may to some extent be reasonable to describe the likelihood that a manual operation will succeed or fail in the same way that a first generation HRA does. In this respect, the second generation HRA methods such as CREAM are supposed to provide the corresponding probability value (Hollnagel, 1998a; Kontogiannis, 1999; Hollnagel, 2005).

4.2.1. The introduction of CREAM

The term cognition of CREAM actually means with the full complexity of the human mind during an action in the context of human, organisational and technological factors. Therefore, any attempt to understand human performance at work must include the role of human cognition under the impact of context. As a result, cognition, context, and action (competence) control cannot be separated (Hollnagel, 1993; Hollnagel, 1998a; Hollnagel, 2005). Since erroneous human actions usually develop due to causes and consequences going wrong, inevitably they involve a degree of cognition. In this respect, CREAM accounts for cognitive reliability importance by indicating the upper and lower bounds of the variability of human performance (Hollnagel, 1998a; Kontogiannis, 1999; Hollnagel, 2005).

The primary purpose of CREAM is to offer a practical bidirectional approach to both performance analysis and assessment. In order to be used properly it is necessary to supplement it with specific information related to its application domain, e.g., values for specific performance parameters that define operational process context knowledge (Hollnagel, 1998a; Kontogiannis, 1999; Adhikari et al., 2009; Bell and Holyroyd, 2009). This will enable an analyst to achieve the following (Adhikari et al., 2009; Hänninen, 2008; Bell and Holyroyd, 2009):

1. Identify those parts of the work as tasks or actions that require or depend on human cognition and therefore may be affected by variations in cognitive reliability.
2. Determine the conditions under which the reliability of cognition may be reduced and where, therefore, these tasks or actions may constitute a source of risk.
3. Provide an appraisal of the consequences of human performance on system safety that can be used in a PRA/PSA.
4. Develop and specify modifications that improve these conditions, hence serve to increase the reliability of cognition and reduce the risk.

Steps 1 - 3 are the core of CREAM. Step 4 is developed in this study to serve the purpose of ensuring that the proper conclusions are drawn from the analysis, and that the necessary changes to a targeted system scenario are correctly specified.

4.2.1.1. Model fundamentals

CREAM application essentially acknowledges that any description of human actions must be recognised to occur in a context, and that the model that is used as a basis for describing human actions is capable of accounting for how the context influences these actions. In this respect the CREAM model is able to account adequately for how context and actions are coupled and mutually dependent (Hollnagel, 1998a; Gore, 2002; Hollnagel, 2005).

While human competence describes what a person is capable of doing, human control describes how the competence is realised over a situation's context. Therefore, if there is better control of the actions, then it is less likely that any given action will fail. Consequently, a higher degree of control means that the person has a better chance of detecting incorrectly performed actions (Hollnagel, 1998a). However, the fundamental principle of cognitive system engineering (see Figure 4.4), which advocates that human action is intentional as well as reactive, is reflected as an outcome of a controlled use of competence adapted to a requirement of a situation, rather than a result of predetermined sequences of responses to events.

Competence can be defined in a relatively small range of cognitive functions that appear, to a greater or lesser extent, in most contemporary attempts to model the essential characteristics of human cognition. In addition, competence includes a person's skills and knowledge that may have been compiled into familiar procedures, and the person's response patterns. As a result, cognition should be described as a controlled use of the available competence (skills, procedures and knowledge) and resources. Yet, the human control mode can be described by referring to a continuum, going from a situation where a human has little or no control over events to conditions where events are under complete control, and by emphasising characteristic modes of control along the continuum. Hollnagel (1993) suggested, as a minimum, the subsequent four control modes: scrambled control, opportunistic control, tactical control, and strategic control. This leads to the Contextual Control Model (COCOM) (see Figure 4.5). The control modes are important. First, they provide a way to include the influence of external conditions in performance assessment, which differs from the traditional HRA PSFs. Second, they open the possibility of linking the classification scheme and the method with semi-dynamic models of cognition in performance analysis. These are of particular interest for attempts to base HRA more explicitly on models of cognition (Hollnagel, 1993; Woods et al., 1994; Hollnagel, 1998a; Hollnagel, 2005).

Figure 4.4: The principles of cognitive systems engineering (Hollnagel, 1998a; Woods et al., 1994)

Figure 4.5: COCOM of cognition adapted from Hollnagel (1998a)

4.2.1.2. Four control modes

Control is necessary to organise an action within a person's time horizon. Practically, effective control is an ability to plan future actions. Operator level of control is influenced by contexts as it is experienced, by operator cognition goals (Bainbridge, 1991), by knowledge or experience of dependencies between action preconditions; and by expectations about how a situation is going to develop, in particular about which resources are and will be available to an operator for use. In COCOM a distinction is made among four characteristic control modes (see Figures 4.6 and 4.7) (Hollnagel, 1993; Woods et al., 1994; Hollnagel, 1998a; Hollnagel, 1998b; Gore, 2002; Hänninen, 2008; Bell and Holyroyd, 2009).

Figure 4.6: Representation of COCOM-CMs (Gore, 2002)

Figure 4.7: Proposed relation between control mode and reliability (Hollnagel, 1998a)

The four control modes of an operator, which may occur during performance of an action, are defined as follows (Hollnagel, 1998a):

- **Scrambled control**: the choice of the forthcoming action is unpredictable. The situation in question may be portraying rapid alterations in unexpected ways, thus eliminating the operator's ability or opportunity to make deductions about the next action required.

- **Opportunistic control**: the next action is determined by superficial characteristics of the situation, possibly through habit or similarity matching. The situation is characterised by lack of planning, and this may possibly be due to the lack of available time (De Keyser, et al., 1988).

- **Tactical control**: performance typically follows planned procedures while some *ad hoc* deviations are still possible.

- **Strategic control**: plentiful time is available to consider actions to be taken in the light of wider objectives to be fulfilled and within the given context.

A particular control mode determines the level of reliability that can be expected in a specific setting and this in turn is determined by the collective characteristics of the relevant CPCs.

4.2.1.3. Basic principles of the classification scheme

The classification scheme obviously contains description of most, if not all, possible manifestations of erroneous actions as well as the majority of possible causes. Clearly, the classification scheme on one hand must be detailed enough to prevent valuable information from being lost, and on the other hand sufficiently simple to make the assignment of events to categories manageable. This optimum level of detail cannot be defined analytically but must be based on practical experience. Therefore, clear principles are given in CREAM for how the classification scheme can be modified, either making it simpler or more detailed (Hollnagel, 1998a; Adhikari et al., 2009; Hänninen, 2008 Holyroyd, 2009).

CREAM' classification scheme for human performance analysis clearly separates genotypes (causes) and phenotypes (manifestations), and furthermore proposes a non-hierarchical organisation of categories, as they are linked by means of the sub-categories called antecedents and consequents (Hollnagel, 1998a). A more detailed elaboration on CREAM' classification scheme will be provided in Chapter 6.

4.2.1.4. Context evaluation, CPCs' level descriptors and their specific effects on performance conditions

CREAM context CPCs are limited in number and dimensions (effect levels) for practical reasons (see Table 4.1). CPCs are intended to have a minimum degree of overlap, although they are not independent of each other. Table 4.1 shows the basic qualitative descriptors that are suggested for each CPC.

Context CPCs' evaluation descriptors/effect levels have typical values they can take; and it is necessary to relate these values to the potential effect on performance reliability. This can be done using the general principle that advantageous performance conditions may improve reliability, and then the operators are expected to fail less often in their tasks, whereas disadvantageous conditions are likely to reduce reliability and then operators will fail more often. However, the CPCs' descriptors are directly amenable to such an assignment in terms of their semantic contents, and their results are shown in Table 4.2. The middle region corresponds to the category of no significant effect. This means that it is impossible to predict whether the effect will be positive or negative, and furthermore that the effect in general will be relatively small (Hollnagel, 1998a; Adhikari et al., 2009; Hänninen, 2008; Holyroyd, 2009).

Table 4.1: Context-CPC evaluation and effect level descriptors (Hollnagel, 1998a)

Table 4.2: CPCs' level descriptors and their expected effect on performance reliability (Hollnagel, 1998a)

4.2.1.5. Dependency between CPCs

To determine the effects of CPCs on performance it is necessary to describe the dependency between CPCs. In other words, it is necessary to develop a model that describes how the CPCs affect each other, subsequently describing how they affect performance (Hollnagel, 1998a; Kim et al., 2006). However, by referring to the CPCs' evaluation and level descriptors stated in Table 4.1 and the general understanding of human performance, rather than to any specific domain or type of situation, the following is an illustration of what this might produce (Hollnagel, 1998a).

The dependencies can be summarised as shown in Table 4.3 and also shown by means of a diagram, in Figure 4.8, where they are shown by means of arrows, indicating that each CPC influences another. Black arrows denote a direct influence (increase-increase, decrease-decrease) while light gray arrows denote an inverse influence (increase-decrease, decrease-increase). For instance, adequacy of organisation has an influence on working conditions, adequacy of training and experience, availability of procedures/plans, and adequacy of MMI. As can be seen from Figure 4.8, adequacy of organisation has a direct influence, and does not depend on any of the other CPCs. Adequacy of organisation is therefore a background variable, which can be assumed to be available during variant conditions. Similarly, the main dependent CPCs with inverse influence are available time and number of simultaneous goals, corresponding to the recognised importance of the level of workload (Hollnagel, 1998a). Both CPCs - number of simultaneous goals and available time - are assumed to depend on the working conditions. If the working conditions improve, then the number of simultaneous goals, i.e., the number of tasks that the operator has to attend to at the same time, is assumed to reduce. Similarly, if the working conditions are improved then the available time is also assumed to improve. Both of these are assumed to be direct influence dependencies.

Hollnagel (1998a) stated that in the case of working conditions and available time, the criterion for changing the primary assigned effect level is that four out of five of the related CPCs are pointing in the same direction (indicating reduced or improved reliability). In the case of the number of simultaneous goals, the criterion is that two out of three related CPCs are pointing in the same direction. In the case of crew collaboration quality, the criterion is that both related CPCs point in the same direction. These simple rules provide a way of taking the interaction between the CPCs into account, without making unnecessarily complex modelling assumptions and without requiring excessively difficult computations (Hollnagel, 1998a).

Table 4.3: CPCs dependencies (Hollnagel, 1998a)

Figure 4.8: CREAM CPCs' dependency model (Hollnagel, 1998a)

4.2.1.6. CREAM assessment models

CREAM, compared to other second generation methods, takes a very different approach to modelling human reliability. It is provided in basic and extended versions of technique, both of which have in common two primary features: first, an ability to identify the importance of human performance in a given context; and second, a helpful cognitive model-associated framework, usable for both prospective and retrospective analysis. While prospective analysis allows for the likely human errors to be quantified, retrospective analysis identifies the causes of initiating events that have already occurred (Hollnagel, 1998a). Retrospective analysis has been widely researched in literature. Therefore, this study will focus on prospective analysis.

4.2.1.7. CREAM basic method

The basic method is used to assess the overall human performance reliability. Its outcome is a generic estimate of COCOM-CMs' probability for the task as a whole. As a result, this outcome is used in an extended method, to take a closer look at the parts of the task that should be investigated more precisely, to provide a probabilistic estimate.

The first step of the CREAM basic method is to identify the safety task or event scenario to be analysed. An event sequence is then constructed and the CPCs are assessed to describe the effects of the context. Nine CPCs and their evaluation level descriptors are listed in Table 4.1 and 4.2. For each of the CPCs, a set of discrete possible descriptors are defined. For example, the adequacy of organisation descriptors is: *very efficient, efficient, inefficient and deficient*. Also, for each descriptor, the expected effect level on performance reliability is described using an identical set of states: *improved, not significant, significant*. Based on CPCs' dependency effects on performance reliability, a combined CPCs score can be expressed as

CPCs score = (∑reduced, ∑not significant, ∑improved).

In CREAM basic it is assumed that the value of CPCs score ∑not significant will not make a serious difference. In other words, it is the values of ∑reduced and ∑improved that are important. Although this does not reduce the number of values of the combined CPC score, it reduces the components of assessment to two. This suggests that the possible values of the CPC score can be plotted in a Cartesian co-ordinate system. If this is done, the control modes can be defined as regions or areas in the system, as delineated in Figure 4.9.

In COCOM, a HFP is assessed based on the degree of control mode that a person has over a situation. The control mode can be estimated based on the CPCs score and the plot, which originally shows the number of improved reliability CPCs (0...7) on the vertical axis and the number of reduced reliability CPCs (0...9) on the horizontal axis (see Figure 4.9). For example, if the CPCs score is (2, 5) then the control mode is opportunistic. Generic HFP intervals have been assessed for the control modes, and they are also presented in Table 4.4.

The intention of the CREAM basic is to provide a screening technique for the purpose of identifying whether a detailed analysis is required and further studies need to be carried out in an extended CREAM (Kim et al. 2006; Adhikari et al., 2009; Hänninen, 2008).

Table 4.4: COCOM-CMs' features and their corresponding HFP interval (Hollnagel, 1998a)

Figure 4.9: Basic diagram of CREAM for operator COCOM-CMs (Konstandinidou et al., 2006)

4.2.1.8. CREAM extended

The extended method needs to be done in cases where the generic action probability derived from the basic method is unacceptably high; in other words, the uncertainty is unacceptably large. The method consists of the following three steps: (1) to identify the cognitive activities of the tasks performed in order to build a cognitive profile; (2) to identify a most likely CFF for each identified cognitive activity; and (3) to determine the probability for each identified CFF. The method provides a total of 13 generic failure types in cognitive activities of observation, interpretation, planning and execution; and each has a nominal failure probability, as presented in the work by Hollnagel (1998a). Subsequently, the characteristics of nine CPCs are used to adjust the nominal CFP values to get the final error probability. The extended method cannot be used without the basic method generating information (see Figure 4.10) (Hollnagel, 1998a).

Figure 4.10: CREAM basic and extended method framework (Hollnagel, 1998a)

4.3. The proposed methodology

In this technical chapter, a new methodology for application of CREAM in the maritime domain is developed to estimate seafarers' error probability in marine engineering operations. The developed generic methodology incorporates BN characteristics to model CPCs' dependency. CPCs will be coupled according to their direct influences on the newly designated attributes and sub-attributes. CPC coupling will be tailored to match BN characteristics, in terms of conditional independence properties and nodes divorcing concept. As a result, both FRB and Bayesian inference will be used effectively to simplify incorporation of expert judgments in the assignment of the CPT of the COCOM-CMs node and to employ a Bayesian inference mechanism to aggregate all the rules associated with a seafarer's task, to estimate its failure probability. Consequently, the developed framework can be used consistently to model the relationship between the nine CPCs and the four COCOM-CMs in a simple way. The outcomes of this work can also make available an observable assessment tool to realise the instant estimation of human performance reliability for a specific scenario/task. A real case analysis will be described and evaluated with the use of the developed CREAM methodology for the assessment of seafarers' failure probability. Finally, the BN model sensitivity analysis is verified and the interpretation of the model findings is justified to help explain how the model reacted to different sets of evidence. The methodological framework steps are shown in Figure 4.11.

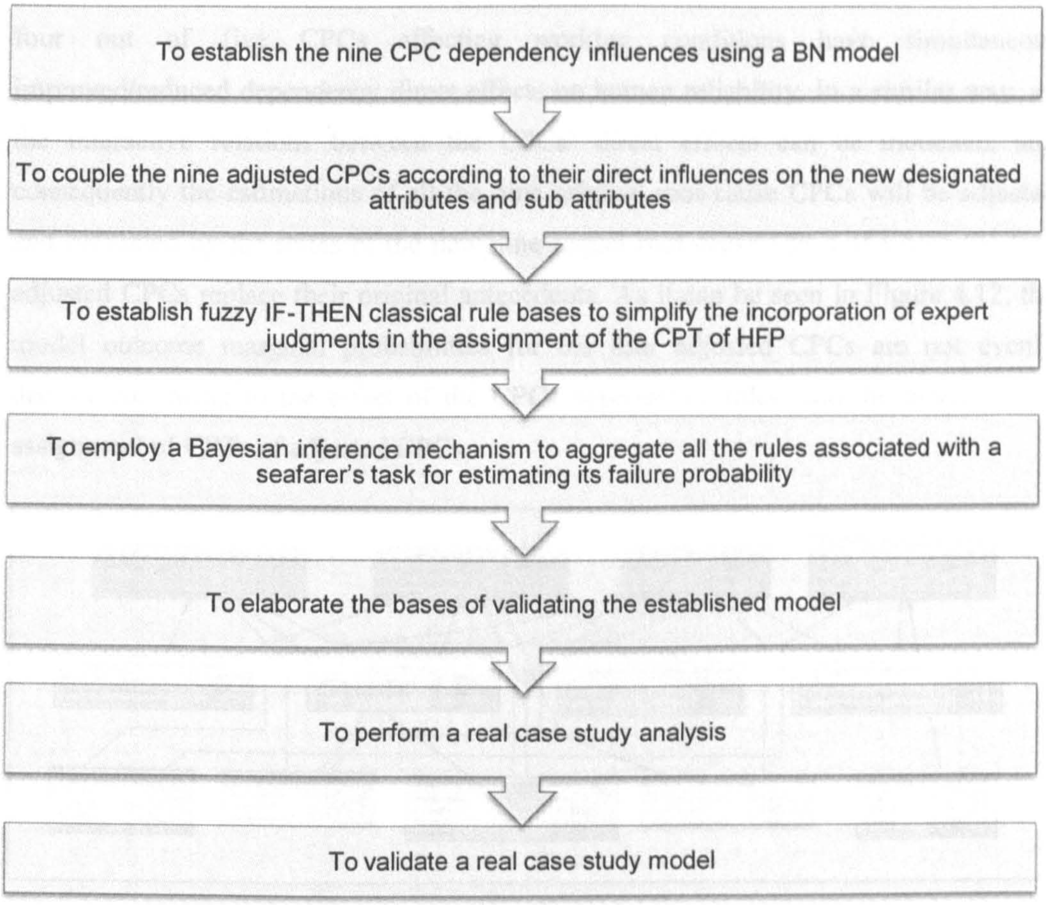


Figure 4.11: Methodological framework

4.3.1. The use of BNs to adjust CPCs' dependency

BN technique is used to model the nine CPCs dependency in a graphical representation, adjusting their direct effects as shown in Figure 4.12, where four newly adjusted CPCs are created to simplify the complex relationships between the nine CPCs. The newly adjusted CPCs are "Adjusted working condition", "Adjusted number of simultaneous goals", "Adjusted available time" and "Adjusted crew collaboration quality". The adjusted CPCs' CPTs are assigned deterministically as per CREAM dependency criteria (See Table 4.5). For instance, the direct effect state of "Adjusted crew collaboration quality" will be automatically updated into the improved/reduced state when "Crew collaboration quality" has no significant effect on human reliability, provided the two CPCs that affect "Crew collaboration quality" have a simultaneous improved/reduced dependency direct effect on human reliability. The direct effect state of "Adjusted working condition" will be automatically updated into the improved/reduced status when "Working condition" has no significant effect on human reliability, provided that four out of five CPCs affecting working conditions have simultaneous improved/reduced dependency direct effects on human reliability. In a similar way, all the interactive relations between the CPCs' direct effects can be modelled, and consequently the estimations of all the nine original root cause CPCs will be adjusted and presented by the states of the new nine sequel root cause CPCs of which the four adjusted CPCs replace their original antecedents. As it can be seen in Figure 4.12, the model outcome marginal probabilities for the four adjusted CPCs are not evenly distributed, owing to the effect of the CPCs dependency rules, and the deterministic assignment of CPTs of adjusted CPCs.

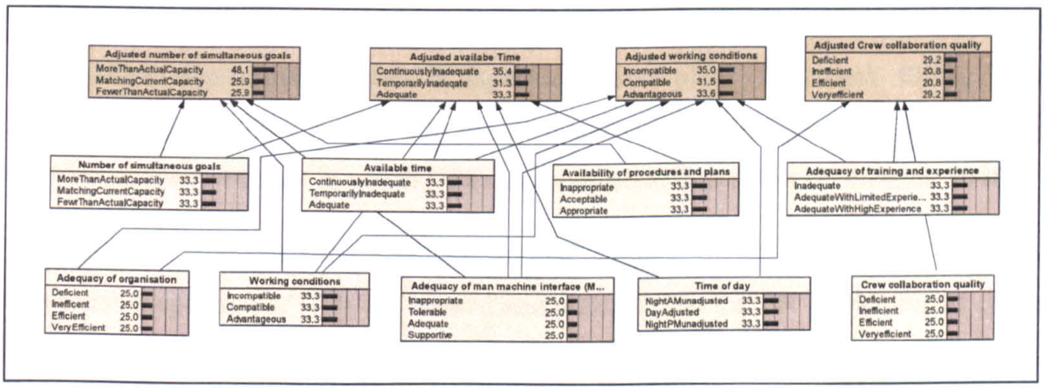


Figure 4.12: BNs for adjusting CREAM nine CPCs dependency direct effect

Table 4.5: Part of the adjusted crew collaboration quality CPT.

Crew collaboration quality	Adequacy of organisation	Adequacy of training and experience	Adjusted crew collaboration quality deterministic probability			
			Deficient	Inefficient	Efficient	Very efficient
Deficient	Deficient	Inadequate	1	0	0	0
Inefficient	Very efficient	Adequate with high experience	0	0	0	1
Efficient	Very efficient	Adequate with high experience	0	0	0	1
Inefficient	Efficient	Inadequate	0	1	0	0
Efficient	Very efficient	Inadequate	0	0	1	0
Very efficient	Deficient	Adequate with limited experience	0	0	0	1
Very efficient	Very efficient	Adequate with high experience	0	0	0	1

4.3.2. Simplifying the assignment of the conditional probability of COCOM-CMs

The assessment of HFP in maritime operations involves the evaluation of CREAM context through the effects level of nine CPCs. By utilising BN characteristics, it is possible to graphically map the influence of the nine CPCs in a convergent connection to infer COCOM-CMs' probability. In this context, each CPC is described by a number of discrete states, including four states for three CPCs, and three states for the remaining six CPCs. Such type of convergent connection will result in 46,656 ($4^3 \times 3^6$) discrete conditional probabilities to be assigned. However, assigning such huge numbers of discrete conditional probabilities subjectively by experts, in the light of a lack of objective data, will be of great difficulty. Therefore, introducing a method that could simplify the task of assigning subjective probabilities will be beneficial and is urgently needed.

Basically, CPCs and human actions are coupled and mutually dependent. The CPCs provide a comprehensive and well structured basis for characterising context conditions under which human performance is expected to take place (Hollnagel, 1998a; Gore, 2002; Hollnagel, 2005). As a result, the derivation of the combined CPCs score must take into account the way in which CPCs are coupled or dependent (Hollnagel, 1998a).

Three newly introduced attributes: "Action load" (A), "Working environment" (W) and "Operator preparedness" (O) are created and presented in the BN model, based on the BN divorcing principle (see Figure 4.13). Basically, divorcing is used to simplify the modelling and to overcome the difficulty of assigning the huge numbers of discrete conditional probabilities subjectively by experts. It is closely related to the bottom-up principle in modelling, often combined with a top-down approach. The bottom-up principle means that one looks at how CPCs combine to define the sub-attributes and attributes that make the BN work (Jensen, 2001). The new attributes are believed to directly influence COCOM-CMs' reliability based on a reasonable qualitative judgment addressed by Marseguerra et al. (2007). Each CPC has a different influence on these attributes, following the lines of reasoning underlying in CPCs' evaluation (Hollnagel, 1998a).

As seen from Figure 4.13, the attribute "Working environments", is influenced by five CPCs. To simplify its CPT assignment, two new sub-attributes, "Adequacy of working culture" and "Adequacy of perception conditions" are introduced. Following the bottom-up modelling principle, the introduction is based on, firstly, when the "Adequacy of organisation" and the "Adjusted crew collaboration quality" CPC are conditionally independent in a convergent connection of the BN shown in Figure 4.13. The "Adequacy of organisation" affects the official structure of "Crew collaboration quality" between crew members, the level of trust, and the general social climate among crew members. These affects will influence the newly introduced sub-attribute "Adequacy of working culture". According to Schein's (1985) theory a culture has two tasks: It maintains internal integration in an organisation collaboration quality and creates ways to meet task demands. Culture is a metaphor for an organisation. As a result, the concept of culture is a tool used to analyse the organisation core task (Reiman and Oedewald, 2007; Reiman, 2007).

Secondly, the introduction of sub-attribute "Adequacy of perception of conditions" is developed based on the causes of "Adequacy of MMI operational support" as information and control options provider, "Adjusted working conditions" as a physical affect that may not always be fully recognised and "Time of the day (circadian rhythm)" related to disruption due to shift work and the changes of time on long vessel routes. The conditional independence properties of these CPCs will affect human external perception of conditions, e.g., observation; as a result, human cognition function, such as interpretation, planning and execution are also affected. In this context, the CPCs' conditional independence concurs with the external perception conditions deemed to be sufficient as a visual input to allow humans to interact with the environment (Shorrock, 2007) in situational awareness (Lockhart et al., 1993; Leveson, 1997; Endsley, 2000).

Attributes and sub-attributes CPTs are assigned reasonably in a uniform distribution, based on the logical order of their defined effect levels, in a way that would result in a **logical distribution of their nodes' marginal probabilities in** a generic BN (see Figure 4.13). Table 4.6 shows the uniform distribution of action load CPT. CPTs of other attributes and sub-attributes are provided in A2.1, A2.2, A2.3, and A2.4.

Table 4.6: Action load CPT distribution

No.	Action load CPT %				
	Adjusted number of simultaneous goals	Adjusted available time	Inappropriate	Acceptable	Appropriate
1	Continuously inadequate	More than actual capacity	100	0	0
2	Continuously inadequate	Matching current capacity	50	50	0
3	Continuously inadequate	Fewer than actual capacity	33.4	33.3	33.3
4	Temporarily inadequate	More than actual capacity	75	25	0
5	Temporarily inadequate	Matching current capacity	25	50	25
6	Temporarily inadequate	Fewer than actual capacity	0	25	75
7	Adequate	More than actual capacity	33.3	33.3	33.4
8	Adequate	Matching current capacity	0	50	50
9	Adequate	Fewer than actual capacity	0	0	100

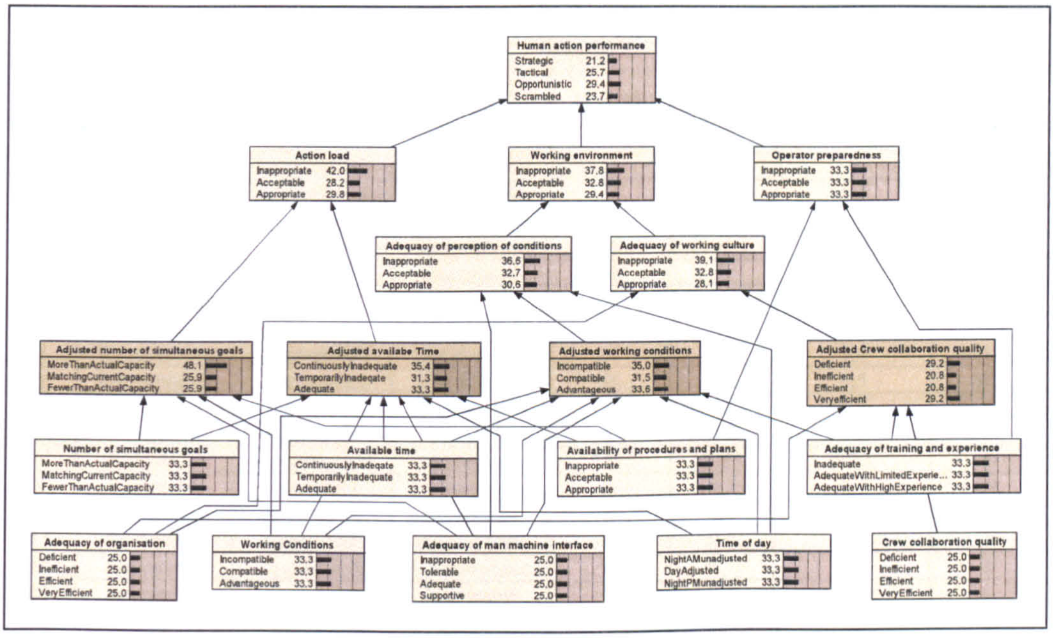


Figure 4.13: CREAM based human performance reliability assessment BNs generic model.

The divorcing concept in a BN has no significant effect on model mathematical inference (Kim et al., 2006), if attributes and sub-attributes CPTs are assigned properly. Finally, the use of the divorcing concept simplifies the assignment of CPTs of the developed CREAM BN model. It also makes it possible to introduce FRB to facilitate experts' subjective elicitation of COCOM-CMs node CPT. The interactive logical relation between the effect levels of the three attributes "Action load", "Working environments" and "Operator preparedness", and the four COCOM-CMs can therefore be established (see Table 4.7).

Table 4.7: The FRB construct for the linguistic variables of the three new attributes (k = 1, 2, 3 descriptor)

Rule No.	Antecedents			Consequence			
	IF	And,	And,	Then			
	Operator Preparedness (L_1^K)	Action Load (L_2^K)	Working Environment (L_3^K)	Strategic (D_1)	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)
1	Inappropriate	Inappropriate	Inappropriate	0	0	0	1
2	Inappropriate	Inappropriate	Acceptable	0	0	0.1	0.9
3	Inappropriate	Inappropriate	Appropriate	0	0	0.2	0.8
4	Inappropriate	Acceptable	Inappropriate	0	0	0.25	0.75
5	Inappropriate	Acceptable	Acceptable	0	0	0.3	0.7
6	Inappropriate	Acceptable	Appropriate	0	0	0.4	0.6
7	Inappropriate	Appropriate	Inappropriate	0	0.1	0.4	0.5
8	Inappropriate	Appropriate	Acceptable	0	0.2	0.4	0.4
9	Inappropriate	Appropriate	Appropriate	0	0.2	0.5	0.3
10	Acceptable	Inappropriate	Inappropriate	0	0.1	0.9	0
11	Acceptable	Inappropriate	Acceptable	0	0.2	0.8	0
12	Acceptable	Inappropriate	Appropriate	0	0.25	0.75	0
13	Acceptable	Acceptable	Inappropriate	0	0.3	0.7	0
14	Acceptable	Acceptable	Acceptable	0	0.5	0.5	0
15	Acceptable	Acceptable	Appropriate	0	0.6	0.4	0
16	Acceptable	Appropriate	Inappropriate	0	0.7	0.3	0
17	Acceptable	Appropriate	Acceptable	0	0.8	0.2	0
18	Acceptable	Appropriate	Appropriate	0	0.9	0.1	0
19	Appropriate	Inappropriate	Inappropriate	0.3	0.5	0.2	0
20	Appropriate	Inappropriate	Acceptable	0.4	0.4	0.2	0
21	Appropriate	Inappropriate	Appropriate	0.5	0.3	0.2	0
22	Appropriate	Acceptable	Inappropriate	0.6	0.4	0	0
23	Appropriate	Acceptable	Acceptable	0.7	0.3	0	0
24	Appropriate	Acceptable	Appropriate	0.75	0.25	0	0
25	Appropriate	Appropriate	Inappropriate	0.8	0.2	0	0
26	Appropriate	Appropriate	Acceptable	0.9	0.1	0	0
27	Appropriate	Appropriate	Appropriate	1	0	0	0

Three maritime experts with significant domain knowledge were interviewed to provide their subjective elicitation on the Consequence of the rules base listed in Table 4.7. The three elicited conditional probabilities are aggregated and normalised by the use of Equation 3.1. For example, the conditional probability CP of scrambled COCOM-CM on rule number 4 listed in Table 4.7 is obtained as follow:

$$CP = \frac{0.75 + 0.73 + 0.77}{3} = 0.75$$

In a similar way the remaining CPs are calculated to develop the CPT listed in Table 4.7. CPT is used to establish the CREAM based human performance reliability assessment BNs generic model.

4.3.3. Use of FRB logic-Bayesian reasoning for human failure quantification

FRB logic has gained a significant achievement due to its application in many fields. It is a relatively new approach. It has the capability of modelling highly complex problems linguistically rather than numerically. The nature of its modelling ensures that the rule structure provides a human-like intuition process and, most importantly, it captures expert knowledge in the real world of experience (Opricovis and Tsang, 2003).

In this technical study a FRB is introduced to structure the interactive relation between the COCOM-CMs and the three parents "Action load", "Working environments", and "Operator preparedness" in a logical form, as described in the following sub section:

4.3.3.1. Construction of multiple-input multiple-output rule base

To model the interactive relations between the new attributes and COCOM-CMs in a logical form, FL can be used to construct IF-THEN rules. These have two parts: an antecedent that responds to the fuzzy input of the three new attributes and a consequence associated with the COCOMs' four control modes which provide the fuzzy output. In classical FRB systems, such input and output are usually expressed by single linguistic variables with 100% certainty, and the rules constructed are considered as multiple-input single-output cases. However, in this study a collection of multiple-input multiple-output FRB is defined as follows (Yang et al., 2010):

R_N: IF $L_1{}^K$ and $L_2{}^K$ and $L_3{}^K$, THEN (D_1, D_2, D_3, D_4).. (4.1)

In a fuzzy rule R_N if the input satisfies the antecedent linguistic vector(s) $L_i{}^K$ (i = 1, 2, 3), the output D_n (n =1, 2, 3, 4) represents the belief degree(s) to which a control mode(s) is believed to be the consequence. Linguistic vector $L_i{}^K$ is defined with its nature of having "Appropriate" (improved), "Acceptable" (not significant) or "Inappropriate" (reduced) effects on COCOM-CMs. Obviously, if L_1 is "Action load", then $L_1{}^K$can be any of the three linguistic variables used to describe "Action load", which are Inappropriate ($L_1{}^1$), Acceptable ($L_1{}^2$), and Appropriate ($L_1{}^3$). The following illustrative rules are developed to interpret the above two R_N (see Table 4.7).

R_1: IF the "Action load" is "Appropriate" AND the "Working environments" is "Appropriate" AND "Operator preparedness" is "Appropriate", THEN the belief degrees of operator COCOM-CMs would be 100% "Strategic", 0% "Tactical", 0% "Opportunistic", and 0% "Scrambled".

R_3: IF the "Action load" is Inappropriate AND the "Working environments" are Appropriate AND "Operator preparedness" is Inappropriate, THEN the belief degrees of operator COCOM-CM would be 0% "Strategic", 0% "Tactical", 10% "Opportunistic", and 90% "Scrambled".

They can be further simplified and presented as a rule base:

R_1: IF $L_1^{\,1}$, AND $L_2^{\,2}$, AND $L_3^{\,3}$, THEN (D_1, 1), (D_2, 0), (D_3, 0), and (D_4, 0).

R_2: IF $L_1^{\,1}$, AND $L_2^{\,3}$, AND $L_3^{\,1}$, THEN (D_1, 0), (D_2, 0), (D_3, 0.1), and (D_4, 0.9)

where $L_i^{\,K}$ (i & k = 1, 2, 3) indicates the L_i new attribute and the associated k^{th} linguistic variable descriptor (see Table 4.8). Such a rule base represents the possible functional mappings of uncertainty between the three new attributes and the four control modes. It provides a more informative, realistic scheme than a simple IF-THEN rule base does on uncertain knowledge representation (Yang et al., 2008).

Table 4.8: Main/sub-attributes' descriptor and their effect levels

No.	Main attribute	Linguistic variable	Effects
1	Action load	Inappropriate	reduced
		Acceptable	not significant
		Appropriate	improved
2	Working environments	Inappropriate	reduced
		Acceptable	not significant
		Appropriate	improved
3	Operator preparedness	Inappropriate	reduced
		Acceptable	not significant
		Appropriate	improved
	Sub-attribute	Linguistic variable	effects
1	Adequacy of perception conditions	Inappropriate	reduced
		Acceptable	not significant
		Appropriate	improved
2	Adequacy of working culture	Inappropriate	reduced
		Acceptable	not significant
		Appropriate	improved

4.3.3.2. Aggregation of rule base output using a Bayesian reasoning mechanism

The established rule base system (see Table 4.7), enables experts to infer, from the observation of given antecedent linguistic variables, the corresponding consequent COCOM-CMs' output belief degrees. The kernel of this inference is to appropriately transform belief degrees in the rule base into subjective conditional probabilities that can be used in a Bayesian mechanism (Yang et al., 2008). For example, the simplified R_2 stated in the first step can be further expressed in the form of conditional probability as follows:

Given $L_1{}^1$, AND $L_2{}^3$, AND $L_3{}^1$, THEN the probability of $D_n(n = 1, 2, 3, 4)$ is (0, 0, 0.1, 0.9) or

$P\,(D_n \mid L_1{}^1,\ L_2{}^3,\ L_3{}^1) = (0, 0, 0.1, 0.9)$ .... (4.2)

where "|" symbolizes conditional probability.

Once the output belief degrees of the rule base are transformed into conditional probabilities, a BN technique can be used to aggregate COCOM-CMs' marginal probability. This could be transformed further into HFP.

By using the established rule base in Table 4.7, the required CPT, $p\,(D_n \mid L_i{}^K)$ for the child node COCOM-CMs' (N_D) associated four control modes (D_n) (see Figure 4.13) are obtained. Having transferred the rule base into a Bayesian format, the marginal probabilities of the three new attributes L_i (see Figure 4.13) and N_D CPT can be used in a Bayesian mechanism to calculate the control modes' (D_n) marginal probabilities - see (Table 4.9). As an example Equation 4.3 can be used to demonstrate the derivation of combination No 1 in Table 4.8.

$P\,(D_n \mid L_1{}^K,\ L_2{}^K, L_3{}^K) \times P\,(L_1{}^K) \times P\,(L_2{}^K) \times P\,(L_3{}^K)$ $(n = 1\ldots 4)$ & $(K=1, 2, 3)$... (4.3)

$P\,(D_4 \mid L_1{}^1,\ L_2{}^1, L_3{}^1) \times P\,(L_1{}^1) \times P\,(L_2{}^1) \times P\,(L_3{}^1)$;

where the value of conditional probability $P\,(D_4 \mid L_1{}^1,\ L_2{}^1, L_3{}^1)$ is stated in Table 4.7 rule No. 1, and the marginal probabilities $P\,(L_1{}^1)$, $P\,(L_2{}^1)$, $P\,(,L_3{}^1)$ are inferred by a BN model (see Figure 4.13).

$1 \times 0.333 \times 0.420 \times 0.378 = 0.0529$;

To marginalize control modes (D_n), $P\,(D_n \mid L_i{}^K)$ (see Table 4.8), Equation 4.4 can be used as (Jenson, 2001):

$P(D_n) = \sum_{k_1=1}^{3} \sum_{k_2=1}^{3} \sum_{k_3=1}^{3} P(D_n \mid L_i^k)$ $(n= 1, 2, 3, 4)$, $(i=1, 2, 3)$, $(k=1, 2, 3)$..... (4.4)

Table 4.9: Control modes' aggregated marginal probabilities (k =1, 2, 3 descriptor)

Combination	$P(D_1 \mid L_1^K, L_2^K, L_3^K) \times P(L_1^K) \times P(L_2^K) \times P(L_3^K)$ Strategic	$P(D_2 \mid L_1^K, L_2^K, L_3^K) \times P(L_1^K) \times P(L_2^K) \times P(L_3^K)$ Tactical	$P(D_3 \mid L_1^K, L_2^K, L_3^K) \times P(L_1^K) \times P(L_2^K) \times P(L_3^K)$ Opportunistic	$P(D_4 \mid L_1^K, L_2^K, L_3^K) \times P(L_1^K) \times P(L_2^K) \times P(L_3^K)$ Scrambled	
1	0	0	0	0.0529	
2	0	0	0.0046	0.0413	
3	0	0	0.0082	0.0329	
4	0	0	0.0089	0.0266	
5	0	0	0.0092	0.0216	
6	0	0	0.0110	0.0166	
7	0	0.0038	0.0150	0.0188	
8	0	0.0065	0.0130	0.0130	
9	0	0.0058	0.0146	0.0088	
10	0	0.0053	0.0476	0	
11	0	0.0092	0.0367	0	
12	0	0.0103	0.0308	0	
13	0	0.0106	0.0248	0	
14	0	0.0154	0.0154	0	
15	0	0.0166	0.0110	0	
16	0	0.0263	0.0113	0	
17	0	0.0260	0.0065	0	
18	0	0.0263	0.0029	0	
19	0.0159	0.0265	0.0106	0	
20	0.0184	0.0184	0.0092	0	
21	0.0206	0.0124	0.0082	0	
22	0.0214	0.0142	0	0	
23	0.0216	0.0093	0	0	
24	0.0208	0.0069	0	0	
25	0.0301	0.0075	0	0	
26	0.0294	0.0033	0	0	
27	0.0293	0	0	0	
Σ	0.2075	0.2605	0.2997	0.2323	1

4.3.3.3. Transformation of COCOM-CMs' probability into HFP

To quantify HFP, the COCOM-CMs' linguistic terms D_n (n = 1… 4) require the assignment of appropriate utility values. In this respect, fuzzy sets are normally used to model the four COCOM-CMs corresponding HFP interval (Yang et al., 2010). COCOM-CMs' fuzzy functions mapping the probability distributions are shown in Figure 4.14. In order to regain calculated crisp HFP values for each control mode, the assignment of appropriate utility values U_{D_n} to the 4 four COCOM-CMs can be obtained using defuzzifecation. The crisp utility values can be obtained by defuzzifying the fuzzy membership functions of the four control modes shown in Figure 4.14, using the centre of gravity Equation 4.5 (Andrews and Moss, 2002; Yang et al., 2010). For example, U_{D_n} can be calculated as follows:

$$U_{D_n} = \frac{a_n+b_n+c_n}{3} \quad (4.5)$$

where (a_n, b_n, c_n) each is the fuzzy number of the ith COCOM-CM mapped in Figure 4.14. As a result, the U_{D_n} values (n= 1... 4) can be calculated as 2.24 × 10^{-4} for strategic, 0.01 for tactical, 0.0708 for opportunistic and 0.316 for scrambled (Yang et al., 2010). Accordingly, a new HEP index can be calculated as:

$$HFP = \sum_{n=1}^{4} P(D_n)\ U_{D_n} \quad (4.6)$$

where the larger the value of HFP, the lower the reliability level of human performance.

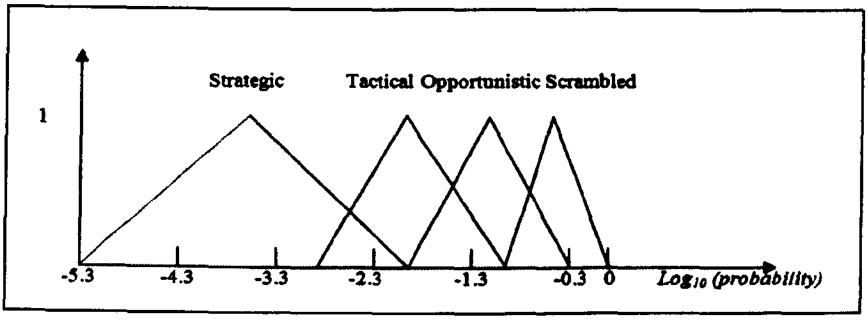


Figure 4.14: Fuzzy membership functions mapping probability distributions for the COCOM-CMs corresponding HFPs adapted from Yang et al. (2010)

4.3.3.4. BN model validation

Validation is an important aspect that provides a reasonable amount of confidence to the results obtained from the established generic model. Therefore, a sensitivity analysis for partial validation of a developed model could be carried out based on the following axioms (Yang, et al. 2008):

Axiom 1: A slight increase/decrease in the prior subjective probabilities of each parent node should certainly result in the effect of a relative increase/decrease of the child node COCOM-CMs' probability.

Axiom 2: The total influence magnitudes of the combined subjective probability variations of the set X CPCs (evidence) on the child node COCOM-CMs' probability values should be always be greater than the total influence magnitudes of the combined subjective probability of the set $X-Y$ ($Y \in X$) CPCs (sub-evidence).

In this technical work the approach for sensitivity analysis is slightly different than the approach used in chapter 3. Sensitivity to finding, tests how sensitive a network model is to changes in overall findings, where the influence of each node on a query node in a network can be measured, by calculating the mutual information or entropy reduction.

The results of a sensitivity analysis can be used for model later development cycle. Axiom 1 and axiom 2 are explicit examples of sensitivity to parameter and implicit examples of sensitivity to finding; such approach aims to find changes in each variable in the model. The goal is to determine whether more precision in estimating variables is required and whether it can be useful in a later iteration of model development cycle (Mittal and Kassim, 2007).

4.4. Case study: Heeling Accident on M/V *Crown Princess*, Atlantic Ocean off Port Canaveral, Florida, 18th July, 2006

The main reasons underlie the selection of M/V *Crown Princess* heeling accident as a case study to validate the developed COCOM-CMs BN model are: the accident analysis results was based on VDR' audible and visual data, which had helped investigators to perform an objective analysis; the vessel age was just about three months off her maiden voyage; the vessel was built in a well reputed ship yard, as well it was classed by two of the IACS' calcification societies; the vessel passenger ship safety certificate was issued by the USCG and her officers competency was well recognised. Although a similar accident was experienced by officers on board other vessel, and its genotype root cause factors was identified and circulated by the USCG to the owners of the vessels that were trading within the premises of the USCG maritime safety administration, stakeholders organisationally did not consider the root cause factors negative consequence. Such hidden information provoked the misuse of M/V *Crown Princess* INS by her officers at full speed and in shallow water; as a result, the vessel was subjected to the heeling accident.

The accident on the cruise ship *Crown Princess* was initiated by the Second Officer's steering action during his command subsequent to the vessel's departure, in which the vessel heeled at a maximum angle of about 24°, resulting in injuries to 298 passengers and crew members. The *Crown Princess* was travelling at 20 knots, nearly full speed, when it heeled. The vessel was in relatively shallow water at the time of the accident.

The ship's Captain, Staff Captain (second in command), relief Captain, Second Officer, two Fourth Officers, and two Helmsmen were on the bridge during an uneventful departure from Port Canaveral, Florida, United States. The analysis refers to those on watch during the accident sequence.

4.4.1. Vessel history and construction information

The *Crown Princess*'s sea trials were conducted in March 2006, subsequent to her construction in Monfalcone, Italy, by Fincantieri Cantieri. The *Crown Princess*'s Dwt is 113,561; she was dual-classed by Lloyds Register (LR) and Registro Italiano Navale (RINA), under a Bermuda flag registration; and her passenger vessel certificate of compliance was issued by the United States Coast Guard (USCG) subsequent to the vessel's examination (NTSB/MAR-08/01, 2008).

4.4.2. Propulsion, steering and voyage data recordering

The *Crown Princess* was powered by electric propulsion motors driving two fixed-pitch propellers. The steering port and starboard rudders were synchronized, so that the same rudder order from the bridge control system went to each steering gear unit. The *Crown Princess* was equipped with an Integrated Navigation System (INS) - the most modern equipment at the time she was launched. The vessel's steering gear units were controlled through one of two electronic steering control systems on the bridge. The first was a basic heading control system or autopilot, including a manual steering-control system. The second was the track-pilot system. A steering mode selector switch was located on the bridge centre control console. In general, the track-pilot was used mainly in open waters, with manual steering normally used when arriving at and departing from port or in pilotage waters. The officer on watch was allowed to select the steering mode with respect to Watch keeping Policies and Procedures stating that watch keepers had the discretion to steer using an automated INS mode or manually, within the standards that the vessel captains established in their standing orders. The *Crown Princess* was equipped with a Voyage Data Recorder (VDR), which recorded inputs from specific audio, data channels, and a video source. The data were retained on a hard disk drive which was removed after the accident for further investigation analysis by the National Transport Safety Board'(NTSB) analysts (NTSB/MAR-08/01, 2008).

4.4.3. Factors included in the scope of the accident analysis

The analysis first identifies factors that can be eliminated as causal or contributory to the accident, such as: the vessel's mechanical condition, weather, sea state, and behavioural or physiological impairment of the crew. It then discusses the following safety issues identified in the accident investigation:

- Actions of Captain, Staff Captain, and Second Officer.

- Training in the use of INS.
- Reporting of heeling incidents and accidents.
- Emergency response following severe incidents.

4.4.4. Accident

The *Crown Princess*'s departure from Port Canaveral was uneventful. After the pilot disembarked and the vessel entered the open ocean, the crew engaged the track-pilot and the Captain ordered an increase in the vessel's speed to stay ahead of forecast adverse weather. The Captain and Staff Captain left the bridge, turning the navigation watch over to the Second Officer. The Second Officer, concerned by indications of a high rate of turn to port, disengaged the track-pilot automatic steering mode of the vessel's INS and began steering the vessel manually in an effort to counteract a perceived high rate of turn to port. His first turn was opposite to his intended direction and then between port and starboard several times. A minute later, the vessel heeled hard to starboard. She was travelling at 20 knots, nearly full speed, when she heeled. The heeling caused passengers and crew to be struck by parts of the vessel's structure or unsecured objects, resulting in injuries to 298 people. The *Crown Princess* incurred no structural damage, although unsecured interior items were damaged. The vessel was in relatively shallow water at the time of the accident, with 8.3 metres (about 26 feet) of water under the keel (NTSB/MAR-08/01, 2008).

4.4.5. Analysis of Captain, Staff Captain and Second Officer's actions

The following analysis is adopted from NTSB/MAR-08/01 (2008)

<table>
<tr><td colspan="2">Scenario 1: Captain and Chief Captain actions</td></tr>
<tr><td colspan="2">Case1.1: Captain's action after the pilot disembarked and the vessel entered the open ocean</td></tr>
<tr><td>Time</td><td>Action description</td></tr>
<tr><td rowspan="10">15:01
15:18</td><td>The Captain ordered an increase in the vessel's speed to stay ahead of forecast adverse weather, and the crew engaged the track-pilot at 15:01</td></tr>
<tr><td>Observations</td></tr>
<tr><td>The vessel began to fluctuate around its designated 100° heading about 15:03. Two minutes later, the track-pilot rudder limit alarm sounded.</td></tr>
<tr><td>Evaluation</td></tr>
<tr><td>The Safety Board therefore concludes that the Captain and Staff Captain did not recognize that high speed and shallow water were adversely affecting the vessel's course stability. The analysis results reflected inappropriate availability of procedures/plans and inadequate training and expertise, for performing this specific task.</td></tr>
<tr><td>Case1.2: Captain and Staff Captain's action (response)</td></tr>
<tr><td>Action description</td></tr>
<tr><td>The Staff Captain increased the rudder limit from 5° to 10°. At the time, the rudder economy was set to level 5, normally intended for rough seas.</td></tr>
<tr><td>Observations</td></tr>
</table>

	In addition to the effects of high speed in shallow water on vessel steering, the Staff Captain further enabled the vessel's course deviations by increasing the rudder limit, without realising the consequence of maintaining the track-pilot's rudder economy. This was inappropriately set at level 5 and was the initiating event of the rudder limit alarm, which should be based on the sea state and weather conditions
	Evaluation
	The Safety Board therefore concludes that the Captain and Staff Captain failed to adjust the rudder economy setting, which was inappropriate for the sea state and was exacerbating the course deviations. The analysis results reflected inadequate training and expertise in use of INS, lack of competence in recognising the effects of high vessel speed in shallow water on course stability, and inappropriate adequacy of MMI and operational support in regard to this specific task.
Scenario 2: Captain, Staff Captain, and Second Officer's actions	
Case 2.1: Captain, Staff Captain, and Second Officer's actions	
Time	**Action description**
	The Captain turned the command over to the Second Officer at 15:18; this was 6 minutes before the Second Officer disengaged the track-pilot
	Observations
	The fluctuations in the vessel's heading that the Captain and Staff Captain had attempted to address through the INS continued.
	Evaluation
	The Captain transferred the command without determining the cause of the heading fluctuations, and worse, left the bridge without verifying that they were lessening. The evidence of his previous experience as Captain and his actions in turning over the command suggest that the Captain believed either that the INS would stabilise the heading or that the Second Officer would remedy the problem. The Safety Board therefore concludes that the Captain should not have transferred the command to the Second Officer and left the bridge unless he could verify that the vessel's heading fluctuations had diminished. The analysis results reflected inefficient quality in crew collaboration, aggravated by inappropriate availability of procedures/plans and inadequate training and expertise in regard to this specific task.
	Case 2.2: Second Officer's actions
	Action description
+15:18 15:26	The *Crown Princess* was operating at nearly full speed when the Second Officer took the command. He immediately faced the problem of navigating a vessel that exhibited both increasing course deviations and high rates of turn. The Second Officer was concerned with the red colour of the rate-of-turn indicator on the bridge, which indicated a high rate of turn to port. He responded immediately by disengaging the track-pilot (disengaging the track-pilot disengaged the rudder limit and rudder economy settings) and turning the wheel 10° to port, when he should have turned it to starboard to counteract the turn. After his initial turn to port, the Second Officer manually steered back and forth between port and starboard in increasingly wider turns, rather than remedying the problem.
	Observations
	The Second Officer's actions exacerbated the course fluctuations and high turn rates, and caused larger and larger heel angles. The result was an increasing heel to starboard that eventually peaked at about 24°. The Second Officer's wheel inputs increased the starboard heel over the duration of the event rather than decreasing it. His actions could be attributed to a "slip" (error of omission) (Reason, 1990a, b) or to a misdiagnosis of the situation, i.e., error of commission.
	Evaluation
	The Safety Board concludes that no deficiencies in the Second Officer's training or background could account for his inappropriate steering commands. The analytical results reflected inappropriate adequacy of MMI and operational support, inappropriate availability of procedures/plans, and inadequate training and expertise, specifically in the use of INS, not being able to recognise the effects of high vessel speed in shallow water on course stability, and the lack of emergency ship handling skills that would have allowed him to respond effectively to the vessel's unexpected behaviour in regard to this specific task.

4.4.6. Reporting of heeling incidents and accidents

In examining other heeling accidents and incidents, the Safety Board found common antecedents – crew members not fully understanding the INS they were using, not anticipating the effect of their actions on the INS, or both. Further, neither the Maritime Administrations such as the Coast Guard nor the IMO requires licensed mariners to complete formal INS instruction before using an INS. There is also no requirement that mariners who have completed INS instruction take courses thereafter. A system that allows users to interact with such sophisticated systems as an INS with the training shortcomings noted is deficient and increases the likelihood that crewmembers will commit INS-related errors. As a result, the Safety Board issued a safety recommendation to the Coast Guard, which was classified as closed-acceptable action, after publicizing the circumstances of the accident. Partly because of this action, information on the squat effect was prominently posted on the *Crown Princess*'s bridge. Such a follow-up could be characterised by inadequate organisation.

4.4.7. Findings

- The Captain and Staff Captain did not recognise that high speed and shallow water were adversely affecting the vessel's course stability.
- The Captain and Staff Captain inappropriately adjusted the track-pilot's rudder limit in response to unintended deviations in the vessel's set heading; and they failed to adjust the rudder economy setting, which was inappropriate for the sea state and was exacerbating the course deviations.
- The Captain should not have transferred the command to the Second Officer and left the bridge unless he could verify that the vessel's heading fluctuations had diminished.
- The *Crown Princess* heeled because, after the Second Officer disengaged the track-pilot and turned the wheel to port rather than turning it to amidships and slowing the vessel as he should have, his subsequent steering commands to both port and starboard, at angles ranging from 10° to 45°, led to vessel responses that he did not expect, did not understand, and was therefore unable to correct.
- No deficiencies in the Second Officer's training or background could account for his inappropriate steering commands.

- The errors of the Captain and Staff Captain in operating the INS resulted from inadequate training.
- The systematic collection of data on mishaps related to INSs will enhance the systems' design, procedures, and training.
- The *Crown Princess* accident demonstrates the need for obtaining and archiving data on vessel angles of heel (NTSB/MAR-08/01, 2008).

4.4.8. Probable Cause

The NTSB determines that the probable cause of the *Crown Princess* accident was the Second Officer's incorrect wheel commands, executed first to counter an unanticipated high rate of turn and then to counter the vessel's heeling. Contributing to the cause of the accident was the Captain's and Staff Captain's inappropriate inputs to the vessel's INS while the vessel was travelling at high speed in relatively shallow water; their failure to stabilize the vessel's heading fluctuations before leaving the bridge; and the inadequate training of crew members in the use of INSs (NTSB/MAR-08/01, 2008).

4.4.9. Human COCOM-CMs marginal probability inference

Based on CREAM CPCs evaluation and their possible descriptors stated in Table 4.1, Table 4.10 is adapted to show (in bold-face) the accident CPCs descriptors' observation and their associated expected effect levels on crew performance reliability. CPCs descriptors are assigned deterministically to be used as input observations of root cause nodes state in the established CREAM BN generic model (see Figure 4.13). CREAM BN mechanism is used to infer the probabilistic beliefs of human action COCOM-CMs' marginal probabilities, i.e., scrambled 71.7%, opportunistic 23.4%, tactical 4.66%, and strategic 0% (see Figure 4.15). Using Equation 4.6 and by substituting each of the above stated belief $P(D_n)$ of COCOM-CM and its related utility value U_{D_n} (nominal human COCOM-CMs probabilities results) provided in Section 4.3.3.3, the following actual HFP portion derived out of the nominal human action control modes probabilities are listed in descending order:

Scrambled $= (71.7 \times 0.316)/100 = 0.226572 \cong 0.2266$

Opportunistic $= (23.6 \times 0.0708)/100 = 0.0223$

Tactical $= (4.66 \times 0.01)/100 = 0.000466 \cong 0.0005$

Strategic $= (0 \times 0.000224)/100 = 0$

Finally, the above control modes results aggregation with use of Equation 4.6 would derive the total HFP as follows:

HFP= 0.2266 + 0.0223 + 0.0005 + 0 = 0.2494 failure/time;

At this stage of validation, it is worthwhile to differentiate between the CREAM basic and the developed CREAM BN model results. In this context, the CREAM basic result is based on CPCs' evaluation scores improved and reduced (1, 4); the plotting of these scores on the graph shown in Figure 4.9 reveals the result of opportunistic control mode and its related generic HFPs, whereas CREAM BN model inference and the associated FS model transformation revealed the final calculation of HFP 0.2494 Failure/time; this HFP inclusively lies within the overlapping range (0.1 < HFP < 0.5) of opportunistic and scrambled control modes related HFPs (see Table 4.4). Comparing the results of both approaches, obviously the specified HFP would provide a more focused result with a better resolution that would enable an assessor to establish the right preventative plan.

Table 4.10: Accident context CPCs levels descriptors and their effect on performance reliability

CPC name	Level/descriptors	Expected effect on performance reliability
Adequacy of organisation (CPC 1)	Very Efficient	Improved
	Efficient	Not Significant
	Inefficient	**Reduced**
	Deficient	Reduced
Working conditions (CPC 2)	Advantageous	Improved
	Compatible	**Not significant**
	Incompatible	Reduced
Adequacy of MMI and operational support (CPC 3)	Supportive	Improved
	Adequate	Not Significant
	Tolerable	Not Significant
	Inappropriate	**Reduced**
Availability of procedures/plans (CPC 4)	Appropriate	Improved
	Acceptable	Not significant
	Inappropriate	**Reduced**
Number of simultaneous goals (CPC 5)	Fewer than capacity	Not significant
	Matching current capacity	**Not significant**
	More than capacity	Reduced
Available time (CPC 6)	**Adequate**	**Improved**
	Temporarily inadequate	Not significant
	Continuously inadequate	Reduced
Time of day (circadian rhythm) (CPC 7)	**Day-time (6:00-18:00hr) (adjusted)**	**Not significant**
	Night(17:00-24:00hr) (unadjusted)	Reduced
	Night-time(0:00-7:00hr) (unadjusted)	Reduced
Adequacy of training and expertise (CPC 8)	Adequate, high experience	Improved
	Adequate, limited experience	Not significant
	Inadequate	**Reduced**
Crew collaboration quality (CPC 9)	Very efficient	Improved
	Efficient	Not significant
	Inefficient	**Not significant**
	Deficient	Reduced

4.4.9.1. Model finding interpretation

Failing to comprehend the affect of shallow water and the increase of vessel speed on large vessel manoeuvring characteristics increased the squat effect. This effect had tangibly changed the designated steering behaviour of the ship. In this respect, the previously set parameters for the track-pilot ability believed to steer the ship would no longer match the resulted ship behaviour observation. Such a hidden situation was partially manifested in that the rudder limits alarm sounded and the vessel turned. The action taken by the Staff Captain in response to the rudder limits alarm sound was to increase the setting range of the rudder limits alarm without realising the main reasons. The Staff Captain and Captain's actions were based on their competences control on observation, interpretation, planning, and execution; these were determined by the salient futures of the context at that time, rather than on more stable intentions or goals. They did very little planning or anticipation, perhaps because the context was not clearly understood. In these situations, they were often driven either by the perceptually dominant feature of the context, or by the most frequently used experience or habit corresponding to a similar matching context. The result was often a functional fixation. Consequently, their corrective actions were structurally based on an opportunistic control mode, reasoning on the set parameters for the track-pilot's ability to steer the ship. However, such actions could not be updated, as command was transferred to the Second Officer. Nevertheless, the effect of squat due to instant speed increase reduced significantly the INS's yaw-checking and steering control ability as well. The new observation left no time for the Second Officer to structure his competence control on interpretation, planning and execution of his action, leading him to act on a scrambled control mode, characterised by disengaging the track-pilot and turning the wheel to port rather than turning it to amidships and slowing the vessel, as he should have done. His hand-steering commands to both port and starboard, at angles ranging from 10° to 45°, led to vessel responses that he did not expect, did not understand, and was therefore unable to correct. Yet, disengaging the track-pilot had eliminated the functionality of rudder limit and rudder economy settings. As a result, the vessel was dependent on the Second Officer's hand-steering action, and he had not realised that the instant squat effect had increased at higher speed and lower water depth, and had an effect on vessel yawing, steering, and heeling conditions. The hand-steering corrective action had aggravated the situation; as a result the vessel was subjected to a high heeling angle, disrupting passenger and crew comfort, and a significant number of passengers and crew members were injured. The Relief Captain was the first person to return to the bridge when the vessel began heeling, and he immediately ordered, "Reduce the speed" Slowing the vessel moderated the situation.

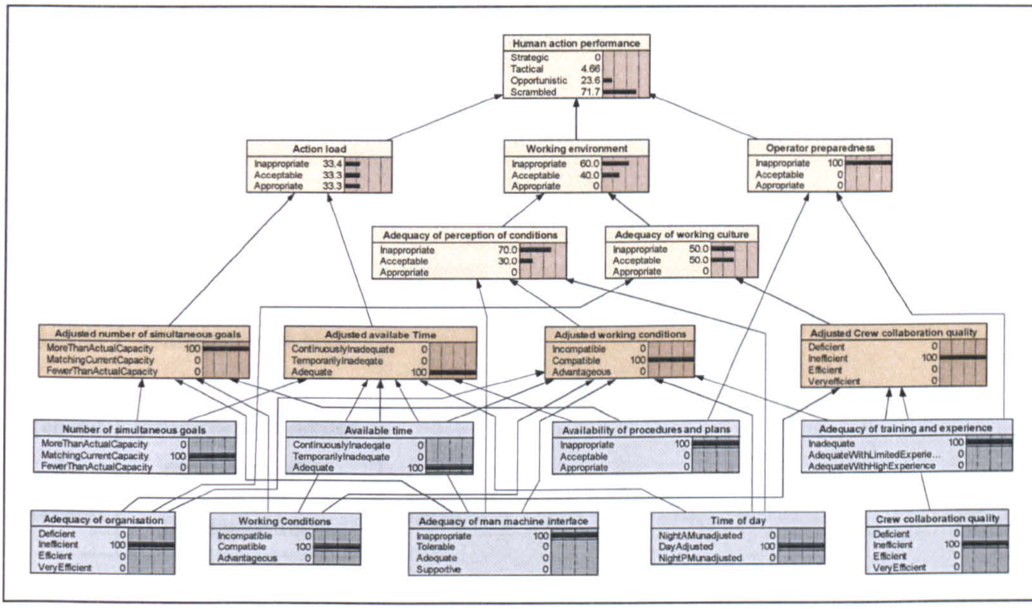


Figure 4.15: BN model for M/V *Crown Princess*'s Officers in charge COCOM-CMs marginal probability

4.4.9.2. Accident BN model validation

A sensitivity analysis is carried out in order to give a partial validation of the model. The model should at least satisfy the two axioms described in Section 4.3.4.4. Firstly, three examination scenarios including CPC "Adequacy of training and expertise" evaluation grades "Adequate with high experience", "Adequate with limited experience" and "Inadequate" are used individually as input observations of the model shown in Figure 4.15. The revised COCOM-CM probabilities and their transformed HFPs findings stated in Table 4.11 satisfy the requirement of axiom 1 described in Section 4.3.4.4. Table 4.12 illustrates four scenarios' revised COCOM-CMs' probabilities and their transformed HFPs due to the combined effect of nine CPC states' being simultaneously set at levels of "Improved", "Not significant", and "Reduced". The results of the four scenarios shown in Table 4.12 show that the model inference and the final probability change are in agreement with logicality of input observations that satisfy the requirement of axiom 2.

The above developed scenarios give a partial validation to the model. In order to carry out a full validation, model CPTs would need to be fine-tuned for a period of time based on experts' knowledge in the applicable domain. Therefore, the established CREAM BN generic model for quantifying human action failure probability can be used with a greater accuracy in utility analysis and decision making than that of traditional qualitative means.

Table 4.11: Human action failure probability change due to adequacy of training and expertise' descriptors' effect (CPC8)

Axiom 1						
CPC8 adequacy of training and expertise						
CPC 8 states assigned input observations		Model Inference output beliefs				
		Strategic (D_1)	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)	Final HFP
Scenario 1	Adequate with high experience 100%	42.3	29.1	20.5	8.14	0.02443
Scenario 2	Adequate with limited experience 100%	14.2	31.5	38.5	15.7	0.080
Scenario 3	Inadequate 100%	7.08	16.5	29.1	47.4	0.1737

Table 4.12: Human action failure probability results due to the combined effect levels of nine CPC involved in the case study scenario

Axiom 2						
Case study scenario nine CPCs						
Scenario	CPCs' states assigned input observations	Model inference output beliefs				
		Strategic (D_1)	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)	Final HFP
1	(CPC 6) Improved 100% (CPC 7) Not significant 100% (CPC 2, 5, 9) Not significant 100% (CPC 1, 3, 4, 8) Reduced 100%	0	4.66	23.6	71.7	0.2493
2	(Non) Improved 100% (CPC 7,6) Not significant 100% (CPC 2, 5, 9) Not significant 100% (CPC 1, 3, 4, 8) Reduced 100%	0	0	14.5	84.5	0.2773
3	(Non) Improved 100% (CPC 7) Not significant 100% (CPC 2, 5,6, 9) Not significant 100% (CPC 1, 3, 4, 8) Reduced 100%	0	0	4	96.6	0.3081
4	(CPC 1, 3, 4, 8) Improved 100% (CPC 7) Not significant 100% (CPC 7) Not significant 100% (CPC 6) Reduced 100%	54.9	30.1	15.0	0	0.0131

4.5. Conclusion

Although a good system design and operation plan normally take every contingency into consideration, practice has shown that even the best designed system can fail in operation due to erroneous human actions. Human actions are inherent characteristics. They are more difficult to regulate and assess than the functions of technological system components, thus presenting a special problem.

The growing complexity of systems design provides ample opportunities for the harmful accumulation of several combined conditions, where each is necessary and none sufficient to bring about an accident by itself. The increased automation and functional sophistication of technology systems have become much more difficult for average seafarers to understand, making them prone to potential failures; this may develop into contributing causes for active failures in the presence of triggering events. The potential failure conditions can arise from oversights or failure in design, construction, procedures, maintenance, training, communication, MMI and the like.

The growing number of cases where human actions are actually the cause of accidents is caused by a combination of human, technological, and organisational factors, and has led to an increasing focus on human actions. Therefore, it is vital to improve understanding of the multiplicity of factors that are at play. This requires a conceptual framework that adequately accounts for how actions are shaped by the context in which they take place, and which effectively enables the identification of the most important conditions that reasonably can be said to be the causes of incorrect actions.

In this respect, a new CREAM BN probabilistic approach is developed. The probabilistic approach is found to have several advantages over the existing method, from the fact that any discrete function can be expressed in a BN; as a result, a BN could produce equivalent results when the levels of CPCs are given discretely. In addition, it can also mathematically produce consistent results when levels of CPCs are given probabilistically for all possible scenarios where the CREAM basic method cannot produce a specific result. However, to enhance the potential of the new CREAM BN model in dealing with incomplete assessment of conditional degrees of belief, a methodological framework that uses an ER algorithm in synthesising experts' partial elicitation of conditional degrees of belief will be investigated in the next chapter.

Chapter 5

Use of evidential reasoning for eliciting Bayesian subjective probabilities under incompleteness uncertainties

Summary

The subjective probability elicitation for a BN is often a daunting and complex task to perform. To create conditional probability values for each given variable in a BN requires high degree of knowledge and engineering effort. This chapter presents the methodology for combining an ER algorithm with Bayesian theory. It enhances the potential of the established CREAM BN model for COCOM-CMs' reliability assessments. The methodological framework uses ER algorithm in synthesising experts' partial elicitation of conditional degrees of belief and aggregation of root cause factors' probability that are symmetrically affecting CREAM CPCs. The kernel of this approach is to develop the best and the worst possible conditional degrees of belief of COCOM-CMs' node. These conditional degrees of belief are then used in two established CREAM generic BN models to aggregate the marginal probabilities of the COCOM-CMs. FS theory is also used to transform the marginal probabilities of both CREAM BN models aggregated COCOM-CMs into HFPs, which are subsequently aggregated to crisp values of HFPs defining the boundaries of HFPs' range that can be averaged for a ranking purpose. A case study is investigated, while a sensitivity analysis to the case analysis is conducted, to validate the established CREAM BN models. Finally, the developed technical work achievements are concluded.

5.1. Introduction

A BN is a high-level representation of a probability distribution over a set of variables which are used for building a model of a specific problem domain. A BN shows the variables' dependence-independence relations in a logical form. This has eased the tasks of decomposition, feature selection and transformation. A BN also provides a sound inference mechanism (Mittal and Kassim, 2007). The flexibility of choosing variables and modelling relationships among variables leads to a high and reliable performance of the BN. Such reliable performance features in computing the distribution probabilities in a set of variables according to the observations of some variables and the prior knowledge of the others (Weber et al., 2010).

Although the BN technique is an effective way of capturing uncertainties, the knowledge and engineering effort needed to create conditional probability values for each given variable in a BN are quite high. As statistical data is not always available, subjective probabilities are often used. Even though prior probabilities can be elicited by experts, it sometimes raises the problem of accuracy in posterior probability values. As a result, translating experts' qualitative knowledge into numerical probabilistic values is a daunting and often complex task to perform (Mittal and Kassim, 2007). Moreover, Bayesian inference requires probability completeness. For these reasons, novel assessment techniques are required to provide precise bases for performing HRA in the context of engineering operations that may be incomplete, for which traditional quantitative approaches do not provide an adequate answer.

Nevertheless, such assessment could be elicited with partial degrees of belief (Binaghi and Madella, 1999). In this regard, an ER algorithm has been developed on the basis of the Dempster-Shafer (D-S) theory of evidence (Dempster, 1968; Shafer, 1976),which is well suited to modelling subjective credibility induced by partial evidence observation (Smets, 1988). The ER synthesising capability of partial degrees of belief has enlarged the scope of traditional probability theory utilisations, particularly in describing and handling uncertain information by using the concept of the degrees of belief. An ER can model information incompleteness and ignorance explicitly (Yang and Singh, 1994; Yang and Sen, 1994; Wang et al., 1995; Wang et al., 1996; Yang and Sen, 1997; Yang, 2001; Yang and Xu, 2002a, b; Liu et al., 2004; Yang et al., 2008). Therefore, the ER belief theory capability will be combined in BN probabilistic reasoning viability. Such a combination will enhance the applications of the BN model developed in Chapter 4 for quantifying COCOM-CMs' probabilities in an incomplete assessment of a context of marine engineering operation. The underlying desire behind combining ER and BN as an integrated tool is to tackle the incompleteness of HRA in BN. This will be solved by combining the best and worst evaluation grade incomplete degrees of belief masses (synthesised by ER) with the unassigned probability masses, to facilitate the elicitation of complete probability masses for two individual assessment scenarios, enabling CREAM BN models to infer the COCOM-CMs probabilities for both assessment scenarios. These probabilities will be transformed to HFPs for each control mode defining the boundaries of the HFP utility interval, which can be averaged into discrete values of HFPs for ranking; and finally aggregated into a crisp HFP value. The combined techniques of ER and BN algorithms will allow them to capture high levels of uncertainty without loss of information.

5.2. Literature review

The literature shows that a large number of BN applications have been reported in various risk analyses. These include the classification of components and systems of NPP safety performance assessments (Ha and Seong, 2003) and the assessment of integrated fire prevention and protection systems (Gulvanessian and Holicky, 2001). Similarly, a BN has also been used to help in the design stage of the decision making process to estimate the distribution of the harm to people produced by fire in a building (Hanea et al., 2006). BN-based reliability formalism has also been used to find a suitable reliability framework for dynamic system component behaviours and interactions. The framework provides a basis for more advanced and useful analysis such as system diagnosis (Boudali and Dugan, 2004). The BN model has also been used in a study investigating the organisational causes of fatal accident in commercial aviation and how to reduce them (Luxhoj, 2003).

The BN has been developed by Trucco et al. (2008) to quantify Human and Organisational Factors (HOFs) in risk analysis carried out at the preliminary design stages of high speed craft. The developed BN model of HOF has been correlated with the Fault Tree Analysis (FTA) of collision accident technical elements. The approach has allowed for the probabilistic correlation between the basic events of a collision accident and its operational and organisational conditions. Conditional probabilities have been estimated by means of experts' judgment (Trucco et al., 2008). A BN has also been integrated with FTA to develop a model for assessment of the impact of organisational risk on accident probabilities in respect of aircraft maintenance planning. The developed model has provided an explicit path from organisational and management factors to the accident causes (Mohaghegh and Mosleh, 2006, 2009). The same problem has been analysed in a framework on reduction of "Signal Passed At Danger" incidents in rail crashes on the UK rail network (Marsh and Bearfield, 2004). In this case a BN has been used to obtain the possible configurations of events leading to an accident and to the understanding of how factors in the organisation have interacted to contribute to the incident.

A BN has also been used for HRA in the context of power transmission line maintenance problems. This method has illustrated the development and application of human reliability elicitation procedure, concerning the replacement of isolator chains in power transmission lines (Firmino et al., 2006). A BN has been used to build a situation awareness assessment model and to conduct cause-effect reasoning and diagnosis of NPP safety. The technique quantitatively has identified the leading external influencing factors affecting operator situation awareness (Licao et al., 2010). An oil well production parameters availability assessment model has been developed by Droguett et al. (2008), in which the system dynamics is described via a continuous-time semi-Markovian process specified in terms of probabilities. The developed model has been integrated into a BN characterizing the cause-effect relationships among IFs affecting the repairman errors' probability during maintenance. The model has been validated in a real case of a mature oil well's management and control (Droguett et al., 2008).

Efficient FRB Bayesian reasoning approach for prioritizing failures in failure mode and effects analysis has been developed by Yang et al. (2008), in which subjective belief degrees are assigned to the consequent part of the rules to model the incompleteness encountered in establishing the knowledge base. A Bayesian reasoning mechanism is then used to aggregate all the relevant rules for assessing and prioritizing potential failure modes. The reliability of the new approach is enhanced by using a well-established FRB ER method, contributing to the development of a more precise failure criticality analysis (Yang et al., 2008). A BN has also been proposed as a probabilistic method for determining the control mode of human performance in CREAM. The proposed BN is an extension of the existing deterministic method (Kim et al., 2006). With the use of a BN, it is expected that the best estimate of the control mode - given the available data and information about the context - can be obtained. A Fuzzy-BN model has been developed by Eleye-Datubo et al. (2008) for the assessment of maritime safety. FL possibility is deployed in the model to integrate the linguistic nature of vital PSF input variables in a probabilistic BN (Eleye-Datubo et al., 2008). A generic methodology has been developed by Yang et al. (2010), in which the prospective analysis of CREAM is modified, to facilitate the quantification of maritime human failures by effectively incorporating both FL ER and Bayesian inference mechanism. The framework uses ER to establish fuzzy IF-THEN rule bases with belief structures, and Bayesian inference mechanism is employed to aggregate all the rules associated with a seafarer's task in order to estimate his/her failure probability (Yang et al., 2010).

The above review revealed that a BN provides a computational model for many purposes in the real world. Large BNs of several nodes often exist in application domains. Their complexity is sometimes beyond the current knowledge of domain experts. In addition, conventional mathematical methods are not simply to apply. Therefore, heuristic methods based on ''causal linkage'' rather than detailed equations are the feasible way to proceed at present (McErleani et al., 1999). In this regard, the established CREAM BN model, as detailed in Chapter 4, cannot cope with the full network if complete and incomplete conditional degrees of belief are assigned by experts. This is also the case if root cause nodes (CPCs) are symmetrically affected by multiple parent nodes. Therefore, a combination of ER synthesising technique and BN probabilistic theory will be investigated in this technical work. The combination of ER and BN allows both algorithms to capture the incompleteness and randomness of uncertainties in marine engineering operations. Therefore, it is very important to understand the operational context and ramifications of applying both modelling techniques. These will be elaborated in the methodological framework proposed in Section 5.3, in that the ER algorithm's synthesising and aggregation capability in handling a number of experts' complete and incomplete degrees of belief elicitation will also be examined. A case study will be explored in Section 5.4, in order to validate the BN model and ER algorithm. Section 5.5 will conclude with the achieved results.

5.3. Methodology

The new methodological framework (see Figure 5.1) can be implemented in the following steps. Firstly, it is to develop the possible rule base of modelling probabilistic causal relation between parent-child nodes in the COCOM BN developed in Chapter 4. Secondly, degrees of belief in COCOM-CMs conditional probabilities could be elicited in a complete or incomplete format by experts. Thirdly, the developed ER approach proposed in Yang and Xu (2002a, b) could be used to synthesise the degrees of belief, and aggregate the root cause factors' probability that are symmetrically affecting CREAM CPCs. This includes a review and examination of the ER algorithm, and the ER-based software. Fourthly, the unknown masses (the unassigned probabilities to grades of the child node) could be distributed back to the "Best" and "Worst" evaluations in BNs. Fifthly, two BN models with the "Best" and "Worst" conditional subjective probability estimations are constructed. Sixthly, COCOM-CMs posterior probabilities could be aggregated by the two BN model inference mechanisms. Seventhly, COCOM-CMs' posterior probabilities could be transformed and presented into HFP intervals. These intervals could be averaged into a crisp HFP value for a ranking purpose. Finally, the newly developed methodology could be validated by the reliability assessment of a specific case study scenario.

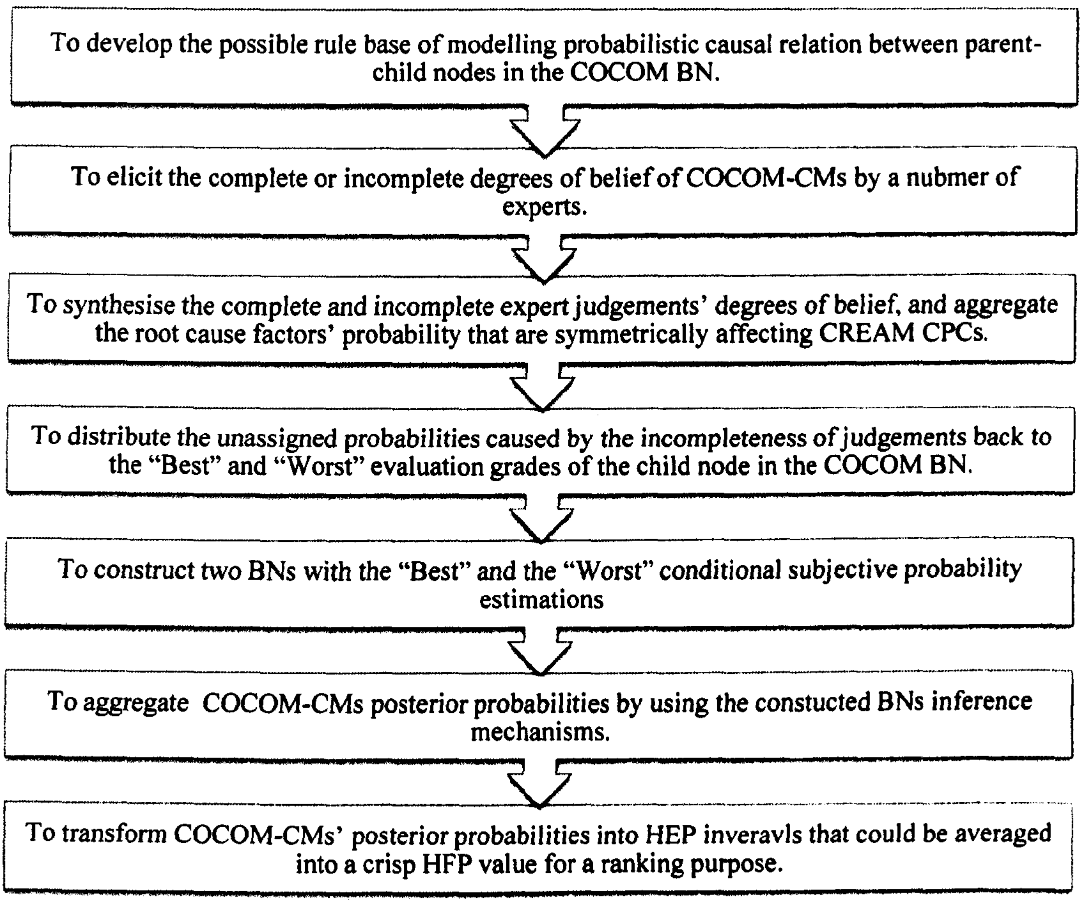


Figure 5.1: The methodology of combining ER and BNs

5.3.1. Developing the rules base of modelling parent-child nodes and eliciting the complete or incomplete degrees of belief of COCOM-CMs

In Section 4.3.2, it was found difficult to assign CPT of COCOM-CMs under new attributes, O, A and W. O, A and W are defined through the distinctive evaluation grades "Inappropriate", "Acceptable" and "Appropriate" as stated in Section 4.3.3.1. However the problem is the incompleteness knowledge encounters by the experts when assigning degrees of belief in the rule base modelling the relation among O, A, W and COCOMs.

The constructed rules base such as the one in Table 4.7 can be used by a number of experts denoted by $E_i(i = 1 \dots e)$, to elicit the degrees of belief of the consequent human action control modes' evaluation grades denoted by D_n $(n = 1 \dots 4)$. However, the problem appears in a situation, where the sum of the elicited degrees of belief is less than 1. In order that they can be used to affect COCOM-CMs probability in a convergent connection of a BN, ER algorithm synthesising capability will be investigated.

5.3.2. Synthesising the complete and incomplete expert judgements' degrees of belief.

5.3.2.1. Basic evaluation of ER algorithm

The ER algorithm has been deduced by Yang and Singh (1994) on the basis of the D-S theory of evidence for characterising and handling uncertainty in decision analysis. It allows the users to develop a framework that aggregates all the evidence available in situations pertaining to various intermediate variables and then make inferences about the variable of interest. The ER algorithm has been updated and modified further by Yang (2001) and Yang and Xu (2002a, b) to model subjective credibility induced by partial evidence observations. ER can be used for synthesising incomplete assessments in terms of combined probability masses associated with unassigned probability mass or unknown mass.

In order to investigate the capability of the ER algorithm in synthesising incomplete assessments, a hierarchy of two levels of attributes is considered, where the top level represents the general attribute' synthesised states D_n (n = 1, 2, 3, 4) of COCOM-CMs, and the bottom level represents a number of basic attributes that are denoted by E_i $(i = 1,2,3)$. In this respect the basic attributes represent the elicitations of states D_n provided by experts on a possible assessment for the combinations.

A granted assessment of D_n by E_i conditional on ${L_r}^k$ mathematically is represented by the following distribution:

$S(E_i), D_n \mid {L_r}^k = (D_n, Bn,i), (n = 1 \dots 4)$ and $(i = 1 \dots e)$ .... (5.1)

where, $0 \leq Bn,i \leq 1, \sum_{n=1}^{4} Bn,i \leq 1$ and Bn,i denotes a conditional degree of belief. The above distribution reads that the set of basic attributes E_i have subjectively assessed the evaluation grade(s) D_n distinctively and conditionally on the new attributes' (O, A and W) evaluation grades ${L_r}^k$ combination with a conditional degree(s) of belief Bn, i.

An assessment by E_i is complete if $\sum_{n=1}^{4} Bn,i = 1$ and incomplete if $\sum_{n=1}^{4} Bn,i < 1$. A special case is $\sum_{n=1}^{4} Bn,i = 0$ or $Bn,i = 0$ for all D_n, which denote a complete lack of information on $L_r{}^k$. Such partial or complete ignorance is not rare in many distinctive evaluation problems.

Suppose the importance or the relative weight of a basic attribute E_i is given by the weight $\omega_i, (i = 1,2,3)$ with the condition that $0 \leq \omega_i \leq 1$. In this regard, the relative importance of E_i plays an important role in a multi attributes' assessment (they may be estimated by using a simple rating method or assessed by using more elaborated methods such as the AHP-Based pair-wise comparisons of distinctive evaluation grades) (Yang et al., 2001; Yang et al., 2010). Collectively, the basic attributes' E_i weights have to be normalised for the consistency of the assessment.

5.3.2.2. ER algorithm for synthesising elicitations of basic attributes

Let $m_{n,i}$ be a given basic conditional probability mass representing a conditional defined degree of belief Bn,i and the relative importance ω_i of the ith basic attribute E_i (in the assessment of nth general attribute conditional degree of belief). Let $\widetilde{m}_i$ be a remaining probability mass unassigned to any individual grade Bn,i after all the nth grades have been elicited as far as E_i is concerned. Thus, $m_{n,i}$ and $\widetilde{m}_i$ could be calculated as follows:

$m_{n,i} = \omega_i Bn,i$ .... (5.2)

and the $\widetilde{m}_i$ is given by:

$\widetilde{m}_i = 1 - \sum_{n=1}^{4} m_{n,i} = 1 - \omega_i \sum_{n=1}^{4} Bn,i$ .... (5.3)

where, $n = 1,2,3,4$ and $i = 1,2,3$.

Given the above definitions and discussions the ER algorithm can be used for synthesising the basic conditional probability masses $m_{n,1}$ and $m_{n,2}$ (developed by Equation 5.2) into a combined probability mass m_{nc}. The combined mass can be synthesised further with a third basic conditional probability mass $m_{n,3}$ to develop the combined probability mass m_{nc+1}. Changing the order of synthesising the three basic conditional probability masses does not change the final result at all.

The basic conditional probability masses $m_{n,1}$ and $m_{n,2}$ $(n = 1,2,3,4)$ are synthesised by using the following ER algorithm.

$\bar{m}_i = 1 - \omega_i \geq 0$, for all $i = (1, 2, 3)$ .... (5.4)

$\bar{\bar{m}}_i = \tilde{m}_i + \bar{m}_i$ .... (5.5)

$K_{(i+1)} = [1 - \sum_{t=1}^{n} \sum_{\substack{j=1 \\ j \neq t}}^{n-1} m_{t,i}\ m_{j,i+1}]^{-1}\ n = (1,2, \dots 4)$ .... (5.6)

$K_{(i+1)} = [1 - (m_{1,1} \times m_{2,2} + m_{1,1} \times m_{3,2} + m_{1,1} \times m_{4,2}) + (m_{2,1} \times m_{1,2} + m_{2,1} \times m_{3,2} + m_{2,1} \times m_{4,2}) + (m_{3,1} \times m_{1,2} + m_{3,1} \times m_{2,2} + m_{3,1} \times m_{4,2}) + (m_{4,1} \times m_{1,2} + m_{4,1} \times m_{2,2} + m_{4,1} \times m_{3,2})]^{-1}$ .... (5.7)

$\{D_n\}: \bar{m}_{ic} = K_{(i+1)}[\bar{m}_i \times \bar{m}_{i+1}]$ .... (5.8)

$\{D_n\}: \tilde{m}_c = K_{(i+1)}[\tilde{m}_i \times \tilde{m}_{i+1} + \bar{m}_{n,i} \times \tilde{m}_{i+1} + \tilde{m}_i \times \bar{m}_{n,i+1}]$ .... (5.9)

$\{D_n\}: m_{nc} = K_{(i+1)}[m_{n,i} \times\ m_{n,i+1} + m_{n,i} \times \bar{\bar{m}}_{i+1} + \bar{\bar{m}}_i \times m_{n,i+1}]$ .... (5.10)

$B_n = \frac{m_n}{1 - \bar{m}_i}$ .... (5.11)

$B_u = \frac{\tilde{m}_i}{1 - \bar{m}_i}$ .... (5.12)

where, $\bar{m}_i, \bar{\bar{m}}_i, K_{(i+1)} (n = 1,2,3,4$ and $i = 1,2,3)$, respectively, denote the remaining relative importance of basic attribute E_i, the unassigned probability mass (remaining probability mass and relative importance) of any individual grade, and the normalizing factor. In addition, , $\bar{m}_{ic}, \tilde{m}_c$, and m_{nc} , $(n = 1,2,3,4$ and $i = 1,2,3)$ respectively, denote the remaining combined relative importance of the two assessments E_1 and E_2, the combined probability mass initially unassigned to any individual grade degree of belief Bn, i, the remaining combined probability mass due to the possible incomplete assessment of Bn, i by E_1 and E_2, and the combined probability mass generated by synthesising the two assessments E_1 and E_2. B_n , is the combined degrees of belief of the two assessment E_1, and E_2, and B_u is the unassigned probability mass to the two assessments E_1, and E_2. In a similar way the above ER algorithm is used to synthesis the combined probability mass m_{nc} (generated by synthesising the two assessments E_1 and E_2 (as one set)) with the basic conditional probability masses $m_{n,3}$ of the third assessment E_3 (as the other) to obtain the synthesised degrees of belief B_n and the unassigned probability mass B_u of the three assessments E_1, E_2 and E_3.

5.3.3. Distributing the unassigned probability masses in the COCOM-CMs BN to obtain HFPs interval

The unassigned probability mass Bu caused by the incompleteness of judgements goes back respectively to the "Best" B_1 and "Worst" B_4 evaluation grades of the child node in the COCOM-CMs BN. Similarly for all the other unassigned probability masses go back to the best and worst scenarios CPT that will be used individually in the constructed generic CREAM BN model in Chapter 4, in order to aggregate COCOM-CMs posterior probabilities for the best and worst scenarios separately. The best scenario will also be used to obtain the lowest HEP value using Bayesian inference and the defuzzifecation method in Chapter 4 (Equation 4.5), while the CPTs associated with the worst case will be used to calculate the highest HEP values. Consequently, the highest and lowest values can be used as the two limits of an interval. It reflects the fact that the HEP analysis with incomplete input deliveries its values in an interval, in which the actual HEP exists. For a ranking purpose, the HEP average value is calculated and presented. However it is noteworthy that a human action is more reliable than the other if and only if its highest value is smaller than the lowest one of the other.

5.4. An illustrative example

To demonstrate the above methodology, this part describes the calculation of obtaining incomplete CPT of COCOM-CMs node in the network in Chapter 4 through interviewing 3 experts.

Step 1: Three domain experts E_i $(i = 1, 2, 3)$ are asked to provide their elicitations on the evaluation grades of the COCOM-CMs in terms of conditional degrees of belief as defined by equation 5.1 and the rule base constructed in Table 4.7. Their input is listed in Table 5.1.

Table 5.1: Basic attributes elicitation of evaluation grades conditional degrees of belief

L	E_1				E_2				E_3			
	$D_{1,1}$	$D_{2,1}$	$D_{3,1}$	$D_{4,1}$	$D_{1,2}$	$D_{2,2}$	$D_{3,2}$	$D_{4,2}$	$D_{1,3}$	$D_{2,3}$	$D_{3,3}$	$D_{4,3}$
	$B_{1,1}$	$B_{2,1}$	$B_{3,1}$	$B_{4,1}$	$B_{1,2}$	$B_{2,2}$	$B_{3,2}$	$B_{4,2}$	$B_{1,3}$	$B_{2,3}$	$B_{3,3}$	$B_{4,3}$
1	0	0	0	1	0	0	0	0.9	0	0	0	1
2	0	0	0.1	0.9	0	0	0.1	0.8	0	0	0.2	0.8
3	0	0	0.2	0.8	0	0	0.2	0.7	0	0	0.3	0.7
4	0	0	0.2	0.8	0	0	0.2	0.7	0	0	0.4	0.6
5	0	0.1	0.3	0.6	0	0	0.3	0.6	0	0	0.7	0.3
6	0	0.2	0.3	0.5	0	0	0.4	0.5	0	0.2	0.8	0
7	***0***	***0***	***0.3***	***0.7***	***0***	***0.1***	***0.3***	***0.3***	***0***	***0***	***0.4***	***0.6***
8	0	0.2	0.4	0.4	0	0.2	0.4	0.3	0	0	0.7	0.3
9	0	0.3	0.4	0.3	0	0.2	0.5	0.2	0.4	0.6	0	0
10	0	0	0.2	0.8	0	0.1	0.8	0	0	0	0.4	0.6
11	0.1	0.3	0.3	0.3	0	0.2	0.7	0	0	0.8	0.2	0
12	0.1	0.4	0.4	0.1	0	0.2	0.7	0	0	0.7	0.3	0
13	0.1	0.3	0.4	0.2	0	0.3	0.6	0	0	0.6	0.4	0
14	0.2	0.4	0.3	0.1	0	0.5	0.4	0	0.3	0.7	0	0
15	0.3	0.4	0.2	0.1	0	0.5	0.4	0	0.2	0.8	0.4	0
16	0	0.3	0.4	0.3	0	0.6	0.3	0	0	0.5	0.5	0
17	0.2	0.4	0.4	0	0	0.7	0.2	0	0.5	0.5	0	0
18	0.3	0.4	0.3	0	0	0.8	0.1	0	0.6	0.4	0	0
18	0	0	0.3	0.7	0.3	0.4	0.2	0	0	0	0.3	0.7
20	0	0.2	0.4	0.4	0.3	0.4	0.2	0	0	0.6	0.4	0
21	0	0.4	0.4	0.2	0.4	0.3	0.2	0	0	0.4	0.6	0
22	0	0.2	0.3	0.5	0.6	0.4	0	0	0	0.5	0.5	0
23	0.2	0.4	0.4	0	0.6	0.3	0	0	0.7	0.3	0	0
24	0.3	0.5	0.2	0	0.7	0.20	0	0	0.8	0.2	0	0
25	0.1	0.4	0.4	0.1	0.7	0.2	0	0	0.5	0.5	0	0
26	0.3	0.5	0.2	0	0.8	0.1	0	0	0.8	0.2	0	0
27	0.5	0.5	0	0	0.9	0	0	0	0.9	0.1	0	0

Next three experts' judgements are synthesised using the ER algorithm. Rule 7 in Table 5.1 is used as an example. The relative importance of the three experts is equal. The synthesising of the three assessments E_1, E_2 and E_3 is approached through. Firstly, synthesising the two assessments E_1, and E_2 (as one set), as follows.

To calculate the basic conditional probability masses $m_{n,i}$ as defined by Equation 5.2.

$m_{1,1} = 0.333 \times 0 = 0; m_{2,1} = 0.333 \times 0 = 0; m_{3,1} = 0.333 \times 0.3 = 0.0999;$

$m_{4,1} = 0.333 \times 0.7 = 0.2331.$

$m_{1,2} = 0 \times 0.333 = 0;\ m_{2,2} = 0.1 \times 0.333 = 0.0333;\ m_{3,2} = 0.3 \times 0.333 = 0.0999; m_{4,2} = 0.3 \times 0.333 = 0.0999.$

$m_{1,3} = 0 \times 0.333 = 0;\ m_{2,3} = 0 \times 0.333 = 0;\ m_{3,3} = 0.4 \times 0.333 = 0.1332;$

$m_{4,3} = 0.6 \times 0.333 = 0.1998.$

Next it is to calculate the remaining probability mass $\tilde{m}_i$ due to the possible incompleteness of any individual grade Bn, i as defined by Equation 5.3.

$\tilde{m}_1 = 0.333[1 - (0 + 0 + 0.3 + 0.7)] = 0;$

$\tilde{m}_2 = 0.333[1-(0+0.1+0.3+0.3)] = 0.0999;$

$\tilde{m}_3 = 0.333[1-(0+0+0.4+0.6)] = 0.$

The remaining relative importance $\bar{m}_i$ for all $i = (1,2,3)$ is obtained as follows using Equation 5.4.

$\bar{m}_1 = 1 - 0.333 = 0.667;$

$\bar{m}_2 = 1 - 0.333 = 0.667;$

$\bar{m}_3 = 1 - 0.333 = 0.667.$

The unassigned probability mass $\bar{\bar{m}}_i$ (remaining probability mass and relative importance) to any individual grade can be computed using Equation 5.5.

$\bar{\bar{m}}_1 = 0 + 0.667 = 0.667;$

$\bar{\bar{m}}_2 = 0.0999 + 0.667 = 0.7669;$

$\bar{\bar{m}}_3 = 0 + 0.667 = 0.667.$

The normalizing factor $K_{(i+1)}$ for combining the two assessments E_1 and E_2 is calculated using Equations 5.6 and 5.7.

$K_{(i+1)} = [1-(0 \times 0.0333 + 0 \times 0.0999 + 0 \times 0.0999) + (0 \times 0 + 0 \times 0.0999 + 0 \times 0.0999) + (0.0999 \times 0 + 0.0999 \times 0.0333 + 0.0999 \times 0.0999) + (0.2331 \times 0 + 0.2331 \times 0.0333 + 0.2331 \times 0.0999)]^{-1} = 1.0464.$

The combined remaining relative importance $\bar{m}_{ic}$ from the two assessments E_1 and E_2 are obtained using Equation 5.8.

$\bar{m}_{ic} = 1.0464(0.667 \times 0.667) = 0.4655.$

The remaining combined probability mass $\tilde{m}_c$ due to the possible incomplete assessment of Bn, i by E_1 and E_2 is defined by Equation 5.9.

$\tilde{m}_c = 1.0464[(0 \times 0.0999) + (0.667 \times 0.0999) + (0 \times 0.667)] = 0.0697.$

To calculate the combined probability mass m_{nc} of the basic conditional probability masses $m_{n,1}$ and $m_{n,2}$, Equation 5.10 is employed as follows.

$m_{1c} = 1.0464[(0 \times 0) + (0 \times 0.7669) + (0.667 \times 0)] = 0;$

$m_{2c} = 1.0464[(0 \times 0.0333) + (0 \times 0.7669) + (0.667 \times 0.0333)] = 0.0232;$

$m_{3c} = 1.0464[(0.0999 \times 0.0999) + (0.0999 \times 0.7669) + (0.667 \times 0.0999)] = 0.1537;$

$m_{4c} = 1.0464[(0.2331 \times 0.0999) + (0.2331 \times 0.7669) + (0.667 \times 0.0999)] =$ $0.2698.$

Finally, the remaining combined probability mass $\bar{\bar{m}}_{ic}$ due to the possible incomplete assessment of Bn, i by E_1 and E_2 is calculated by Equation 5.5.

$\bar{\bar{m}}_c = 0.0697 + 0.4655 = 0.5842.$

Secondly, in a similar way, the result of combining three experts' judgements can be obtained by synthesising the combination of the first two assessments E_1, and E_2 (as one set) with the third assessment E_3 (as the other). Consequently, the synthesised human action control modes' degrees of belief B_n for the 7th rule are *Strategic* $(B_1) = 0$, *Tactical* $(B_2) = 0.0252$, *Opportunistic* $(B_3) = 0.3271$ and *Scrambled* $(B_4) = 0.5713$. The use of the ER algorithm has also resulted in a combined unknown mass $(B_u) =$ 0.0744.

Windows based IDS software was developed by Yang (2001). It is used in synthesising the basic attributes E_i of Rule 7 with the same result obtained in Figure 5.2. The intelligent decision system (IDS) is also used in synthesising the other combined degrees of belief (or probabilities) listed in Table 5.1.

Although the ER algorithm is used to synthesise experts' combined degrees of belief mass B_n, a remaining unknown mass B_u, which is not assigned to any evaluation grades, is also developed. Consequently, the remaining unassigned degrees of belief are assigned back to the best evaluation grade "*Strategic*" and the worst evaluation grade "*Scrambled*" on all rules. Accordingly, two sets of evaluation grades are generated in Table 5.2 and used as prior probabilities in generic COCOM BN model to calculate HEP values.

Table 5.2: Synthesised and combined degrees of beliefs of COCOM-CMs evaluation grades

Alts.	Strategic (D_1)	Strategic (D_1) C Unknown	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)	Scrambled (D_4) C Unknown	Unknown
1	0	0.0211	0	0	0.9789	1	0.0211
2	0	0.0231	0	0.1019	0.8750	0.8981	0.0231
3	0	0.0244	0	0.1973	0.7783	0.8027	0.0244
4	0	0.0248	0	0.2321	0.7431	0.7679	0.0248
5	0	0.0265	0.0279	0.4316	0.5140	0.5405	0.0265
6	0	0.0277	0.1220	0.5323	0.3180	0.3457	0.0277
7	0	0.0759	0.0253	0.3260	0.5728	0.6487	0.0759
8	0	0.0271	0.1164	0.5282	0.3283	0.3554	0.0271
9	0.1227	0.1519	0.3910	0.2979	0.1592	0.1884	0.0292
10	0	0.0274	0.0274	0.4734	0.4718	0.4992	0.0274
11	0.0295	0.0576	0.4495	0.4045	0.0884	0.1165	0.0281
12	0.0284	0.0554	0.4394	0.4768	0.0284	0.0554	0.0270
13	0.0284	0.0555	0.4031	0.4845	0.0569	0.0840	0.0271
14	0.1525	0.1797	0.5789	0.2126	0.0288	0.0562	0.0274
15	0.1512	0.1784	0.6164	0.1767	0.0285	0.0557	0.0272
16	0	0.0271	0.4819	0.4058	0.0852	0.1123	0.0271
17	0.2159	0.2433	0.5757	0.1809	0	0.0274	0.0274
18	0.2851	0.3125	0.5695	0.1180	0	0.0274	0.0274
19	0.0865	0.1153	0.1153	0.2715	0.4979	0.5267	0.0288
20	0.0855	0.114	0.4205	0.3457	0.1198	0.1483	0.0285
21	0.1125	0.1406	0.3815	0.4188	0.0591	0.0872	0.0281
22	0.1758	0.2343	0.3223	0.2822	0.1612	0.2198	0.0586
23	0.5278	0.5817	0.2997	0.1186	0	0.0539	0.0539
24	0.6370	0.6635	0.2810	0.0555	0	0.0265	0.0265
25	0.4437	0.4719	0.3803	0.1182	0.0296	0.0578	0.0282
26	0.6753	0.7016	0.2432	0.0552	0	0.0263	0.0263
27	0.8153	0.8397	0.1603	0	0	0.0244	0.0244

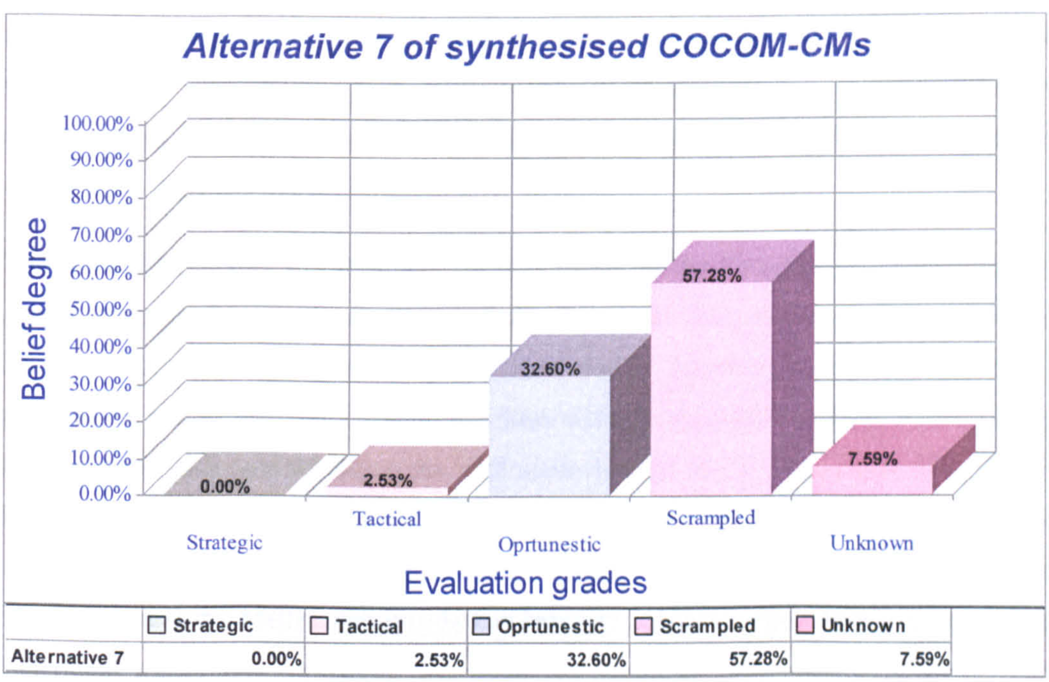


Figure 5.2: Assessment alternative 7 evaluation grads synthesised degrees of belief

5.4.1. Aggregating multi attribute effect on root cause CPCs

The main reasons behind the selection of the ***Deepwater Horizon*** accident as a case study to validate the correlation of ER sensitizing and aggregation technique with the developed COCOM-CMs BN model and are: there were several main governing factors had symmetrically affected the context' CPCs effect level over the whole period of the drilling operations; the uncertainty associated with the available information during the final stages of drilling operation, inevitably stimulated the possibility of utilising the incomplete degrees of belief in the assessment of COCOM-CMs.

5.4.1.1. Case study background

*On the evening of April 20, 2010, a well control event allowed hydrocarbons to escape from Macondo well onto **Transocean's Deepwater Horizon**, resulting in explosions and fire on the rig. Eleven people lost their lives, and 17 others were injured. The fire, which was fed by the hydrocarbons from the well, continued for 36 hours until the rig sank. Hydrocarbons continued to flow from the reservoir through the wellbore and the Blow Out Preventer (BOP) for 87days, causing a spill of a national significance.*

Deepwater Horizon was located approximately 50 miles south of Venice, LA at Mississippi Canyon 252.

The accident on April 20, 2010, involved a well integrity failure, followed by a loss of hydrostatic control of the well. This followed a failure to control the flow from the well with the BOP equipment, which allowed the release and the subsequent ignition of hydrocarbons. Ultimately, the BOP emergency functions failed to seal the well after the initial explosions (BP, 2010).

The evaluation of CPCs in this case study is based on the investigation team's review results specifically presented in *Appendix T of the Deepwater Horizon Accident Investigation Report* (BP, 2010). The review was to identify the relevant practices, procedures, and expectations, comparing them with the rig crew's actions in monitoring the Macondo well and managing the well control event on 20 April 2010. The review included the documents that governed the drilling operation on board the *Deepwater Horizon* at the time of the accident; the available real time data; the witness account interviews; and the MBI testimony. In this respect, Table 5.3 summarizes the specified functional assessment attributes, the identified evidence, and their evaluation. The inherent variability effects that shaped operators' actions and observations in the context of events are used in CPCs' effect level evaluations. The evaluations listed in Table 5.4 have been subjected to experts' review and assessment. CPCs' effect levels are assigned in complete degrees of belief with equal relative importance. IDS software is used to aggregate the assigned complete degrees of belief of CPCs' effect levels probability mass, as shown in Table 5.5.

CPCs' effect level evaluations are used as input observations of root cause nodes in the two established CREAM BN generic models. Their synthesised COCOM-CMs' conditional degrees of belief masses and unknown masses dealt with in Section 5.4.1 are listed in Table 5.2. Two possible assessment scenarios are generated: the first scenario utilises root cause nodes observation and the worst possible set of evaluation grades, which includes the combined probability masses of scrambled evaluation grades (see Figure 5.3).The second scenario utilises root cause nodes observation and the best possible set of evaluation grades, which includes the combined probability masses of strategic evaluation grades (see Figure 5.4). The posterior probabilities of the two assessment models' evaluation grades and their transformed respective HFP results are shown in Table 5.6. HFPs are derived by utilising the nominal HFP values stated in Chapter 4, Section 4.3.3.2. Finally, HFPs are presented in an utility interval rather than a crisp value. Such an interval could be used effectively to specify the uncertainty involved in the assessment, and can also be averaged into a crisp value for ranking. Accordingly, corrective actions and reassessments could be structured.

Table 5.3: Identified relevant practices, procedures, and expectations of rig crew's actions in monitoring the Macondo well and managing the well control event on 20 April 2010

Functional assessment attributes		Investigation team review results	
		Identified evidence	Evaluation
1	Task responsibilities	The manager was not clearly defined	The investigation team could not verify whether anyone fitted the description of manager or had task responsibilities, and who should have made enquiries regarding the results of the negative pressure test that had been conducted to prove that the well structure integrity was intact at the time the negative pressure test results were concluded.
		The well driller's responsibility is to detect a well control situation and shut in the well quickly, and to minimize the kick size used to enhance the safety of a well control operation.	Neither the driller nor the tool-pusher realized that there were impending well control events.

2	Preparation procedures		The review of well control preparation procedures has not occurred	There is no evidence.
3	Prevention	Procedures	On 20 April, 2010 between 13:28 and 17:17 hours drilling mud fluid volume monitoring equipment was not properly used; in addition, it is not known what equipment they were using.	Pressure and flow variations should have been available that would have indicated an abnormality with the oil well. In this regard "extreme caution" could include factors such as pressure changes and flow increases. It would also include isolated individual volume monitoring to enhance well structure intact integrity.
		Witness accounts 1	On 20, April, 2010 from 13:28 hours to 17:17 hours, mud was transferred to the supply vessel. Transferring mud from the pits to the supply vessel impaired the ability of mud-loggers to reliably monitor the pit levels. Mud-logger stated this concern was raised with the assistant driller. The response was that the assistant driller would notify him when the mud transfer was completed and monitoring could resume. Mud-logger indicated that this notification did not occur after mud transfer to the supply vessel stopped at 17:17 hours.	Mud-logger did not effectively monitor pit volumes for the remainder of that day.
		Witness accounts 2	There is no evidence to suggest that either the driller or assistant driller was monitoring the well mud fluid volumes and flow. Although mud-loggers' well monitoring equipment was installed and working, it was apparently not being used due to mud transfer to the supply vessel and mud pit cleaning activities.	A more timely response to well conditions may have occurred if "constant, accurate observation and recording of mud volume" was implemented as defined in high pressure high temperature drilling guide lines stated in the documents governing the drilling operation.
4	Detection	Procedures	Mud pumps were stopped at 21:31 on April 20, 2010, but the driller and the tool-pusher both apparently were trying to understand the deferential pressure just prior to the accident.	Neither the driller nor the tool-pusher realized that there was an impending well control event.
		Real-time data 1	An increase in return flow from the well at 20:58 hours on April 20, 2010, approximately 51 minutes before the first explosion. However, drill pipe pressure also increased and went unnoticed. The real time data indicts that a 39 bbl gain was taken in the mud pits at that time.	Interim reports and the real time data indicate that the trip tank was being emptied at that time. This may have masked the volume change caused by flow from the well.
		Real-time data 2	At 21:08 hours on April 20, 2010, pumping was stopped, and the sheen test intended to indicate the presence of free oil was performed on the spacer returning from the well. From this time forward, the fluid returning from the well was discharged overboard.	If the driller's flow metre had been operating properly, increasing return flow would have been detected at this time.

		Real-time data 3	While fluids were being discharged overboard, the mud loggers' flow meter bypassed.	The mud loggers were unable to monitor flow.
		Witness accounts 1	Mud-logger indicated that mud flow would not be seen if the flow diverter was activated or going through the dump line. The mud logging system is far more accurate.	
		Real-time data 4	Real-time data indicates that circulation continued after flow increased and pump pressure fluctuated between 20:58 hours and 21:31 hours.	By the time the mud pumps were shut down at 21:31hours, an estimated 300bbl gain had been taken into the wellbore and the well was flowing.
		Real-time data 5	Well flow modelling indicates that between 21:36 hours and 21:38 hours a valve was opened and closed on the rig floor, presumably to bleed off pressure from the drill pipe.	Based on wetness accounts, the investigation team concluded that this occurred approximately 4 minutes before mud start flowing onto the rig floor.
		Witness accounts 2	Mud was seen shooting all the way up to the derrick for several seconds, and then it just quit and went down for several seconds after that, and then all of a sudden the degasser mud started to come out of the degasser very strongly onto the deck. Mud flow volume through the rotary table at the surface was significant.	Based on the procedure defined for equipment handling gas in the riser, the mud flow should have been routed overboard. Instead, the mud flow was routed through the mud gas separator. Based on gas dispersion and explosion analyses, the investigation team concluded that, if the rig crew had diverted mud flow to the overboard discharge line rather than to the mud gas separator, the consequences of the event would have been reduced.
5	Blowout emergency response		The emergency response procedure that should be developed jointly by the management and the operator to be used in case of well blowout was requested.	Such document was not received at the time of investigation.
6	Containment		Events stated do not support a conclusion that action was taken to shut the well in the shortest possible time, as required by the documents governing the drilling operation, following the sequence for shutting down a well when either tripping or drilling.	In the opinion of the investigating team, despite the guidance provided in the documents governing the drilling operation, wellbore monitoring did not identify the influx until after hydrocarbons were in the riser, and the subsequent action taken prior to the explosion suggests the rig crew was not sufficiently prepared to mange an escalating well control situation.

The investigation team review and assessment results summarised in Table 5.3 have been used in interviews with three experts to provide their discrete subjective probabilities elicitations on the symmetrical affect of functional assessment attributes' identified evidence and evaluation on each CPC effect levels/ descriptors. CPCs' effect levels are assigned complete degrees of belief with equal relative importance. Final assessment results are listed in Table 5.4, where (x) denotes the irrelevance of effect and the equally distributed probability on all effect levels of a CPC means the effect levels could not be verified.

Table 5.4: Evaluation of functional assessment attributes affect on CPCs effect level/descriptor

CPCs	Level/descriptors	Functional assessment attributes					
		Task responsibilities	Preparation	Prevention	Detection	Emergency response	Containment
Adequacy of organisation CPC 1	Very Efficient	0	0	0	0	25	0
	Efficient	0	0	0	0	25	0
	Inefficient	0	0	100	100	25	0
	Deficient	100	100	0	0	25	100
Working conditions CPC 2	Advantageous	x	33.3	33.3	33.3	33.3	33.3
	Compatible	x	33.3	33.3	33.3	33.3	33.3
	Incompatible	x	33.4	33.4	33.4	33.4	33.4
Adequacy of MMI and operational support CPC 3	Supportive	x	x	0	0	25	0
	Adequate	x	x	0	0	25	0
	Tolerable	x	x	50	50	25	0
	Inappropriate	x	x	50	50	25	100
Availability of procedures/plans CPC 4	Appropriate	0	0	0	0	33.3	100
	Acceptable	100	0	100	100	33.3	0
	Inappropriate	0	100	0	0	33.4	0
Number of simultaneous goals CPC 5	Fewer than capacity	x	33.3	33.3	33.3	33.3	33.3
	Matching current capacity	x	33.3	33.3	33.3	33.3	33.3
	More than capacity	x	33.4	33.4	33.4	33.4	33.4
Available time CPC 6	Adequate	x	100	100	100	33.3	33.3
	Temporarily inadequate	x	0	0	0	33.3	33.3
	Continuously inadequate	x	0	0	0	33.4	33.4
Time of day (circadian rhythm) CPC 7	Day-time (6:00-18:00hr) (adjusted)	x	33.3	50	50	33.3	50
	Night(17:00-24:00hr) (unadjusted)	x	33.3	50	50	33.3	50
	Night-time(0:00-7:00hr) (unadjusted)	x	33.3	0	0	33.4	0
Adequacy of training and expertise CPC 8	Adequate, high experience	33.3	33.3	0	0	33.3	0
	Adequate, limited experience	33.3	33.3	0	0	33.3	0
	Inadequate	33.4	33.4	100	100	33.4	100
Crew collaboration quality CPC 9	Very efficient	25	25	0	0	25	0
	Efficient	25	25	0	0	25	0
	Inefficient	25	25	0	0	25	0
	Deficient	25	25	100	100	25	100

The final assessment results listed in Table 5.4 are used to aggregate the complete degrees of belief of CPCs' effect levels listed in Table 5.4 with use of ER software.

Table 5.5: CPCs effect levels/descriptors assigned degrees of belief aggregation with IDS

CPCs	Level/descriptors	Functional assessment attributes aggregated degrees of belief
Adequacy of organisation CPC 1	Very Efficient	3.51
	Efficient	3.51
	Inefficient	57.09
	Deficient	35.89
Working conditions CPC 2	Advantageous	33.33
	Compatible	33.33
	Incompatible	33.34
Adequacy of MMI and operational support CPC 3	Supportive	5.18
	Adequate	5.18
	Tolerable	29.52
	Inappropriate	60.12
Availability of procedures/plans CPC 4	Appropriate	19.95
	Acceptable	60.10
	Inappropriate	19.95
Number of simultaneous goals CPC 5	Fewer than capacity	33.33
	Matching current capacity	33.33
	More than capacity	33.34
Available time CPC 6	Adequate	78.82
	Temporarily inadequate	10.59
	Continuously inadequate	10.59
Time of day (circadian rhythm) CPC 7	Day-time (6:00-18:00hr) (adjusted)	36.25
	Night(17:00-24:00hr) (unadjusted)	49.13
	Night-time(0:00-7:00hr) (unadjusted)	14.62
Adequacy of training and expertise CPC 8	Adequate, high experience	14.01
	Adequate, limited experience	14.01
	Inadequate	71.98
Crew collaboration quality CPC 9	Very efficient	6.43
	Efficient	6.43
	Inefficient	6.43
	Deficient	80.70

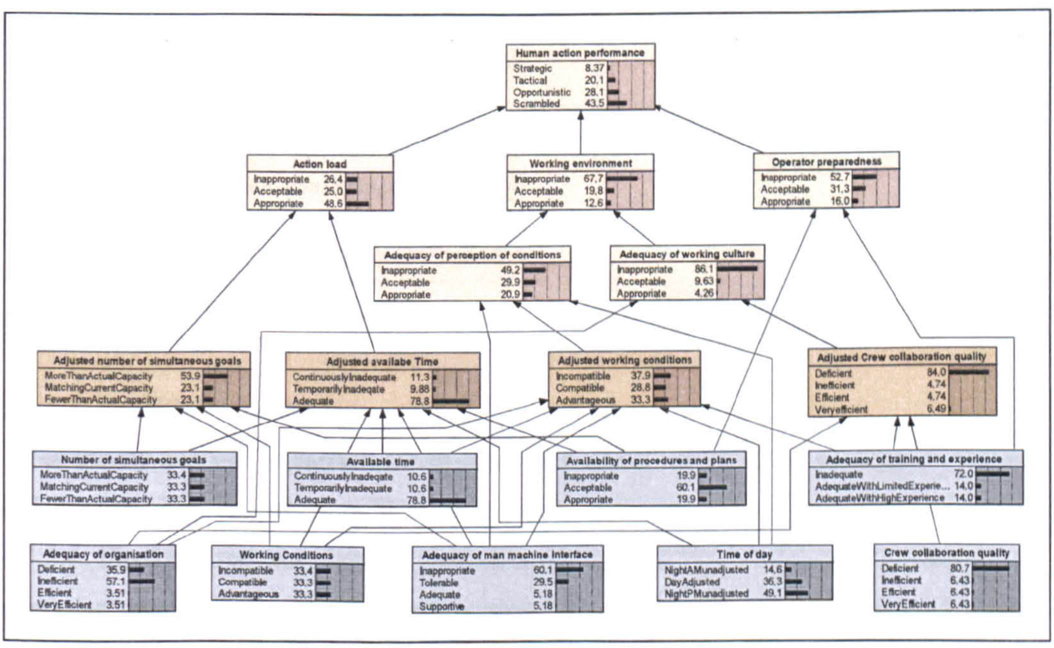


Figure 5.3: BN model displays human COCOM-CMs' posterior probabilities based on the worst possible set of evaluation grades (scrambled evaluation grades' conditional degrees of belief masses are combined with the unknown masses) and CPCs' input observations are complete (condition 1).

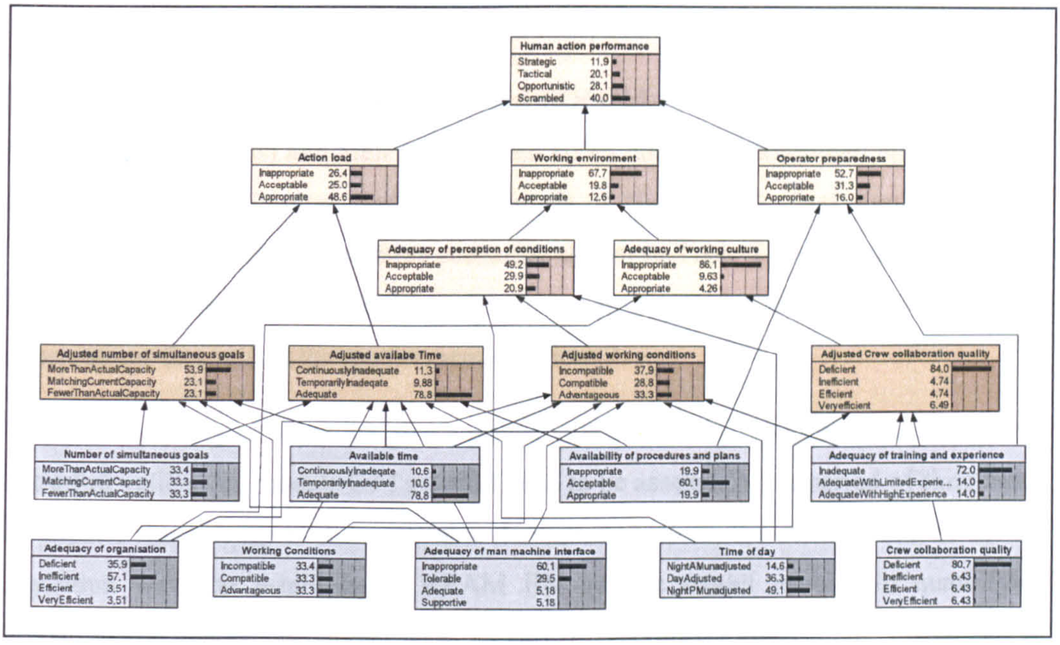


Figure 5.4: BN model displays human COCOM-CMs' posterior probabilities based on the best possible set of evaluation grades (strategic evaluation grades' conditional degrees of belief masses are combined with the unknown masses) and CPCs' input observations are complete (condition 2).

Table 5.6: Final HFPs of both assessed scenarios

Conditions	HFP/time
1.The worst scenario BN aggregated COCOM-CMs probability and their transformed highest HFP	0.0838×0.000224 + 0.201× 0.01+ 0.281× 0.0708+0.435×0.316 = 0.1594
2. The best scenario BN aggregated COCOM-CMs probability and their transformed lowest HFP	0.119×0.000224 + 0.201× 0.01+ 0.281× 0.0708+0.40×0.316 = 0.1483
The highest and lowest values of HFPs interval	0.1483 $\leq$HFP $\leq$0.1594
The HEP average value	$\frac{0.1483+0.1594}{2} = 0.1539$ failure/time

5.4.1.2. Sensitivity analysis

A sensitivity analysis is carried out in order to partially validate the developed CREAM BN models. The models should at least satisfy the two axioms described in Section 4.3.3.4. Firstly, three examination scenarios including CPC "Adequacy of training and expertise" evaluation grades "Adequate with high experience", "Adequate with limited experience" and "Inadequate" are used individually as input observations of the worst and the best scenarios' models shown in Figures 5.3 and 5.4 respectively. The revised COCOM-CM probabilities and their transformed HFPs findings stated in Table 5.7

satisfy the requirement of axiom 1 described in Section 4.3.3.4.

Table 5.8 illustrates three scenarios' revised COCOM-CMs' probabilities (for the worst and the best scenarios) and their transformed HFPs due to the combined effect of seven CPC states' being simultaneously set at levels of "Improved", "Not significant", and "Reduced". The results of the three scenarios shown in Table 5.8 show that the models inference and the final probabilities change are in agreement with logicality of input observations that satisfy the requirement of axiom 2.

The above developed scenarios give a partial validation to the models. In order to carry out a full validation, models CPTs would need to be assessed for a period of time based on experts' knowledge in the applicable domain. Therefore, the combination of the ER algorithm with the established CREAM BN generic model enables to quantifying human action failure probability in a context of incomplete assessment, which can be assessed further for utility analysis and decision making.

Table 5.7: Human action failure probability changes results due to adequacy of training and expertise (CPC8) states effect level.

Axiom 1							
CPC 8 states assigned input observations		Models Inference output beliefs					
		Strategic (D_1)	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)	Final HFP/time
Scenario 1	Adequate with high experience 100% (best)	29.8	30.20	23.10	16.90	0.0728
	Adequate with high experience 100% (worst)	26.60	30.20	23.10	20.20	0.0833
Scenario 2	Adequate with limited experience 100% (best)	12.20	29.50	31.70	26.60	0.1095
	Adequate with limited experience 100% (worst)	9.03	29.50	31.70	29.70	1193
Scenario 3	Inadequate 100% (best)	8.33	16.30	28.3	47.10	0.1705
	Inadequate 100% (worst)	4.70	16.30	28.30	50.70	0.1819

Table 5.8: Human action failure probability changes results due to the combined effect levels of seven CPCs involved in case study scenarios

Axiom 2							
Seven CPCs' states assigned input observations		Model Inference output beliefs					
		Strategic (D_1)	Tactical (D_2)	Opportunistic (D_3)	Scrambled (D_4)	Final probability
Scenario 1	(CPCs 1, 6) Improved 100% (best) (CPC 4) Not significant 100% (best) (CPC 3, 7,8, 9) Reduced 100% (best)	8.29	22.10	31.70	37.90	0.1444
	(CPCs 1, 6) Improved 100% (worst) (CPC 4) Not significant 100% (worst) (CPC 3, 7,8, 9) Reduced 100% (worst)	4.88	22.10	31.70	41.4	0.1555
Scenario 2	(CPC 1,4,6) Not significant (best) 100% (CPC 3, 7,8, 9) Reduced 100% (best)	4.48	12,80	28.00	54.00	0.1770
	(CPC 1,4,6) Not significant 100% (worst) (CPC 3, 7,8, 9) Reduced 100% (worst)	1.58	12.8	28.00	57.7	0.2034
Scenario 3	(CPC 3, 8, 9) Improved 100% (best) CPC 4,7) Not significant 100% (best) (CPC 1, 6) Reduced 100% (best)	20.90	34.20	31.70	13.20	0.0676
	(CPC 3, 8, 9) Improved 100% (worst) CPC 4,7) Not significant 100% (worst) (CPC 1, 6) Reduced 100% (worst)	17.90	34.20	31.70	16.20	0.0770

5.5. Conclusion

ER's synthesising and aggregation capability has enlarged the scope of a BN mechanism inference viability in describing and handling uncertain information in an engineering operation context. By using the concept of degrees of belief, the ER-BN combination can well model context knowledge incompleteness and ignorance explicitly at any BN assessment level. Combining degrees of ignorance with the best and worst evaluation grades explicitly have helped to develop two BNs to aggregate the best and worst scenarios of COCOM-CMs' probabilities. Subsequently, their results are transformed and presented in HFP intervals, where each could be averaged into a crisp HFP value. Consequently, a sound method for dealing with a high level of uncertainties in marine engineering operations is rationally developed to handle the problems to which the traditional methods lack the capability of providing appropriate solutions. Therefore, the established CREAM BN generic model for proactive assessment of human action failure probability will be used with more confidence in CREAM human performance analysis and decision making in the next chapter.

Chapter 6

Decision making methodology for improving human performance reliability based on operational context analysis

Summary

A decision making process can be a feed forward action, needed to integrate the bidirectional approaches of HRA (i.e. CREAM) in reducing HFP. This process is based on the previously developed CREAM models of human performance assessment and analysis in the context of marine engineering operations. The aim of human performance analysis is to identify initiating events or root causes of assessed HFP. To reduce a HFP, the Analytical Hierarchy Process (AHP) is first used to subjectively assign the weights of the chosen decision criteria. Secondly, entropy information with respect to each criterion is calculated to analyse internal relative importance of the chosen criterion. Thirdly, a TOPSIS method is used to model the evaluation of the identified risk control options (RCO) with respect to each criterion and the combined weights of the criteria. This will provide the preference order of the developed RCOs, where decision makers would be able to choose the relevant alternative of RCOs based on their plans and expectation in respect of the reduction of HFP. Finally, the developed technical work achievements are concluded.

6.1. Introduction

A BN model has been developed in Chapter 4 to quantify human action control mode probabilities. The BN model's capability is further enhanced in Chapter 5 by the use of ER belief theory, enabling the capture of incomplete information associated with CPCs and other attributes in a CREAM context. The developed BN is constructed to model CREAM for human performance reliability assessments, which concede that information process and human actions are coupled and mutually dependent (Hollnagel, 1998a).

CREAM shows that human actions depend on the conditions under which an action takes place in both human performance analysis and assessment. The cause and effect relationship specified in the CREAM human performance analysis method can be used to describe a large number of potential pathways, through the use of classification groups, to identify the attribute(s) of an initiating event or "root" cause. Hence, the classification groups' generic framework provided in CREAM can be specified to suit marine engineering operations.

Consequently, a described context in the framework of human performance assessment can be used to identify the possible error modes/phenotypes and the main related groups of people, technological and organisation possible or probable and the likely genotype causes, following the retrospective analysis of CREAM.

Such identification can be detailed to a further analysis level(s) to establish the potential pathways that could be used to identify the well thought-out specific consequent(s) (effects) general consequent(s) (causes/effects), the general antecedent(s) (causes) and the likely specific antecedent(s) attribute(s) of initiating event(s) or (root) cause(s). Such identification will make possible the development of RCOs that will impact the likely causes effecting human performance reliability. A MCDM model will be formed, containing four main parts, namely RCOs developed to mitigate assessed HFP, criteria to be used to evaluate the estimated impact of each RCO on human performance reliability, relative importance of criteria (or weights) and a decision matrix. The decision matrix will be normalized so that RCO comparison becomes relevant. Of the many solution methods available, TOPSIS (Hwang and Yoon, 1981) is selected to rank the developed alternatives of RCO in descending order, enabling DMs to choose the best alternative. The TOPSIS method is selected because of its full utilization of information and the systematic computational procedure, which provides an indisputable ranking order for the developed alternatives. TOPSIS is suitable for cases with a large number of attributes and alternatives, and especially useful for objective or quantitative data for analysis (Tavana and Hatami-Marbini, 2011).

To achieve the aim of this work, this chapter is organised as follows. Section 6.2 provides the description of CREAM retrospective analysis, followed by the review of MCDM methods in general and TOPSIS in particular. Section 6.3 examines the proposed decision making methodology in two parts. The first part specifies CREAM classification groups' generic framework in marine engineering systems operation ergonomics, which would enable users to identify the initiating event or root causes of an incident or accident that are needed to develop a set of RCOs in a decision making model. The second part presents the three phases of the MCDM method combining AHP entropy calculation and the TOPSIS decision making model. Section 6.4

demonstrates the application of the proposed decision making methodology in a case study and its validating sensitivity analysis. Section 6.5 concludes the achieved results with summary and remarks.

6.2. Literature review

6.2.1. Review of the CREAM retrospective approach

This review will be focused on the CREAM performance analysis model. It includes a method, a classification scheme and model of cognition. The classification scheme's groups and the method are intrinsically linked. The classification scheme serves to define the links between possible causes and effects. In this context, the model of cognition is used as an underlying convenient way to inevitably organise some group categories of a human model of cognition in observation, interpretation and planning, which describe the possible causes and effects of human action. This will implicitly map the ways in which actions are typically shaped and the ways in which erroneous actions might happen. The classification scheme and the model of cognition characteristics make the analysis method recursive rather than strictly sequential. The method contains well defined usage conditions that determine when an analysis has come to the end. This is important to ensure that the method usage is consistent and uniform across applications (Hollnagel, 1998a).

6.2.1.1. Basic principles of the classification scheme

The CREAM classification scheme practically describes most possible manifestations of erroneous actions as well as the majority of possible causes, and covers all possible types of erroneous actions. The classification scheme makes a distinction between effects (phenotypes or manifestations) and causes (genotypes) on the high level of analysis. The effects refer to what is observable in the given system. This includes overt human actions as well as system events. The causes are the categories that can be used to describe the concept(s) which has brought about or can bring about the effect(s).

The main phenotypes and genotypes are application dependent, i.e., the details of the classification scheme may vary according to the application. Therefore, the categories must always be specific either to a particular application or to the type of application, for instance, marine ergonomics (Hollnagel, 1998a; Serwy and Rantanen, 2007).

For convenience of analysis the terms antecedent and consequence are used to separate aspects of the classification groups in developing the pathways between the categories. In reality, the antecedent is that which gives rise to a specific consequent, given the premises of the classification scheme. The terms cause and effect are specifically used to denote the end points of the event being considered. The cause can thus be either the "root" cause or the initiating event, while the effect corresponds to the error mode or phenotype resulting from erroneous action (Hollnagel, 1998a; Serwy and Rantanen, 2007; Lee and et al., 2011).

6.2.1.2. The classification scheme

The classification scheme is generally composed of phenotypes and genotypes. Both phenotypes and genotypes are further divided into more detailed classification groups, each of which has been described in terms of general consequents (or effects) and specific consequents (or effects). The phenotypes group is described in ten error modes, which for practical reasons are divided into four classification sub-groups called: (1) action at wrong time, (2) action of wrong type, (3) action at wrong object, and (4) action in wrong place/sequence.

The genotypes describe the categories that in the classification scheme serve as antecedents, hence ultimately as attributed causes. These are divided into ten different classification groups, which in turn are assigned to three main categories. One main category is the person related genotypes (group), which is further divided into categories of: (1) observation, (2) planning, (3) interpretation, (4) temporary person related causes, and (5) permanent person related causes. The first three categories of person related genotypes (group) refer to the underlying model of cognition, where the function of execution is covered by the error modes. The second main category is the technology related genotypes, which is further divided into four groups of: (1) components, (2) procedures, (3) temporary interface problems, and (4) permanent interface problems. Finally, the third main category is the organisation related genotypes, which is divided into five more detailed groups of: (1) communication, (2) organisation, (3) training, (4) ambient conditions, and (5) working conditions (Hollnagel, 1998a; Serwy and Rantanen, 2007). The overall structure of the classification scheme is shown in Figure 6.1. Further details can be found in Appendix 3.1.

The main principle by which the groups can be related to each other can be achieved in that each consequent described by a classification group must correspond to one or more antecedents and these antecedents must occur in the other classification groups. This is shown in a simple way in Figure 6.1: the genotypes are the antecedents of the phenotypes and the phenotypes (error modes) in turn are the antecedents of the general error consequences.

The relation between the classification groups can be established by providing for each group a list of the antecedents that are likely candidates as explanations for the general consequents of that group, where each of these antecedents in turn either appears as a consequent of another classification group or is a "root" cause. It is, of course, necessary to have a well-defined stop rule (Hollnagel, 1998a; Serwy and Rantanen, 2007; Warner and Sandin, 2010; Lee and et al., 2011).

Consequent-antecedent relations in CREAM can be described by going through the classification groups in the following order: error modes (phenotypes), person related genotypes, technology related genotypes, and organisation related genotypes - as shown in Figure 6.1.

- **Error modes (Phenotypes)**

The error modes are the observable features of actions and they are the starting point of an analysis. Table A3.1.1 shows that each error mode can be related to a considerable number of general antecedents. Many of these general antecedents are furthermore common for all error modes. The general antecedents describe the likely first-order explanations for an erroneous action. The purpose of a systematic analysis method is to go beyond the immediate explanations and look for what further details can be found given the available information about the event (Hollnagel, 1998a; Warner and Sandin, 2010; Serwy and Rantanen, 2007; Subramaniam, 2010).

A careful reading of the general antecedents for the error modes will reveal that they all occur as general consequents in the classification groups (see Appendix 3.1). In this context, the possible specific antecedents are used to describe particular conditions that could have contributed to a general consequent. Conditionally, the specific antecedents should only be used as part of the explanation if sufficient information about the event is available. In such cases the specific antecedent is the final or terminal cause, i.e., the analysis cannot go any further (Hollnagel 1998a; Warner and Sandin, 2010).

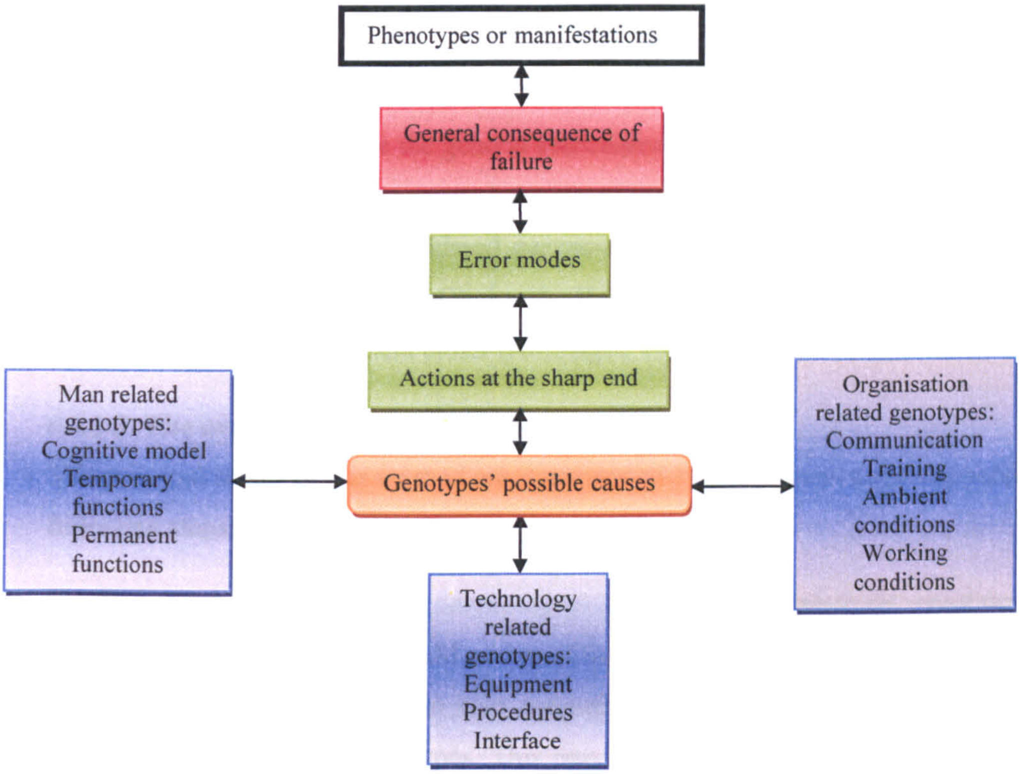


Figure 6.1: High level differentiation and overall grouping of genotype, adopted from (Hollnagel, 1998a)

- **The category of person related genotypes groups**

The category of person related genotype groups is described for the error modes. The categories listed under general antecedents all occur in other classification groups as general consequents. That is actually a defining characteristic of the whole classification scheme. For consistency of the method, in no case can a general antecedent in a group be a general consequent of the same group (Serwy and Rantanen, 2007).

- **The category of technology related genotypes groups**

The category of technology related genotype groups can be proposed in a relatively large number of specific antecedents. In these cases the specific antecedents can be understood either as a specific antecedent of the general antecedent or as an additional antecedent (Warner and Sandin, 2010).

- **The category of organisation related genotypes groups**

The category of organisation related genotype groups describes both general and specific antecedents referring to both technological and psychological factors. To deal with CREAM limitation in organisational factors, further antecedents will be proposed for organisation groups while specifying classification groups in marine ergonomics.

Generally, in all cases where the general antecedent is given as none, this does not mean that none of the general consequents has antecedents. Instead the condition described by the general consequent is considered permanent, and specifying this further may not improve the analysis that much. Obviously, if the general antecedent is none, then there cannot be a specific antecedent either (Hollnagel, 1998a).

6.2.1.3. The overall method description

The principal stages of this method are illustrated in Figure 6.2 and are composed of the following steps:

The first step is to describe the context that existed at the time when the event occurred. This is done by using the CREAM notion of the CPCs. For the sake of the retrospective analysis the CPCs are needed to help determine the possible error modes/phenotypes and the probable causes /genotypes. This may require a detailed analysis of aspects of the application which are not contained in the event report.

The second step is to describe the possible error modes for all possible human actions, without considering a specific one. The description should use the knowledge of the application and the context description to produce a limited set of error modes, and also to define their effect criteria.

The effect of each error mode is determined - whether it is impossible, possible, or very likely. The analysis is to investigate the error modes that are very likely before looking at the ones that are just possible. The possibility of each error mode is determined by checking some essential aspects based on experience and the knowledge of the application, as well as some of human factors.

The third step is to describe the probable genotypes or categories of possible causes, with the use of the given knowledge about the CPCs. This serves to identify in advance the genotype categories' groups that are more likely than others to be relevant as part of an explanation. The purpose of this is to limit and simplify the analysis, and to focus or concentrate on the causes that are likely to be part of the explanation. Generally, the third stage of the analysis addresses the differences in possibilities or the likelihoods of genotypes with the condition that none of cognitive functions' category is completely ruled out (Hollnagel, 1998a; Warner and Sandin, 2010).

The fourth step is to perform a more detailed analysis of the main task steps. This stage will try to trace the possible consequent-antecedent links for the selected error modes. For each error mode it is expected that the analysis will produce a set of candidate causes rather than a single (root) cause. The approach principles and conditions are elaborated in the following sections (Hollnagel, 1998a).

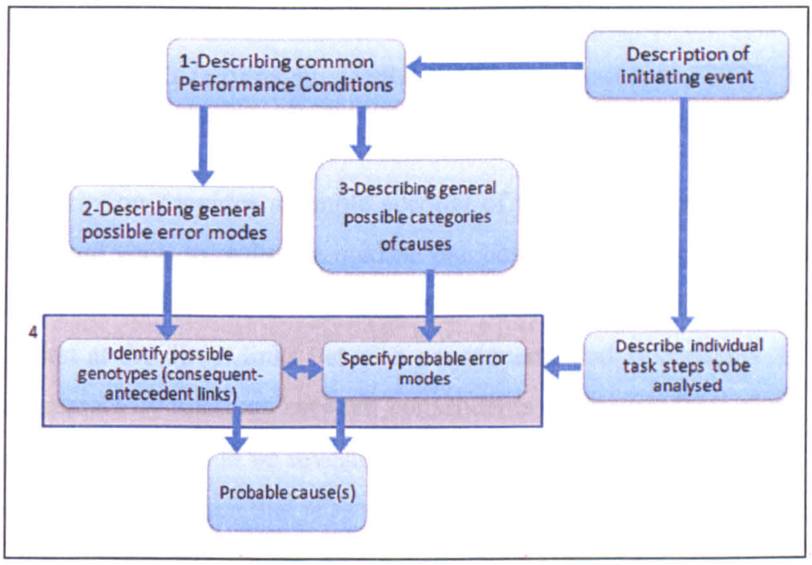


Figure 6.2: Overall method for retrospective analysis, adopted from Hollnagel (1998a)

- **Detailed analysis**

Detailed analysis begins by looking for the most likely error modes associated with the event in question. Once the general consequent/specific consequent error modes for an initiating event are described the analysis can proceed to find the likely causes. This is achieved by a recursive search through the classification scheme that begins by selecting one of the antecedents directly linked to an error mode - either a general antecedent or a specific. If the outcome of this step identifies a specific antecedent then the analysis is completed (Hollnagel, 1998a; Serwy and Rantanen, 2007; Warner and Sandin, 2010). If the outcome identifies a general antecedent then the analysis must continue. Therefore, the next step is to check the classification groups to find the possible indirect link between the general consequent of the first level of analysis and the other matching general antecedent in the next level of analysis. When the relevant general consequent in the next level of analysis is found the analysis continues from there until the end point probable general or specific antecedent (s) is found. In this specific condition a specific consequent cannot replace the general consequent. Therefore, when the general and/or specific consequents are selected their corresponding general antecedent(s) or specific antecedent(s) is identified. On this level of analysis, if the outcome identifies a specific antecedent then the analysis has come to an end. Similarly, if there are no general antecedents, there are most probably no specific antecedents either, and then the analysis must stop. In this way the analysis continues by applying the same principle recursively for all other possible cases until a stop criterion is reached. For further clarification the principles of the detailed analysis are shown in Figure 6.3 (Hollnagel, 1998a; Serwy and Rantanen, 2007; Warner and Sandin, 2010).

The above description provides a simple account of the analysis, but it is necessary to extend it in several ways to make the method practical. The first extension refers to the notion of direct and indirect links. The search for an antecedent within a classification group looks first at the direct links between consequents and antecedents. If, however, there are no satisfactory relations between consequents and antecedents along the direct links, the indirect links should be investigated. Similarly, if the indirect links suggest a consequent-antecedent relation that is as reasonable as the one(s) suggested by the direct links, then the indirect link should also be explored (Hollnagel, 1998a; Warner and Sandin, 2010).

The second revision has to do with tracing the path from consequents to antecedents. Any step in the analysis may show that there is more than one possible general antecedent for the general consequent of that group. This means that the analysis must explore all relevant paths and that it is necessary to keep track of the branching points. Finally, it is helpful to note that the use of the CPCs and the initial selection of possible error modes and probable causes serve to limit the analysis so that it does not have to go through every path as well (Hollnagel, 1998a).

The following stop rules could be applied in the context of the analysis in Figure 6.3:

1. If a general consequent points to a specific antecedent as the most likely candidate cause, then the analysis is stopped.
2. If a general consequent does not have a general antecedent, then the analysis ends (Hollnagel, 1998a).

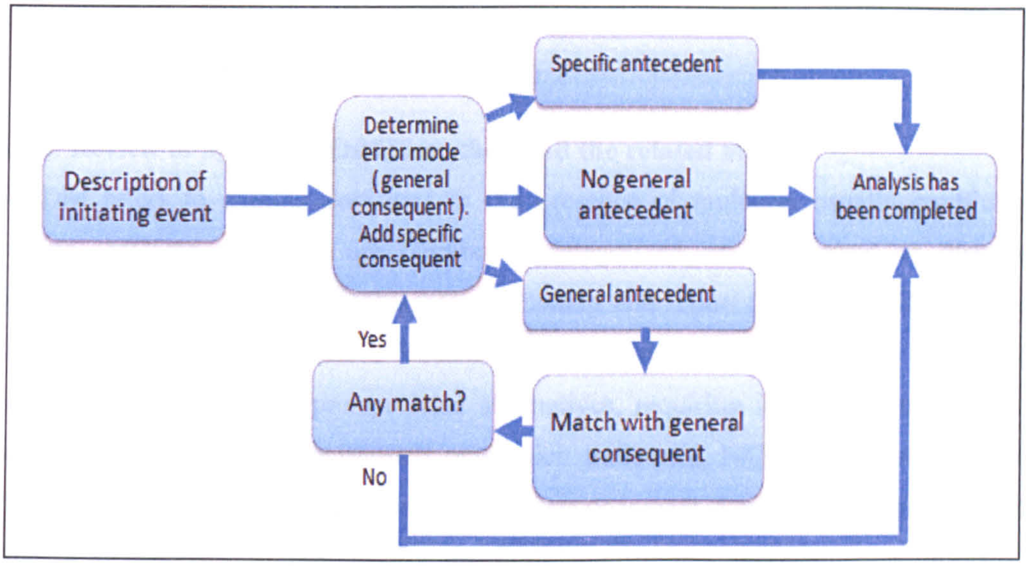


Figure 6.3: Detailed method for retrospective analysis adopted from (Hollnagel, 1998a)

- **Going beyond the stop rule**

The purpose of a stop rule is to ensure that all probable consequent-antecedent links are explored and that the search for consequent-antecedent links is made in a uniform and consistent way. However, it is entirely possible to continue the analysis and, in a sense, go beyond the stop rule, if the classification scheme is suitably extended and the method remains unchanged.

The extension of the classification scheme can be achieved in two different ways. One possibility is that a specific antecedent is changed so that it becomes a general antecedent. Generally, a specific antecedent cannot be changed into a general antecedent without considering the possible consequences for other classification groups. Therefore, such a change cannot be accomplished without revising the whole classification system.

The other extension is to provide a new general antecedent, either as an addition to the existing general antecedents or as new in the cases where no general antecedents are given. The explicit principle according to which the classification groups of CREAM have been defined makes such an extension relatively easy to do. The only thing that must be observed is that the links between general consequents and general antecedents are properly maintained, so that the classification scheme as a whole remains consistent, with no conflicts in the use of specific terms and no loose ends. The basic recursive analysis principle can be retained and the stop rules remain valid. This is necessary not only to be able to use the same analysis method but also to maintain the common basis for analysis and prediction (Hollnagel, 1998a).

6.2.2. Review of MCDM-TOPSIS method and the related models

MCDM refers to making decisions in the presence of multiple, usually conflicting criteria. MCDM problems are commonly categorized as continuous or discrete, depending on the domain of alternatives. Hwang and Yoon (1981) classify them as MCDM and Multiple Objective Decision Making (MODM). MCDM has a discrete, usually finite, number of pre-specified alternatives, requiring inter and intra-attribute comparisons and involving implicit or explicit trade-offs. MODM presents decision variable values to be determined in a continuous or integer domain, of infinite or large number of choices, to best satisfy the DMs' constraints, preferences or priorities. MCDM methods have also been used for combining good MODM solutions based on DMs' preferences (Kok, 1986; Kok and Lootsma, 1985; Zanakis et al., 1998).

The primary aim in MCDM is to provide a set of attribute aggregation methodologies that facilitate the development of models considering the DMs' preferential system and judgment policy (Doumpos and Zopounidis, 2002). Achieving this goal requires the implementation of complex procedures. Several methods have been proposed for solving MCDM problems. A major criticism of MCDM is that different techniques may yield different results when applied to the same problem (Zanakis et al., 1998). The development of MCDM models has often been dictated by real-life problems. Therefore, it is not surprising that methods have appeared in a rather diffuse way, without any clear general methodology or basic theory (Vincke, 1992). The selection of a MCDM framework or method should be done carefully according to the nature of the problem, types of choices, measurement scales, dependency among the attributes, type of uncertainty, expectations of the DMs, and quantity and quality of the available data and judgments (Vincke, 1992). Finding the "best" MCDM framework is an elusive goal that may never be reached (Triantaphyllou, 2000; Tavana and Hatami-Marbini, 2011).

Several discrete methods use a finite number of alternatives, set of objectives, criteria for evaluating alternatives, and methods for ranking alternatives (Ananda and Herath, 2009). Discrete methods are divided into: weighting techniques such as the SAW (Hwang and Yoon, 1981); ranking techniques, such as the Preference Ranking

Organization Method for Enrichment Evaluations (PROMETHEE) (Brans and Vincke, 1985), the TOPSIS (Hwang and Yoon, 1981), and the Ordered Weighted Averaging (OWA) (Yager, 1988); and mixed techniques, such as the ELECTRE (Roux and Elloy, 1985), the AHP (Saaty, 1980), the Multi-Attribute Value Theory (MAVT) (Von-Winterfeldt, 1986), and the Value Focused Thinking (VFT) (Keeney, 1993; Emeka Uzokaa et al., 2011). A detailed analysis of the theoretical foundations of different MCDM methods and their comparative strengths and weaknesses is presented in Larichev and Olson (2001), Belton and Stewart (2002) and Figueira et al. (2005).

In MCDM the accuracy and effectiveness of evaluation results have been directly affected by the determination of weight among the evaluation criteria or attributes. Therefore, the weight determination for each evaluation criterion is a key point and a difficult point in MCDM models. The usually used weight evaluation methods can be divided into three categories: subjective weighting method, represented by the Delphi, AHP, and Expert Method (Samir and Jacques, 2006; Tung and Tang, 1998); objective weighting method, represented by principal component analysis, factor analysis, entropy method, and rough set method (Dongye et al., 2005; Carrara, 1983); and the combination weighting method (Zhao et al., 2004). The third represents a weight calculation method that combines the subjective judgments and the objective analysis. All these methods cannot avoid subjectivity in some degrees when being used to confirm the weight of evaluated criteria (Zhang et al., 2007). Nevertheless, the combination weighting method takes the subjective and objective components into account, and combines expert judgment with objective analysis, thus getting a more ideal and realistic value of weight (Qin et al., 2010; Wang et al., 2009).

AHP has proven to be a popular technique for determining subjective weights in multi attributes problems (Zahedi, 1986; Shim, 1989). The importance of AHP and the use of pair-wise comparisons in decision making are best illustrated in the more than 1,000 references cited in Saaty (2000). AHP calculations are not complex, and if the judgments made about the relative importance of the attributes have been made in good faith, then AHP calculations lead intrinsically to the logical consequence of those judgments. Harker and Vargas (1990) show that AHP does have a clear foundation; the prime measurement of preferences is fully represented by the eigenvector method, and the principles of hierarchical composition and rank reversal are valid. In response, Saaty

(1981and 1990a) contends that rank reversal is a positive feature, when new reference points are introduced.

Entropy could be used as an objective measurement of disorder in order to evaluate the implicit uncertainty of each attribute based on probability theory. Therefore, the implicit information disorder of each attribute can be indicated by its entropy value (Zhang et al., 2007; Han and Xiao, 2009).

TOPSIS has been an important branch of decision making. To clarify its features, the characteristics of TOPSIS and AHP have been compared by Saaty (1990b). The major weaknesses of TOPSIS are in not providing weight elicitation and consistency checking for judgments. However, AHP's employment has been significantly restrained by the human capacity for information processing (Saaty and Ozdemir, 2003). From this point of view, TOPSIS alleviates the requirement of paired comparisons, and the capacity limitation might not significantly dominate the process. Hence, it would be suitable for cases with a large number of attributes and alternatives, and especially useful for objective or quantitative assessed data (Tavana and Hatami-Marbini, 2011).

TOPSIS helps DMs to organize the problems to be solved, and carry out analysis, comparisons and rankings of the alternatives. Accordingly, the selection of a suitable alternative(s) can be made. Section 2.5 provides further information regarding the basic theory of TOPSIS.

In applications, basically raw data measurements in the TOPSIS model are normalized to a compatible unit or measure. In this regard, sensitivity analysis experiments have been carried out by Chakraborty and Yeh (2009) to find the sensitivity levels of different normalization procedures, such as "Vector Normalization", "Linear Scale Transformation (Max-Min)", "Linear Scale Transformation (Max)" and "Linear Scale Transformation (Sum)", under different problem settings. The experimental results have justified the use of vector normalization in the TOPSIS method. It is the most consistent in ranking and is able to handle weight sensitivity quite well. Their study has identified the possible alternatives to the vector normalization procedure under different problem settings. The method also helps researchers to choose the best normalization procedure if the weight is a very important factor in certain decision settings (Chakraborty and Yeh, 2009).

However, in traditional TOPSIS, the evaluation values and the weights of the criteria are given as crisp values. The crisp data might be inadequate to model many real life situations. Therefore, the TOPSIS method was extended to integrate some uncertain information. For example, Jhanshahloo et al. (2006) have extended the TOPSIS method to accommodate fuzzy data. The main advantage of fuzzy formulation - compared to crisp formulation - is that the DM is not forced to give a precise formulation, for the sake of mathematical reasons (Zimmermann, 2001; Ziya Ulukan and Kop, 2009). Chen (2000) has extended the TOPSIS method to fuzzy group MCDM problems by considering triangular fuzzy numbers and defining crisp Euclidean distance between two fuzzy numbers. Ashtiani et al. (2009) have developed an interval valued fuzzy TOPSIS to solve MCDM problems in which the performance rating values as well as the weights of criteria are linguistics terms that can be expressed in interval-valued fuzzy numbers. Wei (2009) has extended TOPSIS to deal with group decision making problems with assessments of information in which the attribute values take the form of linguistic information and attribute weights are incompletely known. Torfi et al. (2010) have proposed AHP and TOPSIS methods' frameworks to deal with the evaluations' uncertainty and imprecision in which the experts' comparisons are represented as fuzzy numbers. The final weights of alternatives are determined by using fuzzy AHP method and a group of experts' comparisons. Wentao and Huan, (2010) have presented an extended TOPSIS method for stochastic multi-criteria decision making problems through interval estimation as a new method.

TOPSIS has been deemed one of the major decision making techniques in recent years (Shih et al., 2007). It has been successfully applied to the areas of human resources management (Chen and Tzeng, 2004), transportation (Janic, 2003), product design (Kwong and Tam, 2002), manufacturing (Milani et al., 2005), water management (Srdjevic et al., 2004), quality control (Yang and Chou, 2005), company financial ratios' comparison (Deng et al., 2000), location analysis (Yoon and Hwang, 1985), human spaceflight mission planning at NASA (Tavana and Hatami-Marbini, 2011), and approximate vessel selection under uncertain environments (Yang et al., 2011). In addition, the concept of TOPSIS has also been connected to multi-objective decision making (Lai, 1994) and group decision making (Shih et al., 2001; Tavana and Hatami-Marbini, 2011).

TOPSIS is attractive in a way that limited subjective input is needed from DMs. The only subjective input needed is weights. According to the observations of Kim et al. (1997) and Shih et al. (2007), four advantages are addressed in TOPSIS, including a sound logic that represents the rationale of human choice; a scalar value that accounts for both the best and worst alternatives simultaneously; a simple computation process that can be easily programmed into a spreadsheet; and the performance measures of all alternatives on criteria can be visualized on a polyhedron, at least for any two dimensions (Tavana and Hatami-Marbini, 2011). In fact, TOPSIS is a utility based method that compares each alternative directly, depending on data in the evaluation matrices and weights (Cheng et al., 2002; Shih et al., 2007). Besides the above, TOPSIS has been shown to be one of the best MCDM methods among the Simple Additive Weighting (SAW), Multiplicative Exponent Weighting (MEW), AHP, and ELECTRE MCDM methods, in addressing the rank reversal issue, which practically featured in alteration of the ranking of alternatives in a TOPSIS model by the addition or deletion of irrelevant alternative(s) (Zanakis et al., 1998; Wang and Luo, 2009). This consistency feature is largely appreciated in practical applications. Moreover, the rank reversal in TOPSIS is insensitive to the number of alternatives and has its worst performance only in the case of a very limited number of criteria (Triantaphyllou and Lin, 1996; Zanakis et al., 1998). However, Ren et al., (2007) has suggested that Modified Technique for Order Preference by Similarity to the Ideal Solution (M-TOPSIS) prevents rank-reversal and it should be used in lieu of the conventional TOPSIS. In this regard, Tavana and Hatami-Marbini, (2011) illustrated that the M-TOPSIS method proposed by Ren et al. (2007) is also subject to the rank reversal. The rank reversal phenomenon is not unique in M-TOPSIS, and changing the decision environment in some MCDM methods may also lead to a rank reversal (Wang and Luo, 2009).

Based on the preceding review the proposed MCDM framework in this technical work integrates the weighting method in the TOPSIS model. The former model combines the aggregation of the AHP model and entropy method, to obtain a realistic value of criteria weights. The latter integrates weighted criteria in a number of pre-specified alternatives, requiring inter and intra-attribute comparisons involving implicit or explicit trade-offs, to rank alternatives of RCO in descending order. The proposed framework structure has some obvious attractive features: the generic nature of the framework allows for the subjective evaluation of a number of decision alternatives on a number of performance attributes by individual or a group of DMs; the mathematical and computational properties of the models are applicable to a wide range of real-world decision making problems in MCDM; and the information requirements of the proposed framework can be differentiated into a hierarchy to simplify information input and allow the DMs to focus on a small area of the large problem. This process is also useful for seeking input from multiple DMs as inconsistencies are inevitable when dealing with subjective information from different DMs. The built-in inconsistency checking mechanism of the proposed framework helps to identify inconsistencies in judgments at very early stages of the computation process. Finally, there are several variations of TOPSIS models in MCDM literature (Olson, 2004; Tavana and Hatami-Marbini, 2011). Examples include conventional TOPSIS (Hwang and Yoon, 1981); A-TOPSIS (Deng et al., 2000) and M-TOPSIS (Ren et al., 2007). This work will include the conventional TOPSIS model.

6.3. Methodology

The framework of the proposed methodology in this technical work is approached in two parts. The first part specifies CREAM generic classification groups in marine engineering operations ergonomics, which would enable users to identify the initiating events or root causes of HFP. As a result, RCOs needed to mitigate HFP are developed for the decision making model. The second part presents the three phases of the MCDM method. The first phase presents the AHP model to be used for subjective weighing of selected criteria in the decision making model. The second phase presents the entropy analysis method to be used for measuring the intrinsic weight of each selected criterion in the decision making model. Both weights would be combined and normalised to standardise their use in TOPSIS models. Finally, the third phase presents the proposed TOPSIS models to be used for ranking the developed alternatives of RCO in descending order. The alternatives of RCO are to be developed based on the finding of human performance analysis through the classification groups specified in the first part of this methodology. Finally, the three phase processes are depicted in Figure 6.4.

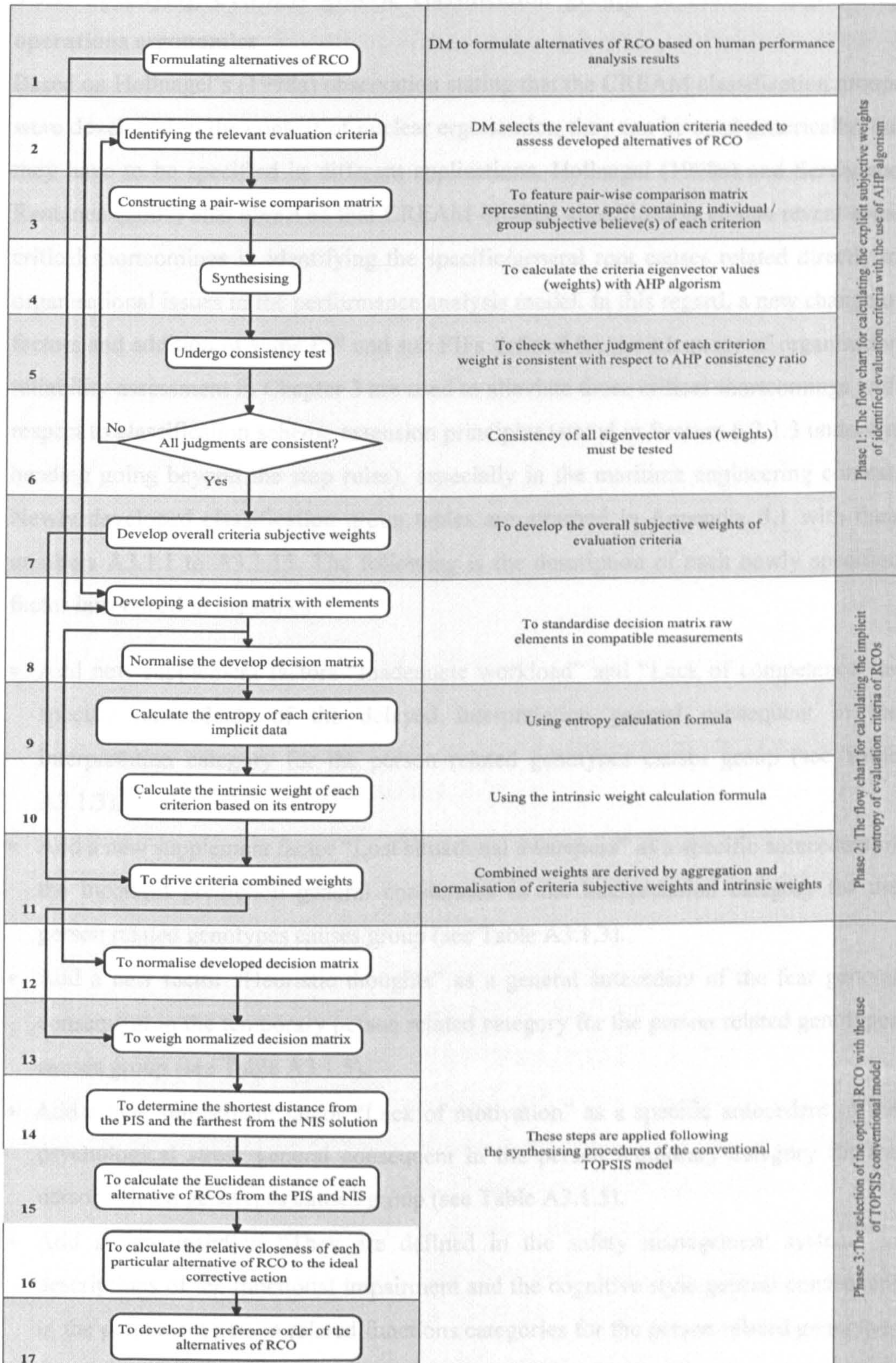


Figure 6.4: The proposed methodological framework

6.3.1. Specifying CREAM generic classification groups in marine engineering operations ergonomics

Based on Hollnagel's (1998a) observation stating that the CREAM classification groups were developed in the context of nuclear ergonomics, they can be used generically, but they have to be specified in different applications. Hollnagel (1998a) and Serwy and Rantanen (2007) also observed that CREAM original classification groups reveal some critical shortcomings in identifying the specific/general root causes related directly to organisational issues in the performance analysis model. In this regard, a new change of factors and addition of some PIF and sub PIFs defined for the adequacy of organisation reliability assessment in Chapter 3 are used to alleviate those critical shortcomings with respect to classification scheme extension principles (stated in Section 6.2.1.3 under the heading going beyond the stop rules), especially in the maritime engineering context. Newly developed classification group tables are attached in Appendix 3.1 with their numbers A3.1.1 to A3.1.15. The following is the description of each newly specified factor introduced in the tables.

- Add new supplement factors "Inadequate workload" and "Lack of competence" as specific antecedents of the delayed interpretation general consequent in the interpretation category for the person related genotypes causes group (see Table A3.1.3).
- Add a new supplement factor "Lost situational awareness" as a specific antecedent of the incorrect prediction general consequent in the interpretation category for the person related genotypes causes group (see Table A3.1.3).
- Add a new factor "Heuristic thoughts" as a general antecedent of the fear general consequent in the temporary person related category for the person related genotypes causes group (see Table A3.1.5).
- Add a new supplement factor "Lack of motivation" as a specific antecedent of the psychological stress general consequent in the person temporary category for the person related genotypes causes group (see Table A3.1.5).
- Add a new insertion "They are defined in the safety management system" in descriptions of the functional impairment and the cognitive style general consequent in the permanent person related functions categories for the person related genotypes causes group (see Table A3.1.6).

- Add new factors "Bias physical fitness tests" as a general antecedent of the functional impairment general consequent in the permanent person related functions for the person related genotypes causes group (see Table A3.1.6).
- Add new factors "Inattention" and "Distraction" as general antecedents and a new factor "Lack of skill" as a specific antecedent of the cognitive style general consequent in the permanent person related functions categories for the person related genotypes causes group (see Table A3.1.6).
- Add a new factor "Wrong reasoning" as a general antecedent and a new factor "Lack of competence" as a specific antecedent of the cognitive bias general consequent in the permanent person related functions categories for the person related genotypes causes group (see Table A3.1.6).
- Add new supplement factors "Running in failure", "Random failure "and "Age dependent failure" as general antecedents of the equipment failure general consequent in the equipment category for the technologically related genotypes group (see Table A3.1.7).
- Add a new supplement factor "Halted processors" as a general antecedent and a new factor "Incompatible programmes" as a specific antecedent of the software fault general consequent in the permanent equipment category for the technologically related genotypes group (see Table A3.1.7).
- Add a new supplement factor "Inadequate standards" as a general antecedent of the inadequate general consequent in the procedure category for the technologically related genotypes group (see Table A3.1.8).
- Add a new supplement factor "Fetching problems" as a specific antecedent of the incomplete information general consequent in the temporary interface problems category for the technologically related genotypes group (see Table A3.1.9).
- Add the new factors "Poor accessibility" and "Low availability" as specific antecedents of the access problems general consequent in the permanent interface problems category for the technological related genotypes group (see Table A3.1.10).
- Add a new factor "Inadequate control "as a specific antecedent of the mislabelling general consequent in the permanent interface problems category for the technologically related genotypes group (see Table A3.1.10).
- Add the new factors "Ineffective safety management system" and "Low management quality" as general antecedents and "Not performed maintenance procedures" and

"Ineffective control" as specific antecedents of the maintenance failure general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).

- Add the new factors "Unclear policies" as a general antecedent and "Not adopted standards" as a specific antecedent of the inadequate quality control general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).
- Add the new factors "Ineffective organisational structure", "Not acquired organisational culture" and "Ineffective safety management system" as general antecedents and "Not clear strategy and objectives" and "Ineffective control" as specific antecedents of the management problem general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).
- Add the new factors "Ineffective resources" as a general antecedent and "Low availability" and "Unreliable" as specific antecedents of the design failure general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).
- Add the new factors "Ineffective organisational structure", "Not acquired organisational culture" and "Ineffective safety management system" as general antecedents and "Ineffective control" as a specific antecedent of the inadequate task allocation general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).
- Add the new factors "Classical organisational structure" and "Not acquired organisational culture" as general antecedents and "Uncommitted to norm" and "Uncommitted to safety culture" as specific antecedents of the social pressure general consequent in the organisation category for the organisation related genotypes group (see Table A3.1.12).
- Add the new factors "Ineffective manning policy" and "Insufficient human resources" as general antecedents and "Recruitment failure" and "Promotion failure" as specific antecedents of the social pressure general consequent in the training category for the organisation related genotypes group (see Table A3.1.13).

- Add the new factors "Incomprehension" as a general antecedent and "Lack of training" as a specific antecedent of the insufficient knowledge general consequent in training category for the organisation related genotypes group (see Table A3.1.13).
- Add the new factors "Ineffective control" and "Out of control" as general antecedents and "Defected control systems" and "Environmental effect" as specific antecedents of the temperature general consequent in ambient conditions category for the organisation related genotypes group (see Table A3.1.14).
- Add the new factors "Poor functionality" as a general antecedent and "Poor design" and "Inappropriate adjustment" as specific antecedents of the sound general consequent in ambient conditions category for the organisation related genotypes group (see Table A3.1.14).
- Add the new factors "Ineffective control" and "Out of control" as general antecedents and "Defected control systems" and "Environmental effect" as specific antecedents of the humidity general consequent in ambient conditions category for the organisation related genotypes group (see Table A3.1.14).
- Add the new factors "Poor design" as general antecedent and "Inappropriate adjustment" as specific antecedents of the illumination general consequent in the ambient conditions category for the organisation related genotypes group (see Table A3.1.14).
- Add the new factors "Local/dispersed disturbance" and "Temporary/permanent disturbance" as general consequents, "Operational defect", "Maintenance failure" and "Dynamical characteristics effect" as general antecedents, and "Inappropriate instruction" and "Inherited defects" as specific antecedents of the vibration specific consequent in the ambient conditions category for the organisation related genotypes group (see Table A3.1.14).
- Add the new factors "Motion" as a general consequent and "Adverse weather conditions" as a general antecedent in the ambient conditions category for the organisation related genotypes group (see Table A3.1.14).

6.3.2. Details of the proposed MCDM method

6.3.2.1. The developments of RCOs

The development of RCOs is intended to reduce/mitigate high HFPs assessed. Basically, RCOs are developed based on HFP initiating events or root cause features. Initiating events or root causes are identified through the use of CREAM classification scheme phenotypes groups, and main genotypes categories of person, technological and organisation classification groups. In this context, it is vital to understand the inherent effect of initiating events or root causes on their related categories. As a result, the explicit interrelation of identified categories and their affect on CPCs can be used as a guide to develop RCOs. Essentially, they should be based on an organisation's SMS and management quality. However, the higher objectivities of the SMS and management quality of a shipping organisation would simplify structuring DMs' targeted potential RCOs.

6.3.2.2. Identification of evaluation criteria

To enable DMs to choose potential RCOs that would effectively reduce/mitigate assessed HFP, it is essential to identify the associated evaluation criteria that are used to communicate the estimated impact of each criterion on each alternative RCO in decision making models. In addition to the "HFP effectiveness" measuring the extent to which developed RCOs could fulfil the desired potential objectives (how far the RCO is effective in mitigating the HFP), the chosen criteria in this decision model are identified and defined as "Technical difficulty of implementing a RCO", "Time required for implementation of a RCO", and "Cost of implementing a RCO". However, criteria evaluation is model and method reliant. For example, the AHP subjective weighing of a criterion is based on the use of the fundamental 1-9 scale or their reciprocals as defined by Saaty (1980). Such a scale will be used to assess the priority score of each criterion in order to derive its subjective weight. In this context, the assessment of 1 indicates equal importance, 3 moderately more, 5 strongly more, 7 very strongly, and 9 indicates extremely higher importance. The values of 2, 4, 6, and 8 are allocated to indicate compromise values of importance. On the other hand, in entropy objective analysis and TOPSIS models, "HFP effectiveness" criterion will be aggregated by the use of a BN model developed in Chapters 4 and 5, the estimated impact of "Time required for implementation of a RCO" and "Cost of implementing a RCO" criteria will be evaluated using objective databases, while the impact of the "technical difficulty of implementing a RCO" criterion will be evaluated by experts using linguistic variables such as "Very-Low" (VL), "Low" (L), "Medium-Low" (ML), Medium (M), "Medium-High" (MH), High (H) and Very-High (VH). These linguistic terms can be defined by fuzzy triangular membership functions of (0.00, 0.00, 0.167) for VL, (0.00, 0.167, 0.333) for L, (0.167, 0.333, 0.50) for ML, (0.333, 0.50, 0.667) for M, (0.50, 0.667, 0.833) for MH, (0.667, 0.833, 1.0) for H and (0.833, 1.0, 1.0) for VH (Engel and Last, 2006). Such fuzzy numbers will be defuzzified to crisp numbers by using the centre of gravity method (Andrews and Moss, 2002; Yang et al., 2010).

6.3.2.3. Mathematical details of the AHP method

This section is intended to cover the underlying methodology framework of **steps 3, 4, 5, 6, and** 7 in Figure 4. The AHP method could be used to develop a set of subjective weights $(w'_1, w'_2, \dots w'_4)$ for the four evaluation criteria $(c_1, c_1, \dots c_4)$ (Saaty, 1980). Experts could be asked to provide their subjective beliefs based on pair-wise comparison of criteria $c_i, c_k, (i = 1 \dots 4)$ and k of c_k refers to the whole i rows or j columns in a matrix:

$$A = (c_{ij})_{n \times n} \quad \text{(6.1)}$$

However, non uniformity of experts' opinions might occur, so an explicit treatment of experts' judgments is in demand, and then the following formula needs to be applied in order to obtain an average scale of pair-wise comparison (Klir and Yuan, 1995).

$$E(x) = \frac{\sum_{e=1}^{n} e(x)}{n} \quad \text{(6.2)}$$

where $E(x)$ is the synthesised value of n experts' subjective beliefs, $e(x)$ is the value given by the e^{th} expert. $E(x)$ can be used as entry c_{ik} of a matrix A. Each element of a matrix A represents the importance of criterion c_i, relative to criterion c_k:

If $c_{ik} > 1$, c_i, is more important than c_k,

if $c_{ik} < 1$, c_i, is less important than c_k,

if $c_{ik} = 1$, same importance

c_{ik} and c_{ki} must satisfy $c_{ik} \times c_{ki} = 1$.

Because the entry c_{ik} is the inverse of the entry c_{ki}, and for all $i = k, c_{ik} = 1$, such a matrix is said to be a positive and reciprocal matrix. With 1's in the main diagonal, experts need only to provide value judgment according to the AHP scale in the upper triangle of the matrix.

In a matrix A the weights are consistent if they are transitive, that is;

$$c_{ik} = c_{ij} \times c_{jk} \quad \text{(6.3)}$$

for all i, j, and $k = 1 \dots n$. Such a matrix might exist if the entry c_{ij} is calculated from exactly measured data. For matrices involving human judgments, the condition in Equation 6.3 does not hold, as human judgments are inconsistent to a certain degree. In such a case, the weight vector w'_i of each criterion can be found by computing the normalized eigenvector corresponding to the maximum eigen-value of the matrix A. Because the sum of the weights should be equal to 1 the normalized eigenvector is used. The calculation of weight vector w'_i can be deduced by using the following equations.

$$\mu_{ij} = \frac{c_{ij}}{\sum_{n=1}^{4} c_{ij}} \qquad (6.4)$$

where, μ_{ij} is the normalized eigenvector value.

$$w'_i = \frac{\sum_{n=1}^{4} \mu_{ij}}{n} \qquad (6.5)$$

A maximum eigen-value of A is defined as λmax, which satisfies the following matrix equation:

$$Aw' = \lambda max\ w' \qquad (6.6)$$

To calculate λmax the following equation can be used (Kamal et al., 2001).

$$\lambda max = \sum_{n=1}^{n} \{\frac{(A\,w')_i}{w'_i}\}/\mathrm{n} \qquad (6.7)$$

Saaty (1980) suggests a measure of consistency for the pair-wise comparisons. When the judgments are perfectly consistent then, λmax should equal the number of criteria n that are compared. Generally, the responses are not perfectly consistent. In addition, λmax is greater than n. The larger the λmax, the greater is the degree of inconsistency. The consistency index (CI) is defined as:

$$CI = (\lambda max - n)/(n - 1) \qquad (6.8)$$

Saaty (1980) provided the following random index (*RI*) table for matrices of order 3 to 10:

n	3	4	5	6	7	8	9	10
RI	0.58	0.90	1.12	1.32	1.41	1.45	1.49	1.51

This *RI* is based on a simulation of a large number of randomly generated weights. The consistency ratio (CR) calculation is recommended as:

$$CR = CI\,/RI \qquad (6.9)$$

The consistency ratio CR is a measure of how a given matrix compares to a purely random matrix in terms of their consistency indices. A CR of 0.10 or less is considered acceptable. Larger values of CR require the experts to revise their judgments (Kamal et al., 2001).

6.3.2.4. Mathematical details of the entropy measurement method

This section is intended to cover the underlying methodology framework of **steps 8, 9 and 10** in Figure 6.4. The entropy objective analysis method detailed in phase two of the proposed methodology consists of the following steps (Yang et al., 2009):

Step 8: To construct the decision matrix (based on the priority scores assigned to each criterion on each alternative RCO) denoted by:

$M = (r_{ij})_{m \times n}$ and $i = 1, 2 \ldots m; j = 1, 2 \ldots n$ .... (6.10)

where r_{ij} is a criterion of the decision matrix M, m is the number of decision alternatives and n is the number of decision criteria.

Step 9: To normalize the criteria of the decision matrix:

$P_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}$; $j = 1, 2 \ldots n;\ i = 1, 2 \ldots m$ .... (6.11)

where, P_{ij} is a normalized criterion of the decision matrix.

Step 10: To calculate the entropy of each criterion data:

The entropy of the set of normalized outcomes of the j^{th} criterion in the decision matrix is given by:

$E_j = -K \sum_{i=1}^{m} [p_{ij} \times ln\, p_{ij}]; j = 1, 2 \ldots n;\ i = 1, 2 \ldots m$ .... (6.12)

where, E_j is the entropy of j^{th} criterion and K is a constant (normalizing) value taken to be $1/ln(m)$.

Note that if all normalized values for a criterion become identical, $P_{ij} = 1/m$ for all (i, j) then $E_i = 1$.

Next the calculation of the intrinsic weight of each criterion based on its entropy is given by:

$w''_j = \frac{d_j}{\sum_{j=1}^{n} d_j}$; for all ($j$) .... (6.13)

where, d_j is the degree of diversity of the information involved in the outcomes of the j^{th} criterion, and is given by the following equation.

$d_j = 1 - E_j$ .... (6.14)

6.3.2.5. Combined weights w_j calculation

This section describes the details of **step 11** in the proposed methodology. The combined weights w_j of criteria are derived by the aggregation of criteria subjective weights w'_j calculated with AHP model, and the intrinsic weights w''_j calculated as a result of criteria entropy analysis. The normalised combined weights w_j could be derived by using the following equation (Hwang and Yoon, 1981; Milani et al., 2008; Yang et al., 2009):

$$w_j = \frac{w'_j \times w''_j}{\sum_{j=1}^{n} w'_j \times w''_j}; \text{for all } (j) \qquad (6.15)$$

6.3.4.6. The mathematical details of the conventional TOPSIS model

Assuming that A_i $(i = 1 \dots m)$ and x_j $(j = 1 \dots n)$ are a set of m alternatives of RCOs and a set of n criteria, respectively, they are representing a real world problem demanding DMs' preferences. In this respect, the main procedure for the conventional TOPSIS model provided in Phase three of the proposed methodology can be described as follows.

Step 12: To use the constructed decision matrix in Step 8 to obtain the normalized decision matrix as required by the TOPSIS model:

$$R = (r_{ij})_{m \times n}; \qquad (6.16)$$

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}; i = 1 \dots m; j = 1 \dots n; \qquad (6.17)$$

Step 13: To combine the combined weights w_j with decision matrix vectors r_{ij} to obtain the weighted normalized decision matrix $V = (v_{ij})$:

$$v_{ij} = w_j \, r_{ij}; i = 1 \dots m; j = 1 \dots n \qquad (6.18)$$

Step 14: To determine the PIS and NIS:

$$A^+ = (v_1^+, v_2^+, \dots v_n^+) = \{(\max_i\{v_{ij}\}) | j \in B), (\min_i\{v_{ij}\} | j \in C)\},$$

$$A^- = (v_1^-, v_2^-, \dots v_n^-) = \{(\min_i\{v_{ij}\}) | j \in B), (\max_i\{v_{ij}\} | j \in C)\} \qquad (6.19)$$

where B and C are associated with the benefit and cost attribute sets, respectively.

Step 15: To calculate the separation measures denoted by $M = S^+,\ S^-$. The separation measure of each alternative of RCO from the PIS and NIS is calculated by the Euclidean distance given by:

$S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}; \; j = 1 \ldots n; i = 1 \ldots m.$

$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}; j = 1 \ldots n; i = 1 \ldots m$ .... (6.20)

Step 16: To calculate the relative closeness of a particular alternative of RCO to the ideal RCO C_i as expressed by:

$C_i = \frac{S_i^-}{S_i^+ + S_i^-}; \; i = 1 \ldots, m; 0 \le C_i \le 1.$ .... (6.21)

where, C_i is the relative closeness of ith alternative to the ideal solution. The higher C_i is, the better the RCO.

6.4. Case study

The case study presented in Chapter 4, Section 4.4 will be used in this chapter in order to effectively link the derived HEP of the CREAM BN model with the TOPSIS RCO decision model.

6.4.1. The retrospective analysis of M/V Crown Princess accident

The retrospective analysis will follow the principles stated in Section 6.2.2.3 and its related sub section as follows:

Step 1: To use the incident information that existed at the time of the event occurrence to describe CPCs' effect levels in conjugation with CREAM CPCs' description, as stated in Chapter 4, Section 4.4.

Step 2: To include the description of the possible error modes as a result of all possible actions of officers in charge of command of the M/V *Crown Princess* at the time of the incident. Thus, a limited set of error modes are produced, and the criteria for certain error modes (effects) are also defined.

Table 6.1 Table 6.1shows the error modes that are determined. The very likely timing, sequence and speed error modes are determined based on the thought that the officers in charge of command needed to concede the timing, sequence and speed of their actions and the related consequences of each action. These had to be controlled competently with their cognition functions of observation, interpretation and planning in the context of the prevailing conditions.

Step 3: To include the descriptions of the possible categories of genotype probable causes with the given knowledge about the CPCs in order to identify the genotype categories that are most likely relevant. Table 6.2, Table 6.3 and Table 6.4 show the possible qualitative evaluation of each main genotype category group in relation to each CPC. Generally, the third stage of analysis addresses the different possible assessments of genotype categories in relation to CPCs' description, with the condition that none of the cognitive functions (categories) are completely ruled out.

Table 6.1: The impossible, possible and very likely error mode, adapted from Hollnagel (1998a)

Error mode	Controlling questions	Possibility 0 = impossible, 1 = possible, 2 = very likely
Timing	Does the control of the process require timing of actions? Are there clear indicators/signals for the timing of actions? Does the system include lead time indications? Does a signal clearly identify the corresponding action?	very likely
Duration	Is duration a control parameter? Is duration controlled manually or automatically? Is the duration clearly shown or indicated? Does the indication show elapsed time or remaining time, or both?	Possible
Force	Is level of force/effort a control parameter? Is the required/applied level of force clearly indicated? Is there a minimum/maximum limit of force for a control? Can force be controlled without changing position?	impossible
Distance / magnitude	Is distance or magnitude a control parameter? Is the required/applied distance or magnitude clearly indicated? Can distance or magnitude be controlled without changing position?	impossible
Speed	Is speed a control parameter? Is speed controlled manually or automatically (set-point/rate)? Is the required/applied speed clearly indicated?	very likely
Direction	Is direction a control parameter? Is there a direct relation between (movement) direction of controls and direction of system response? Is the required/applied direction clearly indicated?	Possible
Wrong object	Are different objects clearly separated or coded (colour/shape)? Are objects clearly and uniquely identified? Can objects easily be reached and seen when use is required?	Possible
Sequence	Is the sequence of actions/next action clearly indicated? Is the direction of the sequence reversible? Can out-of-sequence actions easily be recovered?	very likely

Table 6.2: Relationship between CPCs and (main) person related genotypes group

Common Performance Conditions	Person related genotypes groups		
	Cognitive model	Permanent functions	Temporary functions
Adequacy of organisation	High	High	Low
Working conditions	Nil	Nil	Nil
Adequacy of MMI and operational support	High	High	Nil
Availability of procedures/plans	High	High	High
Number of simultaneous goals	Nil	Nil	Nil
Available time	Nil	Nil	Nil
Time of day	Nil	Nil	Nil
Adequacy of training and preparation	High	High	High
Crew collaboration quality	Medium	Medium	Medium

Table 6.3: Relationship between CPCs and (main) technology genotypes groups

Common Performance Conditions	Technology related genotypes groups		
	Equipment	Procedures	Interface
Adequacy of organisation	Nil	High	Medium
Working conditions	Nil	Nil	Nil
Adequacy of MMI and operational support	High	High	High
Availability of procedures/plans	High	High	High
Number of simultaneous goals	Nil	Nil	Nil
Available time	Nil	Nil	Nil
Time of day	Nil	Nil	Nil
Adequacy of training and preparation	High	High	High
Crew collaboration quality	Medium	Medium	Medium

Table 6.4: Relationship between CPCs and (main) organisation related genotypes groups

Common Performance Conditions	Organisation related genotypes groups				
	Communication	Organisation	Training	Ambient conditions	Working conditions
Adequacy of organisation	Low	High	High	Nil	High
Working conditions	Nil	High	Nil	Nil	High
Adequacy of MMI and operational support	Nil	High	High	Nil	High
Availability of procedures/plans	Nil	High	High	Nil	High
Number of simultaneous goals	Nil	Nil	Nil	Nil	Nil
Available time	Nil	Nil	Nil	Nil	Nil
Time of day	Nil	Nil	Nil	Nil	Nil
Adequacy of training and preparation	Low	High	High	Nil	Nil
Crew collaboration quality	Nil	Medium	Medium	Nil	Low

Step 4: To perform detailed analysis of main task steps. This approached by tracing the possible consequent-antecedent direct links for the selected error modes in Table

A3.1.1. The following summary provides a set of candidate general antecedent' causes to be used as the key factors for the detailed analysis.

Summary of the candidate general antecedent causes		
Error mode	General consequent (effect)	General antecedents (causes)
Timing	Timing	Inadequate procedures Faulty diagnosis
Sequence	Sequence	Faulty diagnosis Wrong identification
Speed	Speed	Inadequate procedures Faulty diagnosis Performance variability

Since the outcome of the analysis at this level could not produce any direct links between the candidates of general antecedents and their associated specific antecedents (earlier omission and trapping error) (see Table A3.1.1), because they could not be considered as the probable initiating events, the analysis therefore is extended to a further level. Hence, the recursive search through the classification groups started, to find the matching general consequents (effects) of the candidates general antecedents (causes) stated in the above summary. In this context, the cognitive model function categories of observation, interpretation and planning are inevitably searched first in order to justify the competent actions of the officer in command. As a result, the following second level set of general antecedent causes is produced:

- The general consequent "Faulty diagnosis" is effected by the cause of the general antecedent "Cognitive bias" (see Table A3.1.3); given that none of the associated specific consequents can be justified as the probable root cause, the analysis is extended to the next level (see Table A3.1.6). At this level, the indirectly linked general consequent "Cognitive bias" effect, directly linked general antecedent "Wrong reasoning" cause and the associated specific antecedent's **"lack of competence"**, justify the link to likely root cause (see Table A3.1.6).
- The general consequent "Wrong identification" is effected by the cause of the general antecedent "Faulty diagnosis" (see Table A3.1.2); given that none of the associated specific consequents can be justified as the probable root cause, the

analysis is extended to the next level, where none of the indirectly linked general consequent-general antecedents can be justified as the likely causes. Therefore the analysis stopped at this level and the general antecedent "Faulty diagnosis" is considered as a part of the probable set of causes.

- The general consequent "Performance variability" is affected by the cause of the general antecedent "Insufficient skill" (see Table A3.1.5). At this level, the associated specific antecedent **"lack of training"** justifies the link to the likely root cause. Therefore the analysis stopped at this level (see Table A3.1.5).
- The general consequent "Inadequate procedure" is effected by the cause of the general antecedents "Inadequate standards" and "Design failure"; given that the associated specific consequent is none, the analysis is extended to a next level, where none of the indirectly linked general consequent-general antecedents can be justified as the likely causes. Therefore the analysis stopped at this level and the general antecedents **"Design failure"** and **"Inadequate standards"** are considered as a part of the probable set of causes (see Table A3.1.8).

6.4.2. Selection of the best RCO using the devleoped methodology

Phase 1: Calculating the subjective weights of identified evaluation criteria

Step 1: Formulating alternatives of RCOs that are needed to mitigate predicted HFP is based on the finding of performance analysis probable set of causes, **"lack of competence", "lack of training", "Inadequate standards" and "Design failure".** Considering the underlying conditions stated in Section 6.3.2.3 the following alternatives of RCO A_i ($i = 1 \dots 4$) are formulated as follows:

Alternative A_1: A RCO is formulated to provide ship board training to the newly signing on officers. The training is to be performed by a qualified officer. It includes familiarisation with the use of INS' equipment based on maker instruction and with help of training videos.

Alternative A_2: A RCO is developed to provide training to develop crews' competence on the use of INS pertaining to the already developed "model course" proposed in 2005 by the IMO's Subcommittee on Standards on Training and Watch keeping (STW).

However, the National Transport Safety Board (NTSB) marine accident report (NTSB/MAR-08/01, 2008) stated that completing INS training does not assure mastery of the system because mariners are not required to demonstrate mastery of an INS at the completion of most formal INS training programs. Furthermore, neither the IMO nor maritime authorities require licensed mariners who have completed initial INS training take courses thereafter.

Alternative A_3: A RCO is formulated to provide dedicated training to develop crews' competence on the use of equipment based on adapted and implemented specific standards pertaining to the recommendations stated in the National Transport Safety Board (NTSB) marine accident report (NTSB/MAR-08/01, 2008). These are designed to encourage safety improvements for the immediate future as well as for many years to come.

Alternative A_4: In this alternative RCO, all the actions in A_3 will be used. On top of that, INS design characteristics have to be modified by makers in a way that safety alert should be provided to the officers while they are manipulating ship speed. Such safety alert would help to eliminate the possibility of ship heel due to the effect of increased speed in shallow water depth. This alternative is formulated pertaining to the recommendations of the NTSB to enhance INS design, procedures, and training.

In order to quantify each formulated RCO in terms of HFP, to be used as a criterion in the TOPSIS decision model, each alternative of RCO will improve different CPCs' performance and thus their associated HFP through the CREAM BN model developed in Chapter 4. Figure 6.5 displays the aggregation of the BN model, as a result of alternative RCO A_1. The impact of this RCO could help develop officers' "Adequacy of training and experience" to an effect of 100% "Adequate level with limited experience". It is rational to evaluate the improvement of the "Adequacy of man machine interaction" to an effect level of 100% "Adequate" and the "Crew collaboration" to an effect level of 100% "Efficient".

Figure A 3.2.1 displays the aggregation of the BN model, as a result of alternative RCO A_2. The impact of this RCO could help develop officers' "Adequacy of training and experience" to an effect of 100% "Adequate level with high experience". It is rational to evaluate the improvement of the "Adequacy of the man machine interaction" to an effect level of 100% "Tolerable", the "Crew collaboration" to an effect level of 100% "Efficient" and "Adequacy of organisation" to an effect level of 100% "Efficient".

Figure A 3.2.2 displays the aggregation of the BN model, as a result of alternative RCO A_3. The impact of this RCO could help develop officers' "Adequacy of training and experience" to an effect of 100% "Adequate level with high experience". It is rational to evaluate the improvement of the "Adequacy of the man machine interaction" to an effect level of 100% "Adequate", the "Crew collaboration" to an effect level of 100% "Very efficient", the "Adequacy of organisation" to an effect level of 100% "Very efficient" and the "Availability of procedures and plans" to an effect level of 100% "Acceptable".

Figure A 3.2.3 displays the aggregation of the BN model, as a result of alternative RCO A_4. The impact of this RCO could help develop officers' "Adequacy of training and experience" to an effect of 100% of "Adequate level with a high experience". It is rational to evaluate the improvement of "Adequacy of the man machine interaction" to an effect level of 100% "Supportive", the "Crew collaboration" to an effect level of 100% "Very efficient", the "Adequacy of organisation" to an effect level of 100% "Very efficient" and the "Availability of procedures and plans" to an effect level of 100% "Appropriate". Alternative HFPs are derived based on the approach followed in Chapter 4, Section 4.4.8.

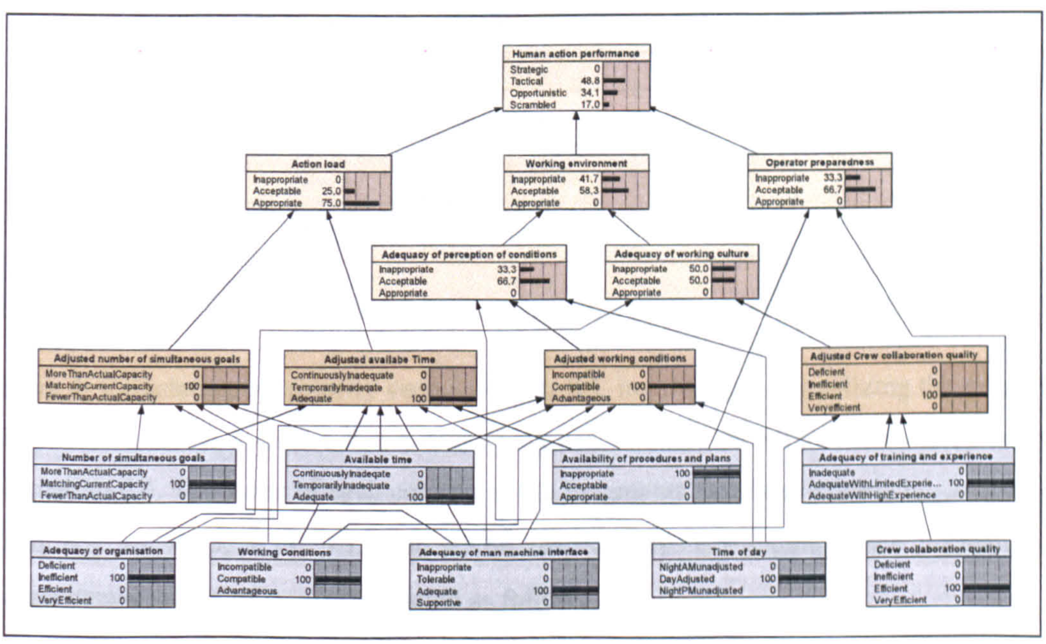


Figure 6.5: M BN model failure probabilities of M/V Crown Princess Officers in charge of command actions' (Alternative A_1)

Step 2: To use the evaluation criteria "HFP effectiveness" denoted by c_1, "Technical difficulty of implementing RCO" denoted by c_2, "Time required for implementation of RCO" denoted by c_3 and "Cost for implementation of RCO" denoted by c_4 as defined in Section 6.3.2.2.

Step 3: Constructing a pair-wise comparison $n \times n$ matrix defined by Equation 6.1 for the evaluation criteria. Three experts were asked to provide a pair-wise comparison of all criteria. The average scales used for the pair-wise comparison are obtained by using Equation 6.2; afterwards they are entered in the comparison matrix (see Table 6.5). An example of calculation to obtain judgment matrix for pair-wise compression of criteria $a_{1,3}$ value by row is shown as follow:

The pair-wise comparison of criterion c_1 to c_3 value,

$$c_{1,3} = \frac{e_1(x) + e_2(x) + e_3(x)}{3}$$

$$c_{1,3} = \frac{2 + 3 + 2.5}{3} = 2.5$$

where, $e_1(x), e_2(x)$ and $e_3(x)$ are the values on the pair-wise compression of criteria c_1 to c_3 by row obtained from expert evolutions.

Table 6.5: Matrix for averaged pair-wise comparison of criteria

	$c_{i,1}$	$c_{i,2}$	$c_{i,3}$	$c_{i,4}$
$c_{1,j}$	1.00	0.4	2.5	4
$c_{2,j}$	2.5	1.00	5	7
$c_{3,j}$	0.40	0.2	1.00	1.60
$c_{4,j}$	0.25	0.14	0.6	1.00

Step 4: Calculating the priority vector weights w'_i involve first normalizing the relative importance values in each column of the judgments matrix shown in Table 6.5 by using Equation 6.4. The sums of each column of the judgments matrix of criteria $c_{1,1}$,$c_{1,2}$, $c_{1,3}$ and $c_{1,4}$ are 4.15, 1.74, 9.13 and 13.60 respectively. For example the normalized eigenvector values of $c_{1,1}$ is calculated as follow.

$$\mu_{1,1} = \frac{1.00}{4.15} = 0.24$$

In a similar way the remaining normalized eigenvector values are obtained and presented in Table 6.6. Then the normalized eigenvector values by rows are used in

Equation 6.5 to obtain the priority vector weights w'_i. For example, w'_1 is calculated as follow.

$w'_1 = \frac{0.24+0.23+0.27+0.29}{4} = 0.260$

In a similar way the reaming priority vector weights are obtained and presented in Table 6.6.

Table 6.6: Resulting matrix

	Eigenvector values				w'_i
	$\mu_{i,1}$	$\mu_{i,2}$	$\mu_{i,3}$	$\mu_{i,4}$	
$\mu_{1,j}$	0.24	0.23	0.27	0.29	0.260
$\mu_{2,j}$	0.60	0.57	0.55	0.51	0.560
$\mu_{3,j}$	0.10	0.11	0.11	0.12	0.109
$c_{4,j}$	0.06	0.08	0.07	0.07	0.071

Step 5: Calculating the maximal λmax value from the judgment matrix as defined by Equation 6.7. For example as follows:

$(A\,w')_1 = (1 \times 0.260) + (0.4 \times 0.560) + (2.5 \times 0.109) + (4 \times 0.071) = 1.041$

In a similar way $(A\,w')_2$, $(A\,w')_3$ and $(A\,w')_4$ are obtained as 2.252, 0.439 and 0.282, respectively.

$\lambda max = \{1.041/0.260 + 2.252/0.560 + 0.439/0.109 + 0.282/0.071\}/4 = 4.006$

Step 6: Computing the CR of the judgments matrix to assure matrix consistency. This step involves the calculation of CI as defined by Equation 6.8:

$CI = (4.006 - 4) / (4 - 1) = 0.002,$

then, the CR is computed as defined by Equation 6.9:

$$CR = \frac{0.002}{0.90} = 0.0022$$

Since CR value is less than 0.1, therefore the matrix is consistent.

Step 7: Developing priority vector weights w'_i as defined in Table 6.6.

Phase 2: Calculating the intrinsic weights of identified criteria

Step 8: Constructing the decision matrix as defined by Equation 6.10 (see Table 6.7);

Table 6.7: Decision matrix

Alternative RCOs (Potential objectives)	Evaluation criteria			
	HFP effectiveness	Difficulty of implementing RCO	Time required for implementation of RCO (day)	Cost of implementing RCO ($)
(A_1)	0.0827	0.315	1	5,000
(A_2)	0.0722	0.555	3	15,000
(A_3)	0.009	0.666	5	25,000
(A_4)	0.0008	0.907	90	70,000

Step 8.1: Normalising each element of the original decision matrix shown in Table 6.7 using Equation 6.11, where each element is divided by its column sum.

$$P_{i1} = \frac{0.0827}{(0.0827 + 0.0722 + 0.009 + 0.0008)} = 0.5021$$

In a similar way, the reaming normalized elements are obtained and provided in the normalised decision matrix Table 6.8.

Table 6.8: Normalised decision matrix

Alternative RCOs (Potential objectives)	Evaluation criteria			
	HFP effectiveness P_{i1}	Difficulty of implementing RCO P_{i2}	Time required for implementation of RCO (day) P_{i3}	Cost of implementing RCO ($) P_{i4}
(A_1)	0.5021	0.1289	0.0101	0.0435
(A_2)	0.4384	0.2272	0.0303	0.1305
(A_3)	0.0546	0.2726	0.0505	0.2174
(A_4)	0.0048	0.3713	0.9091	0.6087

Step 9: Calculating the entropy E_j of each criterion as defined by Equation 6.12. For example, the entropy of "HEP effectiveness" criterion involves the following calculation:

$E_1 = 1/ln\ 4[(0.5021\times -0.689) + (0.4384\times -0.825) + (0.0546\times -2.907) + (0.0048\times -5.34)] = 0.6435$

In a similar way, the E_2, E_3 and E_4 of the other three criteria are obtained as 0.9543, 0.2812 and 0.7473, respectively.

Step 10: Calculating the criteria intrinsic weights based on their entropies as defined by Equation 6.12. This includes calculating first the degree of diversity d_j of the information involved in the outcomes of the jth criterion as defined by Equation 6.14. For example, d_1 involves the following calculation:

$d_1 = 1 - 0.6436 = 0.3565$

In a similar way, the d_2, d_3 and d_4 are obtained and presented in following summary

$d_j = 1 - E_j$	0.3565	0.0457	0.7188	0.2527
$\sum_{j=1}^{4} d_j$	1.3737			

From Equation 6.13 for example w''_1 of "HEP effectiveness" criterion is given by the following calculation:

$w''_1 = \frac{0.3565}{1.3737} = 0.2595$

Consequently, w''_1 is equal to 0.295. In a similar way, the weights of the other three criteria are obtained as 0.033, 0.523 and 0.184, respectively.

Step 11: Aggregating the subjective weights and intrinsic weights

The aggregated and normalised combined weights of criteria (subjective weights and intrinsic weights calculated in **step 4 and 10** could be derived by Equation 6.15.

$w_1 = \frac{0.260 \times 0.259}{0.156} = 0.4313$

In a similar way, the combined weights of the other three criteria are obtained as 0.119, 0.367 and 0.083, respectively.

The application of the conventional TOPSIS model is conducted in the following steps.

Step 12: Constructing the decision matrix based on the priority score of alternatives on each criterion as defined by Equation 6.16 and shown in Table 6.9.

Table 6.9: Decision matrix construct

Alternative RCOs (Potential objectives)	Evaluation criteria			
	HFP effectiveness r_{i1}	Difficulty of implementing RCO r_{i2}	Time required for implementation of RCO (day) r_{i3}	Cost of implementing RCO ($) r_{i4}
(A_1)	0.0827	0.315	1	5,000
(A_2)	0.0722	0.555	3	15,000
(A_3)	0.009	0.666	5	25,000
(A_4)	0.0008	0.907	90	70,000

Step 12.1: Obtaining the normalized decision matrix n_{ij} as defined by Equation 6.17. For example, the normalized n_{i1} is obtained as follow:

$$n_{1,1} = \frac{0.0827}{\sqrt{(0.0827)^2+(0.0722)^2+(0.009)^2+(0.0008)^2}} = 0.7508$$

In a similar way, the normalized elements n_{ij} are obtained and provided in the normalised decision matrix in Table 6.10.

Table 6.10: Normalised decision matrix

Alternative RCOs (Potential objectives)	Evaluation criteria			
	HFP effectiveness n_{i1}	Difficulty of implementing RCO n_{i2}	Time required for implementation of RCO (day) n_{i3}	Cost of implementing RCO ($) n_{i4}
(A_1)	0.7508	0.2435	0.0119	0.0658
(A_2)	0.6555	0.4290	0.0333	0.1974
(A_3)	0.0817	0.5148	0.0554	0.3290
(A_4)	0.0073	0.7011	0.9978	0.9211

Step 13: Obtaining the weighted normalized decision matrix v_{ij} as defined by Equation 6.18. For example, the weighted normalized element v_{i1} is obtained as follow:

$$v_{i1} = 0.7508 \times 0.4313 = 0.3238$$

In a similar way, the weighted normalized elements v_{ij} are obtained and provided in the weighted normalised decision matrix in Table 6.11.

Table 6.11: The weighted normalised decision matrix

Alternative RCOs (Potential objectives)	Evaluation criteria			
	HFP effectiveness v_{i1}	Difficulty of implementing RCO v_{i2}	Time required for implementation of RCO (day) v_{i3}	Cost of implementing RCO ($) v_{i4}
(A_1)	0.3238	0.0290	0.0041	0.0054
(A_2)	0.2827	0.0511	0.0122	0.0163
(A_3)	0.0352	0.06133	0.0203	0.0271
(A_4)	0.0031	0.0835	0.3664	0.0759

Step 14: Determining the PIS and NIS as defined by Condition 6.19 in Section 6.3.4.6. From the weighted normalised decision matrix shown in Table 6.11 the PIS of v_1^+ , v_2^+, v_3^+ and v_4^+ are determined as 0.3238, 0.0835, 0.3664 and 0.0759 respectively, and the NIS of v_1^- , v_2^-, v_3^- and v_4^- are determined as 0.0031, 0.0290, 0.0041 and 0.0054 respectively.

Step 15: Calculating the separation measure of each alternative (denoted by $M = S_i^+$, S_i^- Euclidean distance from the PIS and NIS) as defined by Equation 6.20. For example, S_1^+ and S_1^- is obtained as follow:

$$S_1^+ = \sqrt{\begin{matrix}(0.3238-0.3238)^2+(0.0835-0.0290)^2+(0.3664-0.0041)^2 \\ +(0.0759-0.0054)^2\end{matrix}}$$

$= 0.3731$

$$S_1^- = \sqrt{\begin{matrix}(0.0031-0.3238)^2+(0.0290-0.0290)^2+(0.0041-0.0041)^2 \\ +(0.0054-0.0054)^2\end{matrix}}$$

$= 0.3207$

In a similar way, the separation measure of the remaining alternatives are obtained and presented in Table 6.12.

Table 6.12: The separation measure of each alternative

S_1^+	0.3731	S_1^-	0.3207
S_2^+	0.3629	S_2^-	0.2808
S_3^+	0.4537	S_3^-	0.0530
S_4^+	0.3207	S_4^-	0.3731

Step 16: Calculating the relative closeness of each alternative of RCO to the ideal RCO, as defined by Equation 6.21. For example, C_1 is obtained as follow:

$$C_1 = \frac{0.3207}{0.3731+0.3207} = 0.4622$$

In a similar way, the relative closeness C_2 ,C_3, and $C_4$of the remaining alternative RCOs to the ideal RCO are obtained as 0.4362, 0.1046 and 0.5378 respectively.

Step 17: A set of alternative of RCOs A_i is generated in descending order based on the value of C_i indicating the most preferred and least preferred RCO according to the following preference ranking $A_4 > A_1 > A_2 > A_3$.

The above result of using a conventional TOPSIS model confirms that the alternative A_4 is the first choice, while A3 is the worst choice.

6.4.1.5. Sensitivity analysis

Sensitivity analysis can be used to check the robustness of the decision reached through the model. In this respect the sensitivity analysis would be conducted in order to see the importance of criteria weights in selecting the best alternative among the available alternatives RCOs.

To investigate the impact of criteria weights on the selection of the relevant RCO, the sensitivity analyses were conducted in nine experiments. The details of each experiment are presented in Table 6.13. From Table 6.13 it can be seen that in the first experiment, weights of all criteria are set equal to (0.25). In experiments 2-5 the weight of a criterion is set as highest (0.7525) one by one and the remaining criteria are set to the lowest value (0.0825). The purpose is to see the most important criterion in influencing the decision making process. In experiment 6-7 the weights of three attributes are set as highest (0.3058) simultaneously and the remaining criterion weight is set to the lowest value (0.0825). In experiment 7 the criteria weights are set in the inverse setting of experiment 6. In experiment 8 the weights of a two criterion are set as highest (0.4175) and the remaining weights are set to the lowest value (0.0825) simultaneously. In experiment 9 the criteria weights are set in the inverse setting of experiment 8. It can be seen from the overall sensitivity analysis results presented in Table 6.14 and 6.15; alternative A_4 has the highest score out of the nine experiments. The overall sensitivity analysis results show the definition of the importance of factors and their intrinsic assessment in the TOPSIS model. Therefore, alternative A_4 is recommended as the most sustainable RCO for implementation.

Table 6.13: Sensitivity analysis experiments

Exp. No.	Used criteria combined weights			
	HFP effectiveness w_1	Difficulty of implementing RCO w_2	Time required for implementation of RCO w_3	Cost for implementation of RCO w_4
0	0.4313	0.1191	0.3672	0.0825
1	0.25	0.25	0.25	0.25
2	0.7525	0.0825	0.0825	0.0825
3	0.0825	0.7525	0.0825	0.0825
4	0.0825	0.0825	0.7525	0.0825
5	0.0825	0.0825	0.0825	0.7525
6	0.3058	0.3058	0.3059	0.0825
7	0.0825	0.3058	0.3058	0.3059
8	0.4175	0.0825	0.0825	0.4175
9	0.0825	0.4175	0.4175	0.0858

Table 6.14: Sensitivity analysis results

Exp. No.	Overall score Conventional TOPSIS			
	A_1	A_2	A_3	A_4
Case study	0.4622	0.4362	0.1046	0.5378
1	0.3495	0.3566	0.2282	0.6505
2	0.8305	0.7965	0.1115	0.1695
3	0.1453	0.3969	0.5380	0.8547
4	0.0759	0.0750	0.0607	0.9241
5	0.0862	0.1709	0.3043	0.9137
6	0.4007	0.3971	0.1990	0.5993
7	0.1266	0.1888	0.2501	0.8734
8	0.4574	0.4669	0.2339	0.5426
9	0.1177	0.1838	0.2229	0.8822

Table 6.15: Sensitivity analysis ranking results

Exp. no.	Ranking			
	Conventional TOPSIS			
Case study	$A_4 >$	$A_1 >$	$A_2 >$	A_3
1	$A_4 >$	$A_2 >$	$A_1 >$	A_3
2	$A_1 >$	$A_2 >$	$A_4 >$	A_3
3	$A_4 >$	$A_3 >$	$A_4 >$	A_1
4	$A_4 >$	$A_1 >$	$A_2 >$	A_3
5	$A_4 >$	$A_3 >$	$A_2 >$	A_1
6	$A_4 >$	$A_1 >$	$A_2 >$	A_3
7	$A_4 >$	$A_3 >$	$A_2 >$	A_1
8	$A_4 >$	$A_2 >$	$A_1 >$	A_3
9	$A_4 >$	$A_3 >$	$A_2 >$	A_1

6.5 Conclusion

The introduction of the MCDM method combining the AHP model, entropy analysis method and TOPSIS models enabled integrating CREAM assessment and analysis models. As a result, CREAM bi-directional approaches have provided a high potential to improve assessed human performance reliability. In this context, the beauty of the human performance analysis model was shown by the classification scheme groups' organisation and the model of cognition characteristics. Both made the analysis method recursive rather than strictly sequential. The method also ensured analysis consistency and uniformity across applications, as it contains well defined stop rules and conditions to determine when an analysis has come to an end, and assures that the likely insisting event(s) or root cause(s) affecting HFP are identified. As a result, RCO alternatives could be developed and adapted in CREAM BN assessment scenarios to validate their desired potential for reducing targeted HFP. The proposed MCDM framework features some obvious attractiveness in its structure, allowing experts to evaluate the developed alternatives RCO on the chosen criteria subjectively and objectively. The framework is applicable to a wide range of real-world decision making problems in MCDM. The built-in inconsistency checking mechanism of the proposed framework helps to identify inconsistencies in judgments at very early stages of the computation process.

Chapter 7
Conclusion

Summary

This chapter briefly recaps all the developed approaches and techniques for the adequacy of organisation reliability assessment, human performance reliability assessment and analysis and decision making modelling. The developed approaches and techniques would be of valuable benefits to the designers, managers, operators, and authorities associated with the marine engineering industry, in order for them to retain and increase the safety and profitability of marine engineering operations in maritime ergonomics. Nonetheless, there are areas that require further research for the improvement of the developed approaches and techniques, and these are outlined.

7.1. Research contribution

The effectiveness of safety assessment in the maritime industry has been analysed in the literature from various angles. Until now, research in this area has mostly been focused on determination of the relevant risk factors of marine incidents and accidents, of which erroneous human actions account for 80-90%. Knowing that the maritime industry is clearly dependent on human reliability, HRA can practically be used to provide the suitable approaches and techniques that are needed to retain the maritime industry at a high level of reliability. HRA has been used to inform safety and risk-based decision making in many industries for decades, and a range of techniques have been accepted for its use. Despite the fact that HRA remains a controversial area, it would deliver a practical, powerful, and resource-efficient approach to the assessment and improvement of human reliability. HRA is certainly not an easy task to perform, given the intricacies of human performance, and how humans can be affected by many factors in an operational context.

While it is complicated to practically model operational context in its entirety, in HRA modelling there are levels of compromise. The first level of compromise is to identify the most relevant HRA method to be included in the model. The second level of compromise is the amount of mathematical manipulation to use. Although mathematics has the potential to prove general results, these results critically depend on the consistency of the used HRA method, mathematical model, and the rationality of the prior knowledge of some variables and the observations of others. Using software to handle model inference may never lead to neat results, but it is much more robust against alterations. HRA probabilistic models help to formulate a proactive assessment and identify the underlying assumptions of human performance uncertainty. The selection of the most relevant and suitable probabilistic model is crucial in HRA. Expert judgment is basically an integral part of HRA. Therefore, appropriate expert judgment elicitation is critical to HRA consistency.

The literature review has revealed that few HRA-PSA methodologies are available in the maritime industry. The applicability of the existing HRA methods in marine engineering operations needs to be studied. Thus a new HRA framework for the quantitative HRA in marine engineering operations has been described through the development of several novel HRA methods in Chapters 3, 4, 5 and 6. This includes the adequacy of organisation reliability assessment, human performance reliability assessment and analysis, human performance RCO evaluation, and decision making under uncertainty. The framework has been developed in a generic way in which appropriate tailoring could make it applicable to tackle any specific human, technological and organisational factors in marine engineering operations. In summary, the methods and techniques developed to support the developed framework are concluded as follows:

- Generation of the BN model maps the logical relation of human, technological and organisational factors. This model is needed to infer the adequacy of organisation reliability assessment (Chapter 3).
- Generation of the CREAM-BN probabilistic model analyses CPCs' dependency characteristic and the newly introduced attributes and sub attributes nodes. This model features the BN "divorcing" technique, used to reduce the number of possible combinations of CPTs of CREAM BN nodes. A FRB technique is used to structure the logical relation of the new attributes' evaluation grades to simplify the subjective CPT elicitation of COCOM-CMs' node by experts. FS theory is also used to transform the posterior probabilities of the control modes to a crisp HFP value (Chapter 4).
- Combining the generated CREAM-BN probabilistic model with an ER technique to deal with the incompleteness of information, in which ER is used to synthesise the incomplete degrees of belief elicited by experts, as well as to aggregate the

symmetrical influence factors affecting the prior knowledge of CREAM-BN CPCs' nodes (Chapter 5).

- Specifying a classification scheme of the CREAM performance analysis model by adding new organisational factors in the maritime industry (Chapter 6).
- Formulation of a decision making technique includes AHP algorithm and entropy calculation for generating the combined weights of evaluation criteria of the decision matrix, as well as TOPSIS algorithms for synthesising the impact of the combined weights on the priority score of each criterion in the assessment plans of the decision matrix. As a result the developed alternative RCOs are prioritised. This technique enables DMs to select the potential RCO that would reduce the assessed HFP (Chapter 6).

All the proposed approaches and methods in this thesis are developed in sequence. They provide an integrated approach to increase the safety and profitability of marine engineering operations. Figure 7.1 depicts an overall framework diagram with accompanying description illustrating the interrelation of developed models in a context of HRA process. However, individual use of the proposed methods is a matter of assessing each particular situation. To maintain a human action on a strategic control mode requires a continuum of competencies, efforts and resources that would not practically withstand for long. Basically, human action can be maintained on a tactical control mode in a normal condition. When it tends to overlap with the opportunistic control mode, awareness is required to conduct the human performance analysis to identify and monitor the phenotypes' initiating events and the possible genotype root cause factors. When opportunistic control mode starts to overlap with the scrambled mode the adequacy of organisation reliability assessment is needed to structure an overall organisational belief assessment. When the scrambled mode is prevalent, the entire HRA approach is needed to identify the phenotype initiating events and the likely genotype root cause factors. Accordingly, human performance RCOs could be developed and decision making would be thought of as an active behaviour. In this context, it is essential to realize that humans are capable of performing an action reliably with limitations. Exactly how reliable humans are depends on the situations or contexts under which they are operating and the consistency of the used HRA method. In all respects, human performance reliability bounds need to be understood. The human failure probability range is limited, from 1.0 (unreliable) to 1.0E-3 (quite reliable). Humans are very reliable but not ultra-reliable. They are closer to 1.0E-3 than 1.0E-6 (Spurgin, 2010). When an ultra-reliable system is required, a system of barriers and controls as well as human is needed. One cannot just rely on a person to provide a high level of reliability. Humans make mistakes, so the system has to be designed to reflect what is possible.

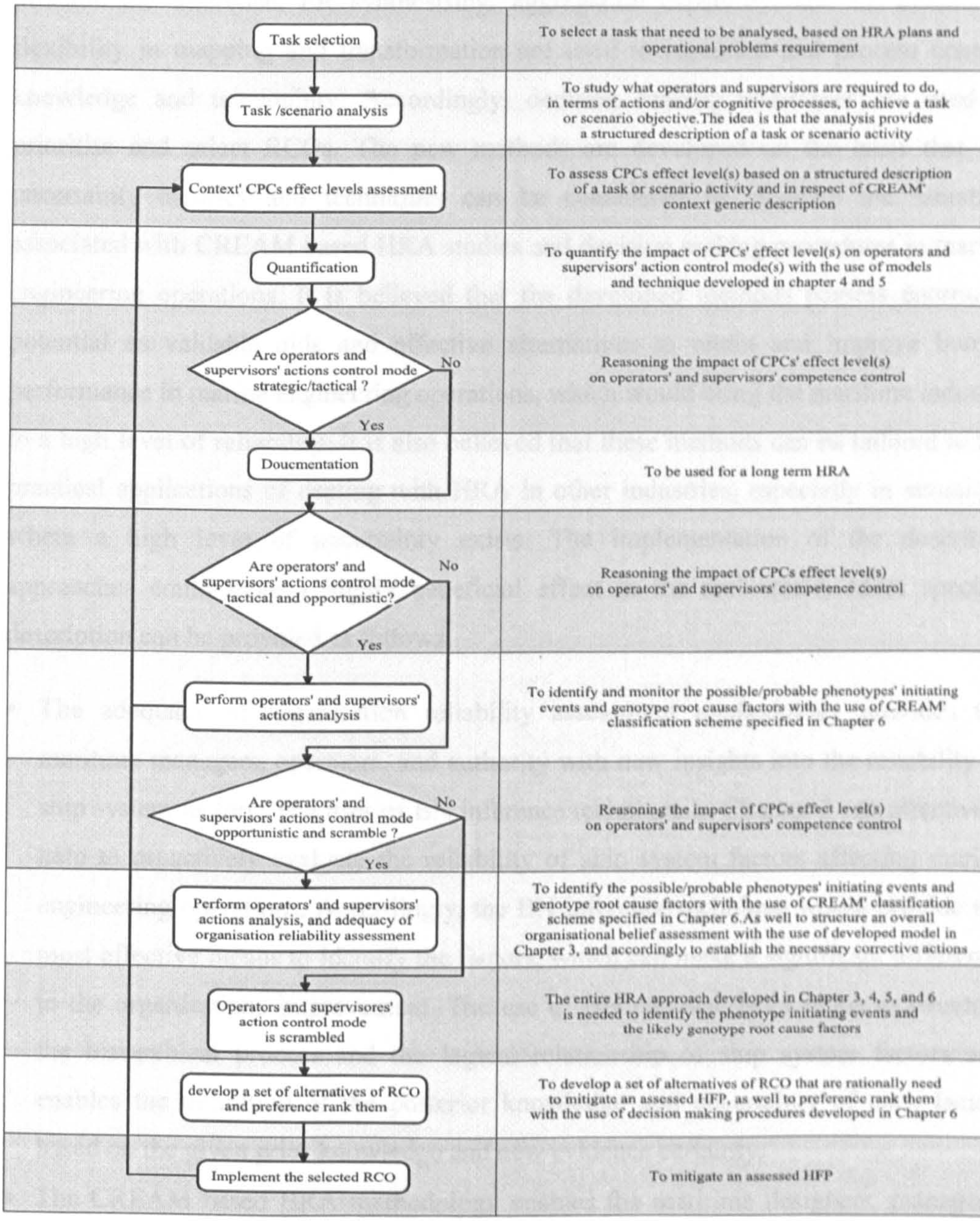


Figure 7.1: An overall framework diagram with accompanying description illustrating the interrelation of developed models in a context of HRA process

The major contributions of the generated methods and techniques in this research focus on both theoretical and practical aspects. Practically, the generated methods and techniques appropriately measure and analyse human performance reliability and the adequacy of organisation reliability. In addition, they also allow the development of human performance RCOs and decision making procedures. Theoretically, BN probabilistic inference, ER synthesising, aggregation capability, and FL distinctive flexibility in mapping and transformation are used to represent and process context knowledge and uncertainty. Accordingly, decision making techniques are used to prioritise and select RCOs. The new methods are developed on the basis that the uncertainty theories and techniques can be considered to facilitate the literature associated with CREAM based HRA studies and decision making procedures in marine engineering operations. It is believed that the developed methods possess enormous potential as valuable aids and effective alternatives to retain and improve human performance in marine engineering operations, which would bring the maritime industry to a high level of reliability. It is also believed that these methods can be tailored to the practical applications of dealing with HRA in other industries, especially in situations where a high level of uncertainty exists. The implementation of the described approaches could have a highly beneficial effect in the real world. More specific description can be provided as follows:

- The adequacy of organisation reliability assessment methodology provides the maritime managers, operators, and authority with new insights into the reliability of ship system factors. The uses of BN inference technique in Chapter 3 can effectively help to proactively evaluate the reliability of ship system factors affecting marine engineering operations. Accordingly, the BN inference technique would provide the most effective means to identify the factors, which can make a significant difference to the organisations improvement. The use of BN characteristics helps to structure the hierarchical process and the logical relationship of ship system factors and enables the definition of the posterior knowledge and uncertainty of each factor, based on the given prior knowledge and new evidence certainty.
- The CREAM based HRA methodology enables the maritime designers, managers, operators and authorities to perceive the impact of the marine engineering operational context on human performance. The uses of BN inference, FRB structure, FS mapping and transformation technique in Chapter 4 can effectively help

to evaluate proactively the HFP of human actions in a variety of contexts. Accordingly, the used techniques would provide the potential for identifying the initiating events or root causes, which can be used to develop the RCOs needed to reduce HFPs.

- The methodology for Bayesian subjective probability elicitation using the ER algorithm for synthesising expert's judgments is used to enhance CREAM based HRA methodology, where ER capability is used to synthesise the experts' incomplete conditional degrees of belief elicitation and to define the unknown probability mass. In addition, it is used to aggregate the symmetrical influence of factors affecting CPCs. ER synthesising and aggregation of degrees of belief masses and the unknown masses enable the development of the best and worst CPT scenarios without loss of much information. The establishment of two CREAM BN models modelling the best and worst CPT scenarios can be used to aggregate HFPs reflecting the input uncertainty.
- The decision making methodology for improving predicted human performance reliability based on operational context analysis enables decision makers to select the potential RCO that would reduce assessed HFPs. In this methodology AHP and entropy algorithms are used to provide consistently combined weights of selected criteria in the developed TOPSIS decision making model. A TOPSIS method is used to prioritise the developed alternative RCOs to provide decision makers with the flexibility in considering their decisions regarding selecting the most relevant RCO that would reduce assessed HFPs.

7.2. Implications for future research

This research attempts to provide a comprehensive analysis based on CREAM and uncertainty treatment techniques to facilitate the quantitative HRA in marine engineering operations. Due to the time limit, the current study does not refer to the problem analysis, which could be desirable in further investigations. They are listed as follows.

- The selection of the representative number of experts within the maritime industry is necessary to reduce the bias involved in the subjective judgements. Data collected from more experts will further validate developed models and improve their credibility in HRA.

- It will be desirable to further validate the adequacy of the organisation reliability assessment BN model through incorporating the data from a well established organisation.
- It will be desirable to perform more test cases to further validate the developed methodologies for HFP assessment, analysis and mitigation.
- It will be desirable to conduct more research studies to determine the appropriate fuzzy function and the defuzzifecation method that can be used to transform BN inferred COCOM-CMs' marginal probabilities into crisp HFP values.
- It will be beneficial to incorporate more powerful and flexible HRA and decision making techniques to facilitate further the application of qualitative human reliability assessment methodology in marine engineering operations' knowledge and uncertainty assessment.
- It would be useful if the available software for CREAM based human performance analysis is further developed by incorporating organisational factors.
- Marine engineering operations are highly affected by human factors, through which human performance is adaptive, flexible and able to manage multi-tasks. Therefore it will be helpful to define the number of simultaneous tasks that humans can carry out. This will affect the human COCOM-CMs' reliability in specifically configured context situations.

In order to deal with the limitations stated above, this research can be extended in the following directions.

- To develop generic BN models for each CPC in a similar way to the one related to organisational reliability assessment mode in Chapter 3, imitating its main variables and their influences in the DAG. This extension is valid for situations that share the attitude of viewing a context's knowledge and uncertainty as two independent entities, and so treating them by means of two distinct loosely-coupled processes. The reasoning process handles the knowledge as if it were exact, while a parallel uncertainty inference process accompanies it, computing the uncertainty affecting each newly derived fact. Such a proactive inference mechanism can be supportive to establish a trend of a reactive diagnostic approach with the necessary follow-up measures, where available recourses can be allocated effectively.

- ER can be applied successively to combine any number of pieces of evidence, in conditions where the variables affecting CPCs are in symmetrical positions. ER uses belief and plausibility values to represent the evidence and the corresponding uncertainty. These values can represent how the uncertainty of a hypothesis can be reduced as more and more evidence becomes available to the system. The advantage of this approach is that researchers can work with incomplete and ambiguous or conflicting evidence without loss of any information.
- FS can be used to map the input and output fuzzy values for the uncertainties. FRB can be used to structure the knowledge base and clarify the ambiguities in the human decision making process. When the relevant ambiguities and uncertainties of the variables affecting CPCs need to be properly taken into consideration, FS can be used to equip FRB with an explanatory interface that facilitates communication between the users and the FRB. This would enable the users to know how the final conclusion can be obtained through the FRB.
- Conduct simulation based HRA studies for specific marine engineering tasks. These would enable researchers to qualitatively analyse specific task procedures and accordingly determine HFPs. During these studies human work load limitation can be defined and probabilistic models for the assessment of multi-tasks' variability affecting operators' workload could be developed. Human workload probabilistic models could also be linked to powerful modelling techniques, which model the reliability assessment of systems' operational components. This would provide the possibility of correlating the HRA models with the operational components' reliability assessment technique on a continuous basis, where the needs of both human resources and operational components can be rationally planned.
- In the CREAM classification scheme, newly specified factors and the added organisational factors in this study should be further examined to satisfy the explicit principle of human performance analysis requirements. Such an approach can be combined with the classification scheme to simplify its use and ensure its robustness against alterations.
- To develop a MCDM technique to be used in a complex decision making process, in which DMs can choose the optimal alternative RCO in a fuzzy environment, where the vagueness and subjectivity are handled with linguistic terms parameterised by fuzzy numbers. Such a technique can be effectively and continuously used to provide

DMs with the relevant decision based on information that has been gathered, modelled, and analysed.

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Appendix 1: Conditional probability tables

Table A1.1: Safety management system "High" CPT

Safety management system C.P.T. (%)								
Management quality	High							
Contingency procedures	Performed				Not performed			
Maintenance procedures	Performed		Not performed		Performed		Not performed	
Operational procedures	Performed	Not performed	Performed	Not performed	Performed	Not performed	Performed	Not performed
Effective	100	65	80	45	70	40	40	15
Ineffective	0	35	20	55	30	60	60	85

Table A1.2: Safety management system "Low" CPT

Safety management system C.P.T. (%)								
Management quality	Low							
Contingency procedures	Performed				Not performed			
Maintenance procedures	Performed		Not performed		Performed		Not performed	
Operational procedures	Performed	Not performed	Performed	Not performed	Performed	Not performed	Performed	Not performed
Effective	85	60	60	30	55	20	35	0
Ineffective	15	40	40	70	45	80	65	100

Table A1.3: Organisational structure "High" CPT

Organisational structure C.P.T. (%)								
Management quality	High							
Communication	Effective				ineffective			
Organisational culture	Acquired		Not acquired		Acquired		Not acquired	
Objective and strategy	Clear	Not clear	Clear	Not clear	Clear	Not clear	Clear	Not clear
Effective	100	85	85	60	70	40	30	20
Ineffective	0	15	15	40	30	60	70	80

Table A1.4: Organisational structure "Low" CPT

Organisational structure C.P.T. (%)								
Management quality	Low							
Communication	Effective				ineffective			
Organisational culture	Acquired		Not acquired		Acquired		Not acquired	
Objective and strategy	Clear	Not clear	Clear	Not clear	Clear	Not clear	Clear	Not clear
Effective	80	70	60	30	40	15	15	0
Ineffective	20	30	40	70	60	85	85	100

Table A1.5: Resources management "High" CPT

Resources management C.P.T. (%)								
Management quality	High							
Human resources	Sufficient				Insufficient			
Equipment and records	Effective		Ineffective		Effective		Ineffective	
Condition monitoring and performance control	reliable	Not reliable	reliable	Not reliable	reliable	Not reliable	reliable	Not reliable
Effective	100	75	90	40	85	20	55	15
Ineffective	0	25	10	60	15	80	45	85

Table A1.6: Resources management "Low" CPT

Resources management C.P.T. (%)								
Management quality	Low							
Human resources	Sufficient				Insufficient			
Equipment and records	Effective		Ineffective		Effective		Ineffective	
Condition monitoring and performance control	reliable	Not reliable	reliable	Not reliable	reliable	Not reliable	reliable	Not reliable
Effective	85	45	80	15	60	10	25	0
Ineffective	15	55	20	85	40	90	75	100

Table A1.7: Management quality CPT

Management quality C.P.T. (%)								
Controls	Effective				Ineffective			
Policies	Clear		Not clear		Clear		Not clear	
Standards	Adopted	Not adopted	Adopted	Not adopted	Adopted	Not adopted	Adopted	Not adopted
High	100	60	80	20	80	20	40	0
Low	0	40	20	80	20	80	60	100

Table A1.8: Human resources CPT

Human resources C.P.T. (%)								
Knowledge	Good				Pour			
Skill	High		Low		High		Low	
Motivation	High	Low	High	Low	High	Low	High	Low
Sufficient	100	75	70	20	80	30	25	0
Insufficient	0	25	30	80	20	70	75	100

Table A1.9: "Controls" CPT

Controls C.P.T. (%)				
Reactive control measures	Good		Poor	
Proactive control measures	Good	Poor	Good	Poor
Effective	100	50	50	0
Ineffective	0	50	50	100

Table A1.10: "Equipment and records" CPT

Equipment and records[1] C.P.T. (%)				
Availability[1]	High		Low	
Quality	High	Low	High	Low
Effective	100	60	40	0
Ineffective	0	40	60	100

Table A1.11: "Condition monitoring and performance control" CPT

Condition monitoring and performance control[2] C.P.T. (%)				
Availability[2]	High		Low	
Trust	High	Low	High	Low
Reliable	100	60	40	0
Not reliably	0	40	60	100

Table A1.12: "Organisational culture" CPT

Organisational culture C.P.T. (%)				
Norm	Committed		Not committed	
Safety culture	Committed	Not committed	Committed	Not committed
Acquired	100	50	50	0
Not acquired	0	50	50	100

Table A1.13: "Norm" CPT

Norm C.P.T. (%)				
Management commitment	High		Low	
Crew involvement	High	Low	High	Low
Committed	100	50	50	0
Not committed	0	50	50	100

Table A1.14: "Safety culture" CPT

Safety culture C.P.T. (%)				
Management commitment	High		Low	
Crew involvement	High	Low	High	Low
Committed	100	50	50	0
Not committed	0	50	50	100

Appendix 2: The main /sub attributes CPTs

Table A2.1: Operator preparedness CPT

No.	Operator preparedness CPT %				
	Adequacy of training and expertise	Availability of procedures/ plans	Inappropriate	Acceptable	Appropriate
1	Inadequate	Inappropriate	100	0	0
2	Inadequate	Acceptable	66.7	33.3	0
3	Inadequate	Appropriate	33.4	33.3	33.3
4	Adequate with limited experience	Inappropriate	33.3	66.7	0
5	Adequate with limited experience	Acceptable	33.3	66.7	0
6	Adequate with limited experience	Appropriate	0	33.3	66.7
7	Adequate with high experience	Inappropriate	33.4	33.3	33.3
8	Adequate with high experience	Acceptable	0	33.3	66.7
9	Adequate with high experience	Appropriate	0	0	100

Table A2.2: Working environments CPT

No.	Working environments CPT %				
	Adequacy of working culture	Adequacy of Perception conditions	Inappropriate	Acceptable	Appropriate
1	Inappropriate	Inappropriate	100	0	0
2	Inappropriate	Acceptable	50	50	0
3	Inappropriate	Appropriate	50	0	50
4	Acceptable	Inappropriate	50	50	0
5	Acceptable	Acceptable	0	100	0
6	Acceptable	Appropriate	0	50	50
7	Appropriate	Inappropriate	50	0	50
8	Appropriate	Acceptable	0	50	50
9	Appropriate	Appropriate	0	0	100

Table A2.3: Adequacy of perception of conditions CPT

No.	Adequacy of perception of conditions CPT (%)					
	Adjusted working conditions	Adequacy of man-machine interface MMI and operational support Skill	Time of the day	Inappropriate	Acceptable	Appropriate
1	Inappropriate	Inappropriate	Day-time (adjusted)	100	0	0
2	Inappropriate	Inappropriate	Night-time PM (unadjusted)	100	0	0
3	Inappropriate	Inappropriate	Night-time AM (unadjusted)	100	0	0
4	Inappropriate	Tolerable	Day-time (adjusted)	80	20	0
5	Inappropriate	Tolerable	Night-time PM (unadjusted)	80	20	0
6	Inappropriate	Tolerable	Night-time AM (unadjusted)	80	20	0
7	Inappropriate	Adequate	Day-time (adjusted)	66.7	33.3	0
8	Inappropriate	Adequate	Night-time PM (unadjusted)	66.7	33.3	0
9	Inappropriate	Adequate	Night-time AM (unadjusted)	66.7	33.3	0
10	Inappropriate	Supportive	Day-time (adjusted)	50	50	0
11	Inappropriate	Supportive	Night-time PM (unadjusted)	50	50	0
12	Inappropriate	Supportive	Night-time AM (unadjusted)	50	50	0
13	Acceptable	Inappropriate	Day-time (adjusted)	70	30	0
14	Acceptable	Inappropriate	Night-time PM (unadjusted)	70	30	0
15	Acceptable	Inappropriate	Night-time AM (unadjusted)	70	30	0
16	Acceptable	Tolerable	Day-time (adjusted)	33.3	66.7	0
17	Acceptable	Tolerable	Night-time PM (unadjusted)	33.3	66.7	0
18	Acceptable	Tolerable	Night-time AM (unadjusted)	33.3	33.7	0
19	Acceptable	Adequate	Day-time (adjusted)	33.3	33.7	0
20	Acceptable	Adequate	Night-time PM (unadjusted)	33.3	33.7	0
21	Acceptable	Adequate	Night-time AM (unadjusted)	33.3	33.7	0
22	Acceptable	Supportive	Day-time (adjusted)	0	30	70
23	Acceptable	Supportive	Night-time PM (unadjusted)	0	30	70
24	Acceptable	Supportive	Night-time AM (unadjusted)	0	30	70
25	Appropriate	Inappropriate	Day-time (adjusted)	0	50	50
26	Appropriate	Inappropriate	Night-time PM (unadjusted)	0	50	50
27	Appropriate	Inappropriate	Night-time AM (unadjusted)	0	50	50
28	Appropriate	Tolerable	Day-time (adjusted)	0	33.3	66.7
29	Appropriate	Tolerable	Night-time PM (unadjusted)	0	33.3	66.7
30	Appropriate	Tolerable	Night-time AM (unadjusted)	0	33.3	66.7
31	Appropriate	Adequate	Day-time (adjusted)	0	20	80
32	Appropriate	Adequate	Night-time PM (unadjusted)	0	20	80
33	Appropriate	Adequate	Night-time AM (unadjusted)	0	20	80
34	Appropriate	Supportive	Day-time (adjusted)	0	0	100
35	Appropriate	Supportive	Night-time PM (unadjusted)	0	0	100
36	Appropriate	Supportive	Night-time AM (unadjusted)	0	0	100

Table A.2.4: Adequacy of working culture CPT

No.	Adequacy of organisation	Adjusted Crew collaboration quality	Adequacy of working culture CPT %		
			Inappropriate	Acceptable	Appropriate
1	Deficient	Deficient	100	0	0
2	Deficient	Inefficient	50	50	0
3	Deficient	Efficient	75	25	0
4	Deficient	Very Efficient	33.4	33.3	33.3
5	Inefficient	Deficient	100	0	0
6	Inefficient	Inefficient	50	50	0
7	Inefficient	Efficient	50	50	0
8	Inefficient	Very Efficient	0	50	50
9	Efficient	Deficient	50	50	0
10	Efficient	Inefficient	33.3	66.7	0
11	Efficient	Efficient	25	75	0
12	Efficient	Very Efficient	0	0	100
13	Very Efficient	Deficient	33.4	33.3	33.3
14	Very Efficient	Inefficient	0	75	25
15	Very Efficient	Efficient	0	25	75
16	Very Efficient	Very Efficient	0	0	100

Appendix 3.1: Retrospective analysis classification groups

Table A3.1.1: Categories groups of specific effects, general effects (general consequent), general antecedents and specific antecedent for the error modes

Categories	Definition / explanation	Specific effects	General effects	General consequent	General antecedent		Specific antecedent
Action at wrong time	**An action started too early, before a signal was given or the required conditions had been established. (Premature action)**	**Too early**	**Timing**	**Timing** / duration	Communication failure **Faulty diagnosis** Inadequate plan	**Inadequate procedure** Inattention Observation missed	Earlier omission Trapping error
	An action started too late. (Delayed action)	Too late					
	An action that was not done at all (within the time interval allowed).	Omission					
	An action that continued beyond the point when it should have stopped.	Too long	Duration				
	An action that was stopped before it should have been.	Too short					
Action in wrong place	An action that was not carried out. This includes in particular the omission of the last action(s) of a series.	Omission	**Sequence**	**Sequence**	Access limitations Communication failure **Faulty diagnosis** Inadequate plan	**Inadequate procedure** Inattention Memory failure **Wrong identification**	Trapping error
	One or more actions in a sequence were skipped.	Jump forward					
	One or more earlier action that has been carried out is carried out again.	Jump backwards					
	The previous action is repeated.	Repetition					
	The order of two neighbouring actions is reversed.	Reversal					
	An extraneous or irrelevant action is carried out.	**Wrong action**					
Action of wrong type	Insufficient force.	Too little	Force	Force	Communication failure Equipment failure Faulty diagnosis	Inadequate plan Inadequate procedure Observation missed	Ambiguous label Convention conflict Incorrect label
	Surplus force, too much effort.	Too much					
	A movement taken too far.	Too far					
	A movement taken too far.	Too far	Distance / magnitude		Communication failure	Inadequate plan Inadequate	Ambiguous label Convention

	A movement not taken far enough.	Too short			Equipment failure Faulty diagnosis	procedure Observation missed	conflict Incorrect label
	Action performed too quickly, with too much speed or finished too early.	**Too fast**	**Speed**	**Speed**	Communication failure Distraction Equipment failure **Faulty diagnosis**	Inadequate plan **Inadequate procedure** Observation missed **Performance variability**	None defined
	Action performed too slowly, with too little speed or finished too late.	Too slow					
	Movement in the wrong direction e.g. forwards instead of backwards or left instead of right.	Wrong direction	Direction	Direction	Communication failure Faulty diagnosis Inadequate plan	Inadequate procedure Inattention Observation missed	Ambiguous label Convention conflict Incorrect label
	The wrong kind of movement, such as pulling a knob instead of turning it.	Wrong movement type					
Action at wrong object	An object that is in physical proximity to the object that should have been used.	Neighbour	Wrong object	Wrong object	Access problems Communication failure Wrong identification Inadequate p l a n	Inadequate procedure Inattention Performance variability Observation missed	Ambiguous label Incorrect label
	An object that is similar in appearance to the object that should have been used.	Similar object					
	An object that was used by mistake, even though it had no obvious relation to the object that should have been used.	Unrelated object					

Table A3.1.2: person related genotypes groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for observation

Categories	Definition / explanation	Genotypes causes: Specific consequent	General consequent	General antecedent	Root causes: Specific antecedent
Observation	A signal or an event that should have been the start of an action (sequence) is missed.	Overlook cue / signal	Observation missed	Equipment failure Faulty diagnosis Inadequate plan Functional impairment Inattention	Information overload Multiple signals Noise Parallax
	A measurement or some information is missed, usually during a sequence of actions.	Overlook measurement			
	A response is given to an incorrect stimulus or event, e.g. starting to drive when the light changes to red.	False reaction	False observation	Fatigue Distraction	None defined
	An event or some information is incorrectly recognised or mistaken for something else.	False recognition			
	A signal or a cue is misunderstood as something else. The difference from "false reaction" is that it does not immediately lead to an action.	Mistaken cue	**Wrong identification**	Distraction Missing information **Faulty diagnosis** Mislabelling	Ambiguous symbol set. Ambiguous signals Erroneous information. Habit, expectancy. Information overload.
	The identification of an event or some information is incomplete, e.g. as in jumping to a conclusion.	Partial identification			
	The identification of an event or some information is incorrect. The difference from "false recognition" is that identification is a more deliberate process.	**Incorrect identification**			

Table A3.1.3: Person related genotypes groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for interpretation

Categories	Definition / explanation	Genotypes causes: Specific consequent	General consequent	General antecedent	Root causes: Specific antecedent	
Interpretation	**The diagnosis of the situation or system state is incorrect.**	**Wrong diagnosis**	**Faulty diagnosis**	**Cognitive bias** Wrong identification Inadequate procedure	Confusing symptoms Error in mental model Misleading symptoms Miss learning	Multiple disturbances **New situation** Erroneous analogy
	The diagnosis of the situation or system state is incomplete.	Incomplete diagnosis				
	Faulty reasoning involving inferences or generalisations (going from specific to general), leading to invalid results.	Induction error	Wrong reasoning	Cognitive bias Cognitive style	Too short planning horizon	False analogy Over generalisation Mode error
	Faulty reasoning involving deduction (going from general to specific), leading to invalid results.	Deduction error				
	The selection among alternatives (hypotheses, explanations, interpretations) using incorrect criteria, hence leading to invalid results	Wrong priorities				
	A signal or a cue is misunderstood as something else. The difference from "false reaction" is that it does not immediately lead to an action.	Decision paralysis	Decision error	Fear Cognitive bias Distraction Social pressure	Lack of knowledge Mode error Shock	Stimulus overload Workload
	The identification of an event or some information is incomplete, e.g. as in jumping to a conclusion.	Wrong decision				
	The identification of an event or some information is incorrect. The difference from "false recognition" is that identification is a more deliberate process.	Partial decision				
	Identification is not made in time (for appropriate action to be taken).	No identification	Delayed interpretation	Inadequate procedures Equipment failure Fatigue	Indicator failure Inadequate workload	Response slow- down Lack of competence
	An identification is not made fast enough, e.g. because the reasoning involved is difficult, leading to a time pressure.	Increased time pressure				
	A state change occurred which had not been	Unexpected state	Incorrect	Cognitive bias	Lost situational awareness	

	anticipated.	change	prediction	Ambiguous information Incomplete information	
	The event developed in the main as anticipated, but some side-effects had been overlooked.	Unexpected side effects			
	The speed of development (of the system) has been misjudged, so things happen either too slowly or too fast. Planning.	Process speed misjudged			

Table A3.1.4: Person related genotypes groups of specific consequent general consequent, general antecedents causes and specific antecedents root causes for planning

Categories	Definition / explanation	Genotypes causes			Root causes	
		Specific consequent	General consequent	General antecedent	Specific antecedent	
Planning	The plan is not complete, i.e., it does not contain all the details needed when it is carried out. This can have serious consequences later in time.	Incomplete plan	Inadequate plan	Distraction Memory failure Wrong reasoning Excessive demand Insufficient knowledge	Error in goal Inadequate training Model error Overlook precondition	Overlook side consequent Violation Too short planning horizon
	The plan is wrong, in the sense that it will not achieve its purpose.	Incomplete plan				
	The goal has been wrongly selected, and the plan will therefore not be effective (cf. the conventional definition of a mistake).	Wrong goal selected	Priority error	Legitimate higher priority	Conflicting criteria	

Table A3.1.5: Temporary person related functions groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes

Definition / explanation	Causes	General consequent	General antecedent	root causes	
	Specific consequent			Specific antecedent	
An item or some information cannot be recalled when needed.	Forgotten	Memory failure	Excessive demand	Daydreaming Long time since learning Other priority	Temporary incapacitation
Information is incorrectly recalled (e.g. the wrong name for something).	Incorrect recall				
Information is only recalled partially, i.e., part of the information is missing.	Incomplete recall				
Actions do not seem to follow any plan or principle, but rather look like trial-and-error.	Random actions	Fear	Heuristic thoughts	Earlier error Possible consequences	Uncertainty
The person is paralysed, i.e., unable to move or act.	Action freeze				
The performance of a task is suspended because the person's attention was caught by something else.	Task suspended	Distraction	Equipment failure Communication failure	Boss / colleague Comfort call Commotion	Competing task Telephone
The performance of a task is not completed because of a shift in attention.	Task not completed				
The person cannot remember why something is being done. This may cause a repetition of previous steps.	Goal forgotten				
The person cannot remember or think of what to do next or what happened before.	Loss of orientation				
The person's response speed (physically or mentally) is reduced due to fatigue.	Delayed response	Fatigue	Adverse ambient conditions Irregular working hours	Exhaustion	
Reduced precision of actions, e.g. in reaching a target value.	Lack of precision	**Performance Variability**	Equipment failure Excessive demand	Change of system character	**Lack of training** Over enthusiasm

An increasing number of actions fail to achieve their purpose.	**Increasing misses**		**Insufficient skill**	Illness
A signal or an event was missed due to inattention. This is similar to “observation missed”, the difference being whether it is seen as a random event or something that can be explained by a cognitive function.	Signal missed	Inattention	Adverse ambient conditions	Temporary incapacitation
A general condition caused by physiological stress. This may have many specific effects.	Many specific effects	Physiological stress	Adverse ambient conditions Irregular working hours	Boredom Heavy weather
A general condition caused by psychological stress. This may have many specific effects.	Many specific effects	Psychological stress	Excessive demand Insufficient knowledge	Boredom lack of motivation

Table A3.1.6: Permanent person related functions groups of consequent, specific general consequent, general antecedents causes and specific antecedents root causes

Definition / explanation	causes			Root causes
	Specific consequent	General consequent	General antecedent	Specific antecedent
These specific effects refer to well-defined functional impairments, mostly of a psycho-physical nature. They are defined in safety management system. Specific physiological disabilities may be added to this group if required by the analysis.	Deafness Bad eyesight Colour blindness Dyslexia/aphasia) Other disability	Functional impairment	Bias physical fitness tests	None defined
Search for data and information is accomplished by looking for several things at the same time.	Simultaneous scanning	Cognitive style	Inattention Distraction	Lack of skill
Search for data and information is accomplished by looking at one thing at a time.	Simultaneous scanning			
Search for data and information starts from an assumption of which the various aspects are examined one by one.	Conservative focusing			
The search for data or information changes in an opportunistic way, rather than systematically.	**Focus gambling**	**Cognitive bias**	**Wrong reasoning**	**Lack of competence**
New information does not lead to a proper adjustment of probabilities - either a conservative or a too radical effect.	Incorrect revision of probabilities			
Interpretation of past events is influenced by knowledge of the outcome.	Hindsight bias			
Events are (mistakenly) seen as being caused by specific phenomena or factors.	Attribution error			
Person mistakenly believes that the chosen actions control the developments in the system.	Illusion of control			
Search for data or information is restricted to that which will confirm current assumptions.	Confirmation bias			
Search for information and action alternatives is constrained by a strong hypothesis about what the current problem is.	Hypothesis fixation			

Table A3.1.7: Main technological genotypes groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for equipment category

Definition / explanation	Probable causes	General consequent	General antecedent	Root causes
	Specific consequent			Specific antecedent
An actuator or a control either cannot be moved or moves too easily.	Actuator stick/slip	Equipment failure	Maintenance failure Running in failure Random failure Age dependent failure	Power failure Fire Flooding Tremor External event Impact/ Projectile
Something obstructs or is in the way of an action.	Blocking			
An actuator or a control or another piece of equipment breaks.	Breakage			
Uncontrolled release of matter or energy that causes other equipment to fail.	Release			
The speed of the process (e.g. a flow) changes significantly.	Speed-up / slow down			
An equipment failure occurs without a clear signature.	No indications			
There are delays in the transmission of information, hence in the efficiency of communication, both within the system and between systems.	Performance slow-down	Software fault	Inadequate quality control Halted processors	Incompatible programmes
Commands or actions are not being carried out because the system is unstable, but are (presumably) stacked.	Information delays			
Information is not available due to software or other problems.	Command queues			
There are delays in the transmission of information, hence in the efficiency of communication, both within the system and between systems.	Information not available			

Table A3.1.8: Main technological genotypes groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for procedures category

Definition / explanation	Effects: Specific consequent	General consequent	General antecedent	Root causes: Specific antecedent
The text of the procedure is ambiguous and open to interpretation. The logic of the procedure may be unclear.	Ambiguous text	**Inadequate procedure**	**Design failure** Inadequate quality control **Inadequate standards**	None defined
The descriptions given by the procedure are incomplete, and assume the user has specific additional knowledge.	Incomplete text			
The descriptions of the procedure are factually incorrect	Incorrect text			
The procedure text does not match the physical reality, due to e.g. equipment upgrades.	**Mismatch to actual equipment**			

Table A3.1.9:Main technological genotypes groups of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for temporary interface problems category

Definition / explanation	causes: Specific consequent	General consequent	General antecedent	Root causes: Specific antecedent	
An item is permanently out of reach, e.g. too high, too low, or too far away from the operator's working position	Item cannot be reached	Access limitations	Equipment failure Design failure	Design Distance Localisation problem Obstruction	Ladder / stair Temporary incapacitation
An item is permanently difficult to find. Infrequently used items that are inappropriately labelled fall into this category.	Item cannot be found				
There is a mismatch between the indicated positions of an item and the actual positions, e.g. controls have unusual movements.	Position mismatch	Ambiguous information	Design failure	Sensor failure	Incorrect coding scheme

There is a mismatch in coding, e.g. in the use of colour or shape. This may lead to difficulties in the use of equipment.	Coding mismatch				
The information provided by the interface is incomplete, e.g. error messages, directions, warnings, etc.		Incomplete information	Design failure Inadequate procedure	Indicator failure Display clutter Navigation problems	Inadequate display hardware Fetching problems

Table A3.1.10: Main technological genotypes gropes of specific consequent, general consequent, general antecedents causes and specific antecedents root causes for permanent interface problems category

Definition / explanation	causes	General consequent	General antecedent	Root causes
	Specific consequent			Specific antecedent
An item, e.g. a control, cannot be reached, for instance because it is hidden by something or due to a change in the operator's working position.	Item cannot be reached	Access problems	Inadequate work place layout	Poor accessibility Low availability
An item, information or a control cannot be located when it is needed or it is temporarily unavailable.	Item cannot be found			
The labelling or identification of an item is not correct.	Incorrect information	Mislabelling	Inadequate work place layout Maintenance failure	Inadequate control
The labelling or identification of an item is open to interpretation.	Ambiguous identification			
The labelling or identification of an item is incorrectly formulated, or is written in a foreign language.	Language error			

Table A3.1.11: Main organisation genotypes groups of specific consequent and general consequent, general antecedents causes and specific antecedents root causes for communication category

Definition / explanation	Effects			Root causes	
	Specific consequent	General consequent	General antecedent	Specific antecedent	
The message or the transmission of information did not reach the receiver. This could be due to incorrect address or failure of communication channels.	Message not received	Communication failure	Distraction Functional impairment Inattention	Noise Presentation failure	Temporary incapacitation
The message was received, but it was misunderstood. The misunderstanding is, however, not deliberate.	misunderstood information				
Information is not being given when it was needed or requested, e.g. missing feedback.	No information	Missing information	Mislabelling Design failure Inadequate procedure	Hidden information Presentation failure	Incorrect language Noise
The information being given is incorrect or incomplete.	Incorrect Message				
There is a misunderstanding between sender and receiver about the purpose, form or structure of the communication.	Misunderstanding				
The information provided by the interface is incomplete, e.g. error messages, directions, warnings, etc.		Incomplete information	Design failure Inadequate procedure	Indicator failure Display clutter Navigation problems	Inadequate display hardware

Table A3.1.12:Main organisation genotypes groups of specific consequent and general consequent, general antecedents causes and specific antecedents root causes for organisation category

Definition / explanation	causes	General consequent	General antecedent	Root causes
	Specific consequent			Specific antecedent
Indications (lights, signals) do not work properly due to missing maintenance.	Equipment not operational	Maintenance failure	Ineffective safety management system Low management quality	Not performed maintenance procedures Ineffective control
Equipment / functions is not adequate due to insufficient quality control	Indicators not working			
Faulty reasoning involving inferences or generalisations (going from specific to general), leading to invalid results.	Inadequate procedures	Inadequate quality control	Unclear policies	Not adopted standards
Faulty reasoning involving deduction (going from general to specific), leading to invalid results.	Inadequate reserves			
People in the organisation are not clear about their roles and duties.	Unclear roles	Management problem	Ineffective organisational structure Not acquired organisational culture Ineffective safety management system	Not clear strategy and objectives Ineffective control
There is not clear distribution of responsibility; this is particularly important in abnormal situations.	Dilution of responsibility			
The line of command is not well defined and control of the situation may be lost.	Unclear line of command			
The working environment is inadequate, and the cause is clearly a design failure.	Anthropometric mismatch	Design failure	Ineffective resources	Low availability Unreliable
The interface is inadequate, and the cause is clearly a design failure.	Inadequate MMI			
The organisation of work is deficient due to the lack of clear rules or principles	Inadequate task planning	Inadequate task allocation	Ineffective organisational structure Not acquired organisational culture Ineffective safety management system	Ineffective control
Task planning / scheduling is deficient.	Inadequate work procedure			
Procedures for how work should be carried out are inadequate.	Inadequate managerial rule			
The individual's situation understanding is guided or controlled by the group.	Group think	Social pressure	classical organisational structure Acquired organisational culture	Committed to norm Committed to safety culture

Table A3.1.13: Main organisation genotypes groups of specific consequent and general consequent, general antecedents causes and specific antecedents root causes for training category

Definition / explanation	causes	General consequent	General antecedent	Root causes
	Specific consequent			Specific antecedent
Lack of skills (practical experience) means that a task cannot be accomplished.	Performance failure	Insufficient skills	Ineffective manning policy Insufficient human resources	Recruitment failure Promotion failure
Lack of skills (practical experience) means that equipment is incorrectly used.	Failure Equipment mishandling			
The person is not quite certain about what to do, due to lack of knowledge.	Confusion	Insufficient knowledge	Incomprehension	Lack of training
The person has lost general situation awareness (understanding) due to lack of knowledge.	Loss of situation awareness			

Table A3.1.14: Main organisation genotypes groups of specific consequent and general consequent, general antecedents causes and specific antecedents root causes for ambient conditions category

Definition / explanation	causes	General consequent	General antecedent	Root causes
	Specific consequent			Specific antecedent
Uncomfortably warm.	Too hot	Temperature	Ineffective control Out of control	Defected control systems Environmental effect
Uncomfortably cold.	Too cold			
Noise level is too high.	Too loud	Sound	Poor functionality	Poor design Inappropriate adjustment
Signal level is too low.	Too soft			
Uncomfortably dry.	Too dry	Humidity	Ineffective control Out of control	Defected control systems Environmental effect
Uncomfortably humid.	Too humid			
High luminosity, glare, reflection	Too bright	Illumination	Poor design	Inappropriate adjustment
Low luminosity, reduced colour and contrast.	Too dark			
There may be other "dimensions", depending on the specific type of work.	Vibration	Local/dispersed disturbance Temporary/ permanent disturbance	Operational defect Maintenance failure Dynamical characteristics effect	Inappropriate instruction Inherited defects
Highly context dependent, may coincide with some of the Common Performance Conditions	Motion	Adverse ambient conditions Adverse weather conditions	None defined	None defined

Table A3.1.15: Main organisation genotypes groups of specific consequent and general consequent, general antecedents causes and specific antecedents root causes for working conditions category

Definition / explanation	causes			Root causes
	Specific consequent	General consequent	General antecedent	Specific antecedent
Excessive task demands or insufficient time / resources.	None defined	Excessive demand	Inadequate task allocation Adverse ambient conditions	Unexpected tasks Parallel tasks
Available work space is not large enough for the required activities. This is often the case for maintenance work.	Narrow work space	Inadequate work place layout	Design failure Communication failure None defined	None defined
Work must be carried out in dangerous conditions, e.g. high voltage line work, radiation, unstable mass or energy storage, etc.	Dangerous space			
Work must be carried out where there is a risk of falling down.	Elevated work space			
The roles within the team are not well defined or well understood.	Unclear job description	Inadequate team support	Inadequate task allocation Adverse ambient conditions	None defined
The distribution of work / responsibilities within the team is not mutually agreed.	Inadequate communication			
There is little cohesiveness in the team, hence little collaboration.	Lack of team cohesiveness			
Shift work leading to disturbances of physiological and psychological functions (jet lag, lack of sleep, etc.).	Circadian rhythm effects.	Irregular working hours	None defined	Shift work Changing schedule Time zone change

Appendix 3.2: Displays of alternative corrective action scenarios

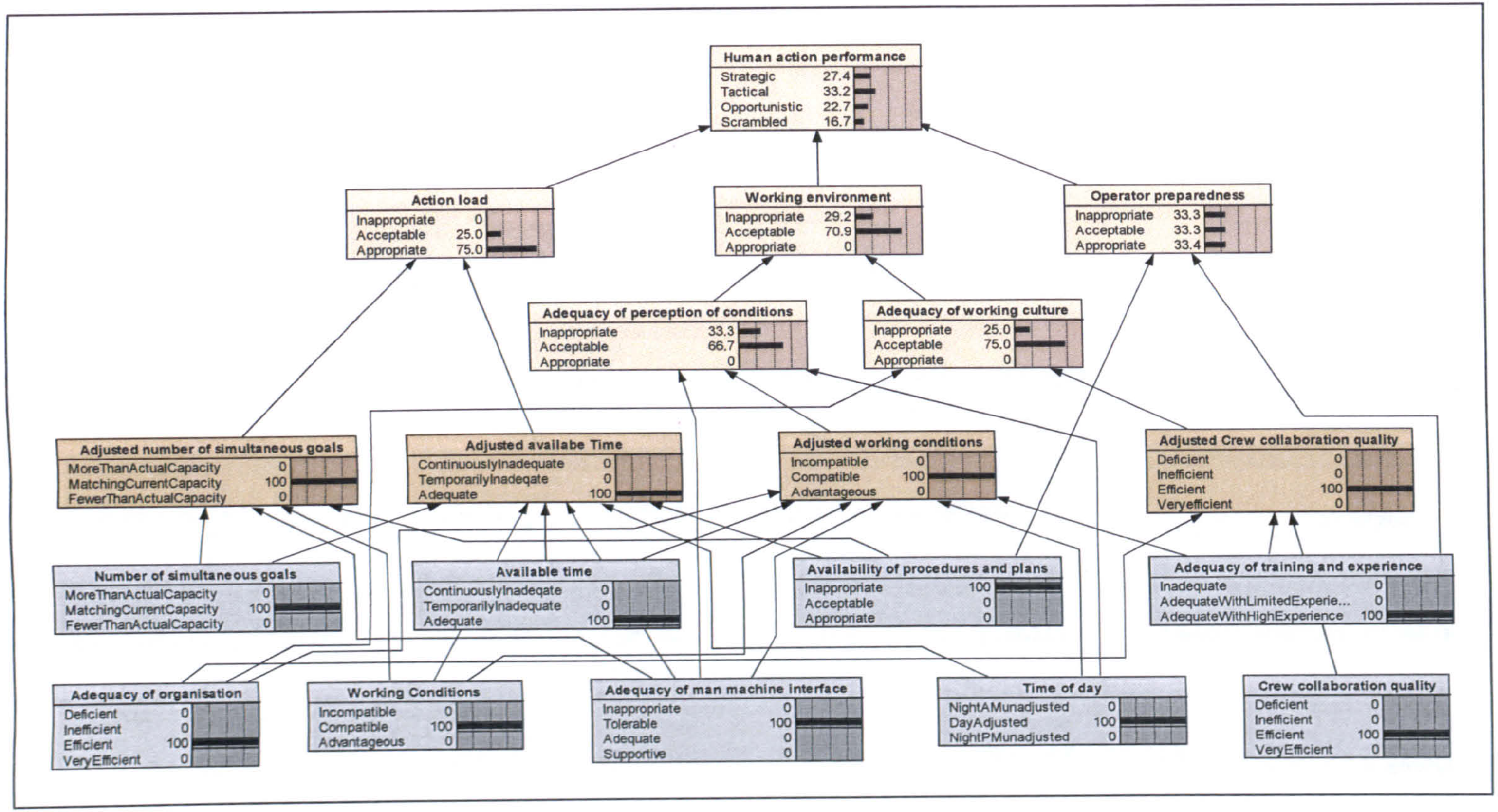

Figure A 3.2.1: M/V Crown Princess Officers in charge command actions failure probabilities BNs model (Alternative A_2)

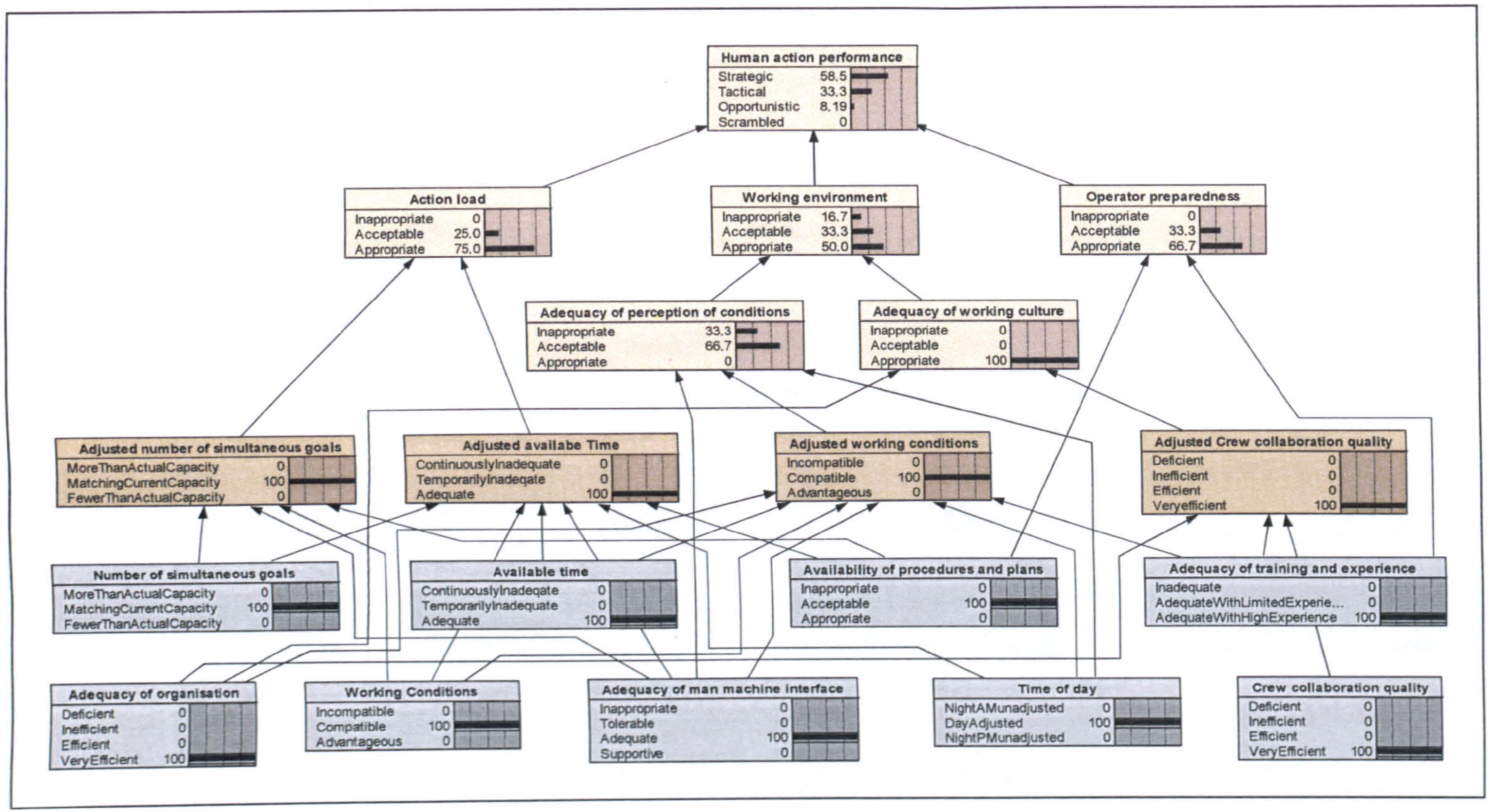

Figure A3.2.2: M/V Crown Princess Officers in charge of command actions failure probabilities BNs model (Alternative A_3)

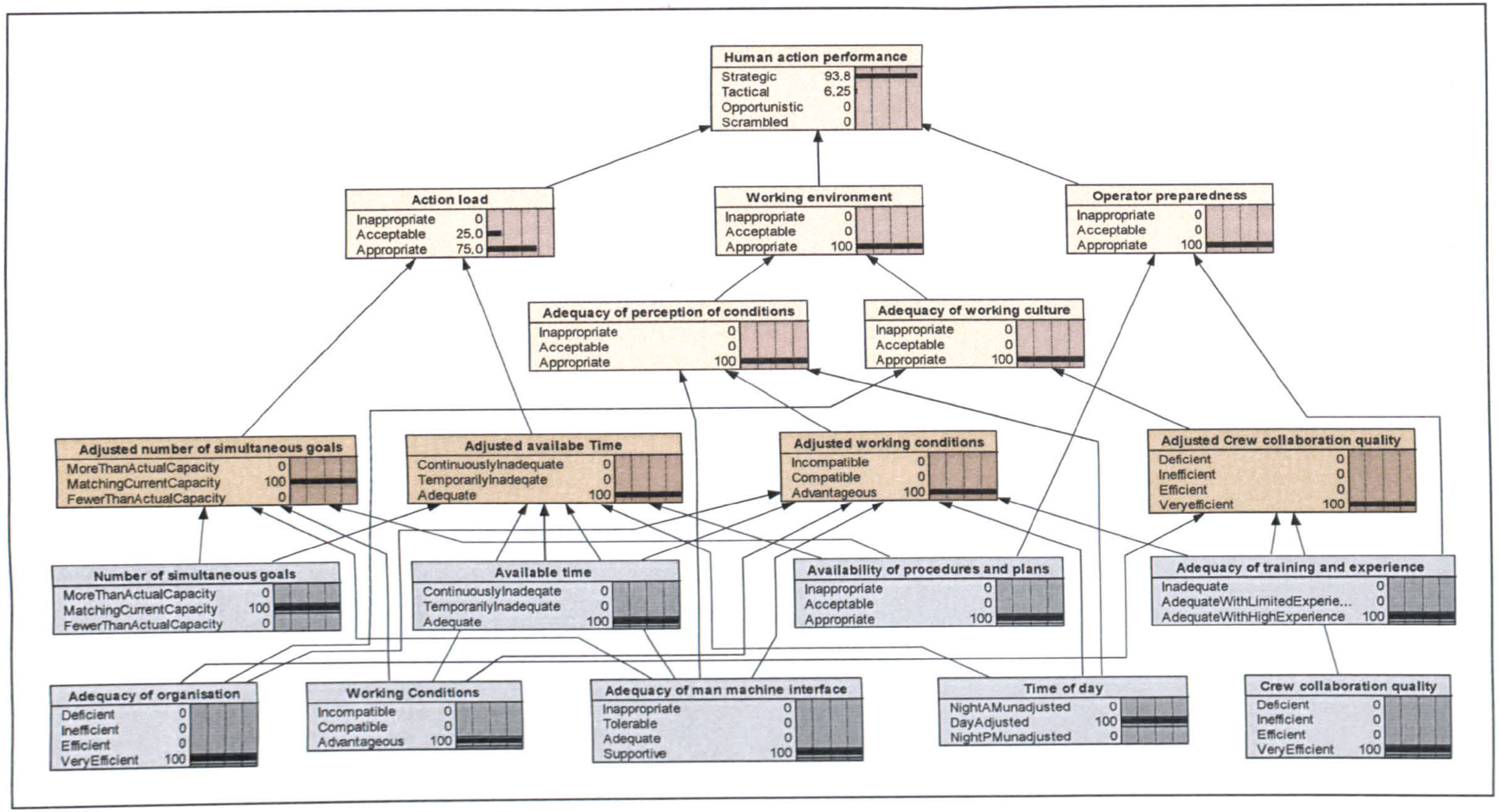

Figure A3.2.3: M/V Crown Princess Officers in charge of command actions failure probabilities BNs model (Alternative A_4)