A Novel Engineering Framework for Risk Assessment of Mobile Offshore Drilling Units

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Abstract

Natural oil and gas has become one of mankind's most fundamental resources. Hence, the performance of mobile offshore drilling units (MODUs) under various conditions has received considerable attention. MODUs are designed, constructed, operated, and managed for harsh geographical environments, thus they are unavoidably exposed to a wide range of uncertain threats and hazards. Ensuring the operational safety of an MODU's system is often a complex problem. The system faces hazards from many different sources which dynamically threaten its integrity and can cause catastrophic consequences at time of failure. The main purpose of this thesis is to propose a methodology to improve the current procedures used in the risk assessment of MODUs. The aim is to prevent a critical event from occurring during drilling rather than on measures that mitigate the consequences once the undesirable event has occurred. A conceptual framework has been developed in this thesis to identify a range of hazards associated with normal operational activities and rank them in order to reduce the risks of the MODU. The proposed methodology provides a rational and systematic approach to an MODU's risk assessment; a comprehensive model is suggested to take into consideration different influences of each hazard group (HG) of an offshore system. The Fuzzy- analytic hierarchy process (AHP) is used to determine the weights of each HG. Fault tree analysis (FTA) is used to identify basic causes and their logical relationships leading to the undesired events and to calculate the probability of occurrence of each undesirable event in an MODU system. The BBN technique is used to express the causal relationships between variables in order to predict and update the occurrence probability of each undesirable event when any new evidence becomes available. Finally, an integrated Fuzzy multiple criteria decision making (MCDM) model based on the Fuzzy-AHP and a Fuzzy techniques for order preference by similarity to an ideal solution (TOPSIS) is developed to offer decision support that can help the Decision maker to set priorities for controlling the risk and improving the MODU's safety level. All the developed models have been tested and demonstrated with case studies. An MODU's drilling failure due to its operational scenario has been investigated and focus has been on the mud circulation system including the blowout preventer (BOP).

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This thesis is dedicated to my family.

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Acronyms and Abbreviations

Abbreviations	Descriptions
AA	Average degree of Agreement
AHP	Analytical Hierarchy Process
ALARP	As Low As Reasonably Practicable
API	American Petroleum Institute
AS	Asset /Resources
BBN	Bayesian Belief Network
BE	Basic Event
BOP	Blowout Preventer
BSEE	Bureau of safety and environmental enforcement
CFP	Crisp Failure Possibility
CPT	Conditional Probability Table
CS	Crew Safety/People
CSE	Concept Safety Evaluations
DAG	Directed Acyclic Graph
DM	Decision Making
DNV	DET NORSKE VERITAS
EN	Environment
Eng-RCO	Engineering Risk Control Option
Equip-RCO	Equipment redesign/replace Risk Control Option
ESD	Emergency Shutdown
ETA	Event Tree Analysis
FL	Fuzzy Logic
FMEA	Failure Mode and Effects Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FST	Fuzzy Set Theory
FTA	Fault Tree Analysis
TOPSIS	Techniques for Order Preference by Similarity to an Ideal Solution
F-VI	Fussell-Vesely Importance
HAZID	Hazard Identification
HAZOP	Hazard and Operability
HG	Hazard Group
HSE	Health & Safety Executive
JDR	Jack-up Drilling Rig
JPD	Joint Probability Distribution
MADM	Multiple Attribute Decision Making
MCDA	Multiple Criteria Decision Analysis
MCDM	Multiple Criteria Decision Making

MCS	Minimal Cut Set
MMS	Mineral Management Services
MODU	Mobile Offshore Drilling Unit
MTBF	Mean Time Between Failure
NCS	Norwegian Continental Shelf
NIS	Negative Ideal Solution
NOPSA	National Offshore Petroleum Safety Authority
NPD	Norwegian Petroleum Directorate
OOA	Object-Oriented Approach
OREDA	Offshore REliability DAta
PHA	Preliminary Hazard Analysis
PIS	Positive Ideal Solutions
PSA	Petroleum Safety Authority
QRA	Quantitative Risk Assessment
RI	Risk Index
RA	Relative Agreement
RCC	Relative Closeness Coefficient
RCO	Risk Control Option
RE	Reputation
Regul-RCO	Regulatory/Human error Risk control option
RRM	Risk Reduction Measure
TE	Top Event
TLP	Tension Leg Platform
TOPSIS	Techniques for Order preference by Similarity to an Ideal Solution
TFN	Trapezoidal Fuzzy numbers
UKCS	United Kingdom Continental Shelf
US GoM	United States Gulf of Mexico
WOAD	World Offshore Accident Dataset

CHAPTER 1: Introduction

Chapter summary

This chapter provides a summary of the main purpose of this research and presents the background and a brief justification of the need for a comprehensive and structured methodology for the risk assessment and analysis of the hazards associated with the offshore operation systems (e.g. Mobile offshore drilling units). The objectives and hypotheses of the research serve to set out a coherent structure for the research, which is aimed at addressing the inherent problems outlined to minimise the offshore operator's risk. This chapter further presents the goals of the study described in this thesis and provides a general characterisation of the structure of the work. This is followed by a brief description of the research methodology and the scope of the study, and concludes with a summary of the thesis structure and its contents.

1.1 Definitions

In the course of constructing a quantitative risk assessment model for an offshore operation system, definitions of the following terms are useful:

MODU: Mobile offshore drilling unit (MODU) means a vessel capable of engaging in drilling operations for the exploration or the exploitation of resources beneath the seabed (e.g. liquid or gaseous hydrocarbons, sulphur or salt) (MODU Code, 2009)[1].

Mode of Operation of MODU: Mode of operation means the condition or manner in which an MODU may operate or function while on location or in transit. The modes of operation of an MODU include the following[2]:

- *Operating conditions*: Conditions where an MODU is on location for the purpose of conducting operations, including drilling and production activities, and where combined environmental and operational loadings are within the appropriate design

[1]-International Maritime Organization. 2009. MODU Code. London, United Kingdom.
[2]-Source: IMO Resolution A.1079 (28), Recommendations for the Training and Certification of Personnel on Mobile Offshore Drilling Units (MODUs). Adopted on 4 December 2013, International Maritime Organization, Regulatory Guidance.

limits established for such operations. The MODU may be either afloat (e.g. Semi-Submersible) or supported on the seabed, as applicable (e.g. Jack-Up drilling unit).

- *Survival conditions*: Conditions wherein an MODU may be subjected to environmental loadings in excess of those established by the MODU's operating manual. It is assumed that routine operations will have been discontinued due to the severity of the environmental loading.
- *Transit conditions*: Conditions wherein an MODU is moving from one geographical location to another.
- *Combined operations*: Operations in association with, or in close proximity to, another mobile offshore MODU or offshore installation, where conditions on the other MODU or installation may have an immediate impact on the safety of the MODU; for example, an MODU attached to a fixed platform.

Hazard: A physical situation with a potential for human injury, damage to property, damage to the environment or some combination of these is called a hazard (Kumamoto and Henley, 2000).

Uncertainty: A situation in which a person does not have the proper quantitative and qualitative data to describe, prescribe or predict deterministically and numerically a system, its behaviour or other characteristics is called uncertainty (Zimmermann, 2000).

Judgements: In the environment of risk assessment, judgements is not simply the final decision but is an integral part of the entire risk assessment process with the essential nature being the ability to make a critical assessment of evidence (Chicken and Posner, 1998).

1.2 Background

The comprehensive offshore oil and gas exploration and production field is a diverse landscape of differing operating and business environments, national regulations and numerous authorities regulating offshore activities. The oil and gas industry plays one of the most important roles in the world. Oil and natural gas are brought to the surface from underground reservoirs through wells that have been drilled and completed to produce these fluids safely and economically. Energy exploration and production, particularly at the frontiers of experience in offshore operations, involve risks for which neither industry nor government has been adequately prepared. In recent years, the drilling of oil and gas wells has presented the industry with many problems, especially in offshore operations. The importance of an offshore operation system has been acknowledged and accepted for a long time, and substantial improvements concerning both design and operating procedures have been made. The offshore industry continues to develop new well designs for challenging reservoir circumstances. For instance, the industry now emphasises finding and developing the smaller/marginal fields in the southern part of the Norwegian continental shelf. In the search for new large and profitable fields, the industry moves north and into deeper water. Because of high oil and gas prices, new technology for increased recovery, and government incentives, it is now possible and profitable to extend production beyond the initially assumed design life. However, life extension may results in more frequent critical failures involving leakages in to the environment. The outcome of such leaks can be catastrophic. These development outcomes in production occur in more environmentally sensitive areas and in operations under more hostile weather conditions, and a similar development is seen in the world where offshore fields are being planned. In spite of these developments, failures still occur and will most likely continue to occur in the future. An analysis of past accidents and events has been performed based on the database WOAD (World offshore accident dataset) of DET NORSKE VERITAS (DNV). This is one of the most reliable and most complete databases of failures, incidents and accidents in the offshore oil and gas sector. WOAD currently contains 6101 records (i.e. incidents, accidents and near-misses). The report shows the geographical distribution of collected accidents: 3505 in the North Sea, 1685 in the Gulf of Mexico, while only 45 in the Mediterranean and 866 in all other regions of the world (Africa, South America, and Australasia). Some of the landmark past accidents will now be briefly described. The need for continued focus on offshore operation system safety is represented by the gas blowout in 2005 on the Snorre tension leg platform (TLP) operating on the Norwegian continental shelf (Aven and Vinnem, 2007). The Montara Blowout accident in Timor sea Australia was the worst that has occurred in the offshore industrial sector and resulted in the third-worst sea pollution in Australian history(Li *et al.*,2010). On 21 August 2009, during drilling operations at the Montara Wellhead Platform, an uncontrolled release of oil and gas occurred from the H1 well. All 69 personnel at the Wellhead Platform were safely evacuated (Li *et al.*,2010).

Subsequently, there was a disastrous accident on 20 April 2010 in the Gulf of Mexico, where an explosion on the drilling rig Deepwater Horizon, exploring oil and gas at the Macondo well about 60 km offshore from the US coast, caused the death of 11 workers, severe injuries to many others and massive sea pollution from the release of 5 million barrels of crude oil (Lavrova and Kostianoy, 2011). The fundamental cause of the accident was an improper safety culture of the operator (i.e. BP Operator) and its contractors (i.e. Transocean, Halliburton). The investigation reports reveal a series of organisational and safety management failures that led to the accident. Amongst them, the following can be stressed (Graham *et al.*, 2011):

- Non-existence of adequate hazard identification, in particular addressing risks increasing from the frontier conditions and from changes to well design and conditions.
- Inadequate level of detail in procedures.
- Lack of timely recognition of and reaction to early warning signals.
- Lack of communication and lack of appropriate training of personnel, especially in reacting to emergency situations.
- Lack of clear leadership, especially lack of a culture of leadership responsibility.
- Lack of the ability to learn lessons from other accidents and recent near-misses.

The investigation reports cover also recommendations for regulatory reform, since the Minerals Management Service (MMS) regulatory structure put in place in April 2010 was found to be completely inadequate to address the risks of deepwater drilling projects like Macondo. In Norway, the NORSOK D-010 standard describes offshore well integrity requirements, where well integrity is "the application of technical, operational, and organizational solutions to reduce risk of uncontrolled release of formation fluids throughout the life cycle of the well" (NORSOK, 2004). Well integrity has always been focused on the design of new wells, but well integrity in the operational phase is now of increasing concern. The increased emphasis on well integrity in the operational phase is reflected in recent regulations and standards. In Norway, for example, NORSOK D-010 describes the requirements for Well Integrity in drilling and well operations, while the American petroleum institute (API) has recently developed a recommended practice for handling of annular casing pressure in the United States Gulf of Mexico (US GoM). Well integrity is also a major concern in the US GoM. A study carried out on behalf of the MMS concluded that more than 8,000 wells in the US GoM Outer Continental Shelf experienced well completion leaks (Bourgoyne *et al.*, 2003). Ten percent of the offshore wells in the United Kingdom continental shelf (UKCS) were shut-in due to well integrity problems over a five-year period (Corneliussen *et al.*, 2007). The article refers to a study based on interviews with 17 UKCS operators; approximately 83% of these operators experienced well integrity problems. This issue is therefore particularly important for the study of offshore drilling operation and drilling units (i.e. MODUs). Fundamental technology of drilling and production of oil and gas is common to onshore and offshore areas, but environmental conditions of the offshore field affect facilities and engineering works in the field. These aspects mean that processes for life management established for on-shore structures and equipment may not be applicable to the offshore operation system, where a different treatment might be more appropriate.

In consideration of the magnitude of the offshore safety problems, it is clear that safety studies require continuous efforts aimed at eliminating or reducing hazards (Lois *et al.*, 2004). The task of safety analysis in this context will mainly concentrate on the prevention and/or mitigation or control of risks through the entire life of the project. This clearly resides within the concept of safety management. However, it is pertinent to note that risk management is not about complete removal of risks but to encourage an explicit decision-making process, which will be used to mitigate the potential effects of certain risks and facilitate approval for the project. The consensus of opinion among the experts on risk is unanimous in accepting the inadequacy of software-only solutions to the risk management problem (Raftery, 1993). The trends mentioned above indicate that new technology applied in more challenging fields will require continued focus on risk assessment and management in the future. In general, the tendency of offshore risk assessment is that it is not only used for verification purposes in the design and operational processes of marine and offshore systems, but also for making decisions from the early stages (Wang, 2002). Risk-based approaches are gaining currency as the offshore industry looks for rational, efficient and flexible approaches to managing their offshore installations. When applied to MODUs as industrial assets, risk-based approaches differ from other approaches mainly in their assessment of failure in its wider context and consequences. These advanced techniques provide more insight into the causes and avoidance of system failure and competing risks, as well as the resources needed to manage them. Measuring risk is a challenge that is being met with state-of-the-art technology, skills, knowledge and experience. In the light of the above development risk, analysis techniques are increasingly being deployed to assess risk and minimise losses in several industries such as railways, nuclear, chemical processing, oil & gas, *etc*. The tremendous benefits brought about by risk management efforts can be summarised as follows:

- Provided better opportunities for collation of reliable data for further research and improvement in the area of analysis of risks.
- Established the basis for making explicit decisions.
- Discovered the full potential of risk personnel based on skills and experience.
- Provided clearer opportunity for identification of atypical risks.

1.3 Aims and objectives of the research

The main objective of this thesis is to develop a novel quantitative risk assessment (QRA) methodology for an effective risk assessment and management of offshore operation systems; the kinds of offshore operation systems being considered include MODUs such as: Semi-Submersible, Jack-Up, Drill ship, *etc*. More precisely the aims of this research can be listed as follows:

- To review previous studies undertaken on the MODUs.
- To develop a novel QRA methodology for an effective risk assessment and management of MODUs.
- To examine the MODU availability and associated risks

In order to achieve such an aim, a clear understanding of the offshore operation and the system boundaries is an essential aspect in any analysis, including risk assessment. Offshore operation systems are often complex and operate in a hostile environment. They may be more vulnerable to failure and their failure may have different consequences in relation to those of their on-shore matching parts. The efficient management of these systems and equipment during their life to ensure fitness-for-service is an important duty for operators. The management includes all activities that can affect the life of an asset (e.g. design, manufacturing, operations, monitoring, maintenance, *etc*.). There are a diversity of approaches to life management demanding increasing levels of information and judgement, running from the failure and replacement approach at one end of the spectrum, to the relatively more advanced risk-based approach at the other end of the spectrum. The oil and gas industry, particularly the offshore operation, has moved into an era of pro-active risk assessment and safety management where the availability of various systems and equipment has been enhanced by the application of risk analysis. QRA is a novel approach in offshore operation systems, which has developed after the occurrence of some serious accidents, emphasising the need to use a risk-based management system in order to proactively ensure a strategic and scientific oversight of offshore operation systems. A proper methodology for making appropriate risk assessment of offshore operation systems is necessary, and the development of an advanced QRA is a vital part of this thesis as it sets the foundation of the whole scheme. From this overall goal, this thesis has the following lower-level objectives in order to achieve the stated aims:

- To develop qualitative frameworks for representing the hierarchical relationships of components, subsystems and entire MODUs. Frameworks of risk assessment are developed based on the concept of an object-oriented approach (OOA) (Elshorbagy and Ormsbee, 2006) and characteristics of MODUs.
- To identify the hazard group (HG) and the concepts of hazard and causing events.
- To develop a method to evaluate risks of components, subsystems and overall MODUs failure. The modelling techniques used to achieve the objective are a combination of Fuzzy risk assessment method and AHP. The integration of Fuzzy risk assessment and AHP addresses the problems associated when a large amount of subjective expert judgements is required.
- To provide a method for assessing FTs and BBN of MODUs. The results of this assessment are the likelihood of the occurrence of a specific event and important measures of possible contributing causes.
- Considering the risk assessment as a basis for decision-making and based on the above risk analysis results, a multiple attribute decision making (MADM) technique Fuzzy techniques for order preference by similarity to an ideal solution (TOPSIS) is used to rank the alternatives RCOs.

The objectives are also carried out to test the hypothesis of the research. This thesis is designed to test the hypothesis that it is possible to develop a new QRA capable of tackling a variety of systems in industry, with special consideration placed on MODUs. This hypothesis requires historical data, current data and expert judgements to be presented in risk-based tools and techniques.

1.4 Limitations and statement of problem

The MODU's field data are mainly obtained from the daily drilling reports that record the activities of rigs ordered chronologically. They also comprise records of most of the main system and equipment (e.g. BOP, Mud system, *etc*.) operations at whatever time they interact with the drilling unit activities. However, daily drilling reports either are not adequate or are not prepared for risk analyses and, in some circumstances, the data are incomplete and some aspects of MODU failures cannot be examined entirely. The data are principally concentrating on the operations and equipment; also, the data concerned specifically with human factors are not available. On the other hand, often the information available suggests that aspects of failure may be associated with human factors. The importance of human factors has already been emphasised in this research. Nevertheless, given the information available they cannot be evaluated objectively in order to establish the effect of human error on MODU failures and their associated risks. As mentioned above, due to non-existence of data or incompleteness of information, uncertainties may considerably undermine the conclusion developed based on the traditional QRA techniques. Consequently, the research limitations and problem for this thesis are presented as follows:

- In order to develop a QRA framework, extracting the required information from objective and subjective sources is one of the challenges of this research.
- The process of gathering data, the use of existing data or confidence in expert judgements has been shown to be a troublesome process in terms of accuracy (Pillay and Wang, 2003).
- The gathering of objective data in order to apply a modelling technique can be difficult as it generally requires many months or even years to attain sufficient data.

- The use of subjective data collected from expert judgements can often come in a form that requires adjustment with existing data in order to establish a consistency of data to give certain confidence in the modelling results.
- The combining of both objective and subjective data requires elicitation in order to establish the data that are required to apply advanced modelling techniques to the offshore operation systems.

Since the objective of this research is to provide a platform for risk assessment addressing offshore operation systems' safety with confidence in circumstances of the lack or incompleteness of data, the subjective data for the test cases demonstrated in this study are hypothetically prepared by the author together with supervisors and experts specialising in the offshore industry. This is because of the difficulty of acquiring real industrial data due to many reasons including the confidentiality of data of this kind.

1.5 Justification of research

In risk assessment and safety management research, management of the effects caused by uncertainty and complexity of systems is an important issue. A hierarchical framework is an effective way to deal with complexity. It decomposes the complex problem into more manageable subsystems or components, and represents the contributions to the overall system by its components and subsystems. Thus, it has the ability to perform risk evaluations at both the component and system levels. As aforementioned, causes of uncertainty are diverse. Thus, regardless of what approaches are to be applied, human judgement is always required to manage such negative effects. In other words, the deficiencies of risk modelling resulting from lack of data or high level of uncertainty must be addressed up by means of the general evaluation capacity of humans capable of grasping the essence of an object, even if it is vague and unclear. One feasible way to model such a situation under a high level of uncertainty is to use Fuzzy set theory. Fuzzy set theory, formalised in 1965, has been applied in different fields. Its application in system safety and reliability analysis could prove to be useful since such analysis often requires the use of subjective judgements and uncertain data. When dealing with the safety of a system using Fuzzy set theory, the parameters including occurrence likelihood and severity of possible consequences can be judged and described using linguistic terms and their associated memberships. Over the years there have been successful applications and implementations of Fuzzy set theory in industrial engineering (King & Mamdani, 1977). Industrial engineers face many problems with incomplete and vague information. FST developed by Zadeh (1965) is an excellent tool to solve these problems. Kahraman (2006) presents some application examples of Fuzzy sets in different areas of industrial engineering which Fuzzy set theory can contribute. These areas are Fuzzy control and reliability, Fuzzy engineering economics and investment analyses, Fuzzy group and MCDM, human factors engineering and ergonomics, manufacturing systems and technology management, optimization, and statistical decision-making. Washing machine is an example of application of Fuzzy logic control in industrial engineering. The conventional washing machines required the human interruption to decide upon what should be the wash time for different cloths. Agarwal (2007) presents the idea of controlling the washing time using Fuzzy logic control and also describes the procedure that can be used to get a suitable washing time for different cloths. These Fuzzy variables can then be synthesised with confidence using an AHP (Lee, 1996; Chen, 2001; Sadiq & Husain, 2005; Zeng *et al.*, 2007; Wang & Elhag, 2008) or some other technique such as FTA (Andrews & Moss, 2002; Henley & Kumamoto, 1981; or TOPSIS (Hwang & Yoon, 1981; Chen, 2000; Li & Yang, 2004; Herrera *et al.*, 2005). With the awareness of the effectiveness of hierarchies in dealing with complexity, this study adopts hierarchies, but based on an object-oriented approach to represent the relationships in offshore operation systems, and to develop frameworks for risk assessment. Meanwhile, Fuzzy set theory, AHP, BBN and FTA are integrated with these hierarchies to generate quantitative results.

1.5.1 OOA to MODUs

Firstly, an OOA is proposed in this research to deal with the complexity (Simons, 1982; Courtois, 1985) of MODUs and to generate a hierarchical structure for risk assessment. OOA is a method that represents engineering systems in terms of objects (Booch, 1994; Solomatine, 1996; Ross *et al.*, 1992; Black & Megabit, 1995; Liu & Stewart, 2003; Crossland, *et al.*, 2003; Elshorbagy & Ormsbee, 2006). Every component in an MODU is viewed as an object, and the overall system is viewed as a set of objects that are interconnected. All risk factors about the components are considered as attributes or behaviours of objects. Furthermore, with the generalisation and aggregation relationships, object-oriented hierarchical structures can be easily formed to represent the whole/part relationships and interconnections between objects in an MODU.

Aggregative risk assessment is composed of two stages, the component level and the subsystem level. Firstly, the diagrams of objects describe the relationships between hazards, object failure, and object risks, which thus provide a hierarchical framework for risk assessment at the component level. In this hierarchical framework, the risk of an object is at the top level followed by its relative failure states, which are at its immediate lower level. Hazards or threats are at the bottom level in this framework. This indicates that risks of an object are determined by its failure states, which are in turn determined by the threats or hazards directly related to them. This research represents each hazard or threat in terms of its likelihood of occurrence and severity of possible consequences, which are represented by Fuzzy numbers. The risk of a component is thus an aggregative measure that is determined by aggregating the risks of threats or hazards along the hierarchical structure. Secondly, for the risk assessment at the system level, an object-oriented whole/part relationship structure is used to determine aggregative risks of MODUs. In this hierarchical framework, the MODU is at the top level; its subsystems and components are at relatively lower levels. Therefore, the risk of the overall system is an aggregative measure which is contributed to by the risks of its subsystems and components along the hierarchical structure. With the development of the conceptual framework for aggregative risk assessment, Fuzzy set theory and an aggregation method (i.e. AHP) (Leung & Cao, 2000; Bozdağ *et al.*, 2003; Kwong & Bai, 2003; Kahraman *et al.*, 2003; Büyüközkan, 2004; Büyüközkan *et al.*, 2004; Erensal *et al.*, Huang *et al.*, 2005; 2006; Tüysüz & Kahraman, 2006; Chan & Kumar, 2007) are used to produce quantitative evaluations.

1.5.2 Fuzzy FTA of MODUs

FTA is considered in this study to represent the cause-effect relationships in MODUs. FTA, a deductive reliability and risk analysis technique, can answer the question of how the system could produce a failure. With the help of FTA, risk analysts will know which component in the system is more critical and which risk scenario is more significant (Pillay & Wang, 2003). Meanwhile, risk contributions and uncertainty contributions can also be obtained to support selection of mitigation measures (Furuta & Shiraishi, 1984; Shu *et al.*, 2006) and asset management. However, the development of FTs is still as much an art as a science. This research uses an object-oriented approach to generate FT structures via two steps. Firstly, the diagram is used to generate the FTs at the component level. Then, interconnections between components in an MODU are used to develop FTs at system level. After FTs have been constructed, Fuzzy FTA (Misra & Weber, 1990; Liang & Wang, 1993; Cheng & Mon, 1993; Lin & Wang, 1997; Dong & Yu, 2005; Ping *et al.*, 2007; Pan & Wang, 2007) is adopted to obtain quantitative results.

1.5.3 Application of BBN

Fundamental to the idea of BBNs is the concept of modularity, whereby a complex system is built by combining simpler parts of components that are related in a causal manner. A BBN is a probabilistic graphical model that represents a set of random variables and their conditional dependencies through a directed acyclic graph. Quantitative probability information is specified in the form of conditional probability tables (CPT). For each node the table specifies the probability of each possible state of node given each possible combination of states of its parents. In general, a BBN is a graphical representation of a probability distribution over a set of variables and it consists of two parts:

- The directed network structure in the form of a directed acyclic graph.
- A set of the joint probability distributions, one for each node, conditional on each value combination of the parents.

The reasons for choosing BNs can be summarised as follows:

- They are graphical models, capable of displaying relationships clearly and intuitively.
- They are directional, and are thus capable of representing cause-effect relationships.
- They can be used to represent indirect causation in addition to direct causation.

The approach is based on conceptualising a model domain or system of interest as a graph of connected nodes and linkages. In the graph, nodes represent important domain variables and a link from one node to another represents a dependency relationship between the corresponding variables. Given their network structuring, Bayesian networks successfully capture the notation of modularity (i.e. a complex system can be built by combining simpler parts). Due to their Bayesian probability formalism, Bayesian networks provide a rational technique to combine both subjective (e.g. expert opinion) and qualitative (e.g. monitoring data) information (Das & Teng, 2000). The flexible nature of Bayesian networks also means that new information can easily be incorporated as it becomes available. Only the conditional probabilities of the affected variable require redetermination. Moreover, Bayesian networks are helpful for challenging experts to articulate what they know about the model domain, and to join those influences into a dependency network. The graphical nature of Bayesian networks therefore facilitates the easy transfer of understanding about key linkages. In addition, because subjective expert opinions are made explicit in the formal structure of the network, they can be challenged and revised, and can also be directly evaluated to determine whether the results are robust. In this research, BBN analysis for the assessment of the risk level of MODUs is presented and a combination of a BBN technique and an AHP method is used to determine the degree of influence and importance of factors of each HG.

1.5.4 Application of MADM in a Fuzzy environment for selection of the best RCO in MODUs

Due to the complexity of MODUs, conventional QRA may not be capable of providing sufficient risk management information. The selection of different mitigating and preventive alternatives (i.e. RCOs) often involves competing and conflicting criteria (cost and benefit), which requires sophisticated decision-making methods. The decision-making in this study is the analysis of multiple objectives that have both a quantitative and a qualitative nature. It is obvious that much knowledge in the real world is Fuzzy rather than precise. In an MODU ranking/selecting problem, decision data of MADM problems is usually Fuzzy, crisp, or a combination of the two. Hence, a useful model should be capable of to handleing both Fuzzy and crisp data. Since imprecision and ambiguity in the calculation of a performance rating are incorporated into MADM, Fuzzy set theory provides a mathematical framework for modelling them. The research method employed is a Fuzzy TOPSIS approach (Zimmermann & Zysno, 1985; Teodorovic, 1985; Zanakis *et al.,* 1998; Chen, 2001; Yong, 2006; Li, 2007). It is one of the techniques that have been developed to solve MADM problems.

1.6 Logic relationships among the methods

By using this technique, subjective judgement with uncertainty and precise data can be consistently modelled under a unified framework. Figure 1.1 demonstrates the logical relationships among the proposed methods in this PhD research. As illustrated in Figure 1.1, in Chapter 3 the object-oriented approach and hierarchy structure are used to generate conceptual frameworks for risk assessment and to demonstrate the cause-effect relationships for specific risk in the MODUs.

In the next step (Chapter 4), a combination of the Fuzzy-AHP and Fuzzy FMECA approaches is adopted to assess the risk of each HG quantitatively and to identify the most critical hazards in MODUs using Fuzzy set theory. Fuzzy sets are used to represent likelihood, severity, vulnerability and risk associated with each hazard, AHP is used to obtain risk levels of events, HGs, and the overall system by performing aggregation along the hierarchical structure.

In Chapters 5 and 6, Fuzzy FTA and BBN are used to quantitatively evaluate the proposed hierarchy structure. Finally, in Chapter 7 Fuzzy TOPSIS is used to select the best RCOs for MODUs: Fuzzy TOPSIS is adopted here to identify the best RCO from a finite number of RCOs.

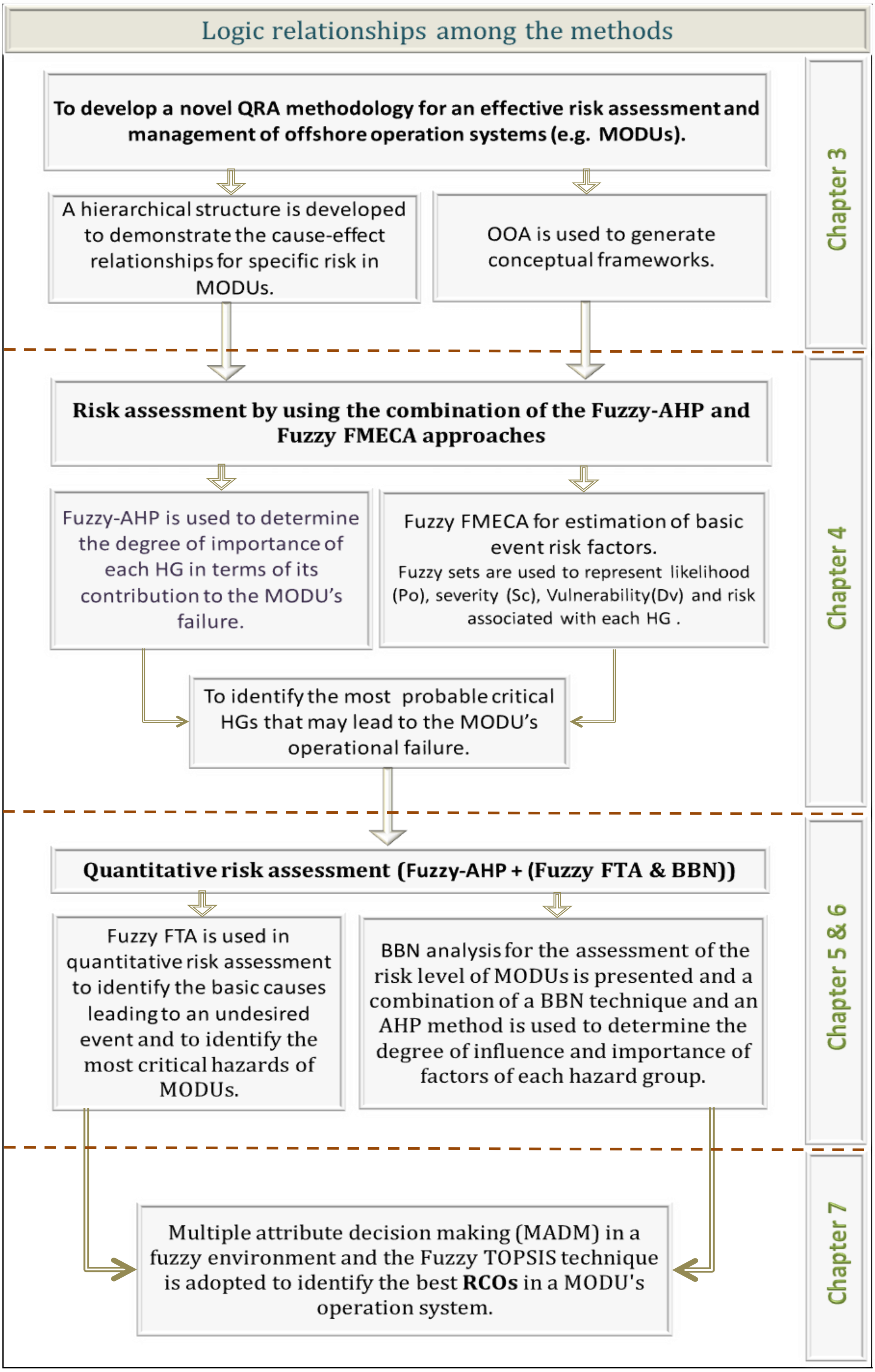


Figure 1.1: Logic relationships among the methods used in this research

1.7 Structure of the thesis

The scope of this research is to develop an advanced QRA methodology, utilising varying information from both objective and subjective sources. The purpose of the advanced QRA is to:

- Present the relationships among components, subsystem and the overall offshore operation system.
- Estimate risk of components, subsystem and the overall offshore operation system.
- Identify a HG: an event or a group of events that has the highest contribution to the failure of the MODU.
- Provide the best RCOs for mitigating risk of the system.

The chapters in this thesis have been organised to express a certain flow of thought or line of argument. This thesis consists of eight Chapters; Figure 1.2 illustrates the structure of the thesis.

Logically, the structure starts with an introductory platform chapter that sheds light on the much-needed risk-based approach to the offshore operation system as it is Chapter 1. This chapter has outlined a brief introduction relating to the background of the research, an introduction of the research principle, a statement highlighting the problems currently encountered, aim and objectives of the research, limitations, methodology and structure of the thesis.

Chapter 2 comprises a literature review on offshore operation systems and risk assessment techniques that are appropriate to the study of the MODU risk assessment. The shortcomings of offshore operation systems' risk assessment techniques commonly applied are measured, providing a critical review for their current practices. According to the review, comments are studied to express the limitations associated with the conventional methods and to propose possible determinants overcoming these limitations. Then the methodology background of the current study is justified and briefly discussed at the end of the chapter. The basis behind this section is to explore the framework of the offshore operation system risk assessment. The results of the analysis serve to explore what has been done in offshore operation system risk assessment, to identify the problems generated from the current system, and to verify what is needed for the continual improvement of offshore operation systems.

Chapter 3 states the methodologies applied in the research and aims to develop conceptual frameworks for aggregative risk assessment of MODUs. Firstly, it introduces the object-oriented approach and its potential application in categorising complex information in MODUs. Then a hierarchical structure of MODUs is developed based on the concept of the offshore operation system. Transition illustrations are used to represent the cause-effect relationships of risks at the component level (i.e. BEs). The proposed methodology is capable of identifying the hazards and possible consequences, estimating magnitude of consequences, estimating probability of consequences and determining significance of the risk.

Frameworks of aggregative risk assessment are formed based on the hierarchical whole/part relationships of MODU operation systems and also these frameworks can provide beneficial information for decision-makers in offshore operation systems.

Chapter 4 introduces the method to quantitatively evaluate the hierarchical frameworks of aggregative risk assessment developed in Chapter 3. Fuzzy set theory is adopted here to determine the risk levels of hazards, which are at the bottom level (i.e. BEs) of the hierarchical structure. Fuzzy-AHP is used to determine the degree of significance of each HG in relation to its influence on the MODU's failure. By using the combination of the Fuzzy-AHP and Fuzzy FMECA, the risks of significant items are quantified and the most critical event will be identified for further analysis in Chapter 5.

Chapter 5 applies Fuzzy FTA to quantitatively evaluate the FT of the most critical subsystem or event. Fuzzy FTA is used in QRA to identify the basic causes leading to an undesired event and to identify the most critical hazards of MODUs. In the Fuzzy FTA method, the likelihood of a top event (TE) and the importance measures of contributing factors are investigated. The results of this analysis are used to prioritise the components and hazards for specific risks and assist risk analysts in making rational decisions.

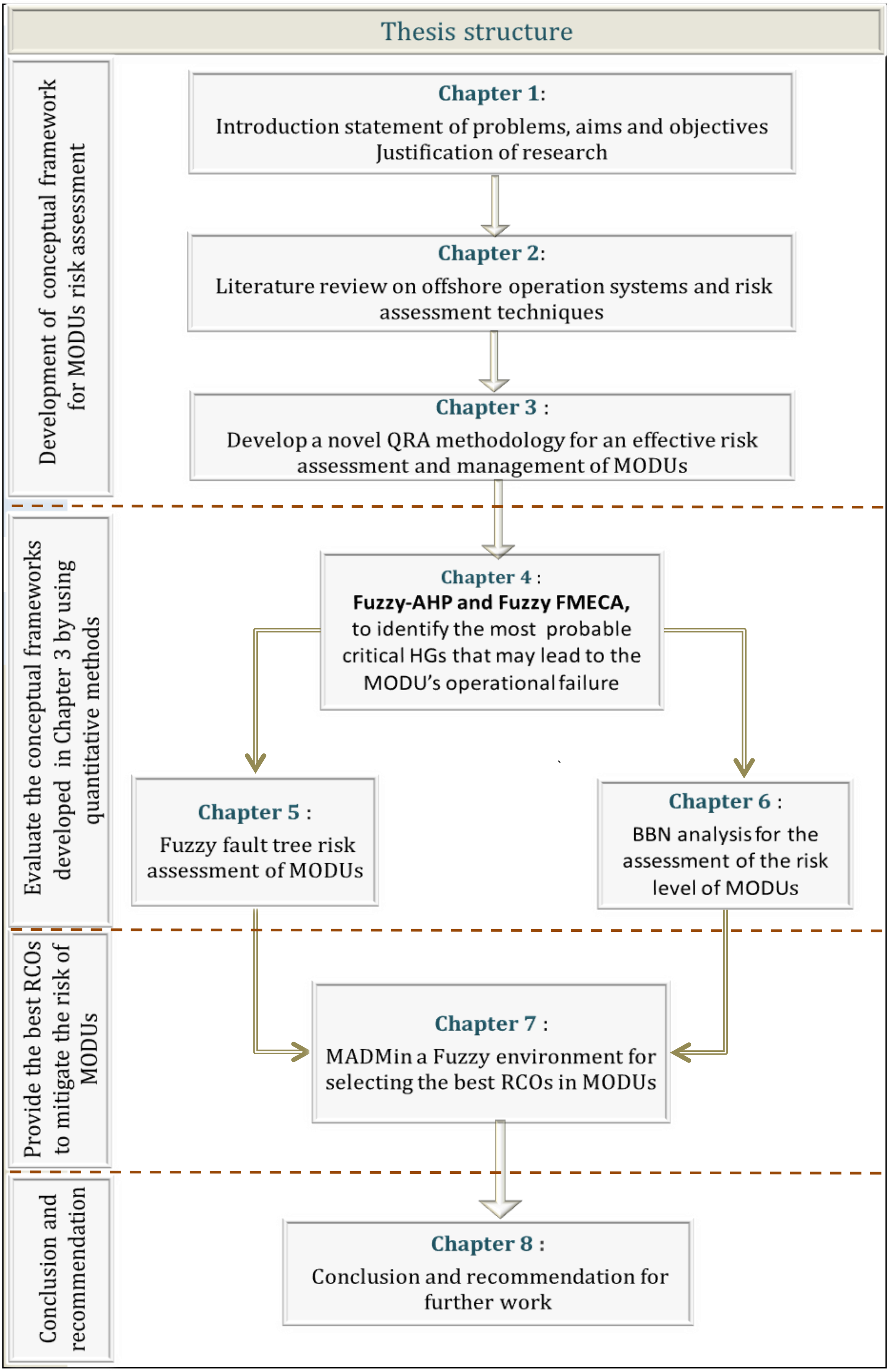


Figure 1.2: Thesis structure showing the organisation of the chapters

Chapter 6 presents a BBN analysis for the assessment of the risk level of MODUs and a combination of a BBN technique and an AHP method is used to determine the degree of influence and importance of factors of each HG.

Chapter 7 uses the outcomes of Chapters 4, 5 and 6 to help the analyst select the best RCOs for mitigating the risk of a subsystem/event of MODU. Fuzzy TOPSIS is adopted to identify the best RCO and MADM is used in a Fuzzy environment for selecting the best RCOs in an MODU operation system. A decision-maker often encounters the problem of selecting a solution from a given set of alternatives. The chosen alternative is the one that most likely meets certain predefined objectives/goals. A MADM method provides engineering and management decision aids in evaluating and/or selecting the best RCO from a finite number of alternatives which are characterised by multiple attributes. Recommendations for decision-making can be provided based on the level of cost-effectiveness for each risk control measure.

Chapter 8 summarises the knowledge obtained from this research as a whole with respect to the development of a proactive risk assessment methodology, as well as the limitations and recommendations for future research to improve offshore operation risk management.

CHAPTER 2: Literature review, hazard identification and risk assessment technique

Chapter Summary

In this chapter, the current status of the offshore industry is reviewed, which provides an overview of technical aspects of the offshore drilling operation system that is necessary for appropriate understanding of the course of the MODU's risk assessment. This chapter also identifies the hazards groups associated with the MODU's operation system. The main purpose of this assessment is to make sure that all categories of the most significant hazards related to normal operational activities are identified and that measures will be taken to reduce risks, with reference to statistical reports, and taking into consideration the events in the chain together with the functions which occur in offshore operations for different types of units. It is essential to note that the vast majority of events/occurrences happen during the drilling phase. Therefore this needs to be taken into consideration for risk assessment purposes. The frameworks of the safety regulations and offshore operation safety guidelines are also discussed. The strengths and shortcomings of risk assessment techniques currently and commonly applied are observed.

2.1 Overview of technical aspects of the MODU

This section provides basic information on the offshore drilling operation system and technology that is needed for a proper understanding of the course of the MODU's risk assessment.[3]

Drilling process: offshore drilling is similar in many ways to drilling on land. It uses drill pipe, casing, mud, and cement in a series of carefully calibrated steps to control pressure while drilling thousands of feet below the seafloor. A sophisticated blend of synthetic fluids, polymers, and weighting agents is used to lubricate and cool the drill bit during drilling.[4] Drilling mud and drill bits are used to bore a hole into the earth. The

[3] Oil Spill Commission, Chief Counsel's Report. http://www.oilspillcommission.gov/chief-counsels-report .

[4] How to Improve Safety in Regulated Industries What Could We Learn From Each Other safety in EU" © ENCO - Background Material, ENCO FR-(12)-44

mud is pumped down through a drill pipe that connects with and turns the bit. The mud flows out of holes in the bit and then circulates back to the rig through the space between the drill pipe and the sides of the well (the annulus or annular space). As it flows, the mud cools the bit and carries pulverised rock (called cuttings) away from the bottom of the well. When the mud returns to the surface, rig equipment sieves the cuttings out and pumps the mud back down the drill string. The mud thus travels in a closed loop (Williams, 1974).

Pore and fracture pressure: The weight of the rocks above a pay zone can generate significant pressure on the hydrocarbons. The principal challenge in deep-water drilling is to drill a path to the hydrocarbon reservoir in a manner that simultaneously controls these enormous pressures and avoids fracturing the geological formation in which the reservoir is found. In addition to carrying away cuttings, drilling mud also controls pressures inside the well as it is being drilled. The pore pressure is the pressure exerted by fluids (such as hydrocarbons) in the pore space of rock. If the pore pressure exceeds the downward hydrostatic pressure exerted by mud inside the well, the fluids in the pore spaces can flow into the well, and unprotected sections of the well can collapse. An unwanted influx of fluid or gas into the well is called a "kick". An uncontrolled discharge is known as a "blowout". The fracture pressure is the pressure at which the geological formation will break down or “fracture”. When fracture occurs, drilling mud can flow out of the well into the formation such that mud returns are lost instead of circulating back to the surface. Both pore pressure and fracture pressure vary by depth (Walsh, 1981).

Casing and cement: At some point as the drilling proceeds, the pore pressure in the bottom of an open hole section will exceed the fracture pressure of the formation higher up in this open hole section. When this happens, the drillers can no longer rely on mud to control pore pressure. Casing is high-strength steel pipe that comes in 20- to 40-foot sections that are screwed together on the rig to make a casing string. The casing string serves at least two purposes: (i) it protects more fragile sections of the hole outside the casing from the pressure of the drilling mud inside, and (ii) it prevents high-pressure fluids (like hydrocarbons) outside the casing from entering the well. Once cemented in place, it isolates the wellbore from the previously penetrated formations and serves as a conduit from the wellhead to the bottom of the well for drilling and any subsequent production activity. The cement flows down the drill string, out the bottom of the casing and back up against gravity into the annular space around the casing (between the casing and open holes). When cementing is complete, the cement fills the annular space around the casing, reinforcing the casing and creating the mechanical foundation for further drilling. This process continues as the hole is drilled using progressively smaller diameter casing and cementing. Once set, the cement does two things: it seals off the interior of the well (inside the casing) from the formation outside the casing, and it anchors the casing to the rock around it, structurally reinforcing the wellbore to give it mechanical strength (Thiercelin *et al.*, 1997).

The blowout preventer (BOP): The BOP is a giant assembly of valves that latches on to the wellhead. The BOP stack serves as both a drilling tool and a device for controlling wellbore pressures. The BOP stack is connected back to the rig by the riser. The riser is a sequence of large diameter high-strength steel pipes that serves as the umbilical cord between the rig and the BOP during all remaining drilling operations. In the completed well, the BOP stack is a potential barrier that can prevent hydrocarbon flow up the well and into the riser. This is done by using either the annular preventers, which can slow or stop the flow, or the blind shear rams, which shut it off completely. The annular preventer is a large rubber element designed to close around the drill pipe and seal off the annulus. Upon activation, the annular preventer expands and fills the space within that part of the BOP; if there is something in the annular preventer (such as a pipe), the annular preventer seals around it. If there is no drill pipe in the hole, the annular preventer can close off and seal the entire opening. The blind shear ram consists of two metal blocks with blades on the inner edges. It is designed to cut the drill string and seal off the annulus and the drill string in the well below. It can withstand and seal a substantial amount of pressure from below. Blind shear rams are designed to cut through the drill pipe. BOP rams can be activated in several ways: manually from the rig, automatically or by remotely operated vehicle (ROV). Electrical signals are sent to subsea control pods on the BOP stack. The signals electrically open or close a solenoid valve, which in turn sends a pilot signal that activates the hydraulic system (Holland, 1997).

Drilling rigs: There are three types of MODUs, which are used for different environment. As illustrated in Figure 2.1, drilling ships are used in the very deep sea (i.e. about 2000 m water depth); for water depth between about 120 m to 1500 m, semi-submersible rigs are used; and jack-up drilling rigs are used in shallow water less than about 120 m deep (Liao *et al.*, 2012).

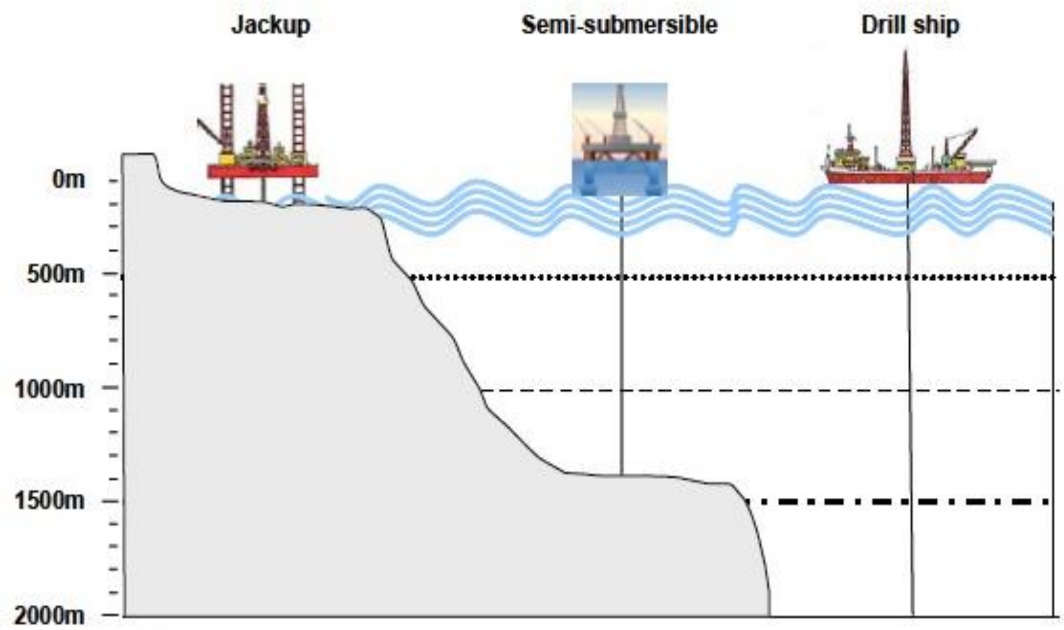


Figure 2.1: Drill Rigs: (a) Jack-up rig; (b) Semi-submersible rig; (c) Drilling ship (Source: Deutsche bank)

Jack-up rigs have lattice legs that are lowered to the seabed before the floating section carrying the derrick is raised above sea level.

Semi-submersible rigs float at all times, but when in position for drilling they are moored and ballasted to float lower in the water with their pontoons below wave-level. The drilling rig itself is a derrick towering above the drill floor where most of the human activity is concentrated. The derrick supports the weight of the drill string, which is screwed together from nine-metre lengths of drill pipe. Hoisting equipment in the derrick can raise or lower the drill string up to three pipe lengths. At the bottom of the drill string is a drill bit, which can vary in size and type (Williams *et al.*, 1998)

An offshore single hull drilling ship having the characteristics of a tanker provided with a vertical drill well is located near the ship's pitching axis. A double-sectioned vertically adjustable work platform is located within the well and a rail-mounted hoist mechanism travels from a position over each section to a position over the main deck transferring gear between the areas. Pressure tanks, ballast water, and drill water are stored in the outboard wing tanks of the hull and mud pumps, agitators, and other equipment are located in the centre compartments on a mid-deck or fiat. A platform above the drill well supports the derrick for drilling operations. A passive stabiliser is provided to roll-stabilise the ship. Making use of the reduced size drill ship concept with enhanced drilling technology enables the contractor to drill deep water wells (Fossli & Hendriks, 2008, Liao *et al.*, 2012).

2.2 Introduction to offshore operation risk assessment

Offshore operation safety has developed from a reactive manner towards a risk-based and goal-setting system since the 1990s. It has become an important issue in the offshore industry due to public concern resulting from several catastrophic accidents, and the introduction of safety regulations. The main objective of these safety regulations is to ensure that risks have been reduced to be as low as possible and that the best RCOs to be implemented are cost-effective.

Offshore operators have been dealing with the operational risks for many years and have recognised that, in order to achieve a step change in improvement of operational performance, there is a need to formalise their extensive knowledge, experiences and work practices within a well-thought-out and structured framework represented by a management system. The development of an effective management system is to ensure appropriate risk management efforts will be consistently applied by people at the worksite to manage major hazards and other workplace hazards to ensure safe and reliable operations.

In addition, due to the industry’s competitive nature, it is essential for the development of new approaches, proposal of new operational procedures and invention of innovative technology to constantly conduct risk assessment and safety management of the offshore industry with respect to environment, personnel, assets and reputation. This certainly brings new hazards and uncertainties. Therefore, risk assessment should cover all possible areas including those where traditional techniques are difficult to apply. Consequently, risk assessment has become an essential tool by which to develop strategies and policies to avoid an occurrence and formulate mitigative measures. It is of great relevance and applicability in offshore operation systems due to challenges in protection measures arising from the harsh environment. Offshore environments are typically known as compact areas enclosing a high density of equipment and personnel. In addition, mobile offshore drilling rigs are complex systems having the potential for unexpectedly severe consequences during an occurrence. Complexity has many facets, most of which are increasing in the systems, particularly interactive complexity. The systems are designed with prospective interactions among the components that cannot be thoroughly planned, understood, anticipated or protected against. The operation of a number of systems is so complex that it challenges the understanding of all but a few experts and sometimes even the experts have incomplete information about their potential behaviour. For that reason, the development of a variety of novel risk-modelling and decision-making techniques capable of resolving such encountered difficulties is essential. Risk assessment not only determines if the risk is acceptable, but also identifies major risk-contributing factors for which reducing measures should be applied. To conduct risk assessment for an offshore operation system both the likelihood and consequences of potential hazards need to be estimated.

As a part of risk assessment modelling, the stage or phase of the offshore operation for risk assessment needs to be determined. The reason is that the type and placement of safety barriers for the drilling phase differ from those of the production phase. In addition, in the case of drilling, shallow water or deep water drilling and exploratory or development drilling must be identified; for instance, dividing the drilling phase into sub-operations such as drilling, casing and cementing helps to better identify the primary causes of failure. In the present study, risk analysis is performed for the drilling phase, and also it is assumed that drilling is performed in deep waters and for a development well. Therefore, both primary and secondary barriers are present.

2.3 History of MODU risk assessment and regulations and standards of offshore operation systems

The use of structured risk management in the offshore industry began in the Norwegian Sector of the North Sea. Use of QRA studies in the Norwegian offshore industry dates back to the second half of the 1970s. Several accidents in the Norwegian Sector at this time, including two on the Ekofisk field, demonstrated that even this arrangement involved major hazards (Engen, 2009). A few pioneer projects were conducted at that time, mainly for research and development purposes, in order to investigate whether assessment methodologies and data of appropriate superiority and strength were available. The Norwegian petroleum directorate (NPD) issued their "Regulations Concerning Safety Related to Production and Installation" in 1976 (Vinnem, 2007). The next step in the development of QRA came in 1981 when the NPD issued guidelines for safety evaluation of platform conceptual design (Vinnem, 2007). These regulations required QRA to be carried out for all new offshore installations in their conceptual design phases. These included the requirement that, if the living quarters were to be located on a platform where drilling, production or processing was taking place, a risk evaluation should be carried out. At that stage, such an evaluation would have been mainly qualitative. As part of the approval procedure for a new production platform in the Norwegian Sector, the NPD required submission of a general development plan, containing a safety evaluation of the platform concept. NPD published a new set of regulations in 2001, which replaced the risk analysis and technical regulations from 1 January 2002. The requirement of risk analysis and other analyses were stipulated in the Health, Environment and safety (HES) Management regulations. These regulations have requirements for analysis of risk as well as requirements for the definition of risk acceptance criteria. The NPD was divided into two organisations from 1 January 2004 and its safety division was separated as a new organisation, namely the Petroleum Safety Authority (PSA). The HES management regulations were controlled by the PSA. The SCRs were modified in 2005 and these revisions came into force from 5 April 2006 (Aven and Vinnem, 2007). The resulting studies became known as Concept safety evaluations (CSE). The CSE is a form of overall risk assessment of a platform, addressing the risk of impairment of safety functions.

In the UK sector prior to Piper Alpha, QRA tended to be applied to specific aspects of the design, rather than to overall risks. Consequently, it was mainly used as part of the detailed design when the scope for changes was limited. The Piper Alpha accident in 1988 tragically disproved that the major accident predictions which risk analysts had made were indeed realistic, and it was then felt that QRA could be useful in trying to reduce the risks.

QRA techniques were then applied to many platforms in the UK sector, as operators attempted to discover the extent of their exposure to fire and explosion hazards. QRA was found to be an appropriate tool for evaluating the relevant hazards (e.g. fire and explosion, dropped objects, *etc*.). As a result of this activity, significant reductions of risk were achieved on many platforms by moving or installing isolation valves on risers and sub-sea pipelines, and by relocating accommodation in extreme cases. The influential Lord Cullen Report on the Piper Alpha accident recommended a major change to a more modern system of safety regulation in the UK sector, symbolised by the transfer of responsibility to the health & safety executive (HSE) (Miller, 1991). The effects were not confined to the UK sector, because multi-national oil companies applied similar safety evaluations to their offshore operations. Thus, in the few years following the Piper Alpha accident, QRA was applied to platforms in areas as diverse as Australia, New Zealand, Malaysia, Brunei and Canada (Brandsæter, 2002). Subsequently, the HSE Offshore Safety Division launched a review of all offshore safety legislations and implemented changes. The objective of this work was to seek a more goal-setting regime to replace legislation which was regarded as viewpoint (Wang, 2002). In Australia, the National Offshore Petroleum Safety Authority 2004 (NOPSA 2004) has issued safety case guidelines. These regulations call for safety cases to be prepared for all installations and to demonstrate that risk has been reduced to an as low a level as reasonably practicable (ALARP).

The mainstay of the regulation is the Health and Safety at Work Act, under which a draft of the offshore installation regulations was produced (HSE, 1991). It was then modified to incorporate the comments arising from public consultation. The regulation came into force at the end of May 1993 for new installations and November 1993 for existing installations. The regulation requires operational safety cases to be prepared for all offshore installations, including both mobile and fixed ones. In addition, all new fixed installations are required to have a design safety case in place. For mobile installations, the duty holder is the owner. The Safety Case Regulations (SCR) establish a clear guidance as to what a safety case should include with respect to the design and operation of a particular type of offshore installation. Particular requirements to be included in a safety case for the design, operation, abandonment and well operations of different installations are also given. An installation cannot legally operate without such a safety case demonstration that has been approved by the Offshore Safety Division of the HSE.

Risk criteria are standards that represent the regulators' view of how much risk is acceptable or tolerable (HSE, 1995a). In fact, risks in the intolerable region cannot be justified on any grounds. In the region of ALARP, the risks must be reduced by presenting control measures towards the acceptable region. The residual risks remaining in this region will be tolerable only if further risk reduction is impracticable or the cost required is grossly disproportionate to the improvement gained. There is no need to demonstrate ALARP in the broadly acceptable region. However, it is necessary to take any measure to assure that the risks remain at this level. An accepted operational safety case must be capable of demonstrating that hazards with the potential to cause major accidents have been identified, and that associated risks have been evaluated and reduced to ALARP using appropriate measures. It is noted that since the uncertainties in input may be high the application of QRA may not always be appropriate (Wang, 2002). Therefore, the acceptance of a safety case is unlikely to rely solely on a QRA. QRA only provides one input to decision-making about safety issues, and most of its advocates recognise that it cannot be used to make the decision itself. There are other aspects, such as public dread of particular sources of risk, which QRA does not take into account at present. Decision-making about hazardous activities is legitimately influenced by many other economic, social and political factors besides risk, which need to be considered simultaneously in the decision-making process.

2.4 Hazard identification and data collection

This section identifies the hazards associated with the offshore operation system (i.e. MODU). The main purpose of this review is to ensure that all types of the most important hazards associated with normal operational activities are identified and that measures will be taken to reduce risks. The hazards identified within this research have been assessed to establish which ones are considered to pose a significant risk and thus require detailed evaluation. Hazard identification is a key provision in the regulatory-based safety management systems (e.g., process safety management, safety and environmental management system). This process includes the methodical, systematic examination of causes leading to potential releases of hazardous substances and safeguards that must be implemented to prevent and mitigate a loss of containment, resulting in occupational exposure, injury, environmental impact, or property loss.

Identifying hazards is essential for ensuring the safe design and operation of an MODU. A number of techniques are available to identify hazardous situations, all of which require their rigorous, thorough, and systematic application by a multidisciplinary team of experts. Success rests upon first identifying and subsequently analysing possible circumstances that can cause occurrences with different degrees of severity. Without a structured identification system, hazards can be overlooked, so bringing about inadequate risk-evaluations and potential loss. The importance of adopting and implementing procedures to systematically identify major hazards arising from normal and abnormal operations and to assess their probability and severity is defined in Annex III of the Directive 2003/105/EC[5].

Hazard identification and analyses are mandatory for offshore operation systems (e.g. MODUs) that manage hazardous situations, and there are techniques for analysing equipment, instrumentation, utilities, human factors and external events that might impact on the offshore operations with the aim of identifying what can go wrong; therefore, identifying potential systems' interactions and failures that could result in an occurrence. Hazard identification is the basis of risk assessment and should ensure complete risk evaluations and adequate protection barriers. While hazard identification may be the most important stage for risk assessment, it depends on subjectivity issues (e.g., human observation, good judgements and awareness, creativity, expertise, knowledge) which introduce bias.

2.4.1 Introduction to hazard

In the language of risk specialists, 'hazard' is mostly the preferred designation for something with the possibility to cause harm (HSE, 2001). A hazard is defined as a situation with a potential for causing harm to humans, the environment, property or

[5] Directive 2003/105/EC of the European Parliament and of the Council of 16 December 2003 Amending Council Directive 96/82/EC on the Control of Major-accident Hazards involving Hazardous Materials. Official Journal of the European Union, L 345/97 Brussels, 31.12.2003.

reputation. In practice, the term hazard is often used for the combination of a physical situation with particular circumstances that might lead to harm. The essence of a hazard is that it has the potential to cause harm, regardless of the occurrence rate of the hazard. Hazard Identification (HAZID) is the process of identifying hazards, which forms the essential first step of a risk assessment. Hazard identification is usually a qualitative exercise based primarily on expert judgements. Most HAZID techniques involve a group of experts, since few individuals have expertise on all hazards, and group interactions are more likely to stimulate consideration of hazards that even well-informed individuals might overlook. There are two possible purposes in identifying hazards: the first is to obtain a list of hazards for subsequent evaluation using other risk assessment techniques. This is sometimes known as failure case selection; and the second is to perform a qualitative evaluation of the significance of the hazards and the measures for reducing the risks from them. This is sometimes known as hazard assessment. Hazards are diverse, and many different methods are available for hazard identification. While some methods have become standard for particular applications, it is not necessary or desirable to specify which approach should be adopted in particular cases. The methodology should be chosen by the HAZID leader to meet the objectives as efficiently as possible given the available information and expertise.

Preliminary hazard analysis (PHA) techniques like hazard identification (HAZID), and hazard and operability (HAZOP) studies are the tabular hazard methods most widely used for operational hazard identification. HAZID studies are frequently used in exploration, production, and mid-stream operations, both onshore and offshore. However, compared to other worldwide best practices, such as HSE cases for onshore and offshore facilities, hazard identification by itself falls short of applying the risk management process.[6]

Transferring from the identification of hazards to qualitative risk assessment is achieved by the use of semi-quantitative matrices, which is essentially an interaction of the three attributes of risk severity, likelihood and vulnerability. The exercise amounts to the risk

[6] International Association of Drilling Contractors (IADC), Health, Safety, and Environment Case Guideline for Mobile Offshore Drilling Units, Issue 3.3, Houston, Texas: IADC. 1 December 2010.
International Association of Drilling Contractors (IADC), Health, Safety, and Environment Case Guideline for Land Drilling Units, Issue 1.0.1, Houston, Texas: IADC, 27 July 2009.
Dangerous Goods Safety Management Act 2001, Reprint No. 3, Queensland, Australia: Office of the Queensland Parliamentary Counsel, 18 December 2009.

ranking of these undesired events. The hazard evaluation team must identify ways to reduce the consequence or reduce the likelihood of high or medium risks through preventive or mitigation barriers to ensure that the risk level is either acceptable or as low as reasonably practicable. Although ALARP can be demonstrated for any system, regardless of design definition or focus level, complex, costly decisions often require more accurate information about potential consequences and frequency of occurrence.

2.4.2 Major generic hazards list

Major hazards (i.e. HGs) and other workplace hazards are defined as Hazards with the potential to result in:

- Multiple fatalities or permanent total disabilities.
- Extensive damage to structure at installation, MODU/rig or plant.
- Massive effect on the environment (e.g., persistent and severe environmental damage that may lead to loss of commercial or recreational use, loss of natural resources over a wide area or severe environmental damage that will require extensive measures to restore beneficial uses of the environment).

Table 2.1 shows the typical drilling contractor's major hazards (e.g., toxic release, towing incidents, *etc*.).

Table 2.1: Drilling contractor's major hazards (typical)[7]

Typical Drilling Contractor's Major Hazards	
Toxic Release	Fire
Towing Incidents	Explosion
Mooring	Ship Collision
Major Mechanical Failure	Weather / Storms
Loss of Stability	Blowout
Structural Failure	Dropped Objects
Events from Adjacent Installations	Helicopter Crash

Source: ADC (2011)

Table 2.2 gives an example generic list of major accident hazards for an offshore operation system. It gives a list of major marine accident hazards including blowouts,

[7] Reference: International Association of Drilling Contractors (IADC), 2011, HSE Case Guidelines for Mobile Offshore Drilling Units, Issue 3.4 (1 Nov), Houston, TX.

riser/pipeline leaks, transport accidents and personal accidents. This list is applicable to a typical offshore operation system, and may be incomplete for uncommon offshore operations.

Table 2.2: An example of a generic hazard list

Example Generic Hazard list (CMPT 1999)	
Blowouts	**Structural events**
- Blowout in drilling	- Structural failure due to fatigue, design error, subsidence etc
- Blowout in completion	- Extreme weather
- Blowout in production (including wirelining etc)	- Earthquakes
- Blowout during workover	- Foundation failure (including punch-through)
- Blowout during abandonment	- Bridge collapse
- Underground blowout	- Derrick collapse
Marine collisions - impacts from:	- Crane collapse
- Supply vessels	- Mast collapse
- Stand-by vessels	- Disintegration of rotating equipment
- Other support vessels (diving vessels, barges etc)	**Marine events**
- Passing merchant vessels	- Anchor loss/dragging (including winch failure)
- Fishing vessels	- Capsize (due to ballast error or extreme weather)
- Naval vessels (including submarines)	- Incorrect weight distribution (due to ballast or cargo shift)
- Drilling support vessel (jack-up or barge)	- Icing
- Offshore loading tankers	- Collision in transit
- Drifting offshore vessels (semi-subs, barges, storage vessels)	- Grounding in transit
- Icebergs	- Lost tow in transit
Construction accidents - accidents occurring during:	**Transport accidents** - involving crew-change or in-field transfers
- Construction onshore	- Helicopter crash into sea/platform/ashore
- Marine installation	- Fire during helicopter refuelling
- Construction offshore	- Aircraft crash on platform (inc military)
- Hook-up & commissioning	- Capsize of crew boats during transfer
- Pipe laying	- Personal accident during transfer to boat
Dropped objects - objects dropped during:	- Crash of fixed-wing aircraft during staged transfer offshore
- Construction	- Road traffic accident during mobilisation
- Crane operations	**Riser/pipeline leaks**
- Cargo transfer	- leaks of gas and/or oil from:
- Drilling	**Personal (or occupational) accidents**
- Rigging-up derricks	**Attendant vessel accidents**

Source: (HSE, 2001/063) marine risk assessment.

2.4.3 Accidental events in relation to offshore operations

As has been dramatically demonstrated not only in the Macondo accident but in a variety of other cases, mobile offshore drilling rig activities entail the hazard of a major accident with potentially severe consequences to the life and health of workers, pollution of the environment, direct and indirect economic losses, and deterioration of the security of energy supply. The main hazards include a fire after the ignition of released hydrocarbons, explosion after gas release, formation and ignition of an explosive cloud and oil release on the sea surface or subsea (Skogdalen and Vinnem, 2012). Table 2.3 illustrates the events in a chain together with the function where they occurred (e.g., construction, drilling, production, *etc*.) in an offshore operation system for different types of unit. It is remarkable to note that events have occurred even in Idle function. With reference to blowouts, it is important to note that the vast majority have happened during the drilling phase with a smaller number of accidents occurring during the operation and throughout production (i.e. 228 vs. 86 vs. 43). It is clear that there are lots of drilling events, and this needs to be taken into consideration for risk assessment purposes.

Table 2.3: Accidental events in a chain in relation to the function where they occurred

Event (s)	Construction	Drilling	Idle	Operating	Other	Production	Support	Transfer
Anchor/mooring failure	21	117	16	27	10	13	9	8
Blowout	0	228	1	86	1	43	0	0
Breakage or fatigue	32	141	7	98	23	379	9	70
Capsizing,overturn,toppling	12	44	3	18	8	156	1	43
Collision,not offshore units	17	28	14	2	26	142	1	21
Collision,offshore units	21	130	13	18	51	98	12	35
Crane accident	29	302	4	54	4	251	2	4
Explosion	11	49	0	16	13	98	1	4
Falling load / Dropped object	38	509	4	127	14	403	3	14
Fire	27	195	5	51	43	678	21	10
Grounding	11	18	4	4	5	1	1	40
Helicopter accident	1	14	1	2	1	38	2	0
Leakage into hull	11	17	4	3	8	6	4	31
List, uncontrolled inclination	10	37	2	32	6	9	1	20
Loss of buoyancy or sinking	20	36	0	18	120	27	0	45
Machinery/propulsion failure	1	9	2	0	4	0	3	14
Other	11	65	3	11	226	121	3	6
Out of position, adrift	16	87	15	16	10	4	3	103
Release of fluid or gas	11	240	7	107	22	1499	3	4
Towline failure/rupture	3	1	0	4	0	0	0	102
Well problem, no blowout	0	353	0	152	1	50	0	0

Source: (Safety of offshore oil and gas operations: Lessons from past accident analysis, 2012).http://publications.jrc.ec.europa.eu/repository/bitstream/JRC77767/offshore-accident-analysis-draft-final-report-dec-2012-rev6-online.pdf.

2.4.4 Proposed MODU's HGs

The first activity is to identify all of the potential hazards to which personnel and equipment of the MODU could be exposed. The HGs describe the type of event which, if realised, has the potential to cause serious injuries or fatalities. These HGs are the main areas of interest as a first step of this study, as it is their direct consequences that have the potential for significant adverse consequences. Individual HGs are described in Table 2.4. Hazard Sources are those systems or components which lead to the realisation of HGs. Generally, given adequate safeguards, they are not hazards in themselves as they alone do not have the capacity to cause injury, loss of life, environmental impacts, or extensive asset or earnings losses, but instead require subsequent events to occur in order for these outcomes to be reached. Individual HGs and consequences may be the initiating factor for other HGs (e.g. equipment failure may also result in various hazards).

The main steps within this part of the assessment are:

- To identify the hazards to which personnel and facilities and equipment are potentially exposed.
- To estimate the consequences of these hazards.

With respect to the requirements, either a qualitative or a quantitative analysis can be carried out to study the risks of a system in terms of the probability of occurrence (P_O) of each hazard, its possible consequence severity (C_S) and detection of vulnerability (D_V). A severe hazard with a high occurrence probability requires priority attention whilst that which is not likely to occur and which results in negligible consequences typically needs least attention (Aldwinckle & Pomeroy, 1983).

A proposed list of HGs, with reference to Tables 2.1 to 2.3 and based on in-house experience and expert judgements in performing risk assessments, has been used as the basis for this hazard identification exercise and is presented in Table 2.4. With respect to available data and expert judgements, considering a failure of drilling as the most undesired among such HGs, therefore the potential consequences of this hazard have to be determined and estimated. Drilling failure as a function depends on time and procedures, which have a wide variety of human error, natural hazard and operational failure. In this study, however, the emphasis is placed on probability estimation of operational failure as a significant influence in MODU drilling failure.

Table 2.4: Proposed MODU's HGs

Proposed MODU's Hazard Group	
Hazard Group (HG)	**Description**
Soil failure	In this category both punch through and seabed problem are lumped together. There have been several cases when the MODU (e.g. Jack-up) became a total loss because of soil issues.
Drilling Failure	This covers a number of hazards events, which result in stopping of drilling operation, injury, fatalities, blowout and loss of structure. Drilling failure due to: - Operational Hazard (i.e. drilling system failure, ring control system etc.) - Natural Hazard (i.e. presence of high-speed wind / wave/current etc.) - Human error (i.e. organizational, management and individual)
Towing failure	This covers the events leading up to the operation delay, capsize and total loss of a jackup under and these towing are identified and assessed.
Fire and explosion/ miscellaneous	Release of a hydrocarbon/chemical/toxic substance may be caused either by a failure of the containment system or due to improper operation of the equipment. Ignition of flammable substances may cause fire and explosion hazards whilst simple contact with toxic chemicals can be hazardous to health and life. Smoke and/or radiation generated by a fire will affect personnel either by presenting them with an atmosphere, which is asphyxiating, or by obscuring/heating walkways and escape routes and so hindering escape and evacuation. These factors increase the risk of injury and death hence smoke and radiation are taken as a separate Hazard Group.
Vessel Collision	Collisions with visiting or passing vessels or adjacent barge may have the capacity to cause widespread damage and loss of life.
Mooring Failure	Mooring failure due to: - Using of inappropriate anchor handling and inappropriate mooring system. - Due to insufficient capacity - Uncertainty in the calculation of environmental forces due to wind load - Potential for failures due to mooring points and abrasion (especially for quayside moorings).

2.4.5 Data collection

QRA is a relatively new technique. In general, there is a lack of widely accepted and decided methodologies and approaches and poor circulation of data, resulting in a wide difference in study quality. In some areas, the data have not been collected or examined and no theoretical models are available so that risk estimates are unavoidably very unsophisticated. In other areas, availability of data and analytical techniques are being delivered promptly and the risk assessments have a tendency to fluctuate as a result.

Because it is quantitative QRA appears to be objective. However, in reality it is a very important judgements. These judgements may be explicit in circumstances where data is unavailable. There are also many implicit judgements in the analysis and application of available data which are often unrecognised. Therefore, it is essential to obtain reliable statistical failure and repair data of equipment/components and systems. In general, such failure and repair data of components can be obtained from field experience, lifetime testing under controlled conditions in a test site and/or laboratory testing of similar components (Misra, 2012). However, the collection of such data based on lifetime tests of offshore operation systems is precluded as a very expensive and labour-demanding operation. Extensive use is made of the data collected from laboratory tests and field reports on similar components. Additionally, repair data may also be amassed from the agreed judgementsal estimates of experts (Misra, 2012). How critical the reliability of the failure and the repair data is depends on the aims of the analysis. If the purpose of the analysis is to obtain the best absolute estimate of system safety, as may be required by statutory requirements, the failure and repair data are obviously critical. In such cases, validation of the data becomes as important as the validation of the safety assessments themselves, and verification procedures should be implemented to ensure that the obtained data for components is reliable. Great care should be taken to use failure and repair data obtained from data sets to reflect the environment for which the product is designed. When no data for a component failure mode can be obtained, it may be possible to express the failure in terms of fundamental and quantifiable parameters and to analyse it using limited state reliability analysis (Wang *et al.*, 1993), although there is uncertainty about the relevant distributions. It should be noted that, for some components, there is fairly close agreement between different databanks and, in other cases, there is a wide range of failure rates (Smith, 2011). The latter may be due to a number of reasons. For example failure rates are affected by so many factors that a variation in values exists and, although nominal environmental and quality levels are described in some databases, the range of parameters covered by these broad descriptions is large. The following sources may be useful for obtaining failure and repair data to carry out QRA. In addition, the reliability data of the various electronic and non-electronic components may also be obtained from various published papers and books such as Smith (2011).

i. OREDA- Offshore reliability data (DNV, 1992):

   This document contains a collection of offshore failure rate and failure mode data with an emphasis on safety-related equipment. It covers a great range of components and equipment.

ii. Electronic reliability data - INSPEC/NCSR (1981):

   Published in cooperation between the National Centre of Systems Reliability (Warrington) in 1981 and the institute of electrical engineers, this comprises simple multiplicative models for semiconductors and passive electronic components with tables from which to establish the multipliers according to the environment, temperature and other parameters.

iii. FARADIP.THREE (Smith, 2011):

   The databank is a summary of many useful databases and shows, for each component, the range of failure values. The failure data of various components such as alarms, mechanical items and instruments is included in this database.

iv. US Military Handbook 217:

   This database is formed by the Rome air development centre under contract to the US Department of defence and is an electronic failure databank.

v. Handbook of reliability data for electronic components Used in telecommunications systems, HRD4 (1986):

   This document is produced from field data by British telecom's materials and components centre.

It is also becoming useful to record and utilise data from near misses and errors. Furthermore, to ensure that there is an accurate applicability of the risk assessment carried out, novel techniques should integrate expert judgements with the obtained data in a formal manner. Engineering judgements and experience is essential to carry out a qualitative risk assessment. Measures can be taken to eliminate or control hazards based on the information produced from such an assessment. It should become an integral part of the offshore operation system process. It may be performed with one or more of the following purposes:

- To identify hazards in design and operation.
- To document and assess the relative importance of the identified hazards.

- To provide a systematic compilation of data as a preliminary step to facilitate quantitative analysis.
- To aid in the systematic assessment of the overall system safety.

2.5 Risk assessment techniques

The necessity to improve and continue the performance of offshore operation systems has prompted the application of reliable risk analytical techniques for carrying out their safety and assessment studies. The importance of these techniques is that the results are principally required to quantify risk, and also to facilitate sound risk-based decisions. The quantification process also requires reliable failure and repair data input. As the results of many risk-based studies have led to their high usage, it is very beneficial to apply these risk analytical techniques effectively and efficiently. Thus, the understanding of the techniques will aid risk managers and decision-makers. QRA utilises what is known and assumed about the failure characteristics of each individual component to build a mathematical model that is associated with some or all of the following information:

- Failure rates
- Repair rates
- Mission time
- System logic
- Maintenance schedules
- Human error
- System layout

Typical parameters that need to be obtained in a quantitative risk analysis include both:

- The occurrence probability of each system failure event. A system failure event results from simultaneous occurrence of the basic events (BEs) associated with each of the HGs leading to this system failure.

- The magnitude of its possible consequences. The possible consequences of a system failure event can be quantified in terms of possible loss of lives/human injuries, property damage and the degradation of the environment caused by the occurrence of the failure event. Experts normally quantify the parameters with respect to the particular operating system.

The formulation of a system model can be difficult for the large and sophisticated offshore operation systems (e.g. MODUs) and therefore requires approximations and judgements. Specialist teams who know the operation system comprehensively are usually consulted to provide such subjective inputs. While studying the risk assessment of an offshore operation system, it is almost impossible to treat the system in its entirety. A logical approach may be to break down the system into functional entities comprising subsystems and components. Risk assessment modelling of these functional entities can be carried out to fit such a rational structure, then the interrelationships can be examined and finally an analysis model can be formulated to assess the risk of the offshore operation system.

It is very beneficial to apply risk analytical methods effectively and efficiently in the risk assessment process. Chapter 3 specifies how to deal with such problems. This necessitates an understanding of the concepts of qualitative and quantitative risk analysis and the concepts of top-down and bottom-up risk assessment. A number of methods are useful to aid the assessments of a risk-based nature. The appropriate technique(s) that can be applied to carry out assessment tasks would depend on the clarified hazards, their available data and the stage reached in the analysis.

- *What-if method*: The purpose of this approach is to examine questions that will cause a multidisciplinary team to consider potential failure scenarios and ultimate consequences that such failures might create. Some studies of this method incorporate checklists at the end of the brainstorming. This technique may be beneficial in the problem definition and hazard identification phases of the risk assessment process (Menzies and Sinsel, 2000).

- *Preliminary hazards analysis* (*PHA):* The first step of a risk assessment is preliminary identification of the system components or events that lead to hazards, including consideration of the event sequences that transfer a hazard into an accident, as well as corrective measures and consequences of the accident. A preliminary identification analysis may provide an essential basis for additional analysis of individual hazards, with specific reference to FTA and event tree analysis (Sen, *et al.*, 1989).

HAZOP: A HAZOP study is an inductive technique and can be applied by a multidisciplinary team to stimulate systematic thinking for identifying potential hazards and operability problems, particularly in the process industries. A HAZOP study investigates the proposed scheme systematically for every conceivable deviation, and looks backward for possible causes and forward for the possible consequences (Frosdick, 1997):

- *Event tree analysis (ETA):* An event tree is an adaptation of the more general decision-tree method. A logic tree diagram starts from a basic initiating event and provides a systematic coverage of the time sequence from event propagation to its potential outcomes or consequences. ETA has been used in the safety and reliability assessment of a wide range of technological systems. The ETA may be qualitative, quantitative, or both, depending on the objectives of the analysis, and may be developed independently or follow on from FTA. An event tree is a logic diagram applied to analyse the effects of unintended events. Such a technique first expresses the probability or frequency of an accident linked to the safeguard measures required to be implemented to mitigate or prevent escalation after the occurrence of the event. Success and failure paths lead to various consequences with different magnitudes. The likelihood of each consequence is finally obtained by multiplying the probability of occurrence of the accident by the likelihood of failure or success in each path (Khan and Abbasi, 1998).

- *Cause-consequence analysis (CCA):* Cause-consequence analysis is a diagrammatic approach and it is a marriage of FTA (to show causes) and event tree analysis (to show consequences). Construction of cause-consequence diagrams starts with a choice of a critical event. The “consequence tracing” part of a CCA involves taking the initial event and following the resulting chains of events through the system. The "cause identification" part of a CCA involves drawing the FT and identifying the minimal cut sets leading to the identified critical event (Khan and Abbasi, 1998).

- *Failure mode, effects and criticality analysis (FMECA):* FMECA is probably the most widely applied hazard identification method. It is a combination of failure mode and effects analysis (FMEA) and criticality analysis. Once the criticality numbers of the item under all severity classes have been obtained, a criticality matrix can be constructed to provide a means for criticality comparison. Such a matrix display shows the distributions of criticality of the failure modes of the item and provides a tool for assigning priority for corrective action. Criticality analysis can be performed at different system/subsystem levels and the information produced at low levels may be used for criticality analysis at a higher level (Wang, *et al.*, 1995).

- *FTA:* A FT is a logic diagram presenting the casual relationship between events which individually or collectively contribute to occurrence of a higher-level event. Thus, the probability of occurrence of a specific hazard can be determined. In addition, FTA is capable of considering common cause failures in systems with redundant or standby elements. It also has the capability of contemplating failure events or causes related to human errors. FTA is a top-down approach, systemically considering the causes or events at levels below the top level. Prior to the use of quantitative FTA, the probability of occurrence of each basic event has to be obtained. If two or more need to occur simultaneously to cause the next higher-level event, a logic AND gate is employed to express the operation. If any of two or more lower-level events can cause the next higher-level event directly, an OR gate is applied to demonstrate such an operation. The logic gates determine the addition or multiplication of probabilities to obtain the values for the top event (TE).

- *Bayesian belief network (BBN):* A Bayesian network is a modelling framework that has been used in many applications, such as in diagnostic systems and general reliability modelling (Langseth and Portinale, 2007, Kjaerulff and Madsen, 2008). Bayesian networks offer a compact presentation of the interactions in a stochastic system by visualising system state variables and their dependencies. BBNs are at the cutting edge of expert systems research and development and also BBN has caught the interest of researchers in different research fields since the early 1990s. Perhaps the greatest testament to the usefulness of Bayesian problem-solving techniques is the wealth of practical applications that have been developed in recent years. Researchers succeeded in creating BBN models for practical applications in areas of intelligent decision, safety assessment, information filtering, autonomous vehicle navigation and computer network diagnosis. Since most real-life problems involve inherently uncertain relationships, BBN is a technique with enormous potential for application across various areas. Influence diagrams, which further extend the notion of BNs by including decision nodes and utility nodes, have been used in human reliability assessment (Humphreys, 1995).

- *TOPSIS: Techniques for Order preference by Similarity to an Ideal Solution (*TOPSIS) method is one of the most effective methods and is a widely accepted multi-criteria decision-making technique to identify the best solution from a finite set of points. (Hwang & Yoon, 1981b). In the traditional TOPSIS model, the measurement of weights and qualitative attributes did not consider the uncertainty associated with the mapping of human perception to a number (Makridakis & Wheelwright, 1983), due to this shortcoming, the logic simultaneous consideration of the positive ideal and the negative ideal solutions and easily programmable computation procedure is extensively acknowledged. The basic principle is that the chosen points should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The biggest advantages of the TOPSIS concept are that it is easily understandable, and has good computational efficiency and the ability to measure the relative performance for each alternative in a simple mathematical form (Yeh, 2002).

2.6 Decision-maker and decision-making environment

Different types of decision-makers need support that is adapted to their problem contexts. The greatest advantage of the risk-based approach is its simplicity of use for the decision-maker. This is because risk assessment provides direct input to the decision as such, and not simply the process of decision-making (Aven, 2010). The categories of decisions and their associated decision-making procedures vary a lot between different sectors and levels in organisations. One should consider the whole decision cycle including the various decision activities to understand this problem area (Power, 2002). In general, the typical decision context consists of four elements, such as decision-makers, decision environment, goals and relevant alternatives and, finally, ranking of alternatives.

The classification of decision-makers has been utilised in different notions, such as individual decision-maker, multiple decision-makers, group decision-maker and team decision-maker (Murphy *et al.*, 1999). The individual decision-maker stands alone in the final decision process. The decision rests on his/her unique characteristics with regard to knowledge, skill set, experience, *etc*., and individual biases come to bear in the decision process. Multiple decision-makers comprise several people interacting to reach a decision. Each member may come with a unique motivation or goal and may approach the decision process from a different angle. They do not necessarily meet in a formalised manner to conduct discussions as a unit. In contrast, a group decision-maker is characterised by membership in a more formal structure where members of the group share similar interests in the decision outcome. Each member is involved in the making of a decision based on consensus of the group, but none possesses any more input or authority to make the decision than any of the others. The team decision-maker is a combination of the individual and group classification. The team produces the final decision, but the formalisation of that decision and the authority to make it rest with an individual decision-maker. The decision support may come from several individuals empowered by the key individual decision-maker to collect information. In this context the team produces the final decision, but the authority to make it rests with the individual team leader.

The decision environment may be both internal and external. Factors in the internal environment influencing decisions include (Marakas, 2003):

- People, and their goals, experience, capabilities, and commitments.
- Functional units, including the technological characteristics, independence, interdependence, and conflict among units.
- Organisational factors including goal and objectives, processes and procedures and the nature of the product or service.

The decision process typically consists of different basic steps (i.e. define the problem, collect information, identify and evaluate alternatives, decide, implement and finally, follow-up and assess) (Marakas, 2003). A well-defined problem is of great importance for the quality of decisions. If the problem is wrongly or not thoroughly defined, it may be impossible to make a decision. The complexity of many organisations sometimes makes it hard to identify the real problem. The most creative part of decision-making is the identification of the set of alternatives and determining what criteria should be used in the evaluation of options. A decision or choice made among alternatives is the culmination of one specific decision process. Decisions made under conditions of uncertainty are the most common types for managers. Sometimes there is not enough information to estimate the probability of the potential outcomes. Thus, it is termed as a decision under uncertainty. In well engineering the potential outcomes from main decisions are typically known, but the probabilities are not. Uncertainty is then related to the restricted information or lack of information on which to base the analyses or to reliably estimate the probabilities of known outcomes (Hitt *et al.*, 1983). Decisions made under uncertainty are perhaps the most difficult of all decision situations.

2.7 Conclusion

In order to ensure the originality of the research study, this chapter has provided a literature review associated with analytical methods of risk assessment. It gives emphasis to the explanation of applying uncertainty treatment methods and techniques to risk assessment and decision-making in earlier studies. The offshore industry has been moving towards a risk-based and goal-setting regime since the 1990s. Traditional risk assessment techniques such as FTA and ETA are capable of providing results with confidence if historical data are available. The current offshore operation risk assessment provides appropriate proactive approaches for ensuring improvements in the safe operation of offshore installations and environmental protection, though the overriding problem on the handling of the uncertainty issue is still not well embraced in such risk assessment exercises, despite the fact that the application of both well-established and newly developed (e.g., FTA and Fuzzy logic) risk assessment methods can be integrated in a transparent and justifiable manner. Some of the analytical methods, such as PHA, what-if, FMECA and HAZOP, are most usefully applied in the hazard identification phase, whilst others like FTA and ETA are used mainly in performing risk estimation. However, they may not be applicable in circumstances where there is a lack of data or the information available consists of a high level of uncertainty. Therefore, risk analysis in such circumstances strongly relies on human judgements. Different techniques including AHP, FTA and BBN can be incorporated into risk assessment with Fuzzy set theory to facilitate the analytical performance and provide results with confidence. In a decision-making process, many factors need to be considered when evaluating the best RCOs for an offshore operation system. Under such circumstances where the factors considered have different attributes, the best RCOs will be identified using the Fuzzy TOPSIS approach.

Identification of the HGs, which have the potential for significant adverse consequences to personnel, and equipment of the MODU is the main area of interest in this research. It is important to note that each HG contributes a different weight value to the overall MODU at the system level. As drilling failure is considered to be undesired among the HGs, therefore the potential consequences of this hazard have to be determined and estimated. In order to establish a platform of risk assessment, one risk analysis technique may be used to process the information produced by another. Risk assessment techniques can also be used in an integrative manner to produce a more efficient and convenient risk assessment. The objective of this PhD research is to establish a platform of risk assessment consisting of various frameworks addressing MODU safe operation safety without jeopardising the efficiency of offshore operation systems under circumstances where a lack of data exists or a high level of uncertainty is present.

CHAPTER 3: Development of the framework of the MODU risk assessment

Chapter Summary

In this chapter, the frameworks of risk assessment and hierarchy of the offshore operation system are developed to represent the methodology, a framework of aggregative risk assessment and relationships among equipment, subsystems and the overall MODU system. While studying the risk assessment of an MODU, it is almost impossible to treat the system in its entirety. A reasonable approach may be to break down the system into functional entities comprising equipment and subsystems. Risk assessment modelling of these functional entities can be carried out to develop an appropriate rational structure', then the interrelationships can be examined and an analysis model can be formulated to assess the risk of the offshore operation system. The proposed framework will be used in conducting an aggregative risk assessment despite the fact that the latter will be used in the BBN and Fuzzy FTA in the ensuing chapters based on the object-oriented approach concept.

3.1 Introduction

The necessity to improve and continue the performance of offshore operation systems has encouraged the application of reliable methodology and analytical risk techniques for carrying out risk assessment studies. The importance of these frameworks or techniques is that the results are principally required to quantify risk, and also to facilitate sound risk-based decisions. The quantification process also requires reliable operation, failure, and repair data input. In most circumstances, reliable data are not available; therefore, it is very beneficial to apply the risk analytical techniques effectively and efficiently. Thus, understanding the methodology and using precise techniques will aid risk managers and decision-makers. This chapter is composed of five sections; this section presents an outline and a brief introduction relating to the research and the basic concepts of the object-oriented approach and its potential to deal with the complexity of an offshore operation system. Then, in Section 3.2, the risk assessment process and ordering action required in order to develop an efficient methodology are presented. Section 3.3 aims to develop a hierarchy to represent the relationships among components, subsystems, and the overall offshore operation system. In addition, for the components at the lowest level in the hierarchical structure, BEs are used to describe the transitions due to the influences of each HG. Furthermore, a risk assessment methodology is developed and offered in Section 3.4 and, lastly, a framework of aggregative risk assessment is developed up to BEs and is presented in Section 3.5. Aggregative risk assessment is used to analyse the risk levels and influence of different HGs and events in an offshore operation system in view of their contribution to the failure of MODUs (e.g. component/equipment, subsystem and system). While FTs are used to describe the cause-effect relationships for a given risk in the system, these frameworks are developed at both the component/equipment and subsystem levels in order to meet the requirements of a comprehensive risk assessment and are presented in Chapter 5. Lastly, BBN is used to refer to the cause-effect relationships with dependency for a particular risk in the system. These frameworks are also established at both the component/equipment and subsystem levels in order to meet the necessities of a comprehensive risk assessment, which is discussed in Chapter 6. A Fuzzy MADM method, which is appropriate for considering group decision-making problems in a Fuzzy environment, is proposed for ranking of the RCOs with respect to cost and benefit, and is selected using a TOPSIS technique.

The object-oriented analysis is a method that can logically represent real-world entities and phenomena in terms of objects. In an object-oriented modelling pattern, analysts can effectively manage complex engineering systems. The concept is also effective for classifying risk information in an offshore operation system such as an MODU. Applications of an object-oriented analysis have covered various areas in practice. In software engineering a subject-oriented pattern has been developed that enables the modelling of complex real-world problems, and which represents the solution of a major problem (Martin and Odell, 1994). This comprises development of a framework for decision-making (Liu and Stewart, 2004) and for presentation of pipeline networks (Lewandowski and Detroit, 1994). Objects are models which can be used to represent real-world entities with the capability of communicating with one another (Booch *et al.*, 1994; Martin & Odell, 1994; Embley *et al.*, 1992). One of the most important characteristics of objects is summing up. This means that the attributes and behaviours of a component (e.g., riser, mud pump, *etc*.) or subsystem (e.g., drilling system, jacking system, *etc*.) are entirely summarised within the boundaries of an independent object.

These objects are interconnected to form a system of drilling an offshore well for producing hydrocarbons such as oil and gas. The entire system is thus viewed as the combination of individual objects with different functionalities. Meanwhile, the individual objects communicate with one another in a way that faithfully replicates their interactions in the real world (Booch *et al.*, 1994). In an MODU, for example, a well can be looked at as a specific object encapsulating the attributes of an offshore operation system. Likewise, a drilling pipe in the drilling system can be viewed as an object which encapsulates attributes such as dimension, age and behaviour of delivering a drilling liquid like mud.

The overall MODU is thus a compound object made up of interconnected individual objects including well, drilling pipes, *etc*. In a real operational system there are many objects of a specific kind. It would be extremely inefficient to repeat the use of the same methods in defining every single occurrence of that object. The effectiveness of using this approach to deal with the complexity of systems has also been illustrated in detail by many researchers (Weber & Jouffe, 2006;, Booch *et al.*, 1994;, Martin and Odell, 1994). However, its potential in risk assessment of complex systems has not been investigated to a significant degree in the previous research.

All engineering systems including MODUs are designed, constructed, operated and managed in terms of objects. For an MODU, its performance is determined by the performance of the consistent components or objects. As a result, individual objects contribute to the overall MODU. The above discussion shows the possibility of using an object-oriented approach as an effective tool to organise complex risk information in the offshore operation system. Such awareness encourages this study to implement an object-oriented approach to develop frameworks of risk assessment.

3.2 Risk assessment process

No common definition of safety barriers can be found in the regulations concerning health, environment, and safety within the petroleum activities on the Norwegian continental shelf (NCS) issued in 2001[8], and also no common definition of safety

[8] Regulations relating to management in the petroleum activities (The Management Regulations). 3 September 2001

barriers has been found in the literature, even though different aspects of the concept have been discussed, are required in legislation and standards and have been applied in practice for several decades (Skogdalen & Vinnem, 2011; Sklet, 2006a).

Different risk assessment approaches have been applied in various schemes but, so far, no approach has been commonly applied for practical purposes. Traditional quantitative risk analyses of offshore installation focus on consequence and the main interest has been to estimate the consequences of the assumed initiating event, the harm to humans and environment, and to assess their frequency; the identification of the most effective safety measures to avoid initiating events was very limited (Kafka, 2006).

A QRA approach for an offshore operation system should be exclusive, in which any hypothetical risk to the system can be evaluated to reflect where there may be a need for possible risk reductions or design modifications. Such a risk evaluation process should follow on from the establishment of an occurrence probability or possibility for the defined hazards, and their relative consequence magnitude. QRA can make available an effective approach that will serve as the foundation for avoiding further offshore operation catastrophes. A quantitative approach for an offshore operation system risk assessment should be exclusive, in which any hypothetical risk to the system can be evaluated to reflect where there may be a need for possible risk reductions or design modifications.

The purpose of a QRA is to help the designer to be conscious of the characteristics of the system and to provide him/her with the quantified occurrence probability of each critical failure condition and the associated consequences. The main focus in QRA is on technical safety systems and one of the weaknesses of current QRA is the missing link between the models applied in the analyses and human, operational, and organisational factors (Vinnem *et al.*, 2003). Through risk analysis, it is possible to identify hazards, and evaluate and then mitigate the associated risk. Such an assessment requires the development of an efficient methodology, constructed upon the following ordering of actions:

- Outline the operation system being considered (i.e. offshore operation system).
- Classify/categorise the HGs and the hazard associated with those subsystems/equipment/components of the operation system.

- Data collection and estimation of the likelihood of the hazards occurring and in what way each might progress to different consequences and estimation of the consequences associated with each outcome.
- Aggregation of the risks associated with the outcomes to produce an overall risk.
- Analyse the risk level and check if the risk is acceptable based on the criteria.
- With respect to the overall risk level, carry out risk mitigation for reducing or controlling the risk.
- Decision-making and selecting the best RCOs.

Once the above activities are defined, it is then possible to select from amongst the wide range of methods for risk assessment (Bahr, 2014). Typical ones include:

- Hazard identification tools:
  - Judgements
  - FMECA
  - Structured what-if checklist technique (SWIFT)
  - HAZOP study
- Risk assessment approaches:
  - Rule-based approaches
    (e.g. regulations, codes and practice and classification rules)
  - Engineering judgements
  - Qualitative risk assessment / QRA
  - Value-based approaches
- Risk assessment techniques:
  - Qualitative (e.g. risk matrix)
  - Semi-qualitative use of structured tools (e.g. FTA, ETA, Bow-Tie approach).
  - QRA
- Hierarchy of options approaches for risk reduction:
  - Eliminate the hazard
  - Prevent the occurrence
  - Mitigate the consequences
  - Escape, evacuation, rescue and recover
- Decision-making:

- Level within organisation and tools (i.e. senior management, judgements, cost-benefit analysis).

Such an assessment process can formally be carried out qualitatively or quantitatively, conditional on how much information and data are or have been obtainable / available, in addition to the competence of expert judgements that can be provided to the analyst / risk managers or decision-makers.

3.3 MODU’s operational system hierarchy and complexity

An operational system is any user-defined group of components, equipment, or facilities that support an operational function. These operational functions are defined by mission criticality or by environment, health, safety, regulatory, quality, or other defined requirements. Most systems can be divided into unique subsystems along boundaries. The boundaries are selected as a method of dividing a system into subsystems when its complexity makes an analysis by other means difficult. Since complexity is one of the hurdles limiting the application of conventional risk assessment methods, it is necessary to explicitly discuss the potential of an object-oriented approach in dealing with the complexity of the MODU. In order to effectively analyse complex systems, many researchers have carried out extensive studies on their characteristics. Courtois (1985) suggested a few attributes common to all complex systems following on from the work of Simons (1982). Such attributes are mentioned in the following parts. The characteristics of the MODU make it possible to deal with the complexities effectively. Being one of the complex engineering systems, a general MODU inherently has these attributes and the following discussion is about the effectiveness of using this approach to deal with the MODU attributes.

- Complexity takes the form of a hierarchy, whereby a complex system is decomposed of interrelated subsystems that have in turn their own subsystems/equipment/components until some lowest level (BEs) is reached. This hierarchical structure also provides a possible framework for risk assessment. It is obvious within the hierarchy that risk levels of an MODU are determined by the risk levels of its subsystems as well as the hierarchical relationships among them. The risk levels of a subsystem are further determined by the risk levels of its own components. Once the risk levels of each individual component have been determined, aggregation can then be conducted along the hierarchy to generate risks of the subsystems and the overall system. The object-oriented hierarchical structure depicts the whole/partial relationships in an MODU system, which enables us to understand, describe, and analyse the system and its parts better (Booch *et al.*, 1994).

- Hierarchical systems are usually composed of only a few different kinds of subsystems in various combinations and arrangements. This attribute indicates that complex systems have common patterns (Booch *et al.*, 1994). This is also obvious in the object-oriented structure of MODUs. A general MODU is composed of some common elements (e.g. gas, wells, blow-out preventer, risers, mud treatment facilities, *etc*.). All these elements are further abstracted as fewer common element types such as pipes, compressors and tanks.
- The collection of what components in a system are primitive is relatively arbitrary and is largely up to the discretion of the observer of the system. Primitive elements in this study are deemed as the components that are indecomposable and at the lowest level of a hierarchical structure. They play important roles in risk assessment. On the other hand, the determination of primitive elements is arbitrary and depends a lot on the observers of the system because they have different choices of what components are primitive in practical risk assessment.
- Definition of the subsystem/components' relationships. This information has the effect of separating the high-frequency dynamics of the components, involving the internal structure of the components, from the low-frequency dynamics involving interaction among components. This provides a clear picture of separating various parts of an MODU, which makes it possible to study risk levels of each part in relative isolation.
- A complex system designed from scratch never works and cannot be patched up to make it work, and a complex system that works is invariably found to have evolved from a simple system that worked. This attribute indicates that an MODU will work successfully if all its components and subsystems work normally. An MODU will fail to drill the wells if some components or subsystems have failed. However, direct determination of risk levels of a

complex MODU is difficult or almost impossible. A possible solution to this is indirect evaluation by aggregating the risks of its subsystems (i.e. mud treatment system, BOP, *etc*.) due to their lower complexity. Therefore, risk information can be obtained for a complex MODU by studying the risks of simpler objects in an object-oriented hierarchical structure.

The above discussions not only demonstrate the potential abilities of object-oriented hierarchy in dealing with all of the attributes of complex systems, but also support the development of risk assessment frameworks. With respect to this concept, a hierarchy of an MODU operation system is constructed and presented in Figure 3.1, by viewing all the physical elements in an MODU as objects that encapsulate specific attributes and behaviours and interact with one another.

3.3.1 Proposed operational hierarchy of an MODU

A hazard is defined as a physical situation with the potential for human injury/fatality, damage to property, damage to the environment, economic loss or combination of these. Hazards are classified according to the severity of their potential effects, either in terms of safety, economics or other consequences. Such classifications alone are purely subjective, and usually require qualification and quantification by definition of the precise form of the hazard, and quantified evaluation of the consequences (Warner, 1992). The result from this investigation shows that drilling failure is a critical item within identified events or HGs, and so it is selected to be the decision problem and separated into smaller, manageable subsystems and events of different hierarchical levels as necessary. A four-level hierarchy of an MODU system is developed and is illustrated in Figure 3.1. The highest level of the hierarchy corresponds to the goal prioritisation of importance of the MODU's risk, and the last layer corresponds to the evaluation of BEs. It starts with the MODU system's overall analysis where the HGs are compared with their significance and possible effects of MODU failure are studied. Then, the most important HGs are summarised and their failures investigated according to the operational phases of the MODU. Furthermore, each MODU HG is studied according to its failure modes, causes and criticality. Lastly, the effect of the HG is examined according to failures that occurred whilst the MODU was in operation.

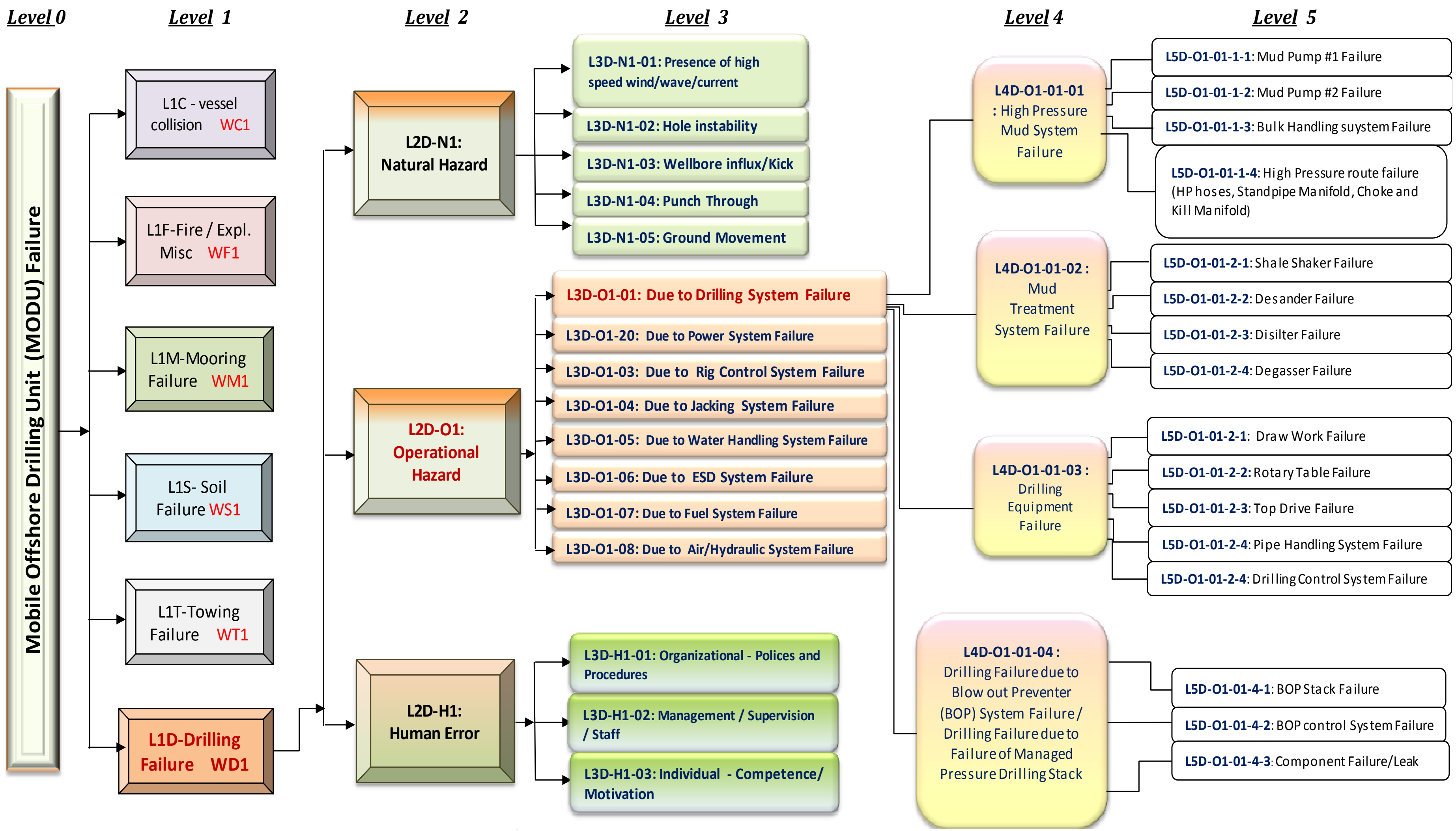


Figure 3.1: Hazard identification and MODU's operational hierarchy model; the highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU's risk, and the last layer corresponds to the evaluation of BEs.

3.4 Proposed risk assessment methodology

It has been appreciated that use of the risk assessment methods in an integrated manner may make risk assessment comparatively efficient and convenient since safety information and the advantages of each method may be more efficiently explored by doing so (Wang *et al.*, 1993).

Several lessons still need to be learnt from the earlier offshore operation systems failure events. There is also no doubt that accidents and incidents which cause few effects, or which are less publicised, as well as certain unsafe acts bringing about errors and those of recovery occurrences, do provide equally valuable lessons from which to learn. In fact, it is possible that accidents may have been propagated from the latter and yet these are often overlooked as likely sources of the safety issue problem in the offshore industry. Therefore, within existing offshore operation regulations, there are several amendments to be undertaken that may be helpful in preventing even the likely occurrence of an incident from developing any further. It is extremely difficult to prevent events in the absence of an understanding as to how they are caused. In complex systems, events usually develop through relatively lengthy sequences of changes and errors. According to Petersen (1978), behind every accident there are improper contributing factors, causes and sub-causes. Hence, throughout offshore operation system risk assessment and in the causal modelling studies, there is a necessity to identify as many of these sources as possible. In order to implement the outlined risk assessment methodology effectively, Figure 3.4 provides a proposed framework for which the risk assessment settings of this research can also be achieved by identifying the best RCOs via a cost-effective means. The previous sections have outlined several risk analysis methods that are widely applied in offshore operation risk assessment. However, in some situations where there is a lack of data, it may be difficult to apply them with confidence to the assessment task.

The selection of the outlined methods, or the decision as to which methods are more appropriate for risk assessment of a particular offshore operation, are primarily dependent on consideration of the level (e.g. system, subsystem or component level) of the operation system breakdown at which the hazard identification is carried out. In addition, it is dependent on the degree of complexity of the inter-relationships of the items at the investigated level of the offshore operation system breakdown. Finally, it is also dependent on the degree of innovation associated with the system design (e.g. the availability of operation failure data for risk assessment). The outlined analytical methods, classified as either top-down or bottom-up event-based, may be applied to study the operational conditions, environmental conditions and other design considerations which contribute to the occurrence likelihood of the hazardous conditions associated with an offshore operation system and define the magnitude of possible resulting consequences.

An innovative methodology framework for risk assessment of an MODU system is developed and demonstrated in Figure 3.4, consisting of the different stages (i.e. 5 stages) which provide a demonstrative view of a generic framework proposed for the purpose of the MODU risk assessment; it comprises the following stages:

Stage 1:

A hierarchy model is illustrated that reflects the operational failure of the mobile offshore drilling units. To have a manageable risk model, a three-level hierarchy is developed and is illustrated in Figure 3.2. The highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU's risk and the last layer corresponds to the evaluation of BEs. By using the combination of the Fuzzy-AHP and Fuzzy FMECA, the risks of significant items (i.e. HGs) are quantified and the most critical ones will be identified for further analysis. Fuzzy-AHP is used to determine the degree of importance of each HG in terms of its contribution to the MODU's failure. The AHP and the Fuzzy theory are combined in this stage by a different means. Moreover, the Fuzzy-AHP is applied in the risk assessment of the MODU operation system. The method includes four steps, as follows:

- Establish the risk factor hierarchy model.
- Define the basic event risk factors that consist of the BE factors; as an example: $R_{f(L3,N1)}$ to $R_{f(L3,N3)}$ for the Natural Hazard BEs and their contributory factors WD3N-1 to WD3N-5; $R_{f(L3,O1)}$ to $R_{f(L3,O8)}$ for the Operational BEs an`d their contributory factors WD3O-1 to WD3O-8; and $R_{f(L3,H1)}$ to $R_{f(L3,H3)}$ for the Human

BEs and their contributory factors WD3H-1 to WD3H-3 are considered and are illustrated in Figure 3.2.

- Define the quantitative basis for risk factors.
- Establish the comprehensive risk assessment model.

The details of the combination of the Fuzzy-AHP and Fuzzy FMECA approaches are presented in Chapter 4.

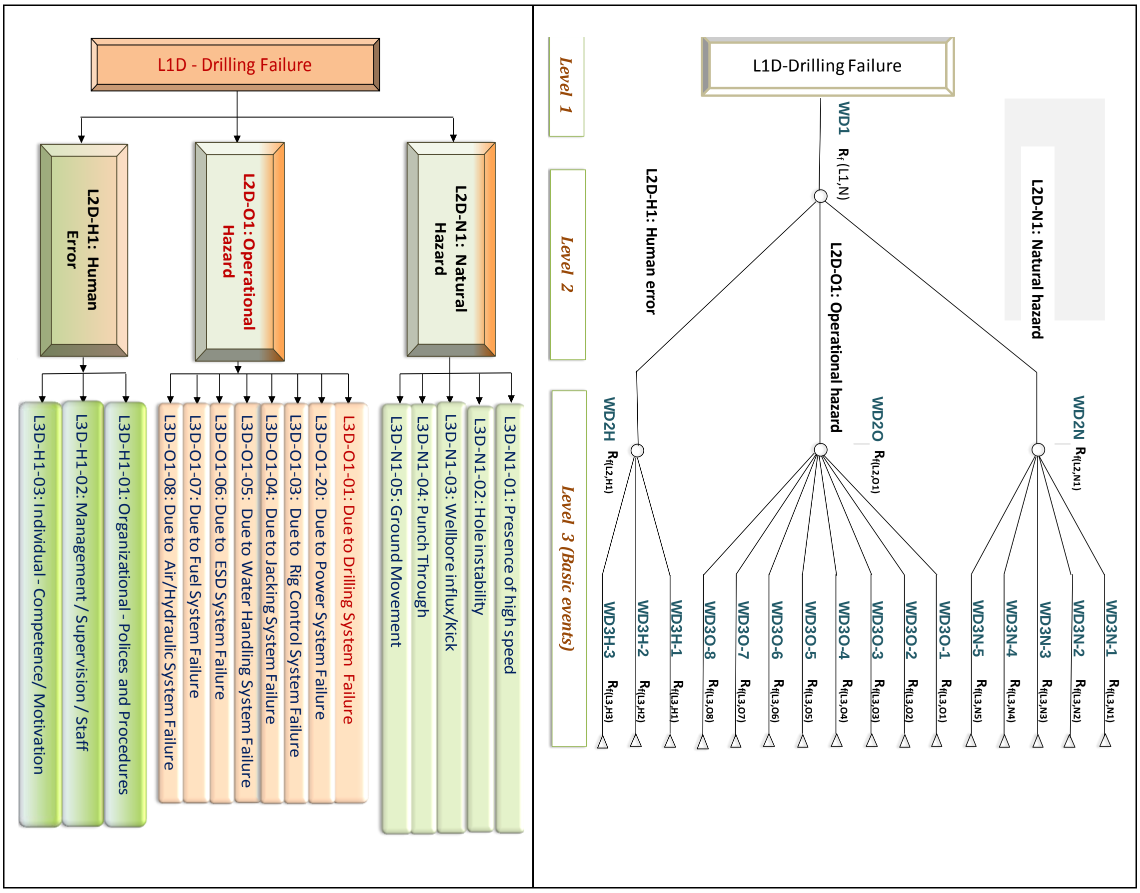


Figure 3.2: Hazard identification and MODU's operational hierarchy model and a three-stage structural model for risk aggregation; the highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU's risk, and the last layer (level 3) corresponds to the evaluation of BEs.

Stage 2 & 3:

These stages identify the relationships between subsystem, events and establishing an operational hierarchy system diagram with a detailed breakdown of the most significant HG (i.e. Drilling Failure: L1D). The hierarchical structure consists of different levels; the aim is to identify the sources of hazards of the top event (i.e. MODU failure in level 0). As presented in Figure 3.1, each HG in level 1 may possibly be influenced by other subsystems or events at other levels (e.g. levels 2 to 5). In fact, the components/subsystems and BEs describe the MODU's operation system, and the failure of each component may influence another component or system at the different levels.

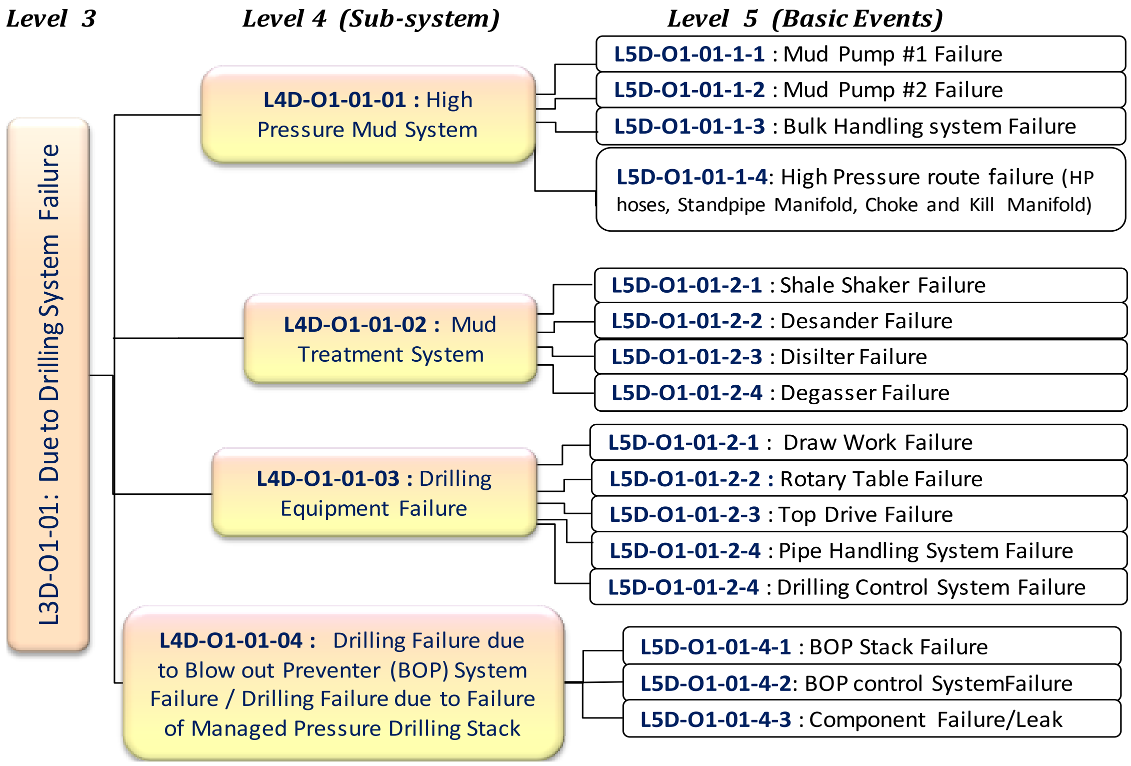


Figure 3.3: Drilling system failure and its subsystem/events in levels 4 and 5 respectively.

As stated in stage 1 of the methodology, by using a combination of the Fuzzy-AHP and Fuzzy FMECA the risks of important systems/events are calculated and the most serious ones are acknowledged (e.g. L3D-O1-01: Drilling system failure) for further analysis. As shown in

Figure 3.3, the event of drilling system failure is expanded to its subsystem and events in two lower levels (i.e. levels 4 and 5).

<u>Stage 4</u>:

QRA by using Fuzzy FTA and BBN to identify the basic causes leading to an undesired event; in order to identify the most critical hazards of MODUs, AHP theory is used to determine the degree of influence and importance of factors of each HG.

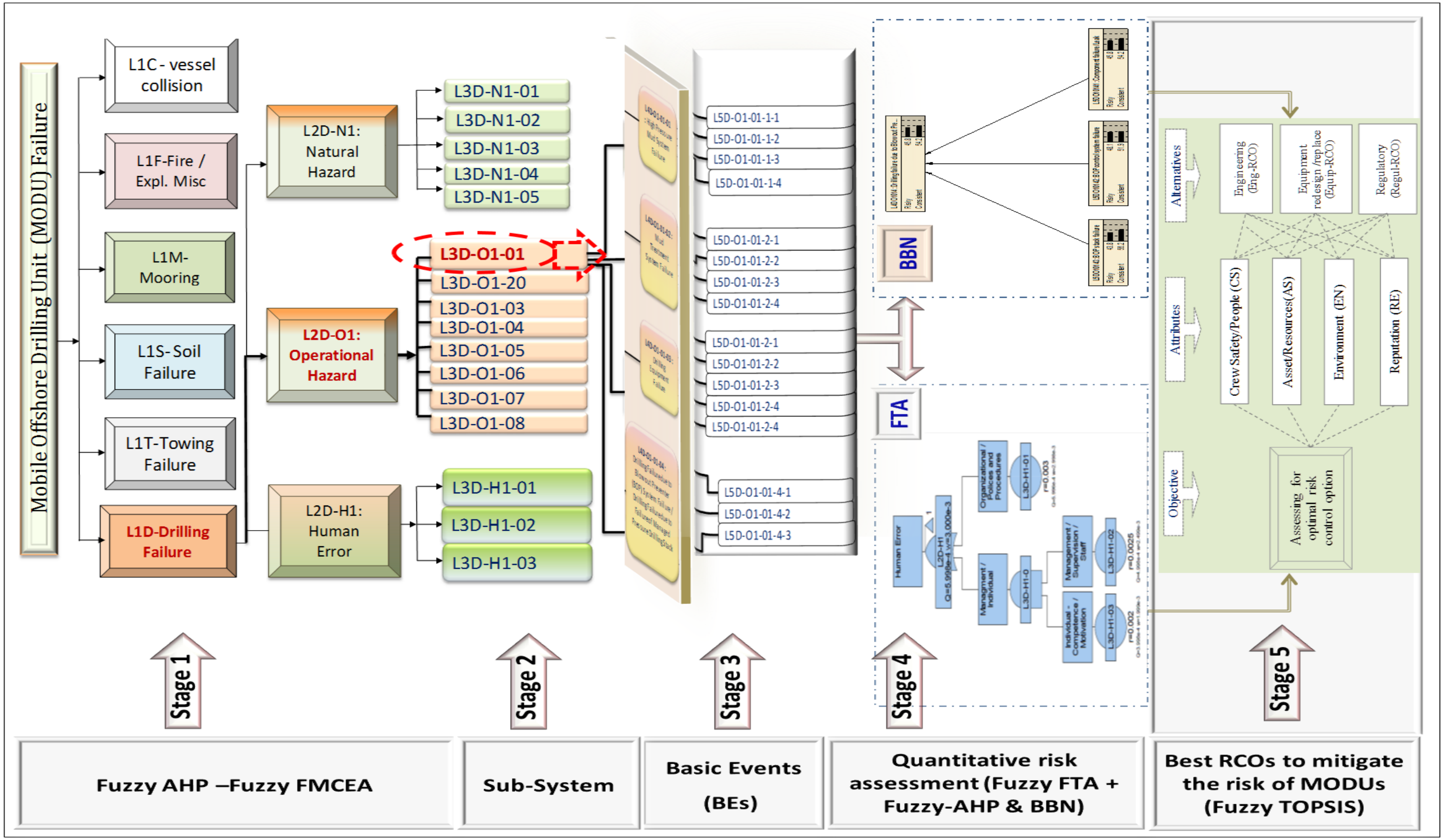


Figure 3.4: Proposed framework for implementation of the risk assessment methodology

By focusing on mud circulation and the BOP systems through using Fuzzy-FTA and BBN, the particulars of the MODU's risk assessment methodology and analysis are presented in Chapters 5 and 6 respectively.

Stage 5:

The aim of this stage is to select the best RCO and barrier to improve the safety level of the MODU in the drilling and operational phase. Fuzzy TOPSIS is implemented to identify the best RCO and MADM is used in a Fuzzy environment to select the RCOs. Different RCOs and barriers with different purposes could be recommended. With consideration of the research findings and recommendations, the best RCOs with respect to cost and benefit in three different aspects are proposed and listed below, and the details are presented in Chapter 7.

- Engineering (Eng-RCO)
- Equipment redesign/replace(Equip-RCO)
- Regulatory/Human error (Regul-RCO)

3.5 Aggregative risk assessment framework

A framework of aggregative risk assessment is developed up to BEs and is presented in Figure 3.5 in which the failure at the top level (level 1) is directly related to consequences or risks in different levels. Thus, the risk level is determined directly by the risk levels of its failure subsystem and BEs. Furthermore, the change from the normal state to a failure state is directly related to and driven by its specific hazard. A specific hazard is usually evaluated in terms of its likelihood of occurrence and severity of possible consequences. Then risks can be estimated for such hazards, by using Fuzzy aggregative risk assessment. A coding system that consists of the BE factors and their contributory factors has been developed and is presented in Figure 3.5. There are three HGs of interest, L2D-N1, L2D-O1 and L2D-H1, which belong to level 2 of the operational hierarchy. L2D-N1, L2D-O1 and L2D-H1 can be inferred directly from the BEs in level 3, which are: L3D-N1-01 to 5, L3D-O1-01 to 8 and L3D-H1-01 to 3 respectively, while the event L3D-O1-01 was expanded to two more levels (levels 4 & 5).

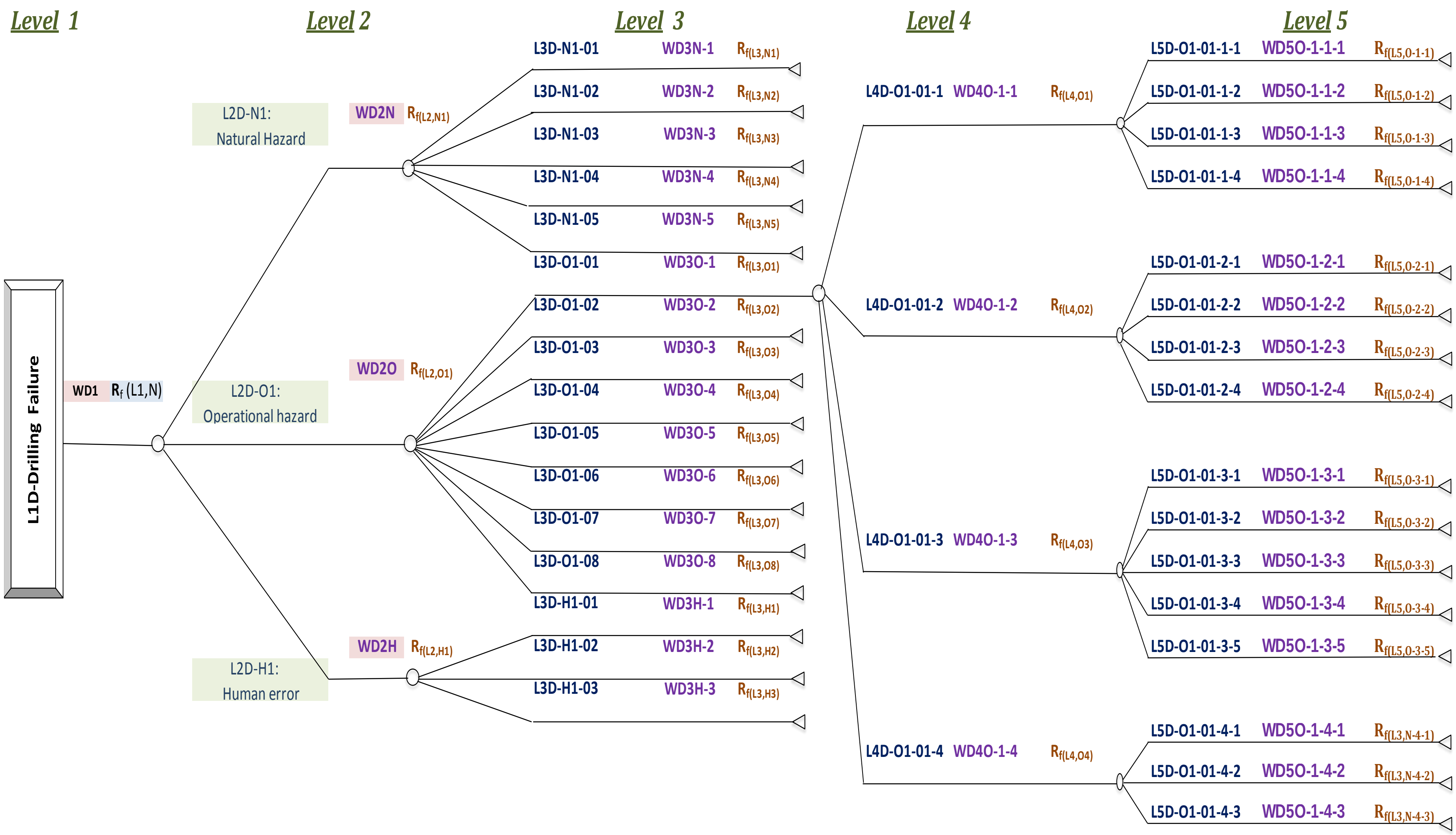


Figure 3.5: Proposed framework for aggregative risk assessment at component level.

The framework of risk assessment of each subsystem and the overall MODU is determined by the whole/partial relationships represented in an object-oriented structure. In this framework, primitive BEs are at the lowest level, whose risk levels are determined by the framework proposed for aggregative risk assessment. This aggregative process explicitly shows that the risk of the overall system is determined by the risks of its subsystems, which are in turn determined by the risks of their consistent events. This hierarchical assessment has the ability to model the intricate relationships among the BEs and subsystems and to account for all the relevant and important elements of risk and uncertainty, therefore rendering the assessment process more tractable and representative. A possible quantitative evaluation of these aggregative frameworks is particularly studied in Chapters 4, 5 and 6.

3.6 Conclusion

The current study utilises qualitative risk assessment for offshore operation systems, and an outline of the methodology adopted in the research is presented in this chapter. Before the scene of this thesis was set, the background work had revealed safety in the offshore operation system as being a reactive response to major accidents. A change in such culture provided for proactive approaches to be applied. A proposed framework for the risk assessment settings of this research has been developed in a generic sense to be effectively applicable to the offshore operation systems. The framework incorporates risk analysis for which data were obtained from industrial databases and/or by expert judgements. Fuzzy logic (FL) was utilised as the modelling tool that dealt with the vague/subjective uncertainties. This study has shown that an object-oriented approach is effective in dealing with the complexity in offshore operation systems and can be used to develop frameworks of risk assessment for the MODUs. Some of the analytical methods, such as FMECA, are most usefully applied in the hazard identification phase, whilst others, like FTA and BBN, are used mainly in performing risk estimation and probability of failure. A framework of aggregative risk assessment is used to evaluate the risks associated with BEs, subsystems, and the overall system. Different hierarchies are proposed to be used in order to represent the cause-effect relationships for specific undesired events in an offshore operation system. By using the effective combination of the different methods as presented in the proposed methodology framework, risk analysts can obtain a more comprehensive view of the risks in an MODU operation system. In particular:

- The proposed methodology can be used by different users. The frameworks can be flexibly established at different hierarchical levels according to the requirements of system observers and/or available information.
- Also, the frameworks can be reused in different offshore operation systems. The frameworks are developed from a general point of view, encapsulating the common features of various offshore operations and being capable of reuse in any specific application.
- It is possible to use and evaluate risks by considering multiple hazards. The frameworks can aggregate natural hazards and human error as well as operational risk along with a consistent hierarchy to generate useful risk information for decision-makers.

The developed risk assessment models provide useful integrative tools for a proactive offshore industry but have limitations owing to the complex nature of the offshore operation systems. And there is still further work required to improve the frameworks developed in this study, which can be summarised briefly as follows:

- A framework for vulnerability assessment needs to be developed. Vulnerability also plays an important role in introducing risk into an MODU. However, detailed study is required in order to make the assessment closer to the real world.
- The process of generating the FMECA, FT and BBN structures at the system level is based on the normal flow directions of an MODU, which is a conservative approximation of the real cases. However, the flow directions might change in real cases of failures.
- On every occasion data for risk assessment are sparse, it may become very challenging for the risk analyst to precisely obtain the influences of basic failure events in order to carry out quantitative analysis using the analytical methods outlined before, since a great deal of uncertainty is involved. Therefore, the need for models that reflect subjective reasoning or understanding will dominate which choices are considered.

CHAPTER 4: Fuzzy risk assessment of MODUs

Chapter Summary

The main purpose of this chapter is to propose a methodology to improve the current procedures used in the risk assessment of mobile offshore drilling units; this chapter will develop a method that can quantitatively evaluate the frameworks of aggregative risk assessment for the MODUs. The failure of MODUs has been considered, focusing on drilling failure due to rig equipment issues including human error, operational hazard and natural hazard. The purpose is to prevent a critical event occurring during drilling rather than focusing on measures that mitigate the consequences once an event has occurred. The aim is achieved by using a combination of the Fuzzy-AHP and Fuzzy FMECA approaches. A generic hierarchy model is presented that considers the operational failure of the MODUs. In this chapter the risks of significant items (i.e. HGs and BEs) are quantified and the most critical ones will be identified for further analysis in Chapter 5. Two mathematical theories will be employed for these frameworks. One is a mathematical evaluation of risks associated with hazards and the other is the mathematical method that can aggregate risk estimates along the hierarchical structure to obtain the risks associated with an MODU. Fuzzy theory is used to represent the characteristics of a hazard such as likelihood of the occurrence, severity of consequence and detection of vulnerability consequences. A Fuzzy-AHP is used to determine the degree of importance of the factors and sub-factors in the model of each HG in terms of their contribution to the MODU's failure. The proposed methodology provides a rational and systematic approach for the unit's risk assessment and comprises a number of stages: 1) Identification of probable critical HGs that may lead to the unit's operational failure, 2) Unique applications of a combination of a Fuzzy-AHP technique and Fuzzy FMECA approach are used, 3) Ranking of events using a Fuzzy-AHP to determine the degree of influence of each HG, and 4) Construction of a hierarchy for the offshore operation system.

4.1 Introduction

Pursuant to the reviewed cycle of potential hazards and consequence mechanisms associated with loss or failure of the MODUs in Chapter 3, the aim of this chapter is to propose a methodology for the MODUs' risk assessment in order to assess the overall risk level of the MODUs, i.e. identify the important HG and its contributory weight factors to classify the BEs. Due to the lack of data, the uncertainty experienced may considerably undermine the conclusion acquired based on the traditional QRA techniques. For that reason, how risk assessment is conducted with confidence under circumstances where a high level of uncertainty is present is still a problem for most academics. Therefore, the first objective of this research is to propose a framework, which is capable of performing risk assessment of the MODUs in situations where a lack or insufficiency of information exists. Thus, this chapter establishes a novel conceptual framework for the QRA and also proposes a methodology that addresses the frequency of the limitations of risk assessment techniques. The purpose of a QRA is to assist the decision-maker to be aware of the characteristics of the system and inform the designer of the quantified occurrence probability of each critical failure condition and the associated consequences. Additionally, it may be essential to carry out risk assessment based on multiple hazards which are represented in different forms, such as probabilistic data, experts' opinions and linguistic representations. Traditional probabilistic risk assessment approaches may be deficient in the ability to deal with such multi-form data and information input. Therefore, there is a need to develop an effective method to address the above characteristics of risk assessment. In risk assessment under circumstances where a high level of uncertainty exists, fairly accurate reasoning methods using the Fuzzy rule-based technique have been demonstrated to be useful. However, such applications may become impractical, as there are multiple parameters to be evaluated, which are described by multiple linguistic terms. In this chapter detailed fundamentals of the Fuzzy approach are discussed to demonstrate how its principles have been integrated within the framework of the proposed methodology for the assessment of risks associated with the MODUs.

The proposed integrated methodology can quantitatively evaluate the frameworks of aggregative risk assessment of the MODUs proposed in Chapter 3. Two aspects are required to be mathematically represented for these frameworks. The first aspect is a mathematical assessment of risks associated with each basic event. A basic event in a hierarchical framework is expressed by a trapezoidal Fuzzy number, which results from the composition of the likelihood of the occurrence, severity of consequence and detection of vulnerability consequence of an MODU operation system. Since the contribution of each HG to the failure of the MODUs is not the same, the weight of each HG should be taken into consideration to represent its relative contribution and importance in terms of its capacity to lead to the failure of the MODUs. Therefore, the second aspect is a mathematical method that aggregates risk along the hierarchical structure to obtain the risks of the BEs, subsystems, HGs, and the MODU. A Fuzzy-AHP methodology is designed to deal with an alternative selection and relative contribution by integrating the concept of Fuzzy set theory (FST) and hierarchical structure analysis. Fuzzy-AHP is then employed to calculate and introduce the weight factors, which indicates the magnitude of the relevant importance of a HG to its belongings in a risk tree. The outcomes of risk assessment of the MODUs are represented by the risk degrees and risk contribution factors that provide analysts, managers, engineers and decision-makers with useful information to improve their safety management and set safety standards for the MODU’s operation systems.

The use of a Fuzzy theory based methodology allows decision-makers to incorporate both qualitative and quantitative data into a decision model. Decision-makers usually feel more confident to provide interval judgements rather than fixed-value judgements (Li, 2007; Chang, 1996). In this approach, Fuzzy numbers are used for the preferences of one criterion over another and then, by using the extent analysis method, the synthetic extent value of the pair-wise comparison is calculated. This chapter concludes with a discussion on the main aspects of the methodology and novelties tailor-made in the direction of effective assessment of the MODU’s associated risks.

4.2 Literature review

QRA techniques were first given wide application in the Norwegian offshore oil and gas industry in the early 1980s. QRA has traditionally been used for optimisation and verification of design. The focus of QRA is on technical measures and resolutions but substantial assumptions are made with respect to the following event processes and measures (Standard, 2001):

- Organisational: Qualifications, emergency teams and staffing.
- Operational: Procedures for transportation, lifting, installation, repair, maintenance and visiting marine vessels.

- Activities: Simultaneous operations, modification and number of helicopter visits.

Among research subjects from the risk assessment aspects of the oil and gas drilling operation there are few on HSE risk management of drilling operations. During the period between 1970 and about 2000, there was extensive new building activity in the North Sea. Since 2000, the new builds have been reduced to one or possibly a couple of new production facilities per year in the entire North Sea, and the trend towards more extensive use of mobile and floating production systems, operations in the Arctic and deepwater suggests that operational aspects of safety will be more important in the future, in order to mitigate hazards and control risks. QRA is therefore of great importance to the oil and gas industry (Skogdalen *et al.*, 2011). An enormous number of methods/approaches exist for the identification of hazards and hazard situations as well as for use in risk estimation. These well-established methods have seen continuous practice within industries because knowledge about the methods is well documented (Mannan, 2004). Besides, use of different techniques/methods might make it easier to discover events for definite hazards, e.g. using deductive logic or top-down approaches, and to find new hazards, e.g. using inductive logic or bottom-up methodologies and approaches (Hansen *et al.*, 2002)When a complex marine and offshore system involves various related risk items with uncertain causes and scales, it often cannot be treated with mathematical thoroughness during the initial or screening phase of decision-making (Lee, 1996). When studying the safety features of offshore structures, it is almost impossible to treat the system in its entirety, owing to the nature of its complex engineering structure (Wang, 1998). It is often challenging to assess likelihood, severity and detectability associated with a hazardous event using probabilistic theory. To begin with, some hazards may be related to many uncertain factors which are hard to express in terms of probabilities. All such factors are subjective and difficult to characterise by a single precise probability distribution function. Furthermore, historical records of some risk scenarios, particularly extreme hazardous events, are often incomplete and insufficient. Therefore, a specialist may have difficulty in developing appropriate probability distribution functions with limited information. Due to lack of data, risk analysts may be more confident with linguistic representations (e.g. very high, slightly low, *etc*.). However, probabilistic variables have limited ability to represent this linguistic or descriptive information. Zadeh (1965) introduced FST as an alternative to probabilistic theory to deal with the problems in which vagueness is present.

Applications of FST have been extensively studied with respect to the ambiguity and vagueness involved in the risk analysis in different engineering areas. FST can be used to represent subjective, vague, linguistic and imprecise data and information effectively. For example, Sadiq and Sadiq and Husain (2005) applied a Fuzzy-based methodology for an aggregative environmental risk assessment of drilling waste. Wang & Elhag (2007) used Fuzzy group decision-making for bridge risk assessment. Zeng et al. (2007) applied a Fuzzy-based decision-making methodology to construction project risk assessment. Chen (2001) used Fuzzy group decision-making for evaluating the rate of aggregative risk in software development. Lee (1996) applied FST to evaluate the rate of aggregative risk in software development.Risk assessments are required to identify and to document the significant risk to the environment, health and safety of employees and any others who may be affected by an undertaking. However, what is the main purpose of performing a risk assessment? The only reason for undertaking a risk assessment is, according to Bley, et al. (1992), to understand a risk in order to do something about it. Such a view, in which risk reduction is considered the main objective of risk assessment, is a typical misconception according to Aven (2010). Risk reduction is never a goal in itself. This is due to the recognition that creating value necessitates risk-taking. The purpose of risk assessment is thus not mainly to facilitate risk reduction, but to provide input to a particular decision in a larger context. The vast majority of references confirm this point, unanimously stating that risk assessment is a tool to inform decision-making in management of risk (HSE, 2001; NASA, 2002; NUREG, 2009; NORSOK, 2001; and IMO, 2002). Common to all situations is the decision-maker's need to reduce their uncertainty regarding the outcome of a decision. At a deeper level, risk assessment can thus be seen as a tool to address and a language to express the uncertainty about the future (Bley *et al.*, 1992). A logical approach may be to break down the system into functional entities comprising sub-systems and components, so that the interrelationships can be examined and, finally, a system safety model can be formulated to assess the safety parameters. This will therefore necessitate risk analysts to utilise some very well-dependable analytical tools and techniques in the formulation of the assessment model. Uncertainties in risk analysis inputs are propagated through the risk assessment and evaluation steps of the safety assessment to obtain estimates of the level of confidence in the assessment outcomes (Chauhan and Bowles, 2004). Such uncertainties require techniques that can handle their treatment efficiently and effectively. Several techniques are used to predict how the systems would behave if they were to be hit by unforeseen catastrophic events such as fire, explosions, collisions and loss of hull integrity. Therefore, a review of related work is necessary for the development and application of uncertainty analysis methods that can appropriately deal with qualitative and quantitative factors of the risk assessment study. The proposed methodology in this chapter is built upon the previous development, and the novel parts of the proposed methodology are to combine both qualitative and quantitative information, and also the weight of the contribution of each hazardous event has been taken into consideration in order to represent its relative contribution and importance in terms of its capacity to lead to the MODU's failure. Each failure mode can be evaluated by three factors: probability of occurrence, consequence of severity and vulnerability of the failure mode. By multiplying the values for these factors, a risk value would be obtained (Chin *et al.*, 2008). Then the risk value of the BE will be aggregated along with its hierarchy by employing a Fuzzy-AHP. AHP technique achieves pairwise comparisons among the criteria or factors in order to prioritise them at each level of the hierarchy using the eigenvalue calculation. In addition to AHP, Analytic network process (ANP) technique is a generalization of the AHP, by considering the dependence between the components/systems, that allows inter-dependencies, outer-dependencies and feedbacks among decision elements in the hierarchical or non-hierarchical structures(Görener, 2012). AHP and ANP are essentially ways to measure especially intangible factors by using pairwise comparisons with judgments that represent the dominance of one element over another with respect to a property that they share (Chung *et al*., 2005). Many decisions problems cannot be structured hierarchically because they involve the interaction and dependence of higher level elements in a hierarchy on lower level elements (Saaty & Özdemir, 2005). While the AHP represents a framework with a uni-directional hierarchical AHP relationship, the ANP allows for complex interrelationships among decision levels and attributes (Yüksel & Dağdeviren, 2007). In fact the ANP uses a network without the need to specify levels as in a hierarchy. Influence is a central concept in the ANP. (Anand & Kodali, 2009). Despite the fact, the AHP technique is appropriate and workable for the MODU operation system, for the reason that the relationship between the components/systems is possible to structure and present with a uni-directional hierarchy.

4.3 Proposed integrated methodology for the MODU risk assessment

QRA can be implemented using many methods, such as failure mode and effects analysis, preliminary hazard analysis (PHA), *etc*. (Kirchhoff *et al.,* 2007). In situations where there is a lack of data, it is required to incorporate expert judgements into the risk study. A framework is established based on Fuzzy set theory, which is capable of quantifying judgements from experts who express their opinions qualitatively. As shown in Figure 4.1, the proposed methodology involves many stages, starting with the establishment of the membership functions for the linguistic terms describing the seven parameters, followed by the risk calculation and aggregations. The aim of the thesis is an assessment of the MODU's risk posed through its BEs and HGs by applying principles of QRA; and also the core of the risk assessment is an evaluation of the MODU's risk with the association of failure probabilities of BEs at the lowest level by means of consideration of the HGs' contribution to the failure of the MODU. Such assessment is required to combine methods of Fuzzy-AHP for calculation of risk contribution factors and Fuzzy FMECA for estimation of basic event risk factors. To achieve that, the proposed method would allow a combination of two sources of information: i) Fuzzy linguistic input typically used for quantifying BE failure and ii) The weight input from the magnitude of the relevant importance of an HG to its belongings in a risk tree from the viewpoint of its capacity to contribute to the failure of the MODU.

Thus, the proposed method, which is based on Fuzzy-AHP and Fuzzy FMECA, has the advantage of an application of different sources of information including expert knowledge. The overall elements of the generic risk model are illustrated in Figure 4.1 and show the different types of input data. Obviously, as such an approach has not been developed in the field of risk assessment of MODUs until now, this thesis could help an operator to carry out MODU risk assessment in a realistic and methodological way. The following steps are used in the proposed risk assessment.The first step of the proposed framework is to obtain the risk factors of each BE by using FST. This step includes a few sub-steps for the application of Fuzzy risk assessment, which are explained in the following sections. The magnitude of a risk can usually be assessed by considering three fundamental risk parameters: Probability of occurrence (P_O), Consequence severity (C_S) and Detection of vulnerability (D_V). P_O defines the number of times an event occurs over a specified period. Risk can be obtained by Equation (4.1), where the risk is associated with each basic event in the MODU's system. R_f represents the likelihood of the hazard and $\otimes$ denotes the multiplication relationship between likelihood, severity and vulnerability. This calculation can be performed by using Fuzzy operation rules.

$$R_f = P_O \otimes S_C \otimes D_V \tag{4.1}$$

The second step is to calculate weight factors for each HG in the framework. Since the study incorporates FST into an AHP method, a set of linguistic priority terms along with the membership functions describing the relationship between elements in each hierarchy of the AHP is adopted. Thus, the pair-wise comparisons between the elements in each hierarchy using FST are established. The Fuzzy expressions are subsequently converted into a single crisp value using an appropriate defuzzification method. The third step is the aggregation and calculation of risk level. The magnitude of a risk can usually be assessed by considering the BE factors and their contribution's weight factor calculation so as to obtain the relative importance of the elements. By repeating the steps above, the risk of each element in the hierarchy is acquired based on the normalised weight factors calculated. Risk assessment can be carried out for each sub-system for the MODU's operation system.To have a manageable risk model, a limited number of generic operation basic hazard events are defined, covering operational risk, which may directly cause an event or introduce latent failures into the system which may cause an event at a later point in time. In this approach, a four-level hierarchy (i.e. Level 0 to Level 3) is developed. The highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU's risk. Fuzzy-AHP is used at the higher levels to synthesise the weight factors that will help to prioritize the MODU's risk. The Fuzzy inference system is applied at the lower levels of the hierarchy to infer the BE parameters. Subsequently, the scores representing the extent of risk are calculated. The methodology consists of many stages, providing an illustrative view of a generic risk assessment framework proposed for the purpose of this research upon which the methodology will be directed. An application of the proposed approach is demonstrated through a case study for the risk assessment of a Jack-up drilling rig (JDR) in Section 4.4.

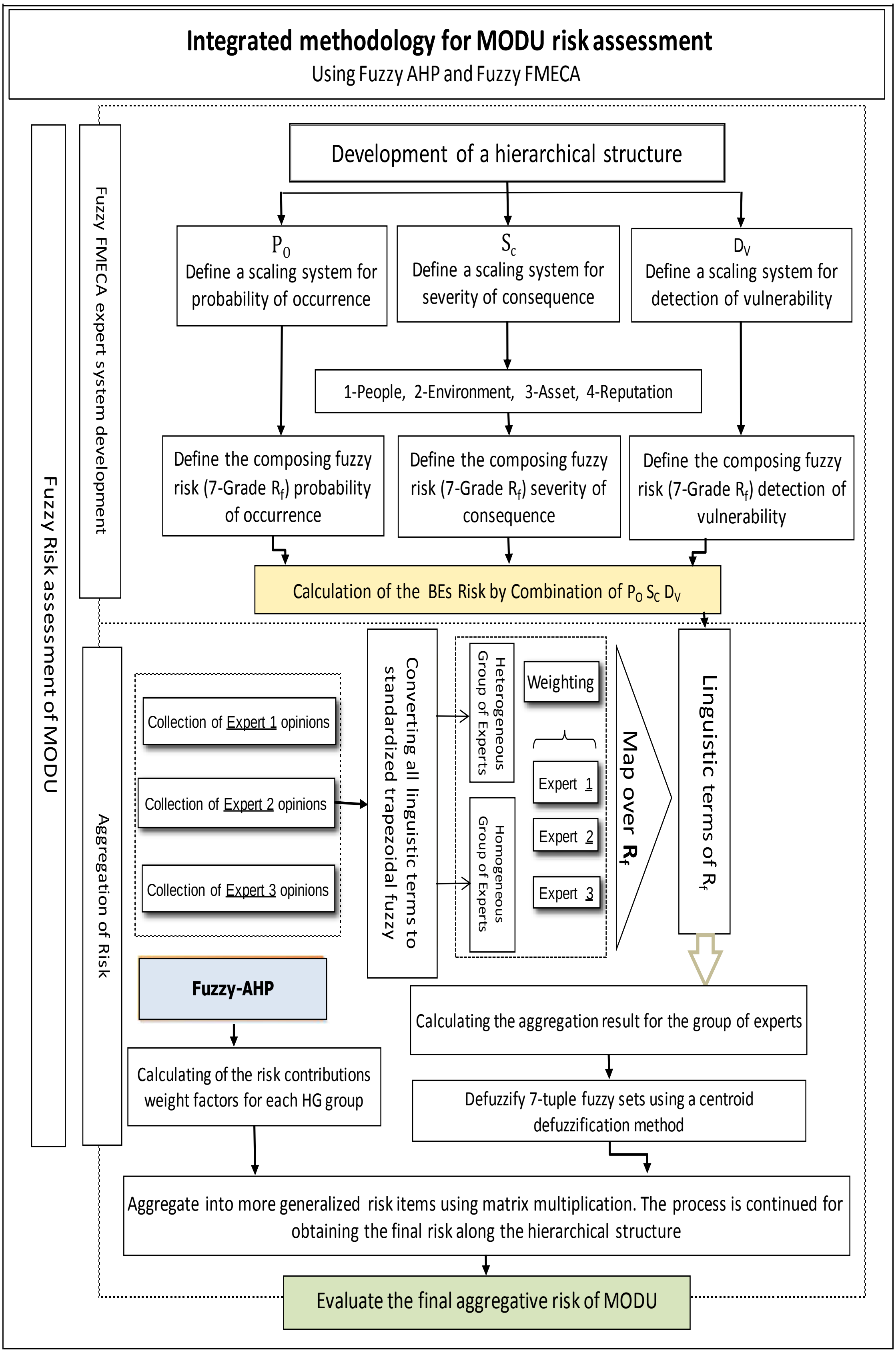


Figure 4.1: Illustration of a generic risk methodology for the MODU's risk assessment, which involves several stages, starting with the setting up of the membership functions, followed by the risk calculation and aggregations.

4.3.1 Fuzzy failure modes, effects and criticality analysis (FMECA)

When assessing a risk level of a specific failure mode, the risk priority number (RPN) method uses linguistic priority terms to evaluate the elements of P_O, S_C and D_V on a numeric scale from 0 to 1. By multiplying the values for these factors, a RPN is obtained. Failure modes with a higher RPN are deemed to be more risky and give a higher priority than those having a lower RPN. There are some shortcomings raised when applying the RPN calculation method, and also traditional approaches lack adequate data concerning the relative frequencies for causes and effects of hazardous events. Some criticisms have been raised with regard to the application of the RPN method (Deng, 1989) as follows:

i. In situations where various sets of $P_{O,}$ S_C and D_V produce an identical value of RPN, the risk implication may be totally different.

ii. There is no precise algebraic rule to assign a score to the possible failure occurrence rate and detection rate. The reason for that is that the relationship between detection rate and its corresponding score is linear, whereas the failure rate and its score do not follow a linear relationship.

iii. The RPN value does not consider the relative importance between $P_{O,}$ S_C and D_V.

FMECA under a Fuzzy environment can be regarded as another solution to prevail over the limitation of the traditional approach. In a Fuzzy FMECA, linguistic variables such as $P_{O,}$ S_C and D_V can be represented as Fuzzy membership functions and described using linguistic priority terms associated with corresponding membership values. In the course of using FST, it is possible to manage the fuzziness involved in the phrase of the occurrence of a basic event or a consequence. Moreover, the state of each basic event or consequence can be explained in a simpler way.

4.3.2 Fuzzy analytical hierarchical process

Since the criteria for the evaluation of the HGs have diverse significance and meanings, we cannot assume that each HG is of equal importance and weight in terms of its capacity to contribute to the failure of the MODU. Therefore, we need to consider the contributory factors of each HG to the failure of the MODU. Four evaluation criteria are considered (i.e. 1- People, 2- Environment, 3- Asset and 4- Reputation) for the hierarchical structure that is used in this chapter. There are many methods that can be employed to determine such weights such as the eigenvector method, weighted least-square method, entropy method, AHP and linear programming technique for multidimensional analysis of preference. The selection of the method depends on the nature of the problems. To evaluate the HGs is a complex and wide-ranging problem, requiring the most inclusive and flexible method. The AHP developed by Saaty (1980 and 1996) is a very useful analysis tool in dealing with multiple criteria decision problems and has been successfully applied to many construction industry decision areas (Cheong and Lan-Hui, 2004). Saaty (2001) also suggested the use of AHP to solve the problem of independence of alternatives or criteria and the use of analytic network process (ANP) to solve the problem of dependence among alternatives or criteria AHP is a popular technique, which is often used to model subjective decision-making processes based on multiple attributes. AHP is widely used in both individual and group decision-making environments (Bolloju, 2001).

Traditional methods of AHP cannot be used when improbability in data of problems is observed. As mentioned, in order to address such uncertainties and as an alternative method, Zadeh (1965) introduced the FST, which was based on the rationality of uncertain due to imprecision or vagueness of data available. A major contribution of FST is its capability to represent uncertainty knowledge. Because of the fact that the world around us is actually full of ambiguities and is of a Fuzzy nature, several researchers have combined Fuzzy theory with AHP. Van Laarhoven & Pedrycz (1983) proposed the first method of implementing Fuzzy-AHP, in which triangular Fuzzy numbers were compared according to their membership functions. Buckley (1985) extended Saaty's AHP to the case where the evaluators are allowed to employ Fuzzy ratios in place of exact ratios to handle the difficulty of assigning exact ratios when comparing two criteria and deriving the Fuzzy weights of criteria by the geometric method. Furthermore, the relative importance derived from these pair-wise comparisons allows a certain degree of inconsistency within a domain. Saaty used the principal eigenvector of the pair-wise comparison matrix derived from the scaling ratio to determine the comparative weight among the criteria (Chiu *et al.*, 2006). Therefore, Fuzzy-AHP is used for the proposed methodology to determine the relative contribution's weight factors of each HG, sub-system and BE of the MODU and also will be implemented on JDR risk assessment as a case study in order to illustrate the applications of the proposed methods. The required steps for application of Fuzzy-AHP in evaluating risk factors will be described in the following sections.

4.3.2.1 Establishing a hierarchical structure

The purpose of this section is to establish a hierarchical structure for aggregative risk assessment for the MODUs. The contents include building a hierarchical structure and determining the evaluation of risk contribution factors at different levels. Pursuant to the reviewed cycle of potential hazards and consequence mechanisms and also based upon literature and expert opinions, the contributory factors of each HG in view of its capacity to contribute to the failure of the MODUs are identified and ranked with the Fuzzy-AHP method. The result from this analysis shows that the drilling failure (L1D-O1-01) is a critical item within identified HGs, as shown in Figure 4.2, and it is selected for assessment.

Developing the hierarchical model includes the decomposition of the complex decision problem into smaller, manageable elements of different hierarchical levels as necessary. To have a manageable risk model, a four-level hierarchy is developed and is illustrated in Figure 4.2. The highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU’s risk, and the last layer corresponds to the evaluation of BEs. The Fuzzy inference system is applied at the lowest level of the hierarchy to infer the major risk parameters. These judgements will be carried out in the form of the pre-defined linguistics variables which will be explained in Section 4.3.3.3. Fuzzy-AHP is used at the higher levels to synthesise the contributory weight factors that will help to prioritise the MODU’s hazards.

The risk factors will be ranked directly as per their numerical priorities in order to show their significance. By use of the experts’ judgements and pair-wise comparison matrices the local weights of the risk factors at different levels will be determined (e.g.. in Level 1: WD1, WT1, WS1, WM1, WF1 and WC1). The global weights for Level 0 risk

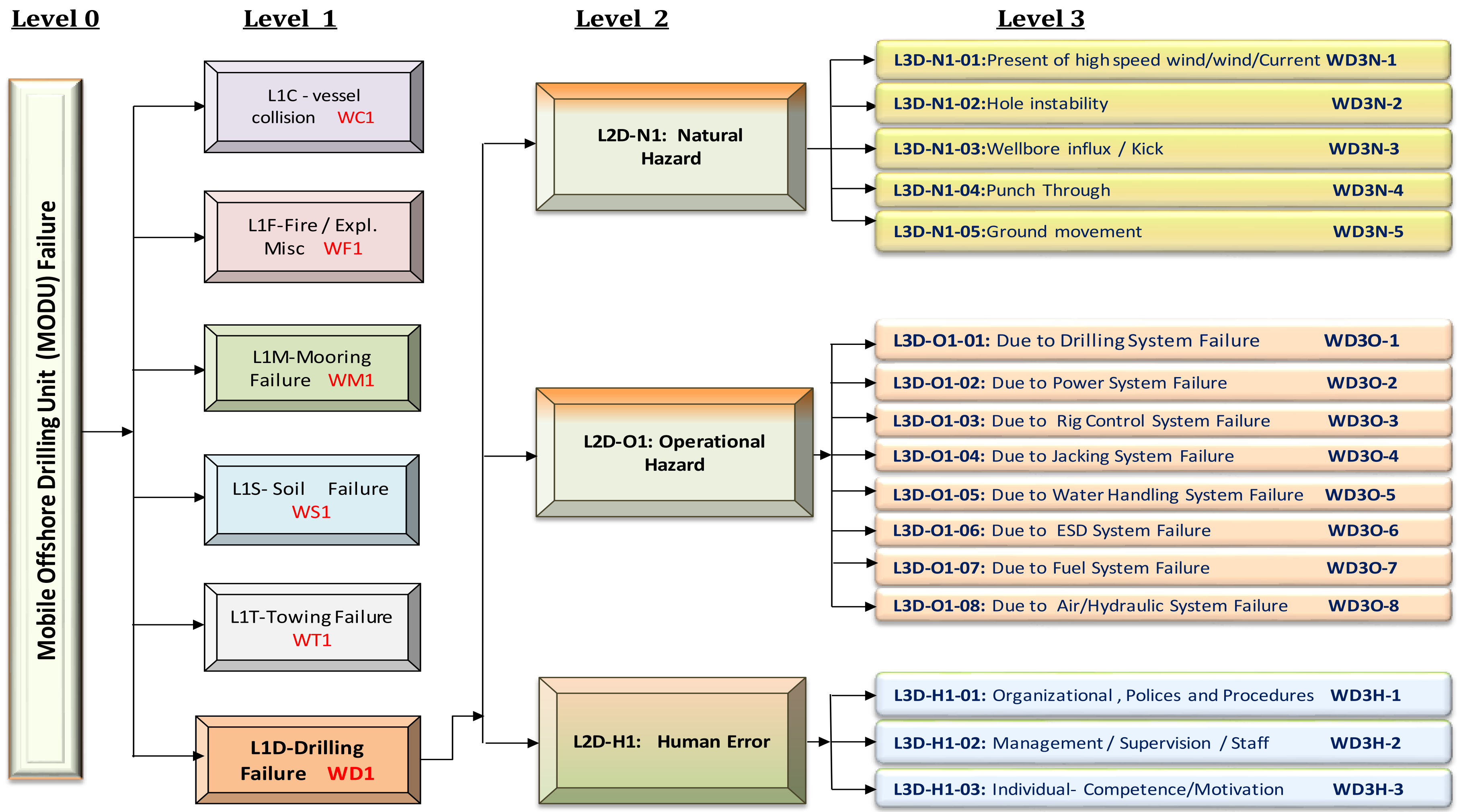


Figure 4.2: Hazard identification and MODU's operational hierarchy model; the highest level of the hierarchy corresponds to the goal prioritisation of significance of the MODU's hazards, and the last layer (level 3) corresponds to the evaluation of BEs.

factors will be calculated directly by multiplying each local contribution's weight factors at each level to its risk factors. After this calculation, the scores representing the degree of the risk for each event. The hierarchy is structured in such a way that the prioritisation of significance of the MODU's risk is the main goal and is placed on the top of the hierarchy, labelled main goal.

4.3.2.2 Establishing pair-wise comparison matrices

The procedure for determining the contributory weights factors by Fuzzy-AHP can be summarised as follows:

Step 1: Construct pair-wise comparison matrices among all the HGs in the dimensions of the hierarchy system. Assign linguistic terms to the pair-wise comparisons by asking which is the more important of each pair of HGs in terms of their capacity to contribute to the failure of the MODU. In AHP, multiple pair-wise comparisons are based on a standardised comparison scale of nine levels, as illustrated in Table 4.1 (Chen *et al.*, 2009; Yeh & Chang, 2009). Let C = [Cj / j = 1, 2 . . . n] be the set of criteria. The result of the pair-wise comparison on n criteria can be summarised in an (n $\times$ n) evaluation matrix, **A**, in which every element a_{ij} (i, j = 1,2, . . . ,n) is the measure of weights of the criteria, as shown below:

Table 4.1: Nine-point intensity of importance scale and its definition

Definition	Intensity of Importance
Equally important	1
Moderately more important	3
Strongly more important	5
Very Strongly more important	7
Extremely more important	9
Intermediate values	2,4,6,8

$$A = \begin{bmatrix} a_{11} \ldots a_{1j} \cdots & a_{1n} \\ \vdots & \vdots \ddots \quad .. \\ a_{i1} \ldots a_{ij} \cdots & a_{in} \\ \vdots & \vdots \ddots \\ a_{n1} \ldots a_{n2} \cdots & a_{nn} \end{bmatrix} \quad \underset{i=j}{a_{ii}} = 1, \underset{i \neq j}{a_{ji}} = 1/a_{ij}, a_{ij} \neq 0, i = 1,2,\ldots,n; \; j = 1,2,\ldots,n \qquad (4.2)$$

The mathematical procedure begins to normalise and discover the relative weights for each matrix. The relative weights are identified by the eigenvector (***W***) corresponding to the maximum of Eigen value ($\lambda_{\max}$), which is essentially the underlying standard scale for the ranking of each element in the ratio matrix. Hence, determining the rankings for a set of elements essentially comes down to solving the eigenvector problem (Dag et al, 2009).

$$\mathbf{A}\boldsymbol{W} = \lambda_{\max} \boldsymbol{W} \qquad (4.3)$$

If the pair-wise comparisons are completely consistent, the matrix **A** has rank 1 and $\lambda_{\max}$ = n. In this case, weights can be achieved by normalising any of the rows or columns of matrix **A** (Wang & Yang, 2007).

The concept of pair-wise comparison for solving AHP is given below:

$$\boldsymbol{W} = \begin{array}{c} \\ w_1 \\ \vdots \\ w_i \\ \vdots \\ w_n \end{array} \begin{array}{c} \begin{array}{ccccc} w_1 & \cdots & w_j & \cdots & w_n \end{array} \\ \begin{bmatrix} w_1/w_1 & \cdots & w_1/w_j & \cdots & w_1/w_n \\ \vdots & & \vdots & & \vdots \\ w_i/w_1 & \cdots & w_i/w_j & \cdots & w_i/w_n \\ \vdots & & \vdots & & \vdots \\ w_n/w_1 & \cdots & w_n/w_j & \cdots & w_n/w_n \end{bmatrix} \end{array} \begin{bmatrix} w_1 \\ \vdots \\ w_j \\ \vdots \\ w_n \end{bmatrix} = n \begin{bmatrix} w_1 \\ \vdots \\ w_i \\ \vdots \\ w_n \end{bmatrix} \qquad (4.4)$$

$$\boldsymbol{Ww} = n\boldsymbol{w} \Rightarrow (\boldsymbol{W} - n\boldsymbol{I})\boldsymbol{w} = \mathbf{0} \quad \text{and} \quad \boldsymbol{w} = (w_1, w_2, \ldots, w_n) \qquad (4.5)$$

In real circumstances, w_i / w_j is unknown, but $a_{ij} \cong w_i / w_j$ and $a_{ij} = 1/a_{ji}$ (positive reciprocal) and as per Equation (4.2):

i. $$\boldsymbol{Aw} \cong n\boldsymbol{w} \Rightarrow (\boldsymbol{A} - \lambda_{\max}\boldsymbol{I})\boldsymbol{w} = \boldsymbol{0} \tag{4.6}$$

find $\lambda_{\max}$ and find $\boldsymbol{w}$ with $\lambda_{\max}$, and the C.I. can be calculated by Equation (4.7),

$$C.I. = (\lambda_{\max} - n)/(n-1) \tag{4.7}$$

ii. $$\min \sum_{i=1}^{n}\sum_{j=1}^{n}\left(a_{ij} - \frac{w_i}{w_j}\right)^2 \quad \text{and} \quad \sum_{i=1}^{n} w_i = 1 \tag{4.8}$$

iii. $$w_i = r_i \Big/ \sum_{i=1}^{n} r_i \text{ and the value of } r_i \text{ obtained by } r_i = \left(\prod_{j=1}^{n} a_{ij}\right)^{1/n} \tag{4.9}$$

iv. When $\boldsymbol{Aw} = \lambda_{\max}\boldsymbol{w}$, then $\lambda_{\max}$ can be estimated by $$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(\boldsymbol{Aw})_i}{w_i} \tag{4.10}$$

The concept of pair-wise comparison for solving Fuzzy-AHP is given below:

I. Fuzzy $\tilde{\boldsymbol{A}} = [\tilde{a}_{ij}]_{n\times n}$ $\rightarrow$ Fuzzy $\tilde{\boldsymbol{w}} = (\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n)$ (4.11)

a) $\tilde{\boldsymbol{A}} \rightarrow$ solve $\tilde{\lambda}_{\max}$ $\rightarrow$ solve $\tilde{w}_i$, i.e. $(\tilde{\boldsymbol{A}} - \tilde{\lambda}_{\max}\boldsymbol{I})\tilde{\boldsymbol{w}} = \boldsymbol{0}$ (4.12)

b) $\tilde{r}_i = [\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \cdots \otimes \tilde{a}_{in}]^{1/n} \Rightarrow \tilde{w}_i = \tilde{r}_i \otimes [\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n]^{-1}$ (4.13)

Inverse operation of triangular Fuzzy number: $(a,b,c)^{-1} = (1/c, 1/b, 1/a)$ (4.14)

II. Fuzzy $\tilde{\boldsymbol{A}} = [\tilde{a}_{ij}]_{n\times n}$ $\rightarrow$ *Crisp* $\boldsymbol{w} = (w_1, w_2, ..., w_n)$ (4.15)

c) $\tilde{\boldsymbol{A}} = [\tilde{a}_{ij}]_{n\times n}$, $\tilde{a}_{ij} \cong \frac{w_i}{w_j}$, $l_{ij} \lesssim \frac{w_i}{w_j} \lesssim u_{ij}$, $i = 1, 2, ..., n-1;\ j = 1, 2, ..., n;\ i < j$ (4.16) where l_{ij} and u_{ij} are the lower level and upper level of the Fuzzy number respectively and for a triangular Fuzzy number, $\tilde{w}_j = (l_j, m_j, u_j)$, and $l_{ij}(\alpha) \tilde{\le} \frac{w_i}{w_j} \tilde{\le} u_{ij}(\alpha)$ in level α, then Fuzzy constraints:

$$\begin{aligned} w_i - w_j u_{ij}(\alpha) &\tilde{\le} 0 \\ -w_i + w_j l_{ij}(\alpha) &\tilde{\le} 0 \end{aligned} \tag{4.17}$$

$$\sum_{i=1}^{n} w_i = 1,\ w_i > 0,\ \ i = 1, 2, \ldots, n \tag{4.18}$$

[**II.** $Crisp\ \ \boldsymbol{A} = [a_{ij}]_{n \times n}$ (4.19)

$$\tilde{\boldsymbol{w}} = (\tilde{w}_1, \ldots, \tilde{w}_j, \ldots, \tilde{w}_n); \tag{4.20}$$

4.3.2.3 Defuzzification and Fuzzy weight calculation

The defuzzification process is capable of creating a single crisp value based on the Fuzzy conclusion set describing the priority level. The defuzzification process is the last step of the Fuzzy inference algorithm where the aggregated Fuzzy output is converted into a crisp number. In other words, defuzzification is a technique to translate the Fuzzy number into a crisp real number, or defuzzification is defined as a function mapping a Fuzzy set to a certain crisp number. The procedure of defuzzification is to locate the best non Fuzzy performance value. There are many defuzzification methods that convert the Fuzzy consequents into crisp values (i.e. weighted by the degree of truth at which the membership functions reach their maximum values (Pillay & Wang, 2002), the algorithm that averages the points of maximum possibility of each priority level and α-cut Method). This research employs the Center-of-Area method due to its simplicity of calling for the analyst's personal judgement and providing sensible results (Abdolvand *et al.*, 2008). The method to calculate the crisp number for a Triangular Fuzzy Number (TFN) is to calculate the centre of the Fuzzy number's triangular area, shown in Figure 4.3 (Mikhailov, 2004 & Karahalios, 2009). The defuzzified value of a Fuzzy number can be obtained from Equation (4.21).

$$TFN = (l, m, u)$$
$$BNP = [(u-l)+(m-l)]/3+l \tag{4.21}$$

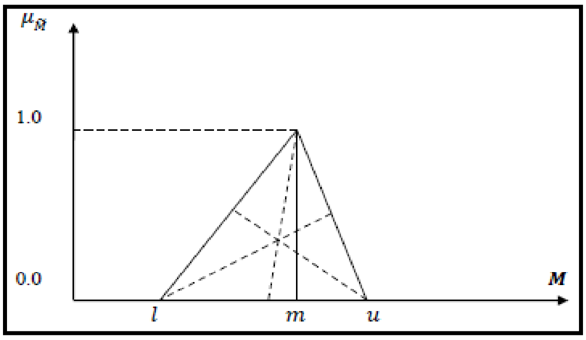


Figure 4.3: Defuzzification of a triangular Fuzzy number

4.3.2.4 Hierarchy consistency ratio checking

Calculating a consistency ratio is the next stage of the AHP process in order to measure how consistent the judgements have been, where the Consistency Index is CI, the Consistency Ratio is CR, λ_{max} is the largest eigenvalue of the pair-wise comparison matrix, n is the matrix order and Random index is RI. Table 4.2 shows a set of recommended RI values presented by Saaty (2005).

Table 4.2: Random index (RI)

N	2	3	4	5	6	7	8	9	10
RI	0	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

When CR values are larger than 0.10 for a matrix larger than 4×4, it indicates an inconsistent judgement. Decision-makers should revise the original values in the pair-wise comparison matrix.

4.3.2.5 Risk aggregation and risk ranking

In order to convert the linguistic expressions into Fuzzy numbers and aggregate the experts' opinions, there are various methods to aggregate Fuzzy numbers. In the process of a ranking, every measure under consideration is ranked in the direction of the decision-makers' preference. To produce principle values for each HG, each factor was weighted according to the estimated contribution to and significance for the MODU's operation system failure. Clemen & Winkler (1999) elucidated that, due to different opinions regarding the possibility of the BEs, it is essential to combine or aggregate the opinions into a single one; Figure 4.4 illustrates the basic building blocks of the proposed hierarchical structural model for the risk aggregation. Each basic event is partitioned into its contributory factors, which are the result of Fuzzy-AHP and each of those can be further partitioned into upper-level contributory factors.

A coding system is considered consisting of the BE factors, i.e. $R_{f(L3,N1)}$ to $R_{f(L3,N3)}$, for the Natural Hazard BEs and their contributory factors WD3N-1 to WD3N-5, $R_{f(L3,O1)}$ to $R_{f(L3,O8)}$ for the Operational BEs and their contributory factors WD3O-1 to WD3O-8, and $R_{f(L3,H1)}$ to $R_{f(L3,H3)}$ for the Human BEs and their contributory factors WD3H-1 to WD3H-3. As was explained, a risk unit without contributory factors is called a BE.

The evaluation of aggregative risk of the MODUs is carried out using a three-step procedure, as shown in Figure 4.4. As illustrated in Table 4.3, the BE factors is described by seven linguistic variables (i.e. L_{f1}, L_{f2}, L_{f3}, L_{f4}, L_{f5}, L_{f6}, and L_{f7}). These linguistic variables were defined as Very Low, Low, Mol. Low, Medium Low, Mol. High, High, and Very High, respectively (Chen & Hwang, 1992).

Table 4.3: Logistics variable where the BEs are described by seven linguistic variables

Grade	linguistic variables	Membership function			
		a	b	c	d
L_{f1}	*Very Low*	0.0	0.0	0.1	0.2
	u(x)	0.0	1.0	1.0	0.0
L_{f2}	Low		0.1	0.2	0.3
	u(x)		0.0	1.0	0.0
L_{f3}	Mol. Low	0.2	0.3	0.4	0.5
	u(x)	0.0	1.0	1.0	0.0
L_{f4}	Medium		0.4	0.5	0.6
	u(x)		0.0	1.0	0.0
L_{f5}	Mol. High	0.5	0.6	0.7	0.8
	u(x)	0.0	1.0	1.0	0.0
L_{f6}	High		0.7	0.8	0.9
	u(x)		0.0	1.0	0.0
L_{f7}	Very High	0.8	0.9	1.0	1.0
	u(x)	0.0	1.0	1.0	0.0

(Chen and Hwang, 1992)

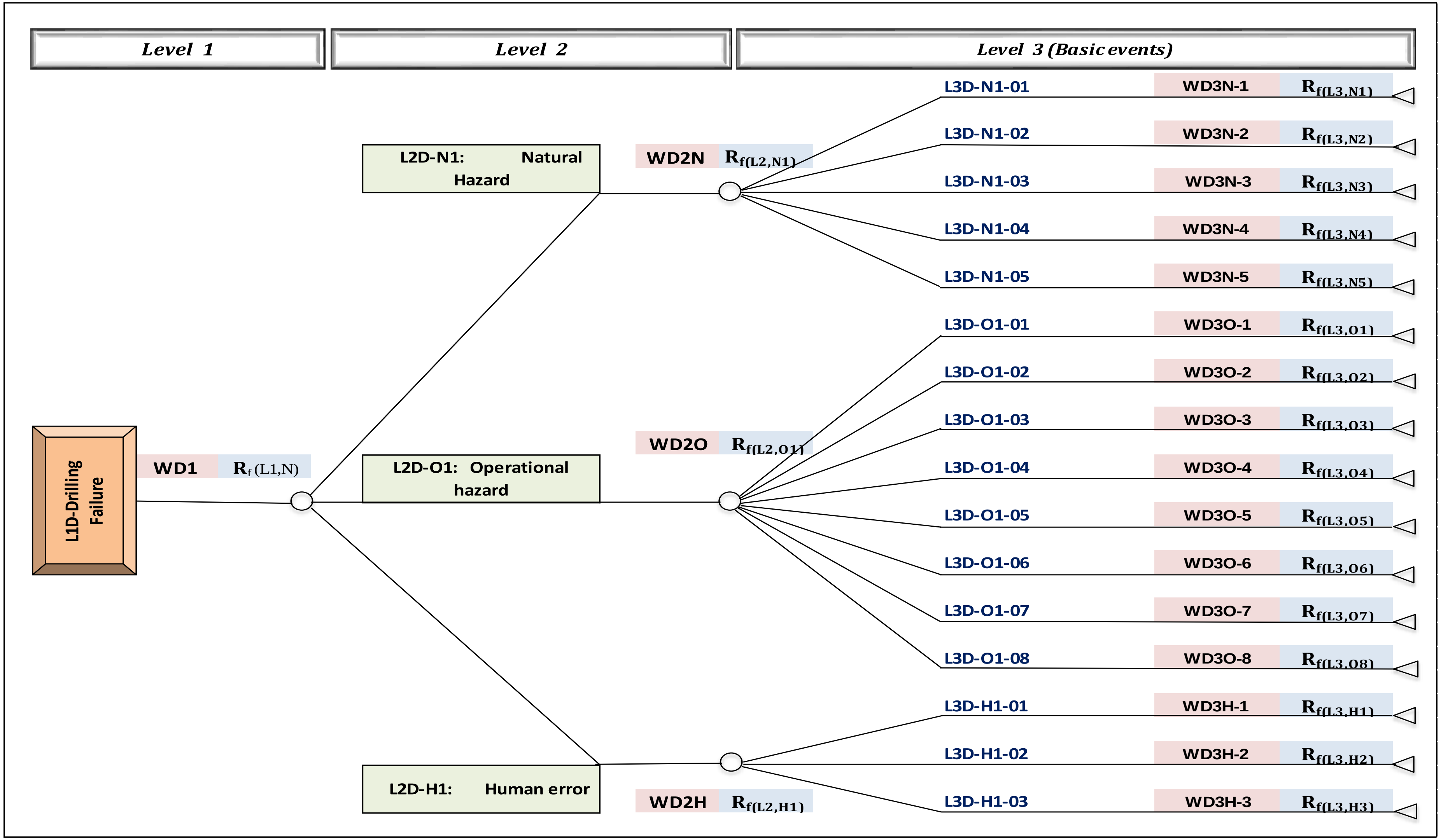


Figure 4.4: A three-stage structural model for risk aggregation

These linguistic variables were then defined by Trapezoidal Fuzzy Numbers (TPFNs) with membership functions shown in Table 4.3. The assessment matrix for risk items of attribute in Level-2 can be established for R_f (L2, N1), Rf (L2, O1) and R_f (L2, H1) individually. As shown in the Risk Aggregation Matrix in Table 4.4, for the R_f (L2, H1), the BEs involved are R_f (L3, H1), R_f (L3, H2) and R_f (L3, H3) while the corresponding contributory weight factors of risk are WD3H-1, WD3H-2 and WD3H-3 respectively.

Table 4.4**:** Risk aggregation matrix

Level 1			***Level 2***			***Level 3 (Basic events)***		
Attribute Level 2	Contribution Weight Factor	Risk Factor	Attribute Level 2	Contribution Weight Factor	Risk Factor	Basic Event	Contribution Weight Factor	Basic Events Risk Factor
						L3D-N1-01	WD3N-1	R_f(L3,N1)
						L3D-N1-02	WD3N-2	R_f (L3,N2)
			L2D-N1	WD2N	R_f (L2,N1)	L3D-N1-03	WD3N-3	R_f (L3,N3)
						L3D-N1-04	WD3N-4	R_f (L3,N4)
						L3D-N1-05	WD3N-5	R_f (L3,N5)
						L3D-O1-01	WD3O-1	R_f (L3,O1)
						L3D-O1-02	WD3O-2	R_f (L3,O2)
						L3D-O1-03	WD3O-3	R_f (L3,O3)
L1D-D	WD1N	R_f (L1,N)	L2D-O1	WD2O	R_f (L2,O1)	L3D-O1-04	WD3O-4	R_f (L3,O4)
						L3D-O1-05	WD3O-5	R_f (L3,O5)
						L3D-O1-06	WD3O-6	R_f (L3,O6)
						L3D-O1-07	WD3O-7	R_f (L3,O7)
						L3D-O1-08	WD3O-8	R_f (L3,O8)
						L3D-H1-01	WD3H-1	R_f (L3,H1)
			L2D-H1	WD2H	R_f (L2,H1)	L3D-H1-01	WD3H-2	R_f (L3,H2)
						L3D-H1-01	WD3H-3	R_f (L3,H3)

4.3.3 Assessment of Fuzzy model

The probability of detecting a failure in advance is not a crisp event and uncertainty is associated with it. When performing FMECA, it may be difficult or even impossible to precisely determine the probability of failure events. Much information about FMECA is expressed linguistically, such as ‘likely’, ‘important’ or ‘very high’. This uncertainty can be better handled with FL using an appropriate membership function to arrive at an estimated appropriate possibility level. It is always difficult to evaluate these linguistic variables objectively and also risk is not absolutely objective in nature, but rather relative and subjective. It is usually a Fuzzy concept in the sense that there is not any unique risk associated with a hazardous event occurring in a given period (Karwowski & Mital, 1986). Therefore, risk assessment deals with quantities which are inherently imprecise and whose future values are uncertain. Linguistic categories or levels (e.g., very high, high, medium, low, very low), instead of absolute numbers, are adopted because each linguistic category or level can deal up to certain extend with the various and uncertain risk values by including a range or set of numbers.

Figure 4.5 shows an overall view of the proposed Fuzzy FMECA assessment system, in which there are three major steps to carry out the assessment, namely fuzzification, rule evaluation, and defuzzification. The system firstly uses linguistic variables to describe the severity, frequency of occurrence, and detectability of the failure. These inputs are then 'fuzzified' to determine the degree of membership in each input class. The resulting 'Fuzzy inputs' are evaluated using a linguistic rule base and FL operations to yield a classification of the riskiness of the failure mode and an associated degree of membership in the risk class. This 'Fuzzy output' is then 'defuzzified' to give the prioritisation level for the failure mode.

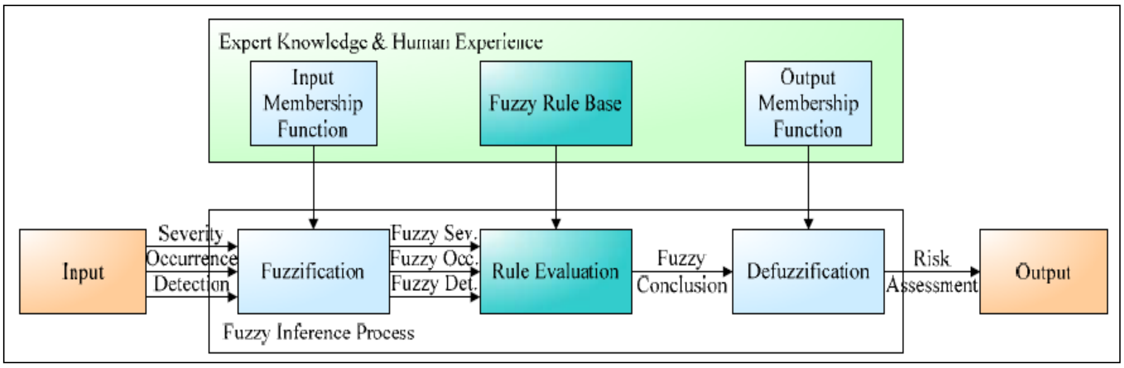


Figure 4.5: Structure of FMECA based on Fuzzy theory.
Source: Ruey (2010)

4.3.3.1 Fuzzy membership functions

The membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. However, the determination of a membership function is difficult and complicated. Any shape of a membership function is possible, but the selected shape should be justified by the available information. Ross

(2004) discussed several methods of determining membership functions. It is also believed that in some cases the expressions of membership functions are not the dominant factors in engineering applications (Klir & Yuan, 1995).

A Fuzzy number is a Fuzzy subset of a real number and it represents an expansion of the confidence interval. According to Dubois and Prade's (1978) definition, a Fuzzy number means a Fuzzy set and its membership function. FST has developed as an alternative to ordinary (crisp) set theory and is used to describe Fuzzy sets and that membership in a Fuzzy set is a matter of degree (Friedlob & Schleifer, 1999).

Let X denote a universal set. Then a Fuzzy subset of X is defined by its membership function: $\mu_{\tilde{A}} : x \rightarrow (0,1)$ which is assigned to each element $x \in X$ a real number $\mu_{\tilde{A}}(x)$ in the interval (0, 1), where the value, of $\mu_{\tilde{A}}(x)$ at x represents the grade of membership of x in $\tilde{A}$. Thus, the nearer the value of $\mu_{\tilde{A}}(x)$ is to unity, the higher the grade of membership of x in $\tilde{A}$ (Sakawa, 2002).

A Triangular Fuzzy Number (TFN) is a special type of Fuzzy number with three parameters, each representing the linguistic variable associated with a degree of membership of 0 or 1. Since it is shown to be very convenient and easily implemented in arithmetic operations, the TFN is also commonly used in practice (Liou & Chen, 2006). A TFN $\tilde{A}$ is defined by a triplet (a, b, c). The membership function $\mu_{\tilde{A}}(x)$ of x is given by (Chamodrakas *et al.*, 2009):

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a} \; (a \le x \le b) \\ \dfrac{c-x}{c-b} (b \le x \le c) \end{cases} \tag{4.22}$$

Suppose a Trapezoidal Fuzzy Number (TPFN), $\tilde{A}$ is defined by a quadruplet (a, b, c, d). The membership function $\mu_{\tilde{A}}(x)$ of x is as below:

$$\mu_{\tilde{A}}(x)=\begin{cases}0, x \leq a\\ \dfrac{x-a}{b-a},(a \leq x \leq b)\\ 1, x=(b,c)\\ \dfrac{d-x}{d-c}(c \leq x \leq d)\\ 0, x \geq d\end{cases} \tag{4.23}$$

The algebraic operation for the TFN can be displayed as follows (Chiu, 2006; Abdolvand *et al.*, 2008) and the same algorithm is applicable for TPFNs.

Addition ($\oplus$):

$$(l_1,m_1,u_1)\oplus(l_2,m_2,u_2)=(l_1+l_2,m_1+m_2,u_1+u_2) \tag{4.24}$$

Multiplication ($\otimes$):

$$(l_1,m_1,u_1)\oplus(l_2,m_2,u_2)=(l_1+l_2,m_1+m_2,u_1+u_2) \tag{4.25}$$

Any real number of k:

$$k(l,m,u\ )=(kl,km,ku\ ) \tag{4.26}$$

Subtraction (-):

$$(l_1,m_1,u_1)-(l_2,m_2,u_2)=(l_1-l_2,m_1-m_2,u_1-u_2) \tag{4.27}$$

Division (÷):

$$(l_1,m_1,u_1)\div(l_2,m_2,u_2)=(l_1\div l_2,m_1\div m_2,u_1\div u_2) \tag{4.28}$$

4.3.3.2 Linguistic variables

According to Zadeh (1975), it is very challenging for conventional quantification to sensibly express those circumstances that are obviously complex or hard to define; therefore, the perception of a linguistic variable is essential in such situations. A linguistic variable is an adjustable whose values are words or judgements in a natural or artificial language. The concept of a Fuzzy number plays an essential role in formulating quantitative Fuzzy variables. These are variables whose states are Fuzzy numbers. When, in addition, the Fuzzy numbers represent linguistic concepts, such as very small, small, medium, and are understood in a particular environment, the resulting hypotheses are usually called linguistic variables (Klir & Yuan, 1995). Subjective linguistic variables will be further defined in terms of membership functions in order to find out how each point in the input space is plotted to a membership value between 0 and 1 (see Figure 4.6, Figure 4.7 and Figure 4.8) and the simplest are the TFN and TPFN (Li & Liao, 2007). In this chapter, it is preferred to use TPFNs to represent the linguistic variables shown in Table 4.3. In creating use of the FL, the experts were invited to define each membership function and the values using the interpretations of the linguistic terms referred to in Table 4.7 (Pillay & Wang, 2003).

Estimating weights of experts

The weighting of experts is determined according to Table 4.5. If an expert is considered better than others, then he/she is given a larger weight.

Table 4.5: Experts' weighting scores

Group	Constitution / Structure	Classification / Organisation	Score (Variety 1-5)
1	Professional Position / Title **(F1)**	Professor, GM/DGM, Chief Engineer, Director	5
		Senior academic	4.5
		Junior academic	4
		Engineer	3
		Supervisors, Foreman, Graduate apprentice	3.5
		Technician	2
		Operator	2.5
		Worker	1
2	Experience / Service Time (years) **(F2)**	> 30 years	5
		20-30	4
		10-19	3
		5-9	2
		< 5	1
3	Qualification / Education Level **(F3)**	Ph.D./M.Phil.	5
		Master (M.Sc.)	4
		Bachelor (B.Sc.)	3
		HND	2
		H. School level	1

Experts' weights are obtained by estimating weight scores and weight factors of experts. Weight scores and weight factors of experts can be obtained by using Equation (4.29) and Equation (4.30) respectively and the weight of each expert is presented in Table 4.6 (e.g. weight factor for Expert 1 is 0.3)

Weight score of expert i = Score of expert i (F1) + Score of expert i (F2) + Score of expert i (F3)

(4.29)

Weight factor of expert i = (Weight score of expert i)/ ($\sum_{i=1}^{n}$ Weight score of expert i) (4.30)

Table 4.6: Experts' weights estimating by using weight from Equation (4.29) and Equation (4.30)

No.	Classification / Organization	Score	Qualification / Education Level	Score	Experience / Service Time (years)	Score	Total Score	Weight Factor
Expert 1	Engineer	3	Bachelor (B.Sc.)	3	20-30	4	10	**0.30**
Expert 2	Engineer	3	Master (M.Sc.)	4	> 30 years	5	12	**0.36**
Expert 3	Junior academic	4	Master (M.Sc.)	4	10-19	3	11	**0.33**
Total							33	**1**

4.3.3.3 Linguistic risk levels

This research uses linguistic variables to denote the risk events, i.e. P_O, S_C and D_V, of each failure mode. With consideration of some limitations on our ability to treat information, in 1956, Miller published a paper entitled "The magical number seven, plus or minus two" (Miller, 1956). With respect to this, it is often suggested that the number of linguistic terms for judgements should be limited to between five and nine (Karwowski & Mital, 1986). In this research, each linguistic variable has seven descriptive linguistic terms and these linguistic terms can be represented quantitatively by a range of probabilities, as illustrated in Table 4.7. Chen & Hwang (1992) recommended different scales of linguistic terms for expert assessment. Scale 6, which encloses trapezoidal membership functions, is implemented to present mathematically the P_O, S_C and D_V levels of hazards in this research.

After the determination of the linguistic levels for P_O, S_C and D_V, one must determine the appropriate mathematical expressions using membership functions for Fuzzy numbers. In the proposed Fuzzy FMECA approach, several experts are required to develop the membership functions of the three variables. Furthermore, the numbers associated with linguistic risk levels are also considered as an important factor in practical risk assessment by many researchers (Military Standard, 1993; Pillay & Wang, 2003). Experts generally use the linguistic variable to assess the importance of a criterion over another criterion or even to rate the alternatives with respect to different criteria.

Table 4.7: Linguistic definitions of grades for $P_{O,}$ S_C and D_V

Grade	Scaling system for probability of occurrence (P_O)	Scaling system for severity of consequence (S_C)	Scaling system for detection of vulnerability (D_V)	Membership function			
				a	b	c	d
L_{f1}	Very Low	Minore	Very High	0.0	0.0	0.1	0.2
	u(x)	*u(x)*	*u(x)*	0.0	1.0	1.0	0.0
L_{f2}	Low	Very Low	High		0.1	0.2	0.3
	u(x)	*u(x)*	*u(x)*		0.0	1.0	0.0
L_{f3}	Mol. Low	Low	Moderate	0.2	0.3	0.4	0.5
	u(x)	*u(x)*	*u(x)*	0.0	1.0	1.0	0.0
L_{f4}	Medium	Moderate	Low		0.4	0.5	0.6
	u(x)	*u(x)*	*u(x)*		0.0	1.0	0.0
L_{f5}	Mol. High	High	Remote	0.5	0.6	0.7	0.8
	u(x)	*u(x)*	*u(x)*	0.0	1.0	1.0	0.0
L_{f6}	High	Very High	Very remote		0.7	0.8	0.9
	u(x)	*u(x)*	*u(x)*		0.0	1.0	0.0
L_{f7}	Very High	Hazardous without warning	Absolutely impossible	0.8	0.9	1.0	1.0
	u(x)	*u(x)*	*u(x)*	0.0	1.0	1.0	0.0

A Fuzzy number describes the relationship between an uncertain quantity and a membership function, μ, ranging between 0 and 1. Let the P_O of a failure be defined by $TPFN_{PO}$, the S_C of failure by $TPFN_{SC}$ and also D_V by $TPFN_{DV}$. Table 4.7 demonstrates a seven-grade qualitative scaling system for the $P_{O,}$ S_C and D_V and the membership functions. Experts need to select linguistic terms for presenting their opinions by their preference. It is not demanded that all experts must use the same linguistic terms and it is not required for all linguistic terms to be placed symmetrically and to have an outcome. Therefore, experts and decision-makers have more independent right to present their opinions; also, each linguistic term should be treated as a whole and the only concern is about its determinacy and consistency (Ma *et al.*, 2007; Karahalios, 2009). Based on the definition of risk, Equation (4.1) and seven grades for $P_{O,}$ S_C and D_V (Table 4.7), the relative grades of risk are obtained and demonstrated in Figure 4.6, Figure 4.7 and Figure 4.8.

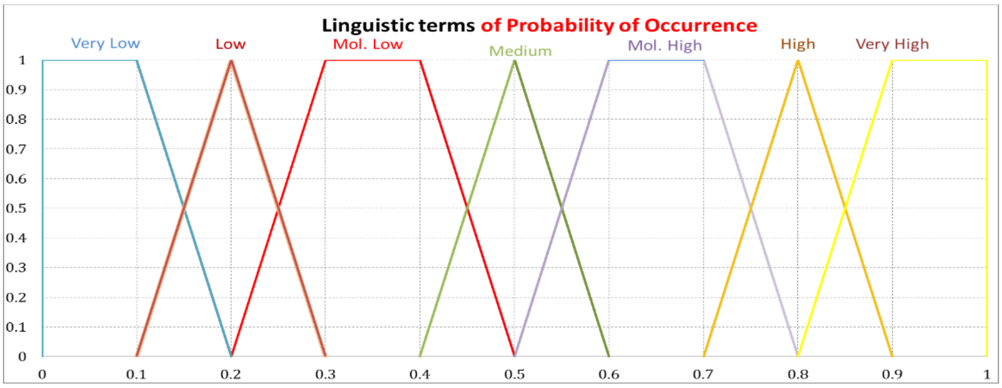


Figure 4.6: Linguistic terms of probability of occurrence (P_O)

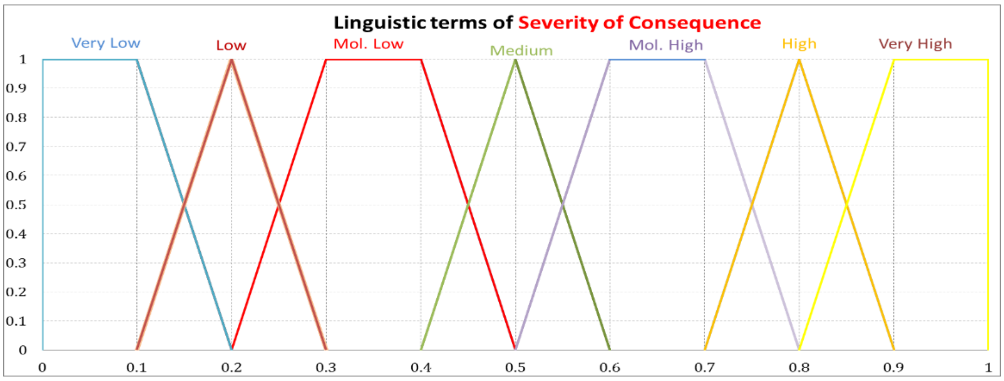


Figure 4.7: Linguistic terms of severity of consequence (S_C)

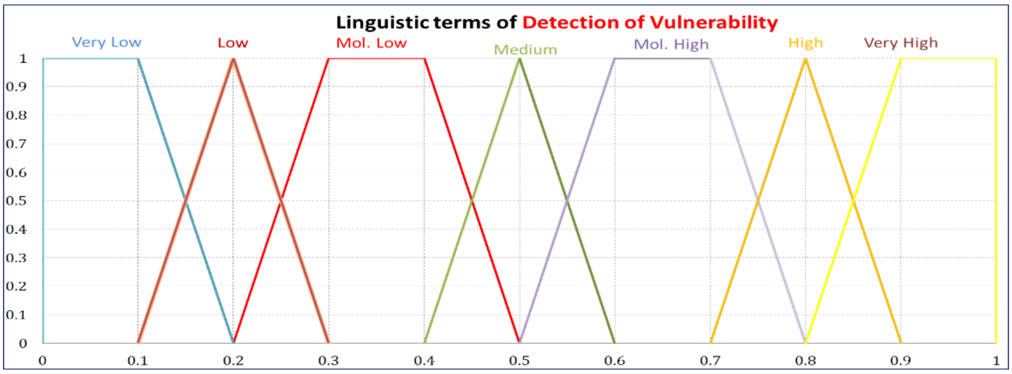


Figure 4.8: Linguistic terms of detection of vulnerability (D_V)

According to the definition in the standard categories of risk level can be determined as shown in the following example: R_f Moderate = P_O Low $\otimes$ S_C Moderate $\otimes$ D_V Remote denotes Fuzzy risk variable and is presented in Figure 4.9 and Table 4.8 shows the qualitative scales for risk and TPFNs.

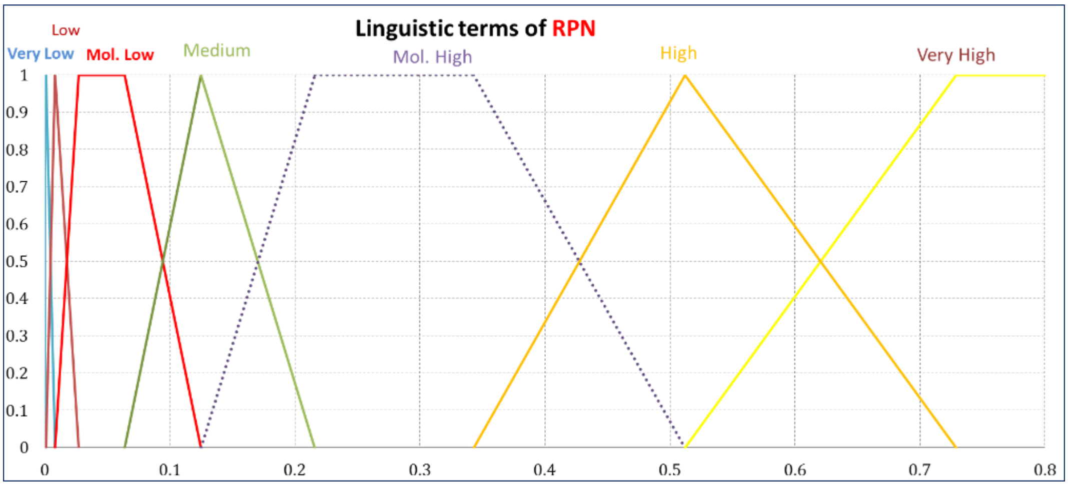


Figure 4.9: Linguistic terms of R_f .

Table 4.8: Qualitative scales for risk and TPFN

NO.	Scaling system for $\mathbf{R_f}$				
1	Very Low	0.000	0.000	0.001	0.008
	U(x)	0.000	1.000	1.000	0.000
2	Low	0.000	0.001	0.008	0.027
	U(x)	0.000	0.000	1.000	0.000
3	Mol. Low	0.008	0.027	0.064	0.125
	U(x)	0.000	1.000	1.000	0.000
4	Medium	0.000	0.064	0.125	0.216
	U(x)		0.000	1.000	0.000
5	Mol. High	0.125	0.216	0.343	0.512
	U(x)	0.000	1.000	1.000	0.000
6	High	0.000	0.343	0.512	0.729
	U(x)		0.000	1.000	0.000
7	Very High	0.512	0.729	1.000	1.000
	U(x)	0.000	1.000	1.000	0.000

4.4 Case study: Fuzzy risk assessment of a JDR

In Section 4.3 of this chapter, a methodology for the MODU's risk assessment is presented and formalised. In this section, the application and how the proposed methodology is implemented and deployed will be discussed. A JDR, one of the most popular types of mobile offshore units, which plays a very important role in the drilling, exploration and production processes in offshore industries, is selected as a case study. MODUs and JDRs also share the common problems of data uncertainty. Therefore, to obtain a general evaluation of the risk level of the JDR, it is necessary to consider the hazards due to operation. It must be noted that the principles used for the HAZID which were presented in Chapter 3 are similar to the ones for the JDR, and the same HG for risk assessment of the JDR is considered. The main step of the research's practical work is that the hierarchy of system components of the JDR is defined and the relevant weight of each of the components has been calculated. As is shown in Figure 4.10, there are many hazards with different natures and categories but in this study only the ones with a high potential failure rate (i.e. Failure due to Drilling) which can directly affect people, the environment, asset and reputation will be examined. That means failure of the JDR will be regarded as an illustrative risk factor for the purpose of this case study. Therefore, the most critical events on the JDR operation can be mitigated in a timely manner before they turn to failure.

4.4.1 Implementation and evaluation of the proposed framework

The general Fuzzy-AHP evaluation method should be an effective approach, because there are many factors that have an effect on the JDR's risk assessment and it is usually very difficult to fully quantify all the factors. However, there is little convincing technical research regarding the use of this method in the JDR's risk assessment. On the basis of investigation and consulting relevant documentations and experts, the HAZID index is established. The data collection process consists of two stages, which are required to develop the Fuzzy expert judgement system, as well as collecting information required for model building and data for the case study of a JDR system. The case study is gathered and analysed to prove the concept of the developed model. An expert panel can determine the grade and importance of risk for each risk item. Expert judgement was used to develop a qualitative scale for both contributory factors and risk factors for BEs. With this qualitative scale, the aggregative JDR risk can then be determined from the hierarchical structural model shown in Figure 4.10.

The JDR's HG consists of six categories, i.e. L1S- Soil Failure, L1D-Drilling Failure, L1T-Towing Failure, L1M-Mooring Failure, L1V - Vessel Collision, L1F-Fire / Explosion Misc. Each category also contains many single performance indexes; for example, L1D-Drilling Failure contains Natural Hazard risk (L1D-N1), Operational Failure risk (L1D-O1) and Failure due to Human risk (L1D-H1).

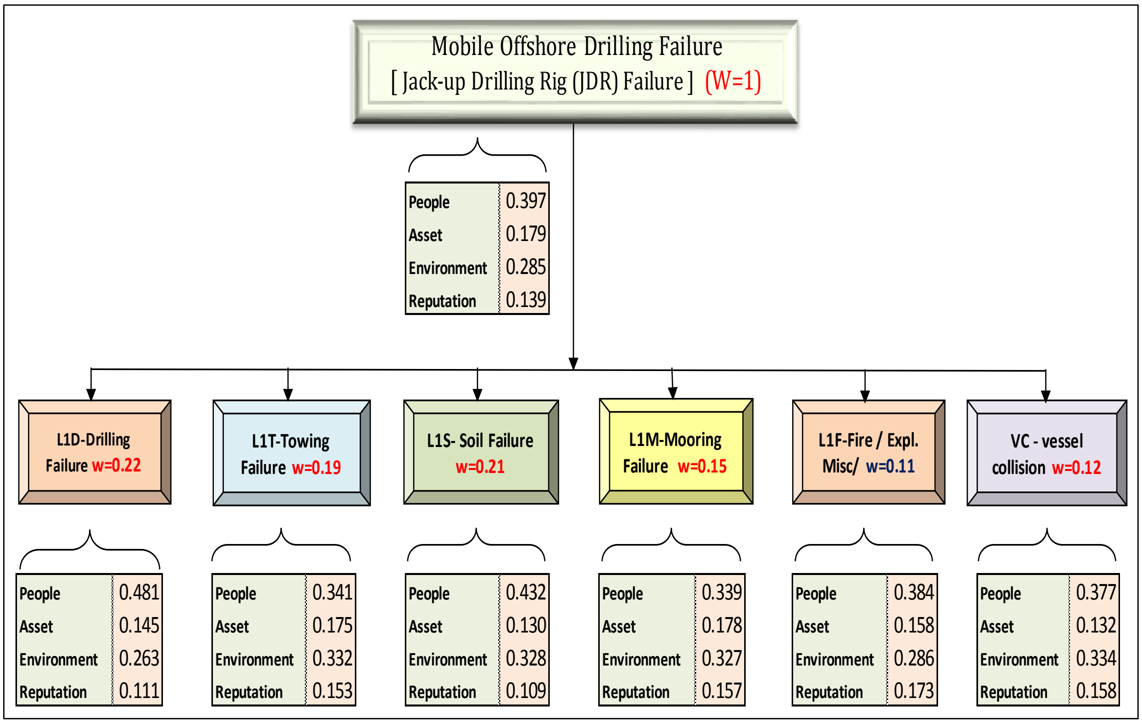


Figure 4.10: JDR's HG ranking

The framework of the evaluation index is demonstrated in Figure 4.2. Linguistic terms are assigned to the pair-wise comparisons by asking which is the more important of each pair of HGs in terms of their capacity to contribute to the failure of the JDRs. Table 4.9 illustrates the pair-wise comparison matrices among all the HGs in the dimensions of the hierarchy system. The result of the pair-wise comparisons of HGs is summarised and ranked in Table 4.10. The result from this analysis shows that the Drilling Failure (L1D) is a critical item within the identified HGs as shown in Figure 4.10 and is selected for further assessment.

Table 4.9: Pair-wise comparisons matrix of HGs of JDR

	L1S- Soil Failure	L1D-Drilling Failure	L1T-Towing Failure	L1M-Mooring Failure	L1V - vessel collision	L1F-Fire / Explosion Misc
L1S- Soil Failure	1	0.90	1.25	1.58	1.75	1.81
L1D-Drilling Failure	1.111	1	1.167	1.542	1.729	1.792
L1T-Towing Failure	0.803	0.86	1	1.450	1.675	1.750
L1M-Mooring Failure	0.631	0.65	0.69	1	1.409	1.545
L1V - vessel collision	0.570	0.58	0.60	0.71	1	1.231
L1F-Fire / Explosion Misc	0.552	0.56	0.57	0.65	0.81	1

Table 4.10: Ranking of HGs of a JDR

No	Ranking	Value
1	L1D-Drilling Failure	0.22
2	L1S- Soil Failure	0.21
3	L1T-Towing Failure	0.19
4	L1M-Mooring Failure	0.15
5	L1V - vessel collision	0.12
6	L1F-Fire / Explosion Misc	0.11

4.4.1.1 Constructing the hierarchical framework of a JDR

Figure 4.2 represents a hierarchical structural model of aggregative risk involving three major attributes of the JDR, i.e. Natural hazard (L2D-N1) with the relevant weight of contribution (WD2N), Operational failure (L2D-O1) with the relevant weight of contribution (WD2O) and failure due to Human error (L2D-H1) with the relevant weight of contribution (WD2H) at attribute Level-2. Each Level-2 attribute is divided further into its Level-3 attributes, (e.g. Failure due to Human error is divided into three levels: Drilling failure due to failure to follow organisational policies and procedures

(L3D-H1-01), Drilling failure due to management/supervision/staff (L3D-H1-02) and individual competence/motivation (L3D-H1-O3)).

The risk factors for BEs are proposed to be implemented at the lower levels of the hierarchy. The hierarchical model structure consists of sixteen BEs at Level 3, which correspond to the three main categories in level 2. The basic risk factor of level 3 will be combined with the results of these fifteen contributions' weight factors of the Fuzzy-AHP hierarchy in order to generate the risk of the JDR's failure. The crisp defuzzified results of the three categories, i.e. Natural hazard (L1D-N1), Operational Failure (L1D-O1) and failure due to Human error (L1D-H1) are combined together through a model hierarchy which calculates the risk of failure index of the JDR.

4.4.1.2 Constructing a Fuzzy-AHP framework and Fuzzy judgement matrix

Table 4.11 shows the comparison matrix for comparing dimensions in level 3 in terms of relative contribution and importance of their capacity to lead to the JDR's failure. After each element has been compared, a paired comparison matrix is formed in Table 4.12 where 8 is the order of matrix.

Table 4.11: Pair-wise comparison matrix for BEs

Ranking alternatives for L2D-O1: Operational											
L2D-O1	L3D-O1-01	L3D-O1-02	L3D-O1-03	L3D-O1-04	L3D-O1-05	L3D-O1-06	L3D-O1-07	L3D-O1-08		Contribution weight Factor	
L3D-O1-01	1.00	1.26	1.37	1.47	1.53	1.58	1.68	1.63		WD3O-1	0.17
L3D-O1-02	0.8	1.00	1.14	1.29	1.4	1.43	1.57	1.5		WD3O-2	0.15
L3D-O1-03	0.7	0.88	1.00	1.2	1.25	1.3	1.50	1.4		WD3O-3	0.14
L3D-O1-04	0.7	0.78	0.86	1.00	1.10	1.20	0.60	0.80		WD3O-4	0.11
L3D-O1-05	0.66	0.74	0.80	0.91	1.00	1.11	1.33	1.22		WD3O-5	0.11
L3D-O1-06:	0.63	0.70	0.8	0.83	0.9	1.00	1.25	1.1		WD3O-6	0.11
L3D-O1-07	0.59	0.64	0.67	1.7	0.75	0.8	1.00	0.83		WD3O-7	0.10
L3D-O1-08	0.61	0.67	0.71	1.25	0.82	0.89	1.20	1.00		WD3O-8	0.11

Then the consistency property in the pair-wise comparison is examined by the stepwise procedure as presented in Section 4.3.

Table 4.12: Weights of contributory factors for BEs

Basic Event	AHP-Weight		Basic Event	AHP-Weight	
L3D-O1-01	WD3O-1	0.17	L3D-N1-01	WD3N-1	0.08
L3D-O1-02	WD3O-2	0.15	L3D-N1-02	WD3N-2	0.37
L3D-O1-03	WD3O-3	0.14	L3D-N1-03	WD3N-3	0.26
L3D-O1-04	WD3O-4	0.11	L3D-N1-04	WD3N-4	0.09
L3D-O1-05	WD3O-5	0.11	L3D-N1-05	WD3N-5	0.20
L3D-O1-06	WD3O-6	0.11	L3D-H1-01	WD3H-1	0.33
L3D-O1-07	WD3O-7	0.10	L3D-H1-02	WD3H-2	0.33
L3D-O1-08	WD3O-8	0.11	L3D-H1-03	WD3H-3	0.33

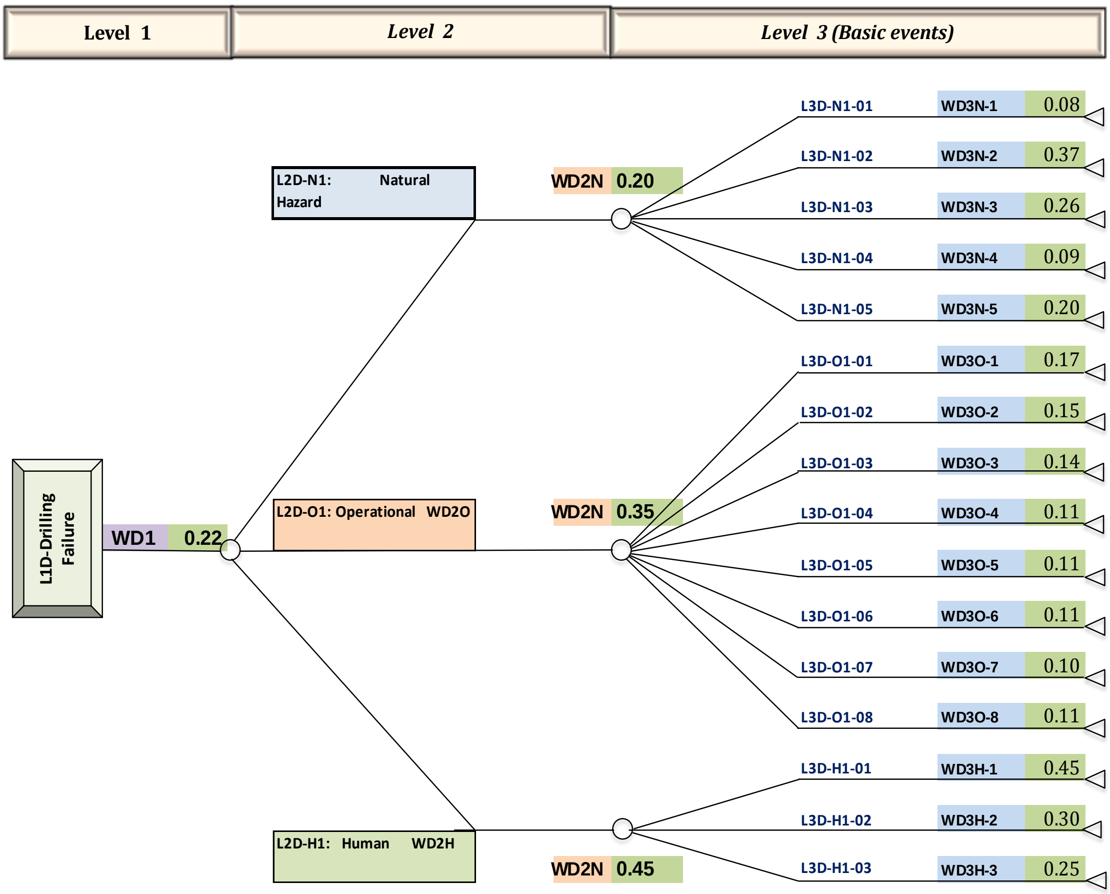


Figure 4.11: A three-stage structural model for risk aggregation of a JDR

Figure 4.11 shows the building blocks of the JDR's hierarchical structural model for risk aggregation. Each BE is partitioned into its contributory factors, which are the result of Fuzzy-AHP, and each of those can be further partitioned into upper-level contributory factors. Each factor was weighted according to the estimated significance of the JDR's failure.

4.4.2 The estimation of the risk and decision-making

The full view of the hierarchical Fuzzy model is shown in Figure 4.2, which details the processing of the observed characteristics of the JDR system. The proposed framework is capable of quantifying judgements from experts who express their opinions qualitatively. The first step of the proposed framework is to obtain the risk of each hazard by using FST.

The second step is to calculate weight factors for each hazard in the framework. Since the study incorporates FST into a Fuzzy-AHP method, a set of linguistic priority terms along with the membership functions describing the relationship between elements in each hierarchy of the AHP is adopted. Thus, the pair-wise comparisons between the elements in each hierarchy using FST are established. The linguistic variables which were defined by R_f s with membership functions are shown in Table 4.13. Then, the Fuzzy expressions are subsequently converted into a single crisp value using an appropriate defuzzification method. This is followed by the weighting contributory factors calculation so as to obtain the relative importance of elements illustrated in Table 4.14. By repeating the steps above, the risk of each element in the hierarchy is acquired based on the normalised weight factors calculated.

Table 4.13: Linguistic definitions of grades for P_{O}, S_{C} and D_{V}

Level 3 (BE)	Risk Element	Linguistic terms	Expert (1)					Linguistic terms	Expert (2)					Linguistic terms	Expert (3)					Crisp No.
	P_O	High		0.7	0.8	0.9	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-N1-01	S_C	Low		0.1	0.2	0.3	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Very Low	0	0	0.1	0.2	0.333	0.13
	D_V	Medium		0.4	0.5	0.6	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Very Low	0	0	0.1	0.2	0.333	
	P_O	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-N1-02	S_C	Very High	0.8	0.9	1	1	0.303	Very High	0.8	0.9	1	1	0.364	Very High	0.8	0.9	1	1	0.333	0.19
	D_V	Low		0.1	0.2	0.3	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Medium		0.4	0.5	0.6	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-N1-03	S_C	High		0.7	0.8	0.9	0.303	Medium		0.4	0.5	0.6	0.364	High		0.7	0.8	0.9	0.333	0.14
	D_V	Low		0.1	0.2	0.3	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	High		0.7	0.8	0.9	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-N1-04	S_C	Low		0.1	0.2	0.3	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Very Low	0	0	0.1	0.2	0.333	0.13
	D_V	Medium		0.4	0.5	0.6	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Very Low	0	0	0.1	0.2	0.333	
	P_O	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	
L3D-N1-05	S_C	High		0.7	0.8	0.9	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	High		0.7	0.8	0.9	0.333	0.13
	D_V	Low		0.1	0.2	0.3	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.333	
L3D-O1-01	S_C	Low		0.1	0.2	0.3	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Medium		0.4	0.5	0.6	0.333	0.11
	D_V	Medium		0.4	0.5	0.6	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Medium		0.4	0.5	0.6	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	
L3D-O1-02	S_C	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	0.14
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-O1-03	S_C	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	0.13
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	High		0.7	0.8	0.9	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	
L3D-O1-04	S_C	Mol. High	0.5	0.6	0.7	0.8	0.303	High		0.7	0.8	0.9	0.364	Very High	0.8	0.9	1	1	0.333	0.16
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	High		0.7	0.8	0.9	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	
L3D-O1-05	S_C	Very High	0.8	0.9	1	1	0.303	Very High	0.8	0.9	1	1	0.364	Very High	0.8	0.9	1	1	0.333	0.18
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-O1-06	S_C	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	0.12
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.333	
L3D-O1-07	S_C	Low		0.1	0.2	0.3	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Medium		0.4	0.5	0.6	0.333	0.11
	D_V	Medium		0.4	0.5	0.6	0.303	Mol. Low	0.2	0.3	0.4	0.5	0.364	Medium		0.4	0.5	0.6	0.333	
	P_O	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Medium		0.4	0.5	0.6	0.333	
L3D-O1-08	S_C	High		0.7	0.8	0.9	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	0.14
	D_V	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	
L3D-H1-01	S_C	High		0.7	0.8	0.9	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	0.18
	D_V	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Medium		0.4	0.5	0.6	0.333	
	P_O	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	
L3D-H1-02	S_C	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	0.17
	D_V	Very Low	0	0	0.1	0.2	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.333	
	P_O	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	
L3D-H1-03	S_C	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.333	0.17
	D_V	Very Low	0	0	0.1	0.2	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.333	

Table 4.14: Weights of contributory factors and crisp value of BEs

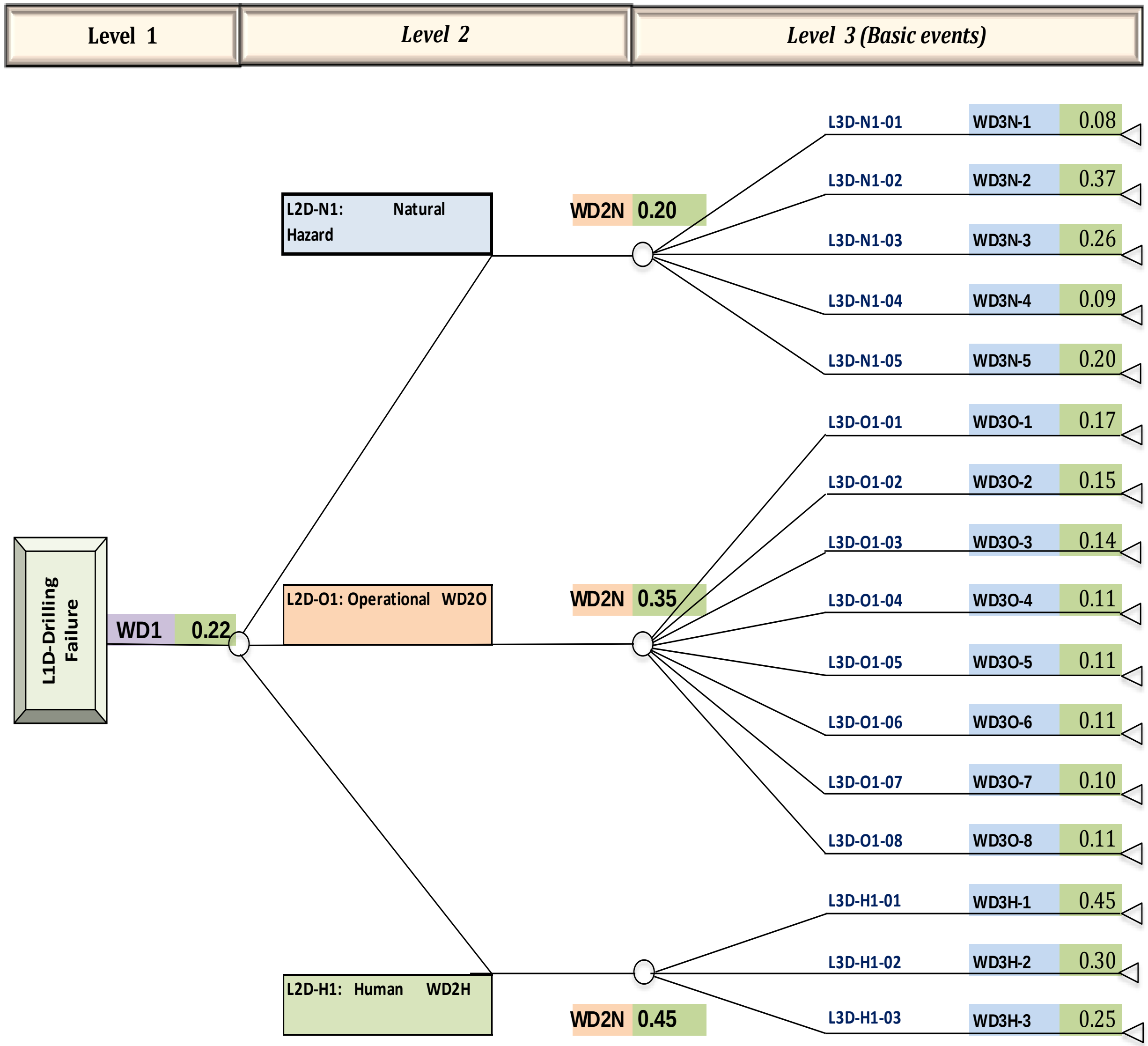
Basic Event	AHP-Weight		Fuzzy-Crisp Value
L3D-N1-01	WD3N-1	0.08	**0.44**
L3D-N1-02	WD3N-2	0.37	**0.64**
L3D-N1-03	WD3N-3	0.26	**0.46**
L3D-N1-04	WD3N-4	0.09	**0.44**
L3D-N1-05	WD3N-5	0.20	**0.42**
L3D-O1-01	WD3O-1	0.17	**0.38**
L3D-O1-02	WD3O-2	0.15	**0.47**
L3D-O1-03	WD3O-3	0.14	**0.43**
L3D-O1-04	WD3O-4	0.11	**0.53**
L3D-O1-05	WD3O-5	0.11	**0.59**
L3D-O1-06	WD3O-6	0.11	**0.41**
L3D-O1-07	WD3O-7	0.10	**0.38**
L3D-O1-08	WD3O-8	0.11	**0.47**
L3D-H1-01	WD3H-1	0.33	**0.58**
L3D-H1-02	WD3H-2	0.33	**0.56**
L3D-H1-03	WD3H-3	0.33	**0.56**

4.4.2.1 Risk aggregation and risk ranking matrix

As illustrated in Table 4.15, the risk aggregation matrix for the JDR is established and as showed in Figure 4.12 the contributory factors as well as the BE calculated factors for all three levels are presented.

Table 4.15: Risk aggregation matrix

Level 1			***Level 2***			***Level 3 (Basic events)***		
Attribute Level 2	Contribution Weight Factor	Risk Factor	Attribute Level 2	Contribution Weight Factor	Risk Factor	Basic Event	Contribution Weight Factor	Basic Events Risk Factor
L1D-D	WD1N	0.22	L2D-N1	WD2N	0.20	L3D-N1-01	0.08	**0.44**
						L3D-N1-02	0.37	**0.64**
						L3D-N1-03	0.26	**0.46**
						L3D-N1-04	0.09	**0.44**
						L3D-N1-05	0.20	**0.42**
			L2D-O1	WD2O	0.35	L3D-O1-01	0.17	**0.38**
						L3D-O1-02	0.15	**0.47**
						L3D-O1-03	0.14	**0.43**
						L3D-O1-04	0.11	**0.53**
						L3D-O1-05	0.11	**0.59**
						L3D-O1-06	0.11	**0.41**
						L3D-O1-07	0.10	**0.38**
						L3D-O1-08	0.11	**0.47**
			L2D-H1	WD2H	0.45	L3D-H1-01	0.33	**0.58**
						L3D-H1-01	0.33	**0.56**
						L3D-H1-01	0.33	**0.56**



Crisp Value	Risk (Level 3)	Risk (Level 2)	Risk (Level 1)
0.44	0.036		
0.64	0.236		
0.46	0.119	0.103	
0.44	0.040		
0.42	0.084		
0.38	0.064		
0.47	0.070		
0.43	0.060		0.114
0.53	0.059		
0.59	0.065	0.158	
0.41	0.045		
0.38	0.038		
0.47	0.052		
0.58	0.263		
0.56	0.168	0.257	
0.56	0.140		

Figure 4.12: Risk aggregation hierarchy and risk ranking

4.5 Results and discussion

In this study, a model is established in order to assess the MODU's risk level. This model is based on determining the most significant HG that may cause failure of the MODUs. Risk assessments of MODUs provide valuable information to the decision-maker regarding the risk level of an operation system, although the quality of risk assessment not only relates to the scientific building blocks of the assessments but is also dependent on the role of the assessments in the decision-making process.

The application and how the proposed methodology takes into account the challenging characteristics of the MODU's risk assessment effectively provides information for decision-makers as well as a reduced risk to the MODU, by estimating risk levels and assessing their significance. This helps decide whether the risks need to be reduced, whist identifying the main contributors to the risk, helps in understanding the nature of the hazards and suggests possible targets for risk-reduction measure. Evaluating risk reduction measures can be linked to a cost-benefit analysis and help choose the most cost-effective ways of reducing the risk.

4.6 Conclusion

QRA is a necessary and critical task for offshore operations. Understanding risk assessment entails understanding the underlying factors that contribute to the MODU's failure, which are often the same regardless of the nature of the offshore installation activities. In this study, Fuzzy set theory is used to represent the characteristics of a hazard such as likelihood of occurrence and consequence severity, and Fuzzy-AHP is used to determine the degree of importance of the factors and sub-factors in the model of each HG in terms of its contributions to the MODU's failure. In risk assessment, the issue of how to manage uncertainty is a major concern. However, the causes of uncertainty are diverse. Thus, regardless of what approach is to be applied, it is always dependent upon human judgement to manage such negative effects. In other words, the deficiencies of risk modelling resulting from the lack of information or a high level of uncertainty must be addressed by means of the general evaluation capacity of humans, who are able to grasp the essence of an object, even if it is vague and unclear. Therefore, the experience of experts consulted is crucial, since the cornerstone of such uncertainty treatment is the professional judgement of such personnel. The risk assessment frameworks proposed and based on FST in this study are capable of handling imprecise, ambiguous and qualitative information from experts in a consistent manner. These can be regarded as reliable reasoning processes with the capability of quantifying the judgement from experts who express their opinions qualitatively. The frameworks have been developed in a generic sense to be applicable to deal with both engineering and managerial problems. It is also believed that these methods can be tailored to practical applications of dealing with safety problems 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 real life. More importantly, these frameworks can be integrated to formulate a platform to facilitate risk assessment of the MODU's operations system without jeopardising the efficiency of operations in a variety of situations where traditional techniques may not be applied with confidence. In offshore safety, under circumstances where a lack of data or a high level of uncertainty exists, a large number of assumptions, judgements and opinions are involved subjectively in the reasoning process. Other than an approximate reasoning approach, new approaches capable of addressing uncertainty and combining expert judgement and empirical data should be developed.

CHAPTER 5: Fuzzy FTA for MODU's risk assessment

Chapter Summary

Risk is a quantitative value which reflects the adverse outcome of an activity or event in terms of the probability of occurrence. Probabilistic risk assessment is a comprehensive, structured method for identifying hazards and assessing risk in complex systems. Many techniques and methodologies are available to conduct both qualitative and QRA. FTA is used in qualitative risk assessment to identify the basic causes leading to an undesired event, to represent the logical relationships of these basic causes in leading to the event, and finally to calculate the probability of occurrence of this event in a system. A new methodology for the assessment of the risk level of the MODUs is presented that considers in detail the operational failure of the drilling systems focusing on mud circulation and the BOP systems. The main purpose is to propose a methodology to improve the present procedures used in the risk assessment of Mobile MODUs. The proposed methodology comprises a number of stages: i) Identifying critical events that may lead to the MODU's operation system failure, ii) Establishing an operational hierarchy system diagram with a breakdown of the events in detail for the most significant HG, iii) Translating into FT and performing the analysis in order to identify areas for further safety improvement, and iv) Determination of minimal cut sets (MCSs) probability analysis and measures to rank the MCSs according to their contributions to the failure of MODU systems. FTA is a widely used reliability assessment tool for complex engineering systems. However, due to the inherent imprecision and uncertainty of the available data, it is often impossible to obtain an exact estimation of the rate of occurrence of an event or its probability distribution function. To reduce the ambiguity and imprecision arising from the subjectivity of data, a Fuzzy approach may be used with the FTA method. The aim is to prevent a critical event occurring during drilling rather than focusing on measures that mitigate the consequences once an event has occurred. For the purpose of developing a risk analysis and decision support model, a realistic and practical approach has been chosen.

5.1 Introduction

Offshore installation and operations involve a very complicated process with attendant risks to people, the environment and property or economic assets. As an offshore operation system, an MODU faces hazards from many different sources which threaten its integrity; thus, it is exposed to a wide range of uncertain threats and hazards. Therefore, its performance under various conditions has received considerable attention. Ensuring the system's operational safety is often a complex problem. The main purpose of this chapter is to introduce a methodology to improve the current procedures using risk assessment and to facilitate decision-making for reducing risk. The traditional methods of carrying out risk assessment during construction or after the occurrence of accidents have proved to be costly and often lack the flexibility to apply alternative remedial options (Khan & Amyotte, 2002). This chapter presents a comprehensive and transparent study on the evaluation of the risk assessment of an MODU using the Fuzzy FTA technique. A methodology for quantification and evaluation of the FT in a Fuzzy environment is proposed. Frameworks of risk assessment are developed based on the concept of object-oriented assessment and characteristics of MODUs, together with an object-oriented hierarchy to represent the relationships between components, sub-systems, and the overall system.

Risk assessment provides a logical and qualitative and/or quantitative base for analysing the circumstances that can lead to the system's failure and for sub-dividing them down into system and component contributions to this failure. Therefore, a risk assessment approach provides a platform for identifying, structuring, and evaluating safety performance measures at different stages of design, construction, transportation, installation and operation. Also, risk assessment provides a convenient basis for linking safety performance with reliability. The objectives of this research are to ensure the achievement of the above through the various steps. The safe performance of any operation and/or production system is to a great extent reliant upon the condition of its components. Closely monitoring the condition of the critical components and carrying out timely system analysis would help to reduce the risk and the frequency of failures. Several analytical methods of reliability analysis and risk management are available. Probabilistic risk assessment (PRA) is a comprehensive, structured and logical approach aimed at identifying hazards and assessing the risks of complex systems (Mohaghegh *et al.*, 2009), of which FTA is one technique (Figure 5.1). The purpose of each method and its individual or combined applicability in evaluating the reliability and availability of a given system or component should be examined by the analysts before starting any analysis, and consideration should also be given to the results available from each method.

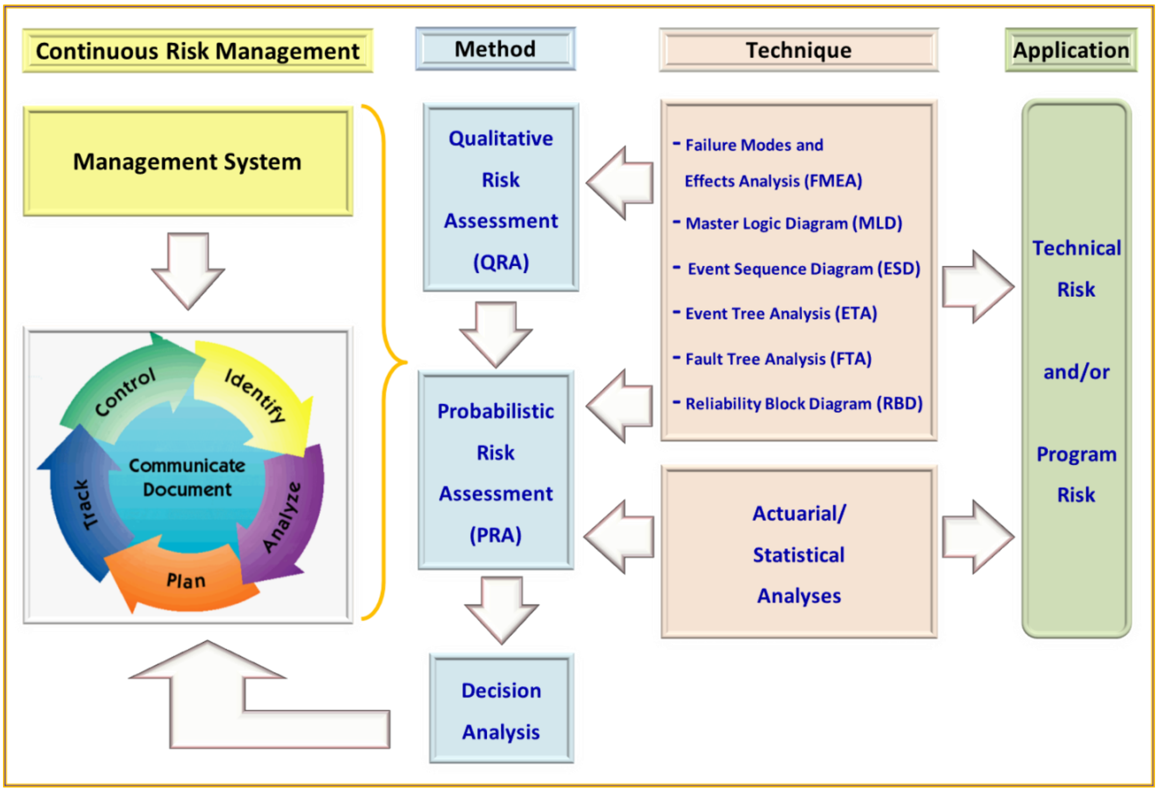


Figure 5.1: Relationship between probabilistic risk assessment and risk

FTA is widely used to evaluate the reliability of complex engineering systems from both qualitative and quantitative perspectives. It provides a graphical representation of combinations of component failures leading to an undesired system failure (Haasl et al., 1981b). However, in many situations, the behaviours of components in a complex system and their interactions, such as failure priority, sequentially dependent failures, functional dependent failures and dynamic redundancy management, cannot be adequately addressed by traditional FTA due to its limited modelling capability. An FTA is a technique for analysing the Top event (TE), which causes the system failure. It is a top-down, deductive analysis structured in terms of events leading to the occurrence of the top event (Ericson, 2005). The FT is useful for understanding the mode of occurrence of an accident. Furthermore, given the failure probabilities of the BEs, i.e. system components, the occurrence probability of the TE can be calculated. In the conventional approach, the probability of the BEs is considered either as a precise point value or as a random, time-dependent variable. However, due to the inherent imprecision and uncertainty of the available data, it is often impossible to obtain an exact estimation of an event's occurrence rate or its distribution function. In such cases, the Fuzzy approach is among the best choices for analysing the system (Sallak *et al.*, 2008). In addition, in calculating the likelihood of a top-level event, FTA also shows the contributions of each of the BEs. There are a number of approaches to FTA, among them minimum cut set is widely used. For a complex FT, thousands of MCSs may be possible. Even if the MCSs can be successfully determined, there exists another problem, which is to rank the MCSs according to their contributions to the top event. The method that is presented in this chapter considers measures of both risk and uncertainty importance associated with each of the BEs. Therefore, a new importance distribution function during the defuzzification process is proposed. Furthermore, the proposed method extends the conventional minimum cut sets, Fussell-Vesely importance measures and risk reduction measures into the Fuzzy environment. These importance measures can be effectively used for the ranking of the minimum cut sets and the BEs according to their contribution to the top event probability (Aksu *et al.*, 2007).

A new methodology for the risk assessment of the MODUs is presented that considers the operational failure of the drilling systems, concentrating on the high-pressure mud circulation including the blow-out preventer system, in which the mud column is the primary barrier and the secondary barrier is the blowout preventer, which protects the well from a disaster as the last resort (NORSOK D-010, 2004). The proposed methodology provides a rational and systematic approach for risk assessment. The main steps in the methodology start with identifying the probable critical events that may lead to operational failure, followed by establishing an operational hierarchy system diagram, and breaking down the events in detail with respect to the main function and then finally translating the operational hierarchy to FT and performing the analysis to identify areas for safety improvement.

5.2 Literature review

FTA is one of many symbolic analytical techniques used in operations research and system reliability. This review is conducted to establish a basis for this research, particularly in identifying the areas where gaps exist as well as supporting decisions about the most appropriate modelling processes to be developed for processing data in order to achieve the objectives. FTA was first introduced in 1961 by H. A. Watson of Bell Telephone Laboratories in connection with a US Air Force contract to study the Minuteman missile launch control system (Watson, 1961). It was implemented relatively quickly into other fields, such as the reliability analysis of computing and electrical systems (Nieuwhof, 1975; Dugan *et al.*, 1993). It was also adopted and extensively applied by the Boeing Company. Another early user was the National aeronautics and space administration (NASA). NASA began using risk analysis by conducting simple analysis of observed failures, and then progressed over time to the use of probabilistic models to predict probability of failures within their systems (Paté-Cornell & Dillon, 2001). One of the main handbooks of FTA, the "Fault Tree Handbook", was written by the US nuclear regulatory commission (NRC) in 1981 to serve as a reference text for the system safety and reliability course (Haasl *et al.*, 1981a). The technique has also been frequently used for accident investigation, as it identifies the relations between causes and their logic. It is a typical tool for system engineering, designed for safety and reliability applications, which has gradually been used in several industrial sectors such as the offshore industry (Umar, 2010).

Probability risk assessment is commonly used to assess uncertainty within a system. One of the strengths of the approach is that it provides a systematic means of quantifying the effect of uncertainties by combining probability estimates for different possible failure mechanisms within the system so that an overall probability of system failure can be assessed. FTA emphasises the causes of failure for a system as a series of individual BEs and provides a visual representation of the series of events that can lead to failure of that system. FTA is useful as not only does it give a visual representation of the system but it also provides a basis for identifying and combining the probabilities of events impacting on system failure through Boolean logic statements (Bedford & Cooke, 2001). Boolean algebra of probability theory and mathematical statistics are the basis of FTA. However, the environmental fuzziness and the imprecision of data have an impact on the probability of the event's occurrence. Thus, it is difficult to estimate the probability of the event's happening by using an exact value. As a result, it is necessary to introduce the Fuzzy concept into FTA (Markowski *et al.*, 2009). The Fuzzy extension principle combined with the FT approach makes it possible to determine the occurrence probability of a top event (Mentes & Helvacioglu, 2011). Singer (1990) reported the analysis of Fuzzy reliability using Fuzzy numbers. In order to facilitate the calculations in Singer's method, Chen et al. (1995) presented revised methods to analyse the FT by specifically considering the failure probabilities of BEs as triangular Fuzzy numbers. Huang (2004) adopted probability theory to analyse a Fuzzy FT and Shu et al. (2006) used intuitionistic Fuzzy methods to analyse an FT in a study on a printed circuit board assembly. He et al. (2007) avoided the deficiency in the traditional FT approach by using a Fuzzy FT approach that was based on probability measures and FL.

These approaches have proven to be very effective in modelling of the risks in complex systems, where causal relations among binary probabilistic events are deterministic (Crowl and Louvar, 2001). However, those causal relationships are often uncertain and non-deterministic. This has led to increased interest in expanding the FT methods to incorporate non-deterministic causal factors. Therefore, a new formal approach is required to capture the fuzziness and imprecision of likelihoods of multiple hazards. With respect to this inadequacy of the conventional FTA, extensive research has been performed by using Fuzzy set theory in FT analysis. The pioneering work on this belongs to Tanaka *et al.*, (1983), who treated probabilities of BEs as TPFNs, and applied the Fuzzy extension principle to determine the probability of a top event. Based on work of Tanaka *et al*., (1983), further extensive research has been performed (Misra & Weber, 1990; Liang & Wang, 1993). Their analysis is based on the possibility distribution associated with the BEs and a Fuzzy algebra for combining these events. Parallel with this, Singer (1990) analysed Fuzzy reliability by using L-R type Fuzzy numbers. In order to facilitate the calculation of Singer's method, Cheng & Mon (1993) & Chen (1994) proposed revised methods to analyse the FT by specifically considering the failure probabilities of BEs as triangular Fuzzy numbers. Yuhua & Datao (2005) used a hybrid method to analyse failure probability of oil and transmission pipelines.

Sawyer and Rao (1994) applied α-cuts to determine the failure probability of the top event in Fuzzy FTs of mechanical systems. Kai-Yuan et al. (1991), Cai et al. (1991) and Huang et al. (2004) adopted possibility theory to analyse Fuzzy FTs. Shu et al. (2006) used intuitionistic Fuzzy methods to analyse FTs on a printed circuit board assembly.

It is obvious from the above reviews that Fuzzy FT analysis has been extensively studied for a long time and effectively applied to many engineering problems. However, its application in risk assessment of mobile offshore drilling units is rarely considered.

As stated in Chapter 4, the complex nature of MODUs is associated with high-level risk arising from continuous expansion and the increased level of innovation demanded by the offshore industry. Many researchers have written about the need for risk assessment but fail to adequately satisfy risk mitigation. Lois et al. (2004) stated that the scale of the offshore safety problems requires continuous efforts with a view to eliminating or reducing hazards. The task of risk assessment in this context will mainly concentrate on the prevention and/or mitigation or control of risks through the entire life of the project. Wang et al. (1995) described the risk correlated with marine systems as a measure of exposure to the possibility of economic or financial loss, physical damage or injury or delay as a consequence of the uncertainty associated with the pursuance of a particular course of action. In considering this topic, a combination of several factors – such as the importance of the subject of safety management for an offshore platform and its overall importance in the oil and gas industry, as well as the applicability of the proposed research work to enhance QRA in the field – provides the basis for the topic. Based on the review conducted so far, it is evident that most efforts made previously are still grappling with the issue of uncertainties associated with data on most marine systems such as MODUs. In this chapter, therefore, the risk assessment methodology to be proposed will deal with such uncertainties to enable informed decision-making based on cost-benefit evaluation. Even though Fuzzy FTA has been applied extensively in many engineering problems, it is still necessary for this study to consider specific characteristics of the MODU systems. One of the most important characteristics is failure dependencies in MODU systems. This indicates that the failure of a component in an MODU system can be either independent or dependent on the failure of another component. Therefore, for proper risk assessment it is necessary to simultaneously consider independency and dependency. Hence, in this chapter the Fuzzy FTA method has been considered for independent failure of a component, and the BBN technique is employed to deal with dependency of events in the process of risk assessment for MODUs in Chapter 6.

5.3 A proposed integrated Fuzzy FTA methodology of MODUs

The information generated through the evaluation of different methods of QRA will be used to establish a firm basis for the development of an appropriate modelling technique to allow for the efficient and effective analysis and assessment of the MODU failure data. The method is critical for the assessment of risk information related to the MODU operation system, especially with consideration of its associated uncertainties; the choice of processing techniques needs to be well thought out. This lays the foundations on which to base a framework for modelling the risk assessment of the system. Many tools and methodologies have been developed in order to assess and analyse risk, either qualitatively or quantitatively, in an extensive variety of disciplines. The particular method used eventually depends upon the environment in which the risk is placed, and upon the system under consideration. The proposed methodology uses the Fuzzy FT technique to express the causal relationship between events, their influence and their contribution to the failure of the system. The methodology focuses on the assessment of the failure of offshore operational systems (i.e. MODUs) posed through the HGs and their BEs. The risk analysis process includes hazard identification from a vulnerability analysis at the start point and is followed by adapting an operational hierarchy of the system into the FT. This allows representation of the MODU operation system with its HGs at different levels of detail. The proposed methodology is created via an object-oriented approach to develop frameworks of FT at the component level by extracting the logic relationships between negative consequences, failure events and hazards, so that it graphically represents the system down to the lowest component level and also describes the influence of hazards. The quantitative solution of the Fuzzy FTA is also presented in order to quantitatively evaluate the cause-effect relationships in an MODU operation system and to facilitate decision-making. This is achieved through detailed examination of related risks, and a review of relevant literature and traditional safety assessment methods. After hazard identification and construction of an operational hierarchy model, a framework is established which is capable of quantifying the judgements from experts.

Since the criteria for the evaluation of the HGs have diverse significance and meanings, it cannot be assessed that each HG is of equal importance and weight in terms of its capacity to contribute to the failure of the MODU. Therefore, it is necessary to consider the contributory factors of each HG to the failure of the MODU. The proposed methodology framework, as illustrated in Figure 5.2, consists of the different stages which provide an illustrative view of a generic Fuzzy FTA framework proposed for the purpose of the MODU risk assessment, and comprises the following:

- Identifying risk contribution factors for each HG which can contribute to the occurrence of the potential risk. This was performed by the Fuzzy-AHP technique described in Chapter 4. The Fuzzy-AHP technique is employed for hazard ranking and also for hazard and operability studies for identifying the probable critical events that may lead to the MODU's operational failure.

- Identifying the relationships between events and establishing an operational hierarchy system diagram with a detailed breakdown of the most significant HG.

- Data collection (using input from experts where there is a lack of data). After hazard identification and construction of an operational hierarchy model, a framework is established which is capable of quantifying the judgements from experts.

- Translating the operational hierarchy system diagram into a detailed Fuzzy FT, which depicts all possible routes for the occurrence of the probable risk, commonly referred to as the TE, and performing the analysis in order to identify areas for further safety improvement.

- MCS determination, probability analysis and importance measures to rank the MCSs according to their contributions to the failures of the MODU system.

The top event probability is calculated using both a probabilistic approach and a FL approach. The details have been structured from the definition of the research aim

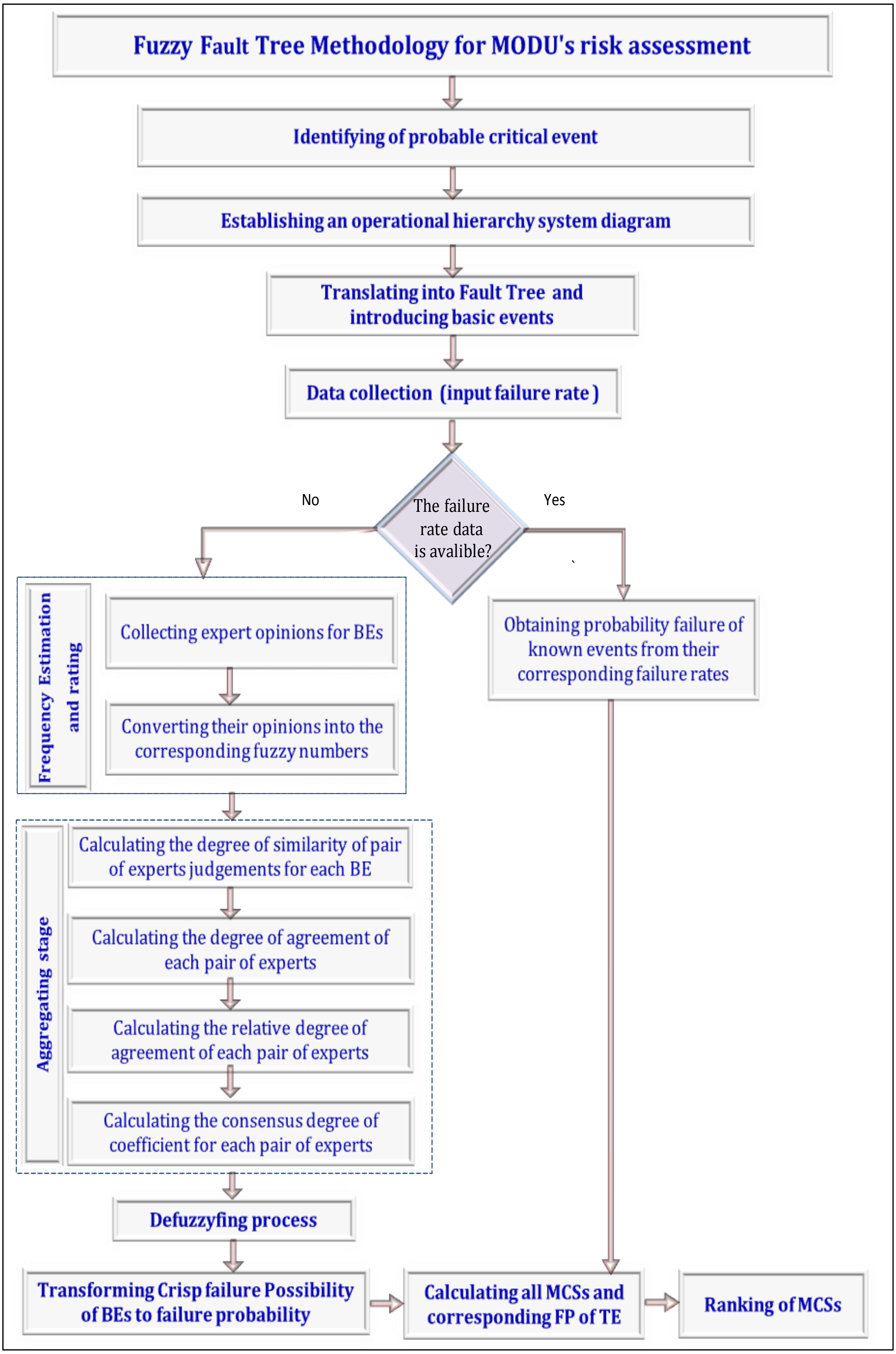


Figure 5.2: Structure of the proposed methodology for MODU's risk assessment

and objectives to data collection and analyses leading up to the development of a proposed risk assessment model. In a real system, the amount of analysis required may be enormous because of the number of nodes and links of the entire system and associated HGs. Because of the complexity of integrating the information, and in order to simplify the assessment processes, a manageable group of hazards has been considered. Each HG may be broken down into a number of simpler system components in different levels, as illustrated in Figure 5.3. This model will then go through practical application of the drilling failure of an MODU, focusing on the high-pressure mud circulation systems including the blow-out preventer. The data are collected from the industry in order to validate its efficiency based on the results obtained. The data collection methods involve surveys, interviews and questionnaires, which together constitute vital information required for testing the model and conducting preliminary validation studies with regard to MODU risk assessment.

5.3.1 The hierarchical structure of the proposed methodology

Complexity is one of the hurdles limiting the application of conventional risk assessment methods. It is therefore necessary to explicitly discuss the potential of an object-oriented assessment in dealing with complexity of the MODU. In order to effectively analyse complex systems, a hierarchical structure of the proposed methodology is developed in a few different stages and presented in Figure 5.3. The hierarchical structure consists of different levels. The aim is to identify the sources of hazards of the TE, in this case Drilling Failure: L1D-O1-01 is positioned at the highest level, while in the second level, three HGs (i.e. Natural hazard: L2D-N1, Operational hazard: L2D-O1 and Human error: L2D-H1) are presented, and in level 3 the sub-systems and the BEs are listed. Each component in this level may be influenced by another event or system at levels 4 and 5, in which the components/systems and BEs describe the MODU's operational system, and the failure of each component may influence another component or system at the different levels (e.g. Drilling Control System Failure (L5D-O1-01-2-4) in level 5 has consequences for Drilling Equipment Failure (L4D-O1-01-03) at level 4 and Drilling System Failure (L3D-O1-01) at level 3

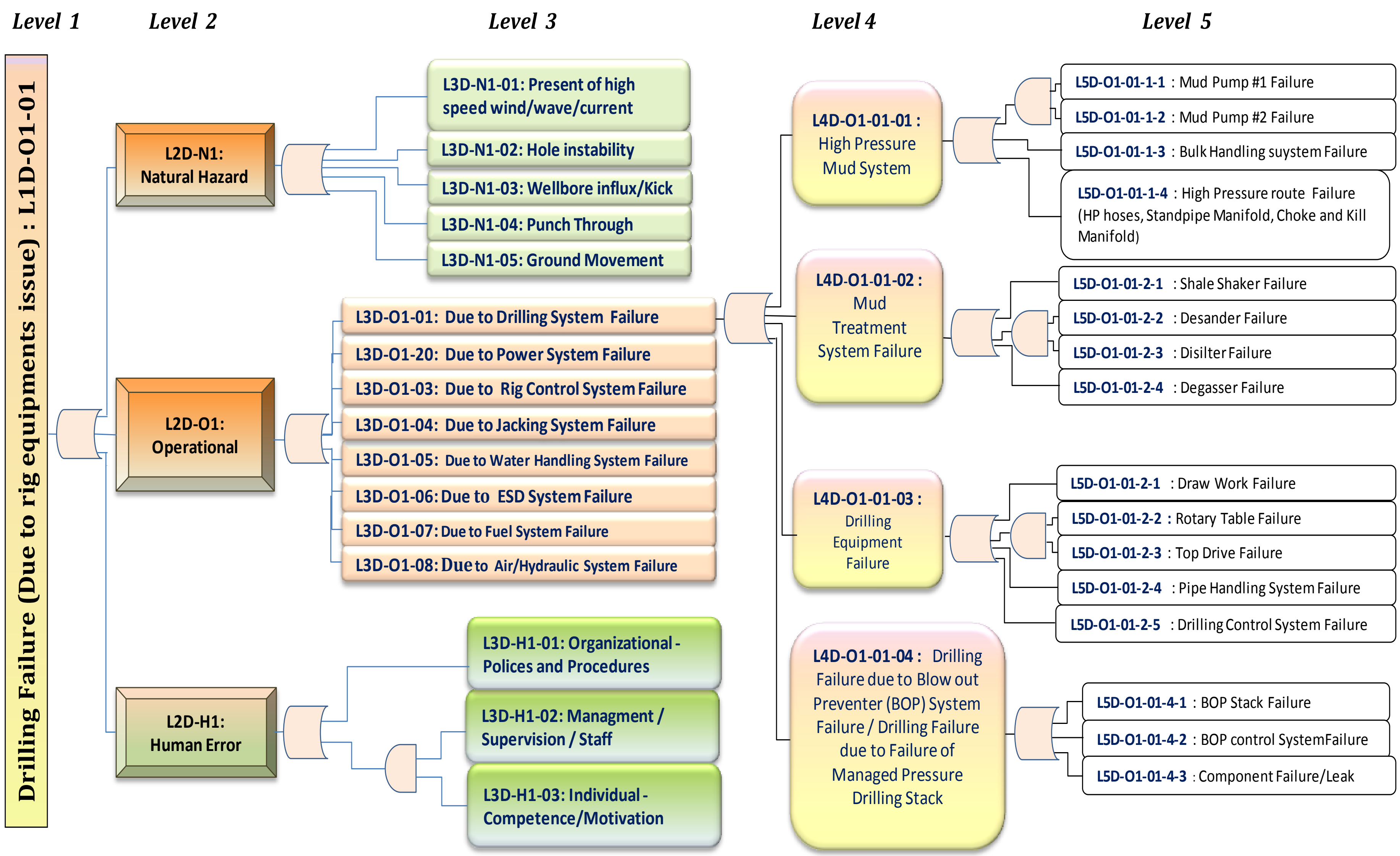


Figure 5.3: Hazard identification and MODU operation system hierarchy diagram

and finally to Operational Failure (L2D-O1) at level 2). The process follows an investigation of the successive combinations of failures of the components until reaching the BEs. In circumstances where a lack or incompleteness of data exists, there is a need to incorporate expert judgements. A framework is proposed based on the Fuzzy set theory and the FTA method that is capable of quantifying the judgement from experts who express opinions qualitatively.

5.3.2 Fuzzy FTA

Fundamentally, a FTA consists of a top-down analysis structured in terms of certain specific causes leading to the occurrence of the top event of interest, through a deductive process that, from a predefined undesired event, searches for the possible causes of such an event. In conventional reliability analysis, the outcome of the top event is certain and specific as long as the assignment of the BEs originates from reliable information. However, in a real operation system the information is rather imprecise and incomplete. In this case, Fuzzy set theory can be used to define the probabilities of various BEs. The probability of the TE calculated thus takes into account the uncertainties associated with the BEs. The great popularity of the FTA results is basically due to the following features:

- The large flexibility of the graphical representation of a complex operation system proportionate to the specific symbology.
- The large computational easiness in function for the probabilities calculation.

5.3.2.1 FTA

FTA is based on boolean algebra and probability theory and is consistent with conventional reliability theory. FTA has traditionally been used in large complex systems in order to find fault-sensitive constructions, e.g. single points of failures that lead to a dangerous or unacceptable event (FTA, 2006). It assumes that the probabilities of events are given and sufficient failure data are available. However, it is often very difficult to obtain sufficient failure data to estimate precise failure rates or failure probabilities. Based on this description, the system is analysed with a top-down approach that starts with the hazardous or unacceptable event, called TE, from which a graphical logical tree is created that consists of independent lower-level BEs combined with logical operators such as AND or OR. The analysis is carried out in iterations until a desired level of detail is achieved in different steps (e.g. single component failure). It assumes that the causes are in a lower level which cannot be sub-divided (i.e. BEs). The first step in a FTA is the selection of the TE, which is a specific undesirable system state or failure. Then the experts analyse the system or process to discover logical dependencies between the TE and all BEs. To represent logical dependencies, basically the AND or OR logical gates and so-called intermediate events can be used. As illustrated in Figure 5.4-a, the AND logical gate should be used if an output event occurs only if all input events occur simultaneously. If an output event occurs or if any of the input events occurs, either alone or in any combination, the OR logical gate should be used, as shown in Figure 5.4-b. A combination of BEs which leads to the hazard is called a cut set. An MCS is a cut set which cannot lead to the top-level hazard, if only one event of the set is prevented in Figure 5.5. This information helps to identify failure events whose elimination secures the system. If, for example, one event occurs in different MCSs, the occurrence probability of the top-level hazard will significantly decrease, if this event can be excluded. Traditionally, it is always assumed that the BEs contained in a FT are independent and could be represented as probabilistic numbers (Andrews, 2002; Henley & Kumamoto, 1981).

In the above formulation, P denotes the probability of the TE, p_i denotes the occurrence probability of BE_i and *n* is the number of BEs associated with the "OR" gate. The OR gate event probability is presented by Equation (5.1)-b, and similarly for an AND gate event, its probability is obtained by Equation (5.1)-a.

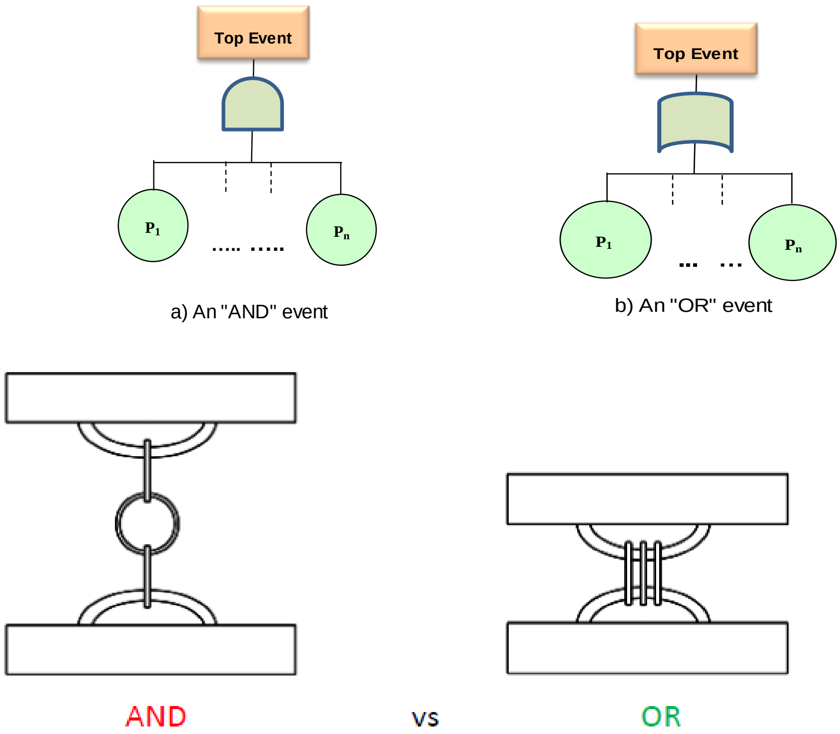


Figure 5.4: a) Structure of an "AND" event b) Structure of an "OR" event

$$P = \prod_{i=1}^{n} p_i \quad \text{(a)} \qquad P = 1 - \prod_{i=1}^{n} (1 - p_i) \quad \text{(b)} \tag{5.1}$$

The aim at this stage is to identify causes or initiating events and their logic combinations using "AND"/"OR" symbols of Boolean algebra (Wang & Ruxton, 1997). The construction of the tree depends on the analyst's skills and ability to conduct the reliable analysis, as the analyst can miss some causes (Suresh *et al.*, 1996)

5.3.2.2 Fuzzy FTA basic concept

Due to the unreliable and vague data, the failure rate is difficult to deal with solely by means of the conventional probabilistic reliability theory. These fundamental problems with probabilistic reliability theory have led researchers to look for new models or new reliability theories which can complete the classical probabilistic definition of reliability. Fuzzy set theory can be used to deal with these issues. Therefore, a Fuzzy FTA algorithm is developed to deal with such issues. Towards this end, Fuzzy sets can help to overcome this situation. Experts utilise Fuzzy sets to subjectively describe the uncertainties of each given failure event and then perform a mathematical operation to evaluate system reliability. The failure events are modelled to be trapezoidal Fuzzy sets (Tanaka *et al.*, 1983). These Fuzzy sets are considered as the possibilities of occurrence of the failure events. Therefore, the problem is to calculate the possibility of failure of the TE as a Fuzzy set, given the occurrence possibilities of the BEs. FL can be described as a type of mathematical logic in which truth value is assumed to belong to a continuum of values ranging between 0 and 1

5.3.2.3 Input failure rate and data collection

As illustrated in Figure 5.2, this stage of the methodology is to separate hazards with known failure rate from vague hazards. Failure rates of some hazards are available in certain sources. By using this data, it is possible to separate hazards with a known failure rate from vague hazards associated with MODU.

5.3.2.3.1 Obtaining failure probability of hazards with known failure rate

Failure rates of some hazards are available in different sources. Offshore drilling takes place in a unique operating environment and has several industry-specific components. As a result, publicly accessible reliability data may be unavailable or may be invalid for deep, subsea conditions. However, one public report on the reliability of subsea BOPs provided some useful failure data (Holand, 1999). If having ample reliability data is necessary, the OREDA handbook can be purchased. Another valuable source of data is the Bureau of Ocean Energy Management, Regulation and Reinforcement (Bureau of ocean energy management, Regulation and enforcement, 2010). The PDS Data handbook also provides reliability data estimates for components of control and safety systems. Data for field devices (e.g. sensors and valves) and control logic (electronics) are presented, including data for subsea equipment.

5.3.2.3.2 Calculation of failure probability

The available failure rate should apply to the particular application of a component, its operating environment, and its non-operating environment. There are three main methods that could be used to determine the occurrence probability of an event, namely the Statistical method, the extrapolation method and expert judgement (Preyssl, 1995). The statistical method uses the treatment of direct test of experience data and the calculation of probabilities. The extrapolation method involves the use of model prediction and similar condition or using the standard reliability handbook. The expert judgement method uses direct estimation of probabilities by specialists. A dimension of the quality of a product's design or a process is reliability. Reliability refers to the probability that the product or process will be functional when used. For example, reliability of a product being 93% means that 93 out of 100 products produced will perform as intended for a stated period of time under specified operating conditions. Failure rate is a measure used to ascertain reliability of a product or a process. For products that must be replaced because they fail, a relevant measure of interest is the mean time to failure (MTTF), and for products that may be repaired and put to service again, a relevant measure of interest is the mean time between failures (MTBF). In order to calculate MTTF and MTBF, ideally, a large number of products would be operated and tested until failure and the time of the failure for each would be recorded. The information about MTTF and MTBF helps ascertain reliability. However, it is time-consuming and costly to collect enough data to build a probability distribution and cumulative distribution curve of time to failure or time between failures. One way we can deal with this problem is by analysing a smaller set of data and identifying a distribution that approximates the distribution of time to failure, such as the Exponential, Weibull, or Gamma distributions. Once we have identified a distribution, we can easily calculate failure rate, MTTF, *etc*. A component is tested periodically with test interval. A failure may occur at any time in the test interval, but the failure is only detected in a test. This is a typical situation for many safety-critical components, like sensors and safety valves. If an event failure is of a kind which can be inspected, the component failure probability can be obtained from Equation (5.2) (Spouge, 1999; Høyland & Rausand, 2009). The following notation is used:

λ = Component failure rate

P(t) = Component failure probability at t

R(t) = Reliability $R(t) = 1 - P(t)$

τ = Inspection interval

$$P(t) = \frac{1}{2}\lambda\tau \tag{5.2}$$

In the case that the distribution functions are approximated by an exponential distribution P(t) is determined from Equation (5.3)

$$P(t) = 1 - e^{-\lambda t} \tag{5.3}$$

5.3.2.4 Fuzzy failure assignment for the failure probability

As an alternative to using the failure rate in probability, a Fuzzy modelling approach is used to assign the failure rate in the FTA. Several experts are required to develop the membership functions of the failure rates. The numbers associated with linguistic risk levels are also considered an important factor for the failure rate. Experts usually use linguistic variables to assess the importance of one criterion or event over another to rate alternatives with respect to various criteria. With consideration of some limitations on the capacity for processing information, Miller (1956) proposed a magical number of seven, plus or minus two. With respect to this, it is often recommended that the number of linguistic terms for judgements should be restricted to between five to nine (Karwowski & Mital, 1986). In this research, each linguistic variable has seven descriptive linguistic terms and these can be represented quantitatively by a range of probabilities, as shown in Figure 5.15. Chen et al. (1992) proposed different scales of linguistic terms for expert assessment. After the determination of the linguistic levels for each hazard failure rate, one must determine the relevant mathematical expressions using membership functions for Fuzzy numbers. Expert knowledge is influenced by individual perspectives and goals (Ford and Sterman, 1998). Therefore, complete impartiality of expert knowledge is often difficult to achieve. An important consideration in the selection of experts is whether to use a heterogeneous group of experts (e.g. both scientists and workers) or a homogenous group of experts (e.g. only scientists). The weighting factors of experts are determined according to Table 4.5 and Table 4.6.

Scale 6 in Chen et al. (1992), which contains trapezoidal membership functions, is adopted to present mathematically the failure rates of hazards in this research. Therefore, the conversion scale of 6, which contains seven verbal terms, is selected for performing the subjective assessment of hazards with an unknown failure rate. Figure 5.15 introduces the Fuzzy linguistic scale that is used in this study to determine the judgements of experts with respect to hazards with unknown failure rate.

5.3.2.5 Aggregating algorithm for linguistic terms

In this stage, all ratings are aggregated for each subjective basic event. Since each expert may have a different opinion according to their experience and expertise in the relevant field, it is necessary to aggregate experts' opinions to reach a consensus. Hsu and Chen (1996) presented an algorithm to aggregate the linguistic opinions of a homogeneous or heterogeneous group of experts. Suppose each expert, E_k $(k = 1,2,\ldots,M)$ expresses their opinion on a particular attribute in a specific context using a predefined set of linguistic variables. The linguistic terms can be converted into corresponding Fuzzy numbers. The detailed algorithm is described as follows:

a) Calculate the degree of agreement (degree of similarity) $S_{uv}(\tilde{R}_u, \tilde{R}_v)$ of the opinions $\tilde{R}_u$ and $\tilde{R}_V$ of a pair of experts, E_u and E_v, where $S_{uv}(\tilde{R}_u, \tilde{R}_v) \in [0,1]$. According to this approach, $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$ are two standard TPFNs. The degree of similarity between these two Fuzzy numbers can be obtained by the similarity function of S, which is defined as:

$$S(\tilde{A}, \tilde{B}) = 1 - \frac{1}{4}\sum_{i=1}^{4}|a_i - b_i| \tag{5.4}$$

where $S(\tilde{A},\tilde{B}) \in [0,1]$. The larger value of $S(\tilde{A},\tilde{B})$, the greater similarity between two Fuzzy numbers $\tilde{A}$ and $\tilde{B}$.

b) Calculate the AA degree, $AA(E_u)$, of the experts.

$$AA(E_u) = \frac{1}{M-1} \sum_{\substack{u \neq v \\ v=1}}^{M} S(\tilde{R}_u, \tilde{R}_v) \tag{5.5}$$

c) Calculate the relative agreement (RA) degree, $RA(E_u)$, of expert E_u *(u=1,2,…or M)*

$$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)} \tag{5.6}$$

d) Estimate the consensus coefficient (CC) degree, $CC(E_u)$, of expert, E_u *(u=1,2,…or M)*:

$$CC(E_u) = \beta \cdot w(E_u) + (1-\beta) \cdot RA(E_u) \tag{5.7}$$

where β $(0 \leq \beta \leq 1)$ is a relaxation factor in the proposed method. It shows the importance of $w(E_u)$ over $RA(E_u)$ .When $\beta = 0$, no importance has been given to the weight of an expert and hence a homogeneous group of experts is used. When $\beta = 1$, the consensus degree of an expert is the same as its importance weight.

e) Finally, the aggregated result of the experts' judgements, $\tilde{R}_{AG}$, can be obtained as follows:

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \cdots + CC(E_M) \times \tilde{R}_M \tag{5.8}$$

5.3.2.6 Defuzzification process

Defuzzification is the process of producing a quantifiable result in FL. Fuzzy number defuzzification is an important procedure for decision-making in a Fuzzy environment. The centre of area defuzzification technique is used here. This technique was developed by Sugeno (1985) and Spouge (1999). This is the most commonly used technique and is the most accurate. This method can be expressed as:

$$X^* = \frac{\int \mu_i(x)xdx}{\int \mu_i(x)} \tag{5.9}$$

where X^* is the defuzzified output, $\mu_i(x)$ is the aggregated membership function and x is the output variable. The above formula can be shown as follows for triangular and TPFNs. Defuzzification of Fuzzy number A= (a_1 ,a_2.,a_3) is:

$$X^* = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} xdx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} xdx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} dx} = \frac{1}{3}(a_1+a_2+a_3) \tag{5.10}$$

Defuzzification of trapezoidal Fuzzy number $\tilde{A} = (a_1, a_2, a_3, a_4)$ can be obtained by Equation (5.11).

$$X^* = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} xdx + \int_{a_2}^{a_3} xdx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} xdx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} dx + \int_{a_2}^{a_3} xdx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} dx} = \frac{1}{3}\frac{(a_4+a_3)^2 - a_4a_3 - (a_1+a_2)^2 + a_1a_2}{(a_4+a_3-a_2-a_1)} \tag{5.11}$$

5.3.2.7 Converting crisp failure possibility of BEs into failure probability

There is inconsistency between failure probabilities of certain hazards and crisp failure possibility (CFP) of vague events. This issue can be solved by transforming CFPs of vague events into failure probabilities. This transformation can be performed by using Equation (5.12). Onisawa and Nishiwaki (1988) proposed a function which can be used for converting CFP to failure probability. This function is derived by establishing some properties such as the proportionality of human sensation to the logarithmic value of a physical quantity. The probability rate can be obtained from the possibility rate, as follows (Onisawa, 1990; Lin & Wang, 1997):

$$FP = \begin{cases} \dfrac{1}{10^K}, CFP \neq 0 \\ 0, CFP = 0 \end{cases}, \qquad K = \left[\left(\frac{1-CFP}{CFP}\right)\right]^{\frac{1}{3}} \times 2.301 \tag{5.12}$$

5.3.3 Scheming the MCSs and calculation of top event occurrence

Based on its description, the system is analysed with a top-down approach that starts with the dangerous or unacceptable event, called the top-level event, from which a graphical logical tree is created that consists of lower-level events (i.e. BEs) combined with logical operators such as AND or OR. The analysis is carried out in iterations until a desired level of detail is achieved (e.g. single component failure). Causes in this level are called BEs; an example of an FT is shown in Figure 5.5. If the FT is traversed from the top, it can be seen that, in order to trigger the top-level event, either IE-1 or IE-2 must occur. In order to trigger IE-1, both events BE-1 and BE-2 need to occur, whereas either event BE-3 or event BE-4 triggers event IE-2. A set of BEs which together activate the top-level event is called a cut set. In Figure 5.5 the encircled basic event (BE-4) is a cut set. In total there are three minimal cut sets (i.e. BE-1 to BE-4). In the right branch of the FT there are two minimal cut sets of size 1, which means that they are single points of failure. In the left branch of the FT there is one minimal cut set of size 2, which means that one fault is tolerated without compromising the safety function. Thus, the minimal cut set sizes have a natural correspondence to the fault tolerance of the system. FTA leads to all possible minimum combinations of basic human, operation, instrument and equipment failures, called MCSs, which could lead to the occurrence of the TE. When FTs have BEs which appear more than once, the methods most often used to obtain the TE probability utilise MCSs.

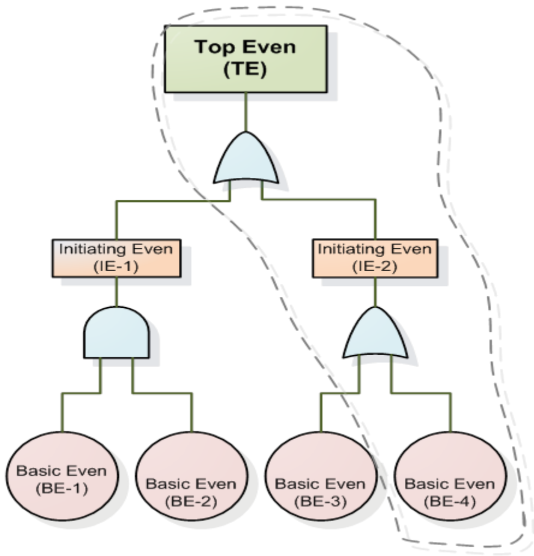


Figure 5.5: Minimal cut set

An MCS is a collection of BEs. If all these events occur, the TE is guaranteed to occur. However, if any BE does not occur, the TE will not occur. Therefore, by using Equation (5.13) if a FT has n_c *MCSs* (MCS_i ,$i=1,\ldots,n_c$) then the TE "T" exists if at least one *MCS* exists (Andrews & Moss, 2002). A quantification of the TE occurrence likelihood can be obtained by Equation (5.14).

$$T = MCS_1 + MCS_2 + \ldots + MCS_N + = \bigcup_{i=1}^{N} MCS_i \tag{5.13}$$

$$P(T) = P(MCS_1 \cup MCS_2 \cup \ldots \cup MCS_N) \tag{5.14}$$

$$\begin{aligned} &= P(MCS_1) + P(MCS_2) + \ldots + P(MCS_N) - P(MCS_1 \cap MCS_2) \\ &+ P(MCS_1 \cap MCS_2) + \ldots P(MCS_i \cap MCS_j) \\ &+ (-1)^{N-1} P(MCS_1 \cap MCS_2 \cap \ldots \cap MCS_N) \end{aligned}$$

where *P(MCSs)* is the occurrence probability of *MCS* i and N is the number of *MCSs*. Any FT will consist of a finite number of *MCS* that are unique for that TE. Single-component *MCSs*, if there are any, represent those single failures that will cause the TE to occur. Two-component *MCSs* represent the double failures that together will cause the TE to occur. TE can be obtained from *MCSs* by using Equation (5.14). The analysis gives the system designers or decision-makers a set where the effort in improvement can be best focused to reduce the risk taking into consideration the costs and benefits. The MCSs can be prioritised according to their importance.

Prioritisation is the recognition that we cannot solve multiple problems simultaneously due to the lack of infinite resources (i.e. operation, equipment, human factor, *etc*.). Therefore, it is necessary to have a foundation in order to evaluate the reliability and availability of the system. FTA uses failure rates, mean time between failure (Dhillon, 1999, Bedford and Cooke, 2001) and minimal cut sets to evaluate the reliability and availability of the system in question (Tang & Dugan, 2004). One of the most important outputs of an FTA is the set of importance measures that are calculated for the TE. Such importance measures establish the significance for all the MCSs in the FT, in terms of their contributions to the TE probability. Both events as well as MCSs can be prioritised according to their importance. Importance measures can also be calculated that yield the sensitivity of the TE probability to an increase or decrease in the probability of any event in the FT. Two types of TE importance measure can be calculated for each MCS in the FT and are described as follows:

Risk reduction measures the decrease in the probability of the TE if a given MCS is certain not to occur. This importance measure can also be called the top decrease sensitivity. Risk reduction measures for a MCS show the decrease in the probability of the TE that would be obtained if the MCS did not occur. Therefore, the risk reduction measure can be calculated by redoing the FT with the probability of the given MCS set to 0. Thus, it measures the maximum reduction in the TE probability. A risk reduction measure's value is determinable for every MCS in the FT.

The Fussell-Vesely importance measure is the contribution of the MCSs to the TE probability and is determinable for every MCS modelled in the FT. This provides a numerical significance for all the FT elements and allows them to be prioritised. The importance is calculated by summing all the causes (MCSs) of the TE involving the particular event. This measure has been applied to MCSs to determine the importance of individual MCSs. The importance measure can be quantified as per Equation (5.15)

(Modarres, 2006), where $Q_i(t)$ is the contribution of MCS_i to failure of the system, and also $Q_S(t)$ is the occurrence probability of TE due to all MCSs.

$$I_i^{FV}(t) = \frac{Q_i(t)}{Q_S(t)} \tag{5.15}$$

5.4 Application of proposed Fuzzy FTA methodology in MODUs

In order to illustrate how the proposed methodology is applied, and also to have a manageable risk model, a limited number of generic BEs are defined, covering the MODU's operations risk which may directly cause an event or introduce latent failures in a system which may cause an event at a later point in time. In this section the application of the Fuzzy FTA is described; in particular, the application of the proposed research methodology for risk assessment of the MODU's operation system is presented. In conjunction with PRA, FTA specifically focuses on the causes of failure for a system as a series of individual BEs and provides a visual representation of the series of events that can lead to failure of that system. Application of the Fuzzy FTA method consists of stages such as the following:

- Hazard identification and elicitation of failure rate data to the events.
- Establishment of an operational hierarchy system diagram which includes the breakdown of a complex decision problem into smaller, manageable elements of different hierarchical levels as necessary.
- Construction of the Fuzzy FTA model in line with the MODU's operational hierarchy
- Establishment of calculations and identifying the area for further safety improvement.

In this study, a five-level hierarchy, illustrated in Figure 5.3, is developed. The highest level of the hierarchy corresponds to the occurrence probability of the TE (i.e. L1D-O1: Drilling failure due to drilling system failure) and the last layer corresponds to the evaluation of the BEs.

According to the requirement of the Norwegian oil and gas regulations (NORSOK D-010, 2004) pertaining to well integrity during drilling activities, all phases of offshore operations must have two separate and independent barriers. An application of the proposed approach is demonstrated through a specific system failure. Well drilling completion is an appropriate example, in which the mud column is the primary barrier and the secondary barrier is the BOP, which protects the well from a disaster as the last resort. In overbalanced processes, the mud column is the primary well barrier and should function within the drilling margin pressure (i.e. a pressure greater than the hole pressure and lower than the fracture gradient). The secondary barrier shall be active on the detection of an influx and the well should be closed, and this also prevents further unwanted flow in the case of failure of the primary well barrier (PSA, 2008). As an instance, the Macondo (BP, 2010) was planned to be abandoned and left underbalanced by replacing drilling mud with sea water, and with two cement barriers in place (Commission, 2010b).

Mud and BOP control are the operation functions and loss of control can lead to an emergency situation. Well control systems are defined in the NORSOK standard (D-001, 2004) defined as the mechanical well control and associated equipment and system. This includes BOP, choke & kill system, rise, and the control system for the BOP. As explained, the mud system and BOP are the key components of the system that provide the well integrity. Therefore, the simple process diagram of the mud circulation and mixing including BOP system, as illustrated in Figure 5.6, is considered in levels 4 and 5 of the MODU's operational hierarchy, as in Figure 5.3.

Drilling mud is the primary requirement to start drilling operations and the mud mixing system provides appropriate mud in an adequate combination of dry cement and water. The prepared mud, stored in mud pit(s), will be pumped by mud pump(s) through the standpipe manifold into the drill string. The mud pump provides adequate pressure to overcome the mud column static pressure at the bottom of the drilled hole. Mud returns through the annular casing, and then the returned mud is directed to the shell shakers via the mud ditch to remove earthen impurities such as sharp rocks. At a later stage, the returned mud will pass through Desander, Desilter and Gas Separator in order to remove smaller impurities as well as mixed gas trapped in the mud. At the last stage, the treated, returned mud will go back to the mud pits for further circulation. This circulation process is repeated throughout the course of drilling. The returned mud pressure is continuously measured by BOP sensors and, in case of over-pressure, the normal circulation line will be blocked and the high-pressure mud will be led to the choke/kill manifold, which is designed for higher pressure, in order to reduce the pressure of the pumped mud going to the atmospheric level. In case of kick (high pressure in the return line because of entry of water, gas, oil, or other formation fluid into the wellbore), the very high-pressure mud will be injected into the well through the kill line by an additional pump. The cement pump is also connected to the choke/kill manifold. It should be noted that the "kick" pressure is lower than the "choke" pressure. As the bit "drills ahead", a specially formulated drilling fluid or mud is continually pumped or circulated from the surface to the bottom of the well, and then back to the surface to cool the bit and remove the cuttings, as illustrated in Figure 5.6.

As is shown in Figure 5.6, the mud and cementing circulation system is composed of the following: bulk and storage system, high-pressure mud pumping system, mud treatment system and cementing system. The BOP, which is one of the major pieces of equipment for drilling, is comprised of the following: BOP stack failure, control system and components. The BOP system stack is made up of a series of pipe rams and annular preventers in charge of sealing and shearing the drill pipe. A common subsea stack is shown in Figure 5.7 and was also the control system of the Macondo Deepwater Horizon, as illustrated in Figure 5.9. In ultra-deepwater drilling operations, the drilling platform is connected to the BOP, installed at the wellhead on the seabed by the drilling riser.

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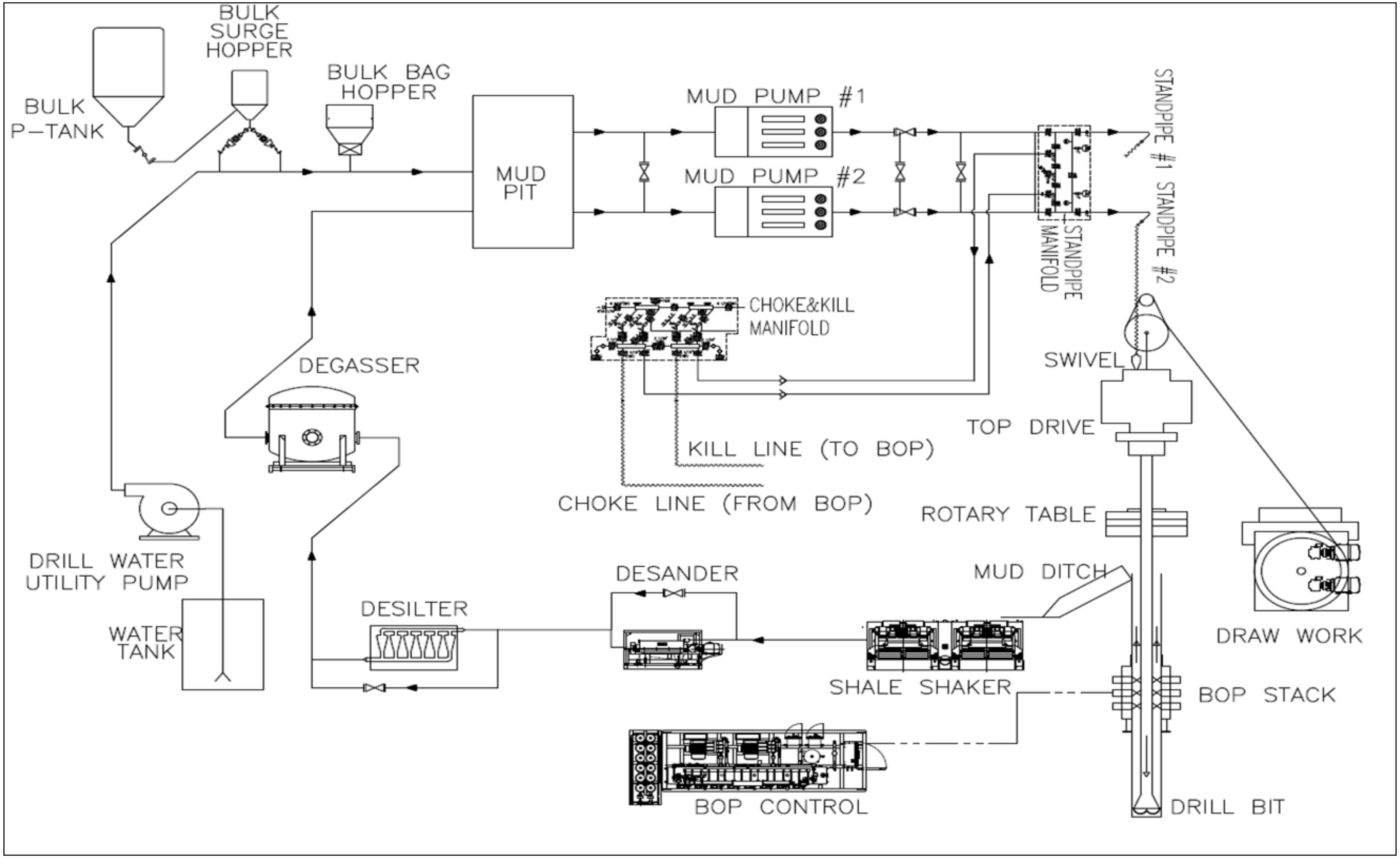

Figure 5.6: Schematic diagram of mud circulation and mixing system/equipment in levels 4 and 5.

The drilling riser is a steel tube containing the drill string which enables the flow of drilling fluids. In most drilling systems, the drilling fluid is pumped into the well flowing through the drill string and returns to the surface by flowing up through the annular space between the drilling riser's internal wall and the outer circumference of the drill string. The BOP could be installed on the platform (surface) for a fixed platform or on the seabed (subsea) for a floating platform where the wellhead is attached to the seabed (Figure 5.8).

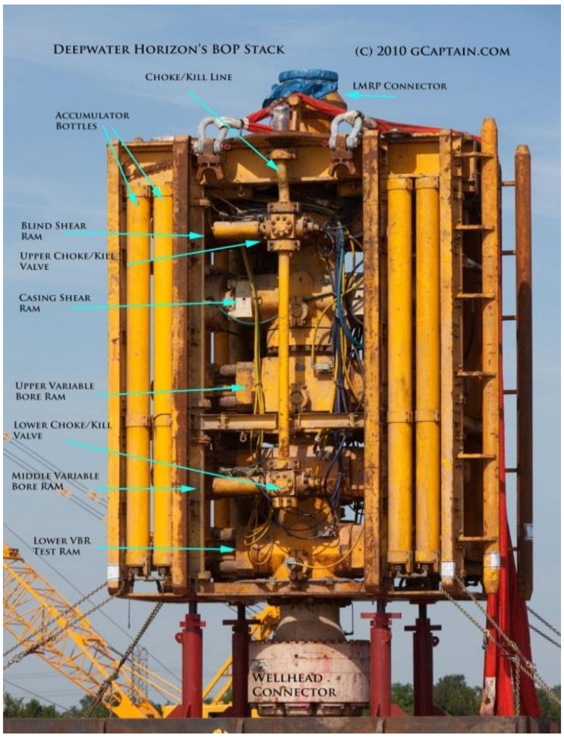

Figure 5.7: BOP control system in the Macondo Deepwater Horizon (Gröndahl *et al.*, 2010)

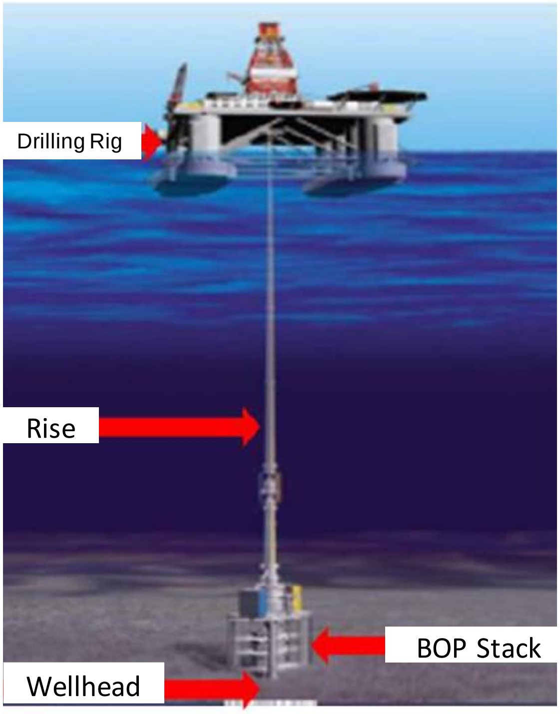

Figure 5.8: Typical position of subsea BOP (Image provided by BP).

The BOP is a critical part of the safety system of an MODU, as proven in the 2010 Macondo accident (Deepwater Horizon). Blowout preventers act as a safety barrier in emergencies or undesired events by controlling reservoir pressures and fluids in the well (Tumer, 2010). A great challenge for the oil and gas industry is to decide what to do when there are indications of failures in the BOP.

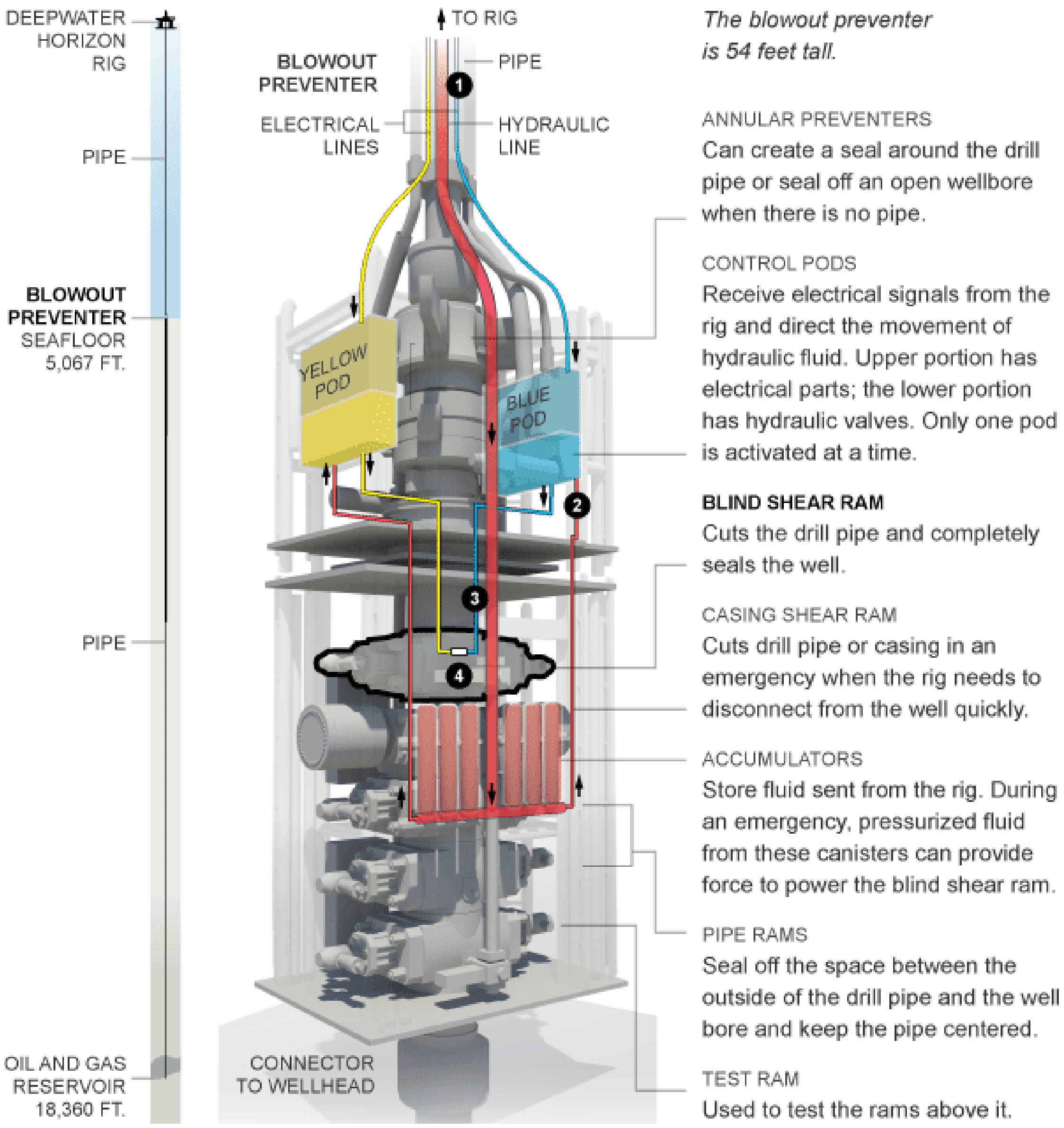

Figure 5.9: BOP control system in Macondo Deepwater Horizon (Gröndahl *et al.*, 2010)

The closing of rams is controlled by the BOP control system, which is driven mainly by hydraulic power. An accumulator attached to the subsea control pod operates the hydraulic system used to close the rams. It passes through a regulator, SPM (Stand Pipe Manifold) valve and a shuttle valve. The closing of the blind shear rams starts when hydraulic fluid from the control pod passes through the shuttle valve and pushes both pistons inward. The BOP control system is a critical component in a BOP stack because this is the heart of a system that drives preventers and rams to close and open with or without using primary rig power. After the explosion of the Deepwater Horizon oil rig, investigators focused on the failure of a component on the well's BOP that was supposed to close-off a well spewing out of control. The device, called a blind shear ram, is the only part of the blowout preventer that can completely seal the well. Minutes after the explosion, at least one rig worker hit an emergency button, which is supposed to trigger the blind shear ram within about 30 seconds and then disconnect the rig from the well. However, that night the blind shear ram never fully deployed. A typical blind shear ram system is shown in Figure 5.10 and also a usual configuration of a subsea BOP system is shown in Figure 5.11.

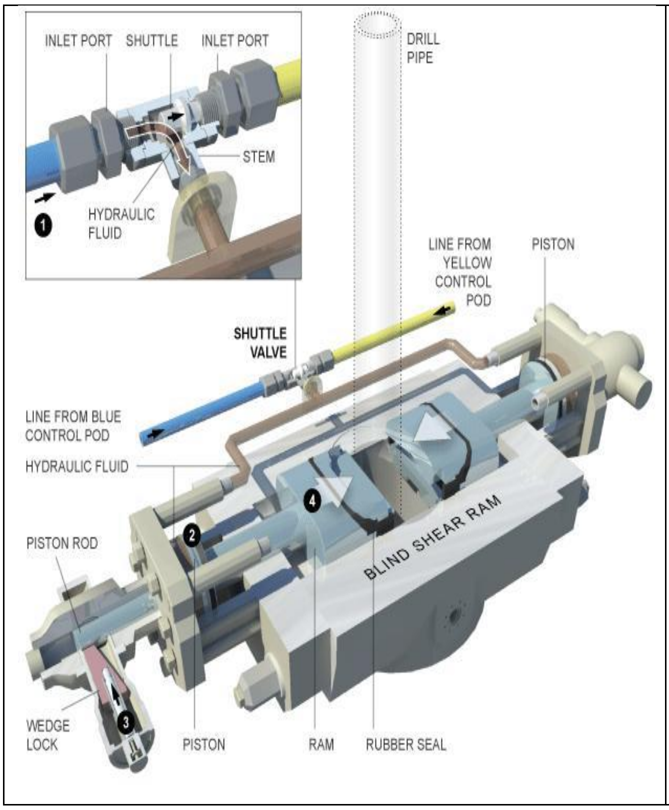

Figure 5.10: Blind shear rams closing (Gröndahl *et al.*, 2010) (Rig Train, 2001)

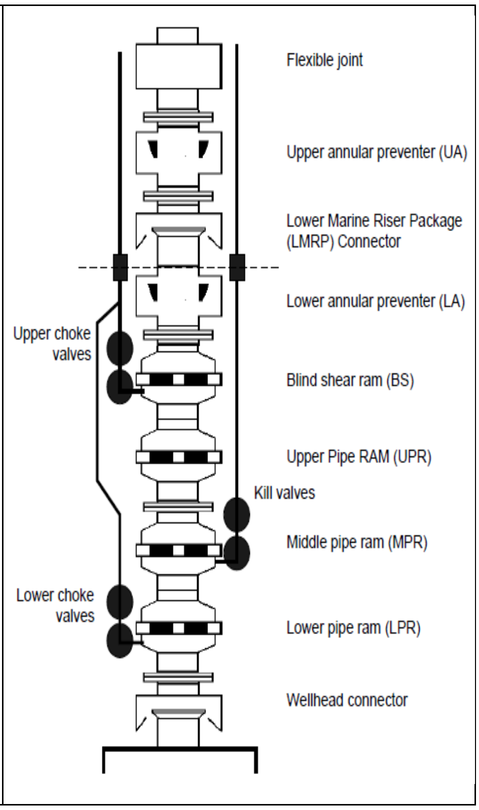

Figure 5.11: BOP stack used for the FTA (Holand, 1999)

5.5 Hazard identification and potential hazard sources/sub-sources

A complete system-level risk assessment is greatly dependent on properly identifying the key events of the area of interest. In particular, the identification of potential hazard sources within the structure of the problem domain should be considered as a fundamental step in operation system risk assessment. The fundamental concept of the proposed methodology consists of the translation of a physical system in a structuralised logical diagram, in which certain specific causes lead to a top event of interest. In Chapter 4, the contextual information on the MODU HGs and the objectives of the application were provided and also a novel methodology was introduced for HGs classification with particular emphasis on drilling failure (L1D-O1-01). A model in association with the circulation and mixing system is developed in Level 4 with special focus on analysis failures of the mud system caused by its HGs. As was shown in Figure 5.3, there are three HGs of interest, L2D-N1, L2D-O1 and L2D-H1, which belong to level 2 of the operational hierarchy. L2D-N1, L2D-O1 and L2D-H1 can be inferred directly from the BEs in level 3, which include: L3D-N1-01 to 5, L3D-O1-01 to 8 and L3D-H1-01 to 3 respectively, while the event L3D-O1-01 was expanded in two more levels (levels 4 & 5) and is dependent on the existence of lower-level events. The following illustrates four of the intermediate events in Level 4, each of which has its own BEs in Level 5,:

- L4D-O1-01-01: High-Pressure Mud System Failure
  - L5D-O1-01-1-1: Mud Pump #1 Failure
  - L5D-O1-01-1-2: Mud Pump #2 Failure
  - L5D-O1-01-1-3: Bulk Handling System Failure
  - L5D-O1-01-1-4: High-Pressure Route Failure
    (HP hoses, Standpipe Manifold, Choke and Kill Manifold)

- L4D-O1-01-02: Mud Treatment System Failure
  - L5D-O1-01-2-1: Shale Shaker Failure
  - L5D-O1-01-2-2: Desander Failure
  - L5D-O1-01-2-3: Disilter Failure
  - L5D-O1-01-2-4: Degasser Failure

- L4D-O1-01-03: Drilling Equipment Failure
  - L5D-O1-01-3-1: Draw Work Failure
  - L5D-O1-01-3-2: Rotary Table Failure
  - L5D-O1-01-3-3: Top Drive Failure
  - L5D-O1-01-3-4: Pipe Handling System Failure
  - L5D-O1-01-3-5: Drilling Control System Failure

- L4D-O1-01-04: Drilling Failure due to Blow out Preventer (BOP) System Failure/ Drilling Failure due to Failure of Managed Pressure Drilling Stack
  - L5D-O1-01-4-1: BOP Stack Failure
  - L5D-O1-01-4-2: BOP Control System Failure
  - L5D-O1-01-4-3: Component Failure/Leak

5.6 Input failure rate and data collection

The process of full application of a Fuzzy FTA involves a number of stages, which start with the definition of a major hazard of the MODU at its system level (i.e. level 1); this is followed by development of the sub-system (i.e. intermediated events) at the next levels; and then a development of a hierarchy up to the BEs is the subsequent stage of this methodology. As stated, the probabilistic FTA is a quantitative analysis method used to calculate the probability of the TE from given failure probabilities of the system's BEs. The estimation of probability of failure has an important role in correctly prioritising the risks involved and also applying adequate corrective measures. Accurate statistical data is vital to most existing techniques but the statistical data of the system and equipment are hardly available. With consideration of availability of failure rates data, the BEs with known failure rates are separated from those BEs with vague failure rates. Therefore, the data collection involves two stages: in the first, the known failure rate required to build the model is collected. In the second stage, an expert system is developed to estimate the failure rate of MODU operational system events. Therefore, to determine the failure rate of an event, utilisation of Fuzzy set theory may be necessary. A Mamdani Fuzzy rules system is used to develop the Fuzzy model.

5.6.1 Scheming of the probabilities of failure of events

At this stage, the real data collected from the industry will be used to test the performance of the proposed model. Limited data such as failure frequency for different equipment are available in different sources (i.e. the OREDA handbook, SINTEF report *etc*.); however, more accurate data may be available within different companies but have not been presented to the market. Failure probability analysis determines the likelihood of an event occurring. A failure rate should apply to the particular application of a component, its operating environment, and its non-operating environment. The component failure probability can be obtained from Equation (5.3) (Spouge, 2000; Rausand, 2004). Calculating the failure probability will require considerable engineering judgement. Since the failure probability has a strong influence on the prioritisation process, it should either be based on validated data or be assessed conservatively.

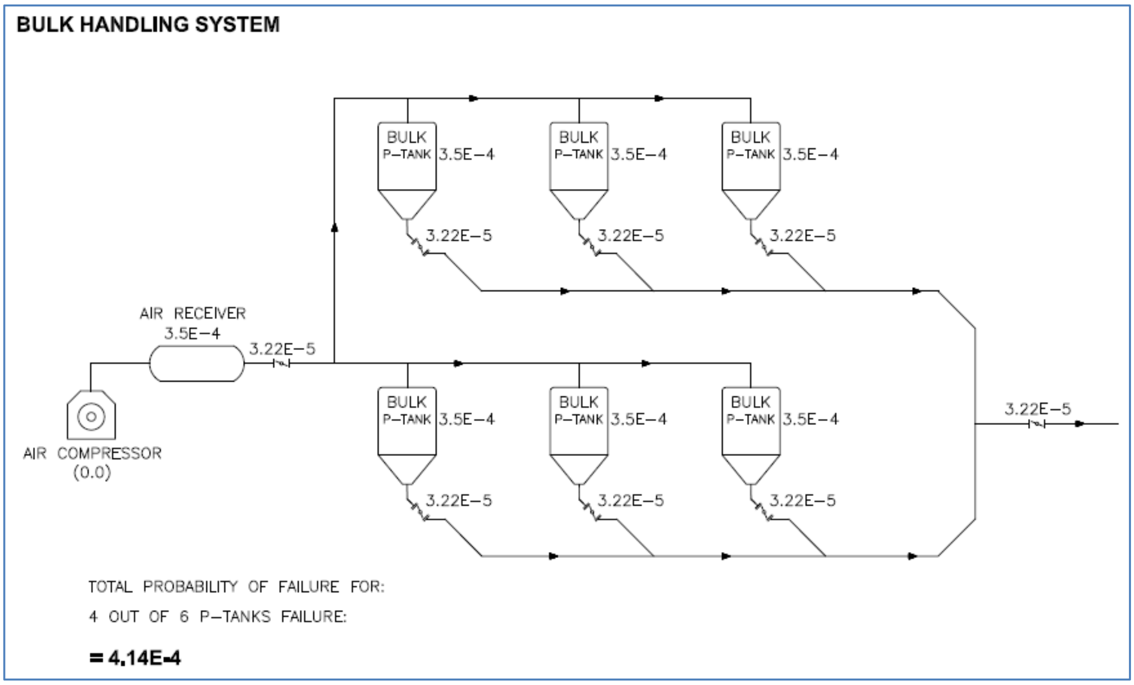

Figure 5.12: Computing of Bulk handling system probability of failure (OREDA, 2002).

In some cases, however, either the data were unavailable for a specific event or the data could not be broken down to the model level of detail. In these cases, expert judgement was used to estimate failure rates for events; however, most of the equipment failure rates used in the quantification of the overall failure probability are time-dependent. The data include failure frequency information and expert responses to the interviews and questionnaires, which together establish the necessary input for gathering information required for test-running the model and its preliminary validation studies with regard to offshore platform risk assessment.

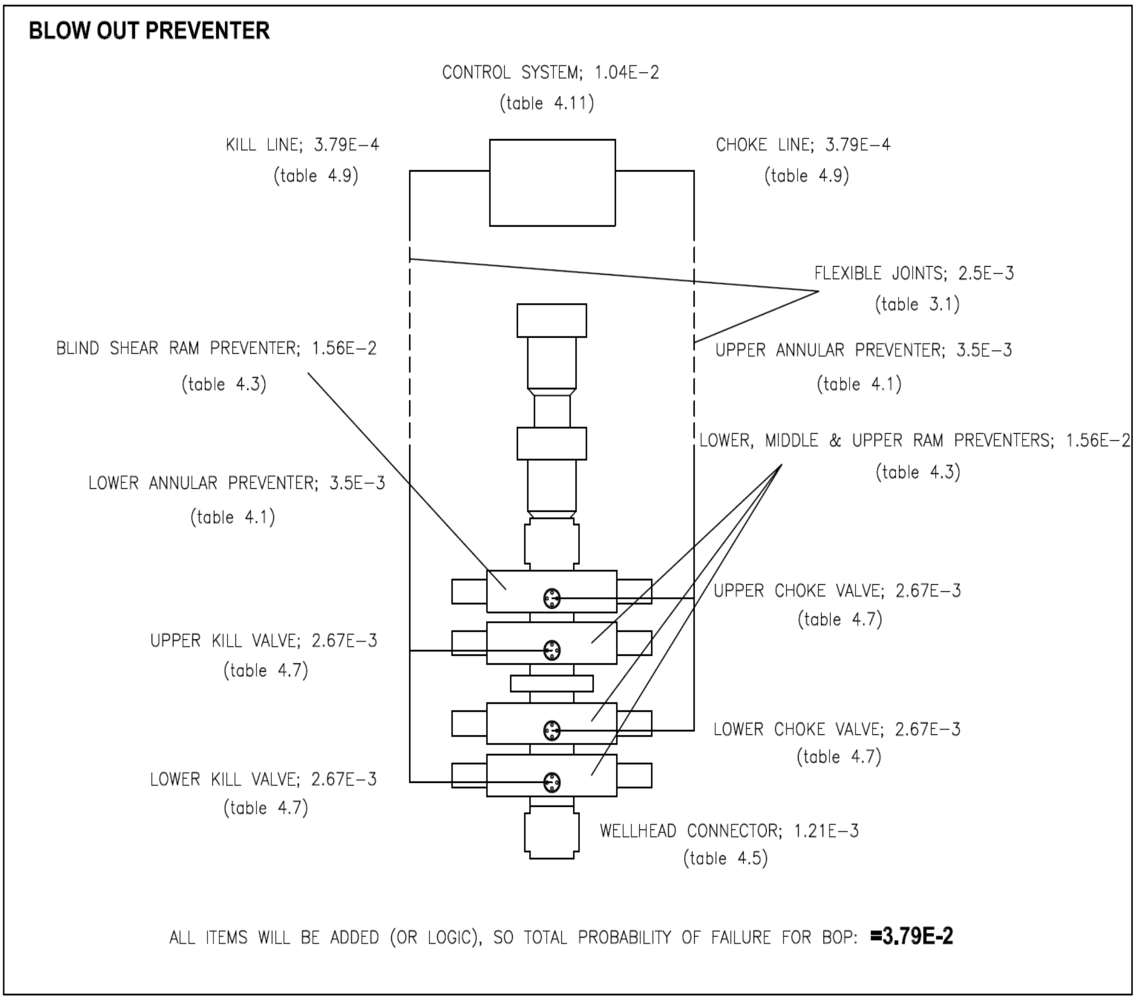

Figure 5.13: Calculating probability of failure of BOP (SINTEF report, 1999)

As illustrated in Figure 5.12 to Figure 5.14, the failure rates were assigned to each BE and its component based on the available detailed data from the OREDA-2002 and SINTEF report-1999. With consideration of the logic of P-Tanks failure (i.e. 4 out of 6), the bulk handling system's probability of failure is 4.14E-4 (Figure 5.12), the probability of failure of the BOP is 3.79E-3 (Figure 5.13), and the power generation system's probability of failure with the logic of 4 out of 5 main generators is 3.04E-7 (Figure 5.14).

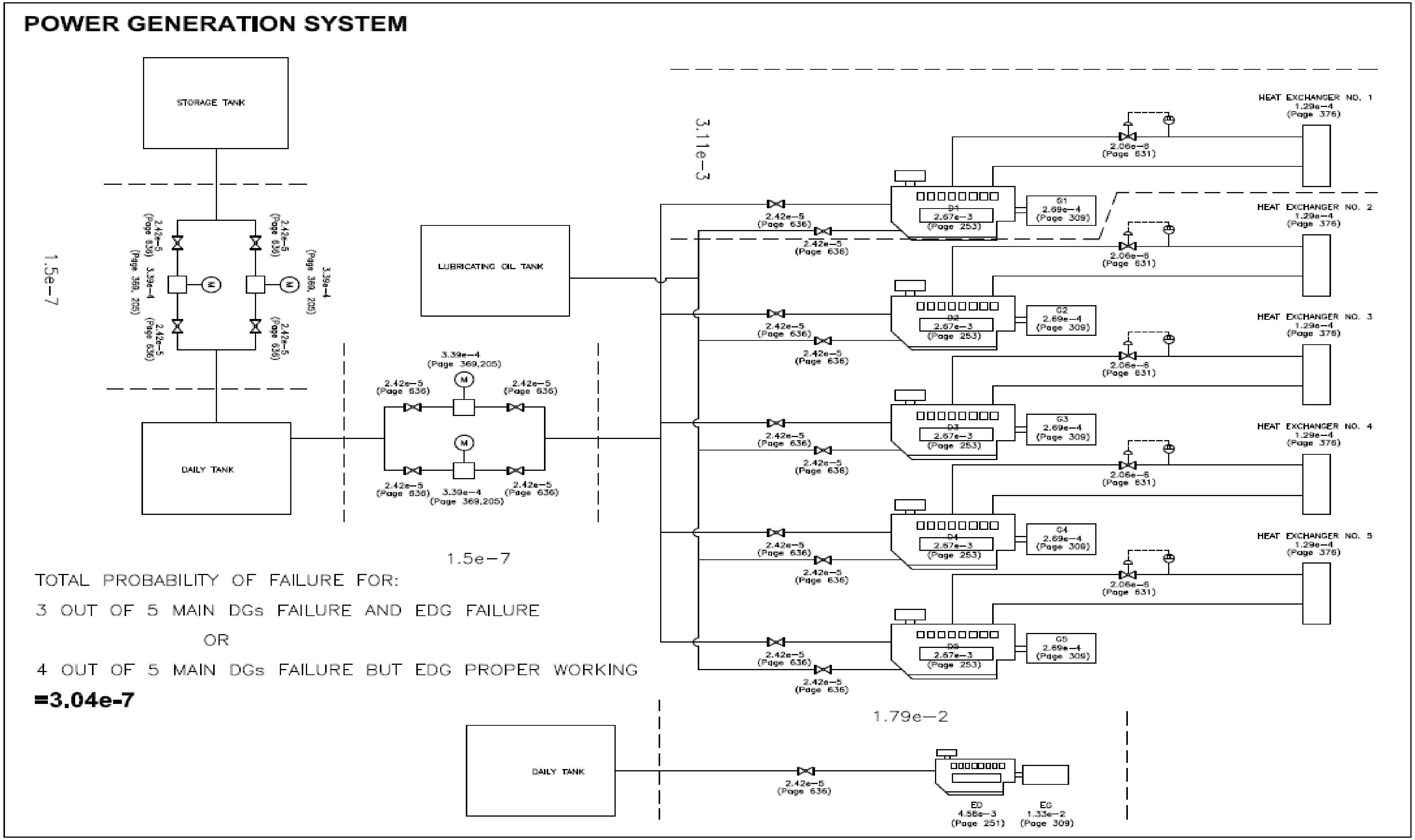

Figure 5.14: Computing of Power generation system's probability of failure with the logic of 4 out of 5 main generators failing (OREDA, 2002).

As mentioned, the FTA is a tool for risk assessment that can combine quantitative information of different accuracy and qualitative data. Risk assessment of the MODU operational system is mostly held up by the absence of appropriate and reliable data. In most circumstances, only descriptive information on the offshore operation system and very limited failure data for components becomes available but quantitative data about cause-effect relations are still missing. To understand these cause-effect relationships expert judgement remains the only available choice. Taking this into account, it is necessary to introduce the probability of BEs in their entirety, so a model with this purpose has been developed using FL. This theory is employed to incorporate expert knowledge, gathered through a questionnaire. Experts usually use the linguistic variable to assess the importance of one criterion over another criterion or even to rate the alternatives with respect to various criteria. The linguistic terms of Figure 5.15 are in the form of both triangular and TPFNs. All of the triangular Fuzzy numbers can be converted into the corresponding TPFNs for ease of analysis. Table 5.1 presents all the Fuzzy numbers of Figure 5.15 in the form of TPFNs.

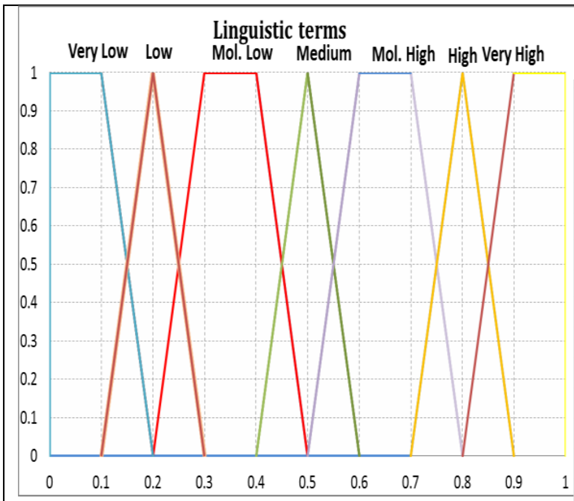

Figure 5.15: Fuzzy linguistic conversion scale 6 (Chen and Hwang (1992))

Table 5.1: Logistics variable, ((Chen & Hwang (1992))

Grade	linguistic variables	Membership function			
		a	b	c	d
L_{f1}	Very Low	0	0	0.1	0.2
	u(x)	0	1	1	0
L_{f2}	Low		0.1	0.2	0.3
	u(x)		0	1	0
L_{f3}	Mol. Low	0.2	0.3	0.4	0.5
	u(x)	0	1	1	0
L_{f4}	Medium		0.4	0.5	0.6
	u(x)		0	1	0
L_{f5}	Mol. High	0.5	0.6	0.7	0.8
	u(x)	0	1	1	0
L_{f6}	High		0.7	0.8	0.9
	u(x)		0	1	0
L_{f7}	Very High	0.8	0.9	1	1
	u(x)	0	1	1	0

A heterogeneous group of experts is employed to perform the judgement for the vague events. The experts' weights can be obtained by using Table 4.5.

Three experts are employed for performing the judgements. Table 5.2 shows the experts' weights.

Table 5.2: Experts' weight factor

No.	Classification / Organization	Score	Qualification / Education Level	Score	Experience / Service Time (years)	Score	Total Score	Weight Factor
Expert 1	Engineer	3	Ph.D	5	20-30	4	12	**0.34**
Expert 2	Engineer	3	Master (M.Sc.)	4	> 30 years	5	12	**0.34**
Expert 3	Senior academic	4.5	Master (M.Sc.)	4	10-19	3	11.5	**0.32**
Total							35.5	1

As illustrated in Table 5.3 and Table 5.4, in the assessment process, verbal statements are used to describe the occurrence probabilities of BEs.

Table 5.3: Occurrence probabilities of BEs (Experts' knowledge) in level 3

Basic Event (Level 3)	Experts																	Crisp No.
	Linguistic terms	Expert 1				Factor	Linguistic terms	Expert 2				Factor	Linguistic terms	Expert 3				Factor	
L3D-N1-01	Very Low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.32	**0.10**
L3D-N1-02	Very Low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.32	**0.03**
L3D-N1-03	Very Low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.32	**0.03**
L3D-N1-04	Very Low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	low		0.1	0.2	0.3	0.32	**0.04**
L3D-N1-05	Very Low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.32	**0.03**
L3D-O1-01	This event of drilling is expanded to its subsystem and events in two lower levels (i.e. level 4 and 5)																		
L3D-O1-02	low		0.1	0.2	0.3	0.34	low		0.1	0.2	0.3	0.34	low		0.1	0.2	0.3	0.32	**0.05**
L3D-O1-03	Mol. Low	0.2	0.3	0.4	0.5	0.34	Medium		0.4	0.5	0.6	0.34	Mol. Low	0.2	0.3	0.4	0.5	0.32	**0.12**
L3D-O1-04	very low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.32	**0.06**
L3D-O1-05	very low			0.1	0.2	0.34	very low			0.1	0.2	0.34	very low			0.1	0.2	0.31	**0.03**
L3D-O1-06	very low			0.1	0.2	0.34	very low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.32	**0.03**
L3D-O1-07	Mol. Low	0.2	0.3	0.4	0.5	0.34	Mol. Low	0.2	0.3	0.4	0.5	0.34	Mol. Low	0.2	0.3	0.4	0.5	0.32	**0.12**
L3D-O1-08	very low			0.1	0.2	0.34	low		0.1	0.2	0.3	0.34	very low			0.1	0.2	0.32	**0.03**
L3D-H1-01	Medium		0.4	0.5	0.6	0.34	Very High	0.8	0.9	1	1	0.34	Medium		0.4	0.5	0.6	0.32	**0.18**
L3D-H1-02	high		0.7	0.8	0.9	0.34	Very High	0.8	0.9	1	1	0.34	high		0.7	0.8	0.9	0.32	**0.23**
L3D-H1-03	high		0.7	0.8	0.9	0.34	Medium		0.4	0.5	0.6	0.34	Medium		0.4	0.5	0.6	0.32	**0.14**

According to these linguistic variables a value on a numerical scale is assigned to each BE. The occurrence probability of each of the MODU operation hazards is calculated on the basis of occurrence probabilities of the BEs. A common approach to deal with these values is the use of semi-quantitative estimation methods, which rely on linguistic judgements of experts. However, these linguistic terms are related to different kinds of uncertainties (i.e. stochastic, lexical and, informal uncertainty).

Table 5.4: Occurrence probabilities of BEs (Experts' knowledge) in level 5

Basic Event (Level 5)	Experts																	Crisp No.
	Linguistic terms	Expert 1				Factor	Linguistic terms	Expert 2				Factor	Linguistic terms	Expert 3				Factor	
L5D-01-01-1-1	low		0.1	0.2	0.3	0.34	High		0.7	0.8	0.9	0.34	High		0.7	0.8	0.9	0.32	**0.14**
L5D-01-01-1-2	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.34	Mol. High	0.5	0.6	0.7	0.8	0.32	**0.13**
L5D-01-01-1-3	Mol. Low	0.2	0.3	0.4	0.5	0.34	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.32	**0.10**
L5D-01-01-1-4	Low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.34	Low		0.1	0.2	0.3	0.32	**0.04**
L5D-01-01-2-1	Low		0.1	0.2	0.3	0.34	Low		0.1	0.2	0.3	0.34	Low		0.1	0.2	0.3	0.32	**0.05**
L5D-01-01-2-2	Medium		0.4	0.5	0.6	0.34	Medium		0.4	0.5	0.6	0.34	Mol. Low	0.2	0.3	0.4	0.5	0.32	**0.12**
L5D-01-01-2-3	Mol. Low	0.2	0.3	0.4	0.5	0.34	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.32	**0.10**
L5D-01-01-2-4	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.34	High		0.7	0.8	0.9	0.32	**0.12**
L5D-01-01-3-1	Low		0.1	0.2	0.3	0.34	Very Low			0.1	0.2	0.34	Low		0.1	0.2	0.3	0.31	**0.04**
L5D-01-01-3-2	Low		0.1	0.2	0.3	0.34	Low		0.1	0.2	0.3	0.34	Low		0.1	0.2	0.3	0.32	**0.05**
L5D-01-01-3-3	Mol. Low	0.2	0.3	0.4	0.5	0.34	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.32	**0.10**
L5D-01-01-3-4	Medium		0.4	0.5	0.6	0.34	High		0.7	0.8	0.9	0.34	Medium		0.4	0.5	0.6	0.32	**0.14**
L5D-01-01-3-5	Low		0.1	0.2	0.3	0.34	Medium		0.4	0.5	0.6	0.34	Mol. High	0.5	0.6	0.7	0.8	0.32	**0.13**
L5D-01-01-4-1	Medium		0.4	0.5	0.6	0.34	Mol. High	0.5	0.6	0.7	0.8	0.34	Medium		0.4	0.5	0.6	0.32	**0.15**
L5D-01-01-4-2	High		0.7	0.8	0.9	0.34	Mol. High	0.5	0.6	0.7	0.8	0.34	Mol. High	0.5	0.6	0.7	0.8	0.32	**0.21**
L5D-01-01-4-3	High		0.7	0.8	0.9	0.34	High		0.7	0.8	0.9	0.34	Medium		0.4	0.5	0.6	0.32	**0.17**

5.6.2 Aggregation scheming of the BEs and defuzzification process

In order to obtain more information for making better judgements, the assessments are performed by three experts. For group evaluation, it is necessary to aggregate different expert opinions into one. The aggregation is a result of the union of two or more membership functions.

Table 5.5: Aggregation calculations for the BE of "L5D-O1-01-01-01"

BE	Linguistic terms						Expert weight factor (E_{wf})		Aggregation for BE			
L5D-01-01-01-01	Expert 1 (E_1)	low	0	0.1	0.2	0.3	**0.34**		0.000	0.499	0.599	0.699
	Expert 2 (E_2)	High	0	0.7	0.8	0.9	**0.34**					
	Expert 3 (E_3)	High	0	0.7	0.8	0.9	**0.32**					
	Aggregation calculations for the BE											
	Degree of similarity		Average Agreement		Relative Agreement		Consensus Coefficient					
	S (E1&E2)	0.55	AA (E1)	0.775	RA (E1)	0.333	CC (E1)	0.336				
	S (E2&E3)	1	AA (E2)	0.775	RA (E2)	0.333	CC (E2)	0.336				
	S (E1&E3)	0.55	AA (E3)	0.775	RA (E3)	0.333	CC (E3)	0.329				
Total				2.325		1		1.000				

Aggregation is used to merge associated ratings for BEs. As an instance, the aggregation calculations for BE of "L5D-O1-01-01-01" are given in Table 5.5. β is considered as 0.5 in the aggregation scheme. These scheming contain characteristic-based aggregation calculations such as average degree of agreement (AA) and relative degree of agreement (RA) of each expert. Table 5.6 presents the results of calculations for aggregation for all the BEs. Based on the features of the commonly used defuzzification techniques, the centre of area defuzzification method is employed to calculate the defuzzification of all the subjective Bes.

Table 5.6: Aggregation calculations and defuzzification of the BEs

Basic Events (BEs)	Aggregation calculations for each subjective BE				Crisp No.
L3D-H1-01	0.056	0.190	0.223	0.256	0.175
L3D-H1-02	0.023	0.045	0.078	0.112	0.065
L3D-H1-03	0.023	0.079	0.112	0.146	0.089
L3D-N1-01	0.090	0.223	0.257	0.279	0.206
L3D-N1-02	0.267	0.300	0.333	0.333	0.307
L3D-N1-03	0.023	0.088	0.122	0.155	0.095
L3D-N1-04	0.000	0.167	0.200	0.234	0.142
L3D-N1-05	0.000	0.200	0.233	0.266	0.164
L3D-O1-02	0.000	0.033	0.067	0.100	0.050
L3D-O1-03	0.056	0.190	0.223	0.256	0.175
L3D-O1-04	0.023	0.045	0.078	0.112	0.065
L3D-O1-05	0.023	0.079	0.112	0.146	0.089
L3D-O1-06	0.054	0.121	0.154	0.188	0.128
L3D-O1-07	0.023	0.188	0.222	0.255	0.164
L3D-O1-08	0.000	0.033	0.067	0.100	0.050
L5D-O1-01-1-1	0.000	0.499	0.599	0.699	0.424
L5D-O1-01-1-2	0.023	0.088	0.122	0.155	0.095
L5D-O1-01-1-3	0.023	0.122	0.155	0.189	0.119
L5D-O1-01-1-4	0.110	0.177	0.211	0.244	0.184
L5D-O1-01-2-1	0.000	0.200	0.233	0.266	0.164
L5D-O1-01-2-2	0.000	0.022	0.055	0.089	0.042
L5D-O1-01-2-3	0.000	0.133	0.167	0.200	0.119
L5D-O1-01-2-4	0.054	0.189	0.222	0.255	0.174
L5D-O1-01-3-1	0.000	0.022	0.055	0.089	0.042
L5D-O1-01-3-2	0.054	0.223	0.256	0.289	0.197
L5D-O1-01-3-3	0.143	0.244	0.277	0.300	0.236
L5D-O1-01-3-4	0.000	0.022	0.055	0.089	0.042
L5D-O1-01-3-5	0.054	0.223	0.256	0.289	0.197
L5D-O1-01-4-1	0.267	0.300	0.333	0.333	0.307
L5D-O1-01-4-2	0.000	0.022	0.055	0.089	0.042
L5D-O1-01-4-3	0.023	0.088	0.122	0.155	0.095

5.6.3 Converting CFP of BEs into failure probabilities

By using Equation (5.12) the CFP of the BEs can be transferred into failure probabilities and the results of all BEs are presented in Table 5.7.

Table 5.7: Converting CFP into failure probability

Level 5 (BEs)	Factor (K)	Failure probability (FP)
L5D-01-01-1-1	4.3934206	4.04E-05
L5D-01-01-1-2	1.7934061	1.61E-02
L5D-01-01-1-3	2.0995299	7.95E-03
L5D-01-01-1-4	1.9093527	1.23E-02
L5D-01-01-2-1	2.1282295	7.44E-03
L5D-01-01-2-2	2.2126602	6.13E-03
L5D-01-01-2-3	1.8476367	1.42E-02
L5D-01-01-2-4	2.2325504	5.85E-03
L5D-01-01-3-1	1.8334902	1.47E-02
L5D-01-01-3-2	1.8334902	1.47E-02
L5D-01-01-3-3	2.3754289	4.21E-03
L5D-01-01-3-4	2.2126602	6.13E-03
L5D-01-01-3-5	2.2325504	5.85E-03
L5D-01-01-4-1	1.7280464	1.87E-02
L5D-01-01-4-2	1.7280464	1.87E-02
L5D-01-01-4-3	1.7280464	1.87E-02

5.6.4 Scheming the MCSs and calculation of TE

Based on the FT hierarchical model, each BE's occurrence probability must be provided in order to measure the occurrence probability for the TE. The BE probabilities can be propagated upward using MCSs. The failure probability of each MCS is presented in Table 5.8. Furthermore, the occurrence probability of the TE is obtained by using Equation (5.14).

Table 5.8: Failure probability and importance level of each MCS

MCSs	Occurrence probability of MCS	F-VIM	Ranking of MCS
MCS1	4.04E-05	0.0003	14
MCS2	1.61E-02	0.1052	4
MCS3	7.95E-03	0.0520	11
MCS4	1.23E-02	0.0805	10
MCS5	7.44E-03	0.0487	13
MCS6	6.13E-03	0.0401	6
MCS7	1.42E-02	0.0928	9
MCS8	5.85E-03	0.0383	12
MCS9	1.47E-02	0.0854	3
MCS10	1.47E-02	0.0959	2
MCS11	4.21E-03	0.0275	8
MCS12	6.13E-03	0.0401	1
MCS13	5.85E-03	0.0383	5
MCS14	1.87E-02	0.1223	7
MCS15	1.87E-02	0.0040	8

5.6.5 Prioritising the MCSs according to their importance

This prioritisation process by definition requires an assessment of each individual MCSs. An unsafe condition may be defined with various specific words but, in general, it refers to any component failure which has the potential to be the cause of a TE. An important objective of many reliability and risk analyses is to identify those components or MCSs that are the most important from a reliability or risk viewpoint so that they can be given priority with respect to improvements. The ranking of MCSs based on their calculated importance levels is presented in Table 5.8

5.6.6 Risk modelling and analysis of an MODU's operation system

Risk modelling and analysis has a fundamental role in the identification of hazard cause potentials, the understanding of the fundamental causal events, the likelihood assessment of these events, the severity evaluation of the potential consequence of catastrophes and the prioritisation of mitigations. The HG hierarchy of the MODU's operation system as illustrated in Figure 5.1 is converted into an FT. For instance, drilling failure due to Drilling System Failure (L3D-O1-01) is converted to the corresponding parent nodes and the consequence of BOP Stack Failure (L5D-O1-01-4-1) is converted to the corresponding root node. The link between L4D-O1-01-04 and L5D-O1-01-04-01 is converted to a corresponding link in the FT. Each category of events consists of some different sub-events that affect the performance of the MODU's operations, as presented in Figure 5.16. For instance, Drilling control system failure (L5D-O1-01-3-5) is the source of failure of L4D-O1-01-3. Likewise, the L5D-O1-01-2-1 (Shale shaker failure) and L5D-O1-01-2-2 (Desander failure) contribute to L4D-O1-01-02 (Mud Treatment system failure) to a certain degree. Figure 5.17 illustrates the results for the FT model of L2D-H1 (Human Error) and Figure 5.18 illustrates the results for the FT model of L2D-N1 (Natural Hazard).

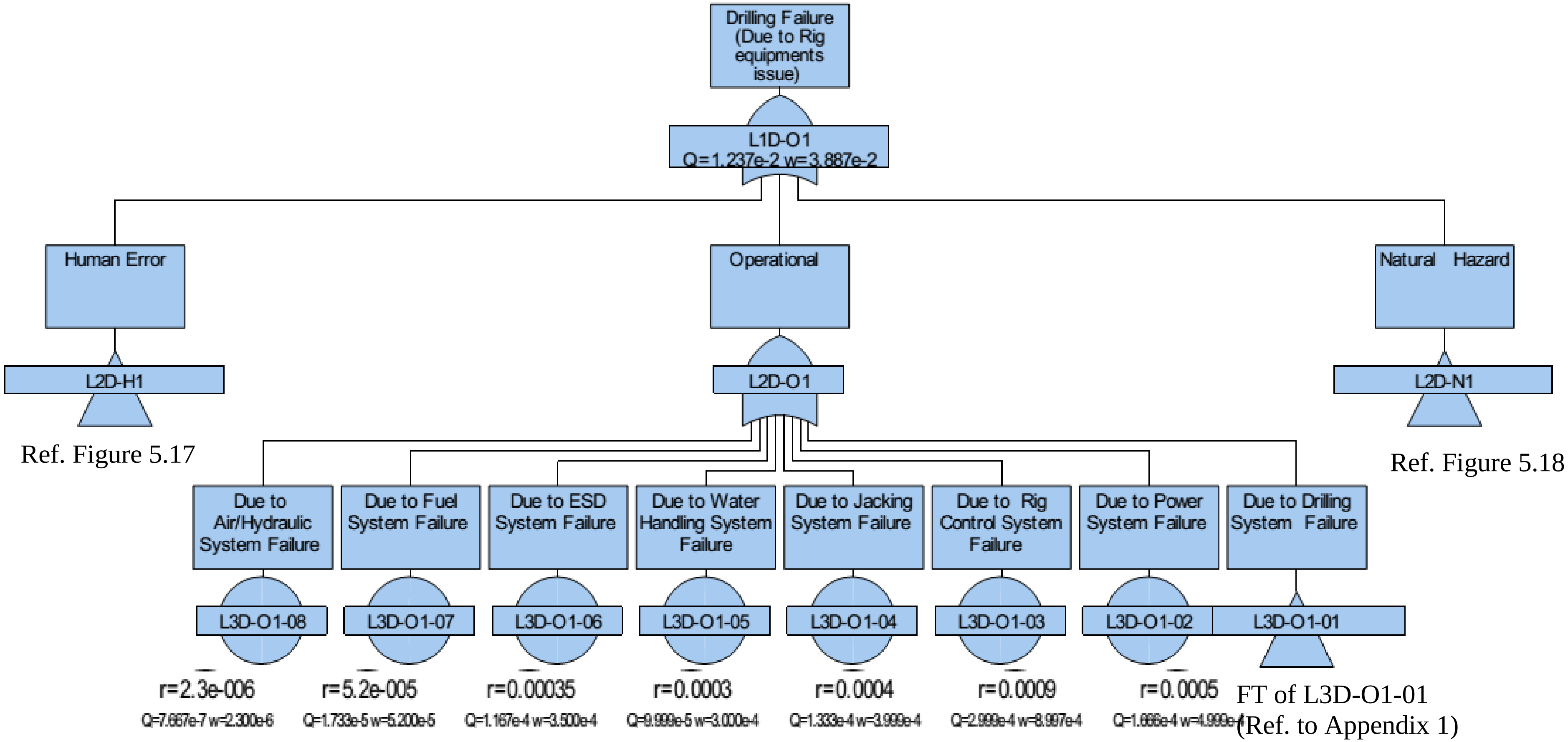

Figure 5.16: FT model of the MODU's drilling system

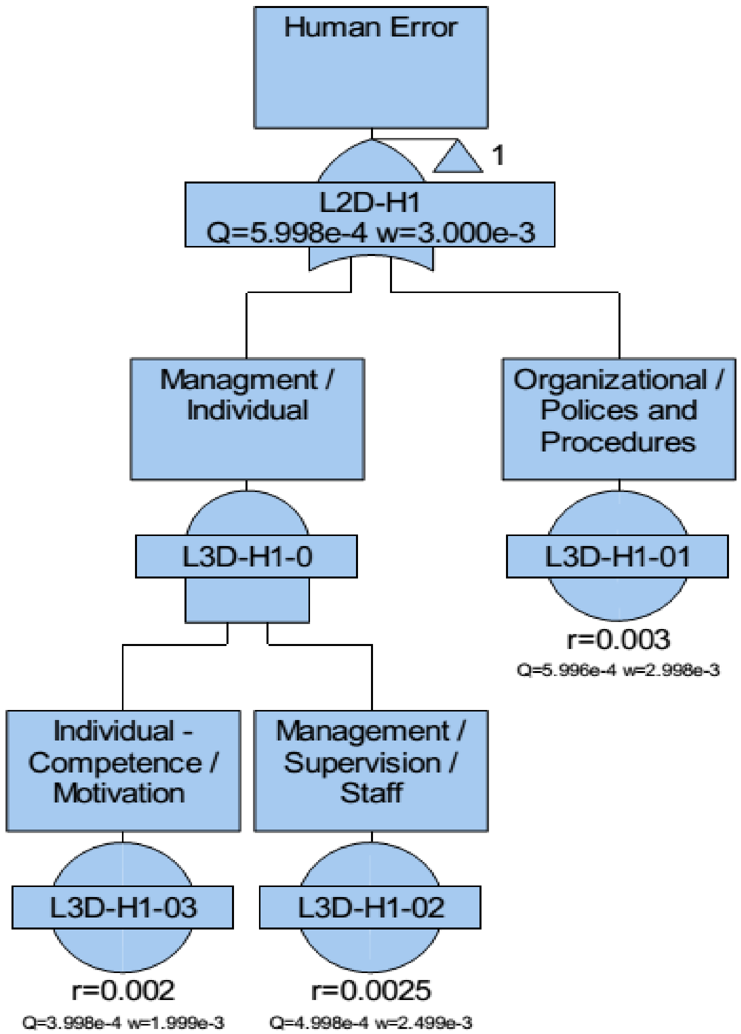

Figure 5.17: FT model of L2D-H1 (Human Error)

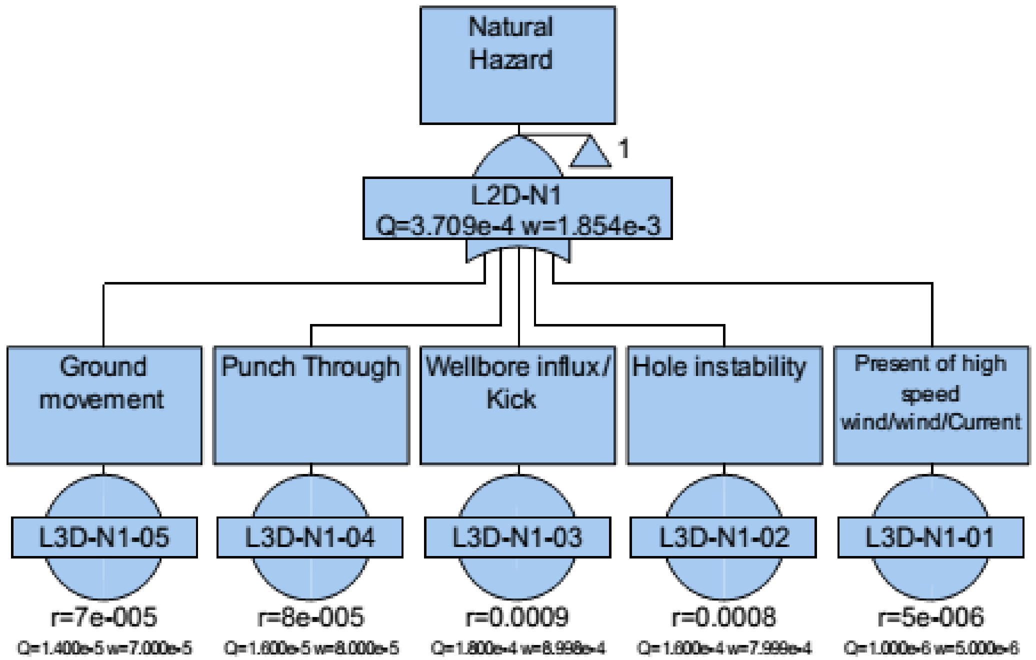

Figure 5.18: FT model of L2D-N1 (Natural Hazard)

5.7 Validation and sensitivity analysis

Validation is an important aspect of a model for the reason that it affords a sensible amount of confidence in the results of the model. It is very useful to be able to compare a model against actual data to verify that the model adequately corresponds to reality and to assess its usefulness as a predictive tool. In this case, in order to carry out a validation of the model, the parameters used need to be closely monitored for a period of time. For MODU system operations, it is obviously an impractical exercise due to the lack of offshore operations data. For validation of the proposed methodology and modelling, three basic principles are considered and should be satisfied. First, a minor oscillation in the prior probability of each parent node should certainly be the result of a relative fluctuation of the posterior probabilities of child nodes. Second, fluctuation in the probability distributions of an individual parent node and its consequent gradation to child node values should be kept steady. Lastly, the size of the entire effect of the group of probabilities' variations from the values of attributes should constantly be more than that from the set of A-b (b ∈A) features (Cai *et al.*, 2013). Validation is the assignment of representations that the model is a realistic demonstration of a real system and is an important aspect of a methodology because it provides a reasonable amount of confidence in the result of the model. Due to lack of real data, the model should at least satisfy the three basic principles as mentioned above. From the above, it can be concluded that increasing each influencing node satisfies the three basic principles, therefore providing a partial validation of the model.

Risk reduction measure (RRM) is employed to conduct sensitivity analysis. The RRM can be calculated by setting an MCS probability to 0. It is expected that elimination of the MCS that has the highest contribution to the occurrence of TE should result in reducing the occurrence rate of the TE more than other MCSs. Therefore, ranking of RRM values is expected to be the same as the ranking result of MCSs in Table 5.8. As shown in Table 5.9, MCS13 has the highest contribution to the TE occurrence probability. Therefore, the RRM value of MCS13 must be the largest. As demonstrated in Table 5.9, the RRM value of MCS13 is 0.0248, which is the highest, as expected.

Table 5.9 shows the ranking result, which remains the same as the one in Table 5.8. The proposed model satisfies the aforementioned expectations.

Table 5.9: Failure probability and importance level of each MCS

No of MCSs	Occurrence probability of MCSs	F-VI M	MCSs rank	New TE	RRW=TE-New TE	RRW rank
MCS1	0.002	0.066867246	5	0.0519	0.0019	5
MCS2	0.0004	0.013373449	11	0.0534	0.0004	11
MCS3	0.003	0.100300869	4	0.0509	0.0029	4
MCS4	0.0006	0.020060174	9	0.0532	0.0006	9
MCS5	0.00000001	3.34336E-07	15	0.0537	0.00001	15
MCS6	0.00066	0.022066191	7	0.053	0.0008	7
MCS7	0.00035	0.011701768	12	0.0535	0.0003	12
MCS8	0.0002	0.006686725	13	0.0536	0.0002	13
MCS9	0.002	0.066867246	5	0.0519	0.0019	5
MCS10	0.005	0.167168115	3	0.049	0.0048	3
MCS11	0.001	0.033433623	8	0.0531	0.0007	8
MCS12	0.014	0.468070723	2	0.0404	0.0134	2
MCS13	0	0	1	0.029	0.0248	1
MCS14	0.0001	0.003343362	14	0.0537	0.0001	14
MCS15	0.0006	0.020060174	9	0.0532	0.0006	9

5.8 Results and discussion

MODU risk assessment and probability of failure has made limited improvement compared to analysis methods developed for other offshore structures' probability estimation. Estimation of probability of failure and analysis of the consequences for MODU operation systems can be facilitated by FTA, as presented in this chapter, allowing modelling with respect to its HG features. This chapter has presented the modelling aspects, including hazard identification and its consequences for MODU failures and offered a methodology for MODU risk assessment which supports a structured approach to all tasks involved in the failure of MODUs due to their HG failure. The presented methodology can easily be extended to include other HGs and the processes should they be considered simultaneously; also, it is possible to propagate uncertainties for different HGs and their BEs through modelling and analysis so that the overall system failure can be indicated in a probabilistic approach (i.e. probability distribution or higher and lower confidence limits). This will benefit the decision-maker, who would appreciate the changeability and sensitivity of failure possibility estimates, which would not be so understandable if a risk assessment was offered as single point estimates only.

5.9 Conclusion

This chapter has presented a methodology for risk analysis and decision support and examined the probability of failure of an MODU operation system by using a Fuzzy FTA. This methodology is used for risk assessment through a unique application of Fuzzy theory, and the proposed methodology can be used as a process for developing a set of decisions for understanding and identifying the range of consequences and trade-offs of actions within an uncertain atmosphere, which allows representation of offshore operation systems such as MODUs in different levels of detail. Risk analysis is performed by assigning probabilities to a certain event failure or evolution, in which a hierarchical breakdown is used to decompose one single component into a more detailed representation of the component. It is assumed that an MODU's system failure is carried out by a series of simple occurrences, each affecting a different component. An event failure can be seen as a path through the evolutionary graph from a start point to an end point.

Risk assessments are subject to many sources of uncertainty and data limitations that hamper the description of model input and the selection of an appropriate model structure. Conceptual model uncertainty and lack of system understanding is demonstrated to have a great impact on risk assessments. FTAs have the advantage that they are based on a logical framework of cause-effect relations. These relations are based on existing knowledge or experience. As little knowledge is available about the individual relations, many assumptions have to be made. For these assumptions expert knowledge is essential. Risk assessment for an offshore operation system with Fuzzy

FTA concepts often involves a portion of information in order to achieve a useful BBN model, especially in the case of an MODU risk assessment, when a large amount of data is vague. Therefore, a combination of various data and information resources is essential. This chapter has proposed a new approach for FTA construction by employing a Fuzzy theory combining domain knowledge from experts where there are limited data. Expert knowledge with Fuzzy set theory was used to estimate the BE failure probability table.

The quantification and assessment of probability of failures allows an engineered design of MODUs and adjustment of an offshore operation system so that risk is appropriately controlled. The largest concern of operators is the disruption of hydrocarbons of delivery to the departure point. An MODU failure has previously caused interruptions in drilling; therefore, operators could use the Fuzzy FTA model to quantify loss frequency, mitigation measures, and mitigation to control or to avoid a specified risk of HGs. By doing so, the expected loss of hydrocarbons and expected costs of construction (depending on the acceptable risk level to the operator) can be determined for establishing budgets for design, construction and installation, and also for operations and maintenance. From this study, it can be concluded that this has the following advantages:

- Assistance in understanding the mitigation process for rare or extreme events, and providing an analysis and structure for strategy creation in situations of uncertainty and risky events.
- When insufficient information concerning the occurrence frequencies of hazardous events is available, a Fuzzy FT methodology for evaluation seems to be a viable alternative solution.
- It can be useful in the process of MODU risk analysis
- By using linguistic variables, it is possible to handle the ambiguities involved in the expression of the occurrence of a hazard (BE).
- It helps the decision-maker as a decision support tool and can be used for cause and effect analysis by, for example, simulating the consequences of a decision.

The validation results show that the proposed model calculates the failure probability of MODUs. However, in spite of their remarkable power and potential in addressing inferential processes, there are some inherent limitations and liabilities in FTA (i.e. the BEs are considered as independent in this chapter), so it is required to develop a method for taking into account dependency between hazards.

CHAPTER 6: Risk assessment of MODUs based on BBNs

Chapter summary

The main purpose of this chapter is to propose a methodology to improve the current procedures used in the risk assessment of MODUs. A new methodology for the assessment of the risk level of MODUs is presented. An operational hierarchy of an MODU is translated into a BBN using a Fuzzy-AHP to determine the degree of influence and importance of factors of each HG in terms of their contributions to the system's failure. The associated values emphasise the chance of occurrence or importance, which is based on prior information that is incorporated into the model. The methodology is developed using a commercial computer-based modelling system to demonstrate how a BBN can facilitate a comprehensive assessment of the risk level of a complex MODU system. A generic model is presented that considers the operational failure of the drilling systems and the focus has been on mud circulation including the BOP system that is implemented to predict the failure of an event during drilling, rather than on measures that mitigate the consequences once an event has occurred. In the model, failure is influenced by the high-pressure mud system, mud treatment system, equipment failure, BOP and the other influences of the BEs shown in level 5 of the model which are involved in operation failure. The proposed methodology provides a rational and systematic approach for the unit's risk assessment and comprises a number of stages: i) Identification of probable critical events that may lead to the unit's operational failure, ii) Unique applications of a combination of a BBN technique and an AHP method are used, iii)Ranking of events using a Fuzzy-AHP to determine the degree of influence of each HG and calculation of the conditional probability table (CPT), and iv) Construction of hierarchy for the offshore operation system and translation into a BBN. The drilling failure of an MODU has been considered, focusing on the mud circulation systems including the blow-out preventer. The aim is to prevent a critical event occurring during drilling rather than on measures that mitigate the consequences once an event has occurred. The study proposes a methodology for developing such an assessment. For the purpose of developing a risk analysis and decision support model, a relatively realistic and practical approach has been chosen.

6.1 Introduction

Ensuring the operational safety of systems used in the offshore industry is often a complex problem. An offshore system faces hazards from many different sources which dynamically threaten its integrity and operators have to be aware of the current and future states of the system in order to make an appropriate decision. QRA techniques have been widely applied to offshore operations to reduce the probability of failure. The conventional FT is one of several deductive logic techniques which have been used extensively for accident investigation, hazard identification and risk analysis of process systems (Khan *et al.*, 2002). Standard fault are assumed to be independent although this assumption is not always valid in many offshore systems.

BBNs have emerged as an alternative technique in risk assessment (Bobbio *et al.*, 2001). Conventional failure assessment techniques such as FTA are often incapable of handling changes in uncertainty which are significant in the operation risk assessment of offshore systems such as MODUs (Aquaro *et al.*, 2010; Lecklin *et al.*, 2011; Helle *et al.*, 2011). A BBN is a graphical technique used to express the causal relationships between variables. It can be used to either predict the probabilities of events or to update the probabilities of events given the state of other evidence, through the process of probability propagation (Mahadevan *et al.*, 2001). The network can perform forward or predictive analyses, and backward or diagnostic analyses. New information can easily be incorporated as it becomes available, as only the conditional probabilities of the affected events require redetermination.

AHP is a technique often used to model subjective decision-making processes based on multiple attributes, and can be applied to both individual and group decisions (Bolloju 2001). The Fuzzy-AHP method has been applied in order to identify and measure the relative importance of the events. It allows input from experts based on previous experience to determine the degree of importance and dependency factors of each event in the model in terms of their contributions to other failure events. The pairwise comparison scheme used in AHP is ideally suited to estimating the relative importance of an event for multiple criteria. The occurrence of a hazardous situation may lead to a range of consequences. It cannot be assumed that each HG is of equal importance and weight in terms of its influence on the failure of the MODU. Therefore, it is necessary to consider the contributory factors of an individual HG to failure. AHP is used to define the consequence of a failure and its contribution to and influence on other events.

In the proposed model, a Fuzzy-AHP is used to determine the relative contribution weight factors of events in terms of their effect on system failure. This overcomes the shortcomings of conventional methods and effectively produces a final decision. The values used throughout the analysis are selected based on their high probability of occurring and/or the high importance of potential impact. The proposed methodology provides a rational and systematic approach for the risk assessment of offshore units. A comprehensive model is proposed which takes into consideration the different influences which impact on the operation of the offshore system. The main steps in the development of this methodology include:

- Identifying the probable critical events that may lead to operational failure, ranking the events in terms of their influence to other events and relative importance of the events with respect to system failure, and calculating the conditional probability table of each node.

- Establishing an operational hierarchy system diagram and breaking down the events in detail with respect to the main function.

- Translating the operational hierarchy to a BBN.

6.2 The case for decision support systems for offshore systems

A MODU comprises a large number of complex sub-systems, which makes decision-making in a time-critical situation extremely difficult. The development of effective decision support systems is an important field of investigation (Lu *et al.*, 2008). Most disasters in offshore operations are not caused by a single event or failure but by a combination of human errors, operational issues and equipment failures. Statistical results have indicated that human actions/errors play a significant role in offshore and marine operation failures. Studies indicate that human failures are responsible for over 70% of the causes in marine and offshore accidents and only 30% are attributed to technical failures (Trucco *et al.*, 2008). The fundamental human issues that have an impact on offshore operations may be at the organisational and individual level (i.e. competence level, stress, and motivation).

In the last several years, human factors have been widely researched using various QRA methods. In the Macondo Well on April 20, 2010, for example, a series of organisational and human errors and hydraulic and mechanical failures resulted in a loss of well control, which finally led to a blow-out, leading to fatalities, damage and a substantial amount of hydrocarbon spill. The fire and explosions that followed the blow-out finally caused the Deepwater Horizon (DWH) semi-submersible drilling rig to explode and sink in the northern Gulf of Mexico on April 20, 2010, killing 11 crew members and initiating the largest marine oil spill in US history (Cleveland *et al.*, 2010, Hickman *et al.*, 2012). The results from the investigations showed that the DWH accident was a result of failures on different levels of a social and technical system involved in the control of safety (i.e. staff; management; company; regulators and associations at government level). According to the BP investigation, a chain of events was to blame for the loss of well control (e.g. poor cementing caused a kick to occur, the failure of the blow-out preventer to close the well, failure to notice the kick indications and wellbore pressure (Skogdalen *et al.*, 2011, Cleveland *et al.*, 2010, Hickman *et al.*, 2012).

Risk assessment is a process that comprises several stages, starting with identification of the variables (hazards) from vulnerability analysis and expressing relationships as conditional probabilities to formulate a risk mitigation measure. Probability theory is the technique of choice for dealing with uncertainty in numerous sciences and for a complex system (Newman, *et al*. 2005).

6.3 Proposed methodology for MODU risk assessment

BBNs are increasingly used to model complex domains for which knowledge and data are uncertain (Henriksen *et al.*, 2007; Cai *et al.*, 2013; Uusitalo, 2007). They have proven effective for capturing and integrating quantitative and qualitative information from various sources (Smith, et al. 2007). They have the ability to support decisions where there is a shortage of empirical data and can be easily updated when new evidence becomes available (Henriksen & Barlebo, 2008).

The proposed methodology uses the BBN technique to express the causal relationships between variables and to combine the evidence from different sources for a QRA of offshore systems. The BBN is used to represent the links between unsophisticated available information and to foresee the occurrence likelihood of events that may have consequences in the operation of the MODU systems. The methodology presented uses a hierarchical model to describe dependencies among the systems or components. A hierarchical relation exists in the model that is analysed on different levels (e.g. level 2 and level 3). A BBN model of a system (i.e. MODU) is the compact representation of a joint probability distribution of the variables or events comprising the system. An MODU's system operation is represented by a combination of the various sub-systems, which comprise both discrete and continuous variables. However, when it comes to modelling uncertainty and to performing probabilistic assessment of a unit's operation system, what BBNs have to offer is quite limited. The reasons for choosing BBN graphical models are their capability of establishing relationships between hazardous events and capacity to show cause and effect relationships of the events by their directional capability. Since decision-making in a real MODU operation system is extremely complicated, the intention of the proposed methodology is to support offshore operators in making rational decisions in uncertain circumstances or hazardous situations and to address all HGs and their root cause issues. The proposed new method concentrates on the assessment of the failure of offshore operational systems (i.e. MODUs) posed through the HGs and root causes (BEs) and presents a novel context to implement a methodology that matches probability theory with the AHP technique to perform assessment with BBN. As presented in Figure 6.1, the proposed methodology comprises the following four important tasks:

- HG identification.
- Data collection (using input from experts where there is a lack of data).
- Identifying the relationships between events and establishment of a suitable hierarchy.
- Expression of events' relationships and influences as conditional probabilities with importance factors.

After hazard identification and construction of an operational hierarchy domain, a framework is established which is capable of quantifying the judgements from experts.

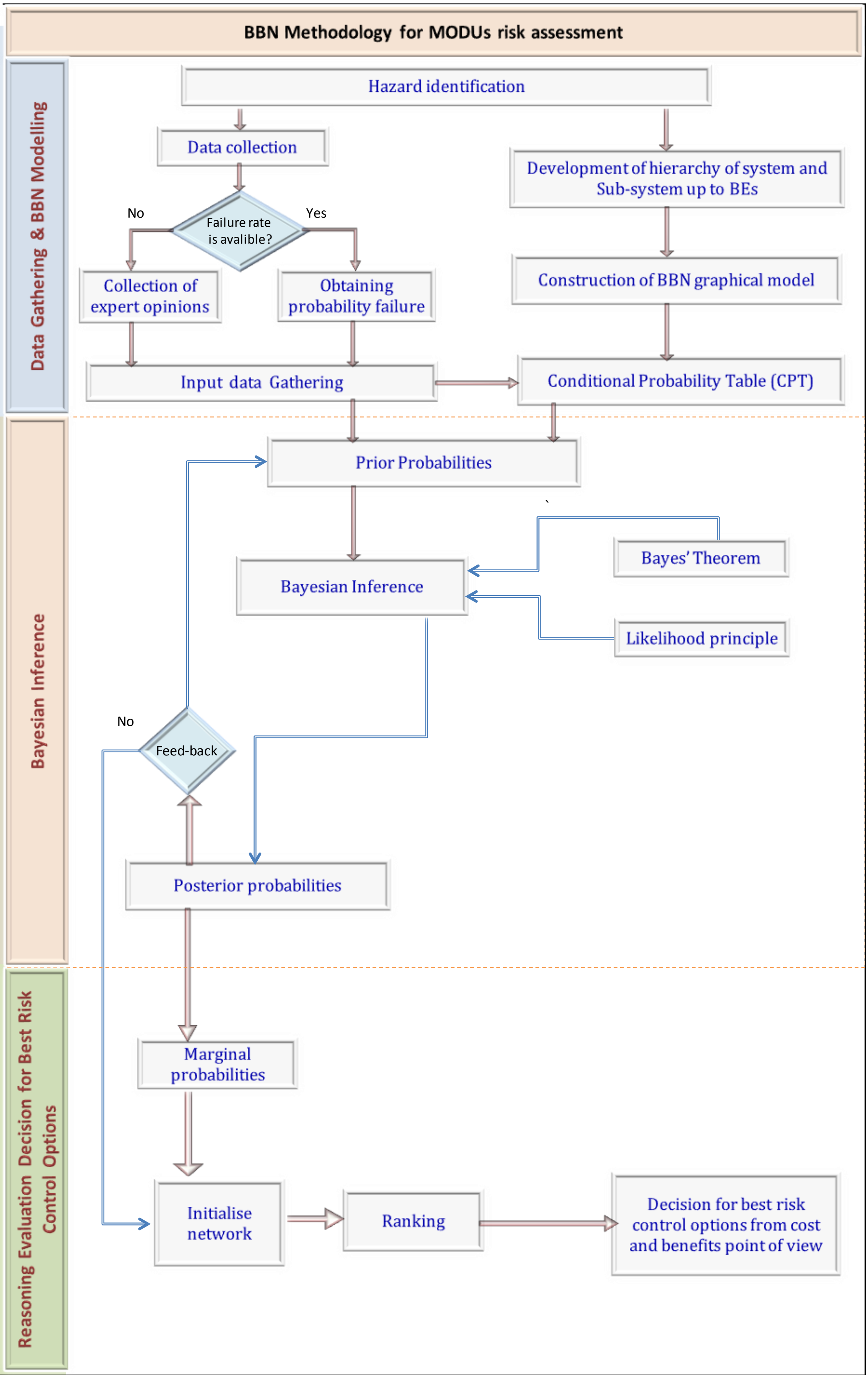

Figure 6.1: Proposed BBN methodology for the MODU risk assessment

This is followed by establishment of their membership functions for the linguistic terms for the BEs. A conditionally probability table is established using AHP to calculate the importance of contributing factors and the weights of the relevant importance of each HG in its risk tree from a viewpoint of their contribution to the failure of the MODU and, finally, BBN calculation.

The risk analysis process includes hazard identification from a vulnerability analysis at the start point and is followed by adapting an operational hierarchy of the MODU's system into the BBN. This allows representation of the MODU operation system with its HGs at different levels of detail. This aims to detect the failure of equipment or systems as well as to support risk mitigation measures (Baiardi *et al.*, 2009). In a real system, the amount of analysis required may be enormous because of the number of nodes and arcs of the entire system and associated HGs. Because of the complexity of integrating the information, and in order to simplify the assessment processes, a manageable group of hazards has been considered. Each HG may be broken down into a number of simpler system components in different levels, as illustrated in Figure 6.2. Three HGs (i.e. Natural hazard: L2D-N1, Operational hazard: L2D-O1 and Human error L2D-H1) are modelled to the BBN, in which the components and routes describe the MODU's operation system. The failure of each component may influence another component or system at the same level or a different level (e.g. ESD System Failure (L3D-O1-06) in level 3 has a consequence for Drilling System Failure (L3D-O1-01) at the same level, as well as Operational Failure (L2D-O1) at level 2).

A BBN can be considered as a representation of static cause-effect relations among the events. The line between two nodes denotes dependencies or direct contributing influences between them. The strength of these dependencies is represented by conditional probabilities. The operational hierarchy model is developed based on the BBN to model the unsafe conditions of the MODU based on occurrence of BEs. A structural hierarchy model with a list of the MODU's hazardous events employed in this model is shown in Figure 6.2. The set of values for each event is also given along with the relevant code of reference to be used throughout. This method of assessment can help the operator to carry out the MODU risk evolution in a realistic and methodological way.

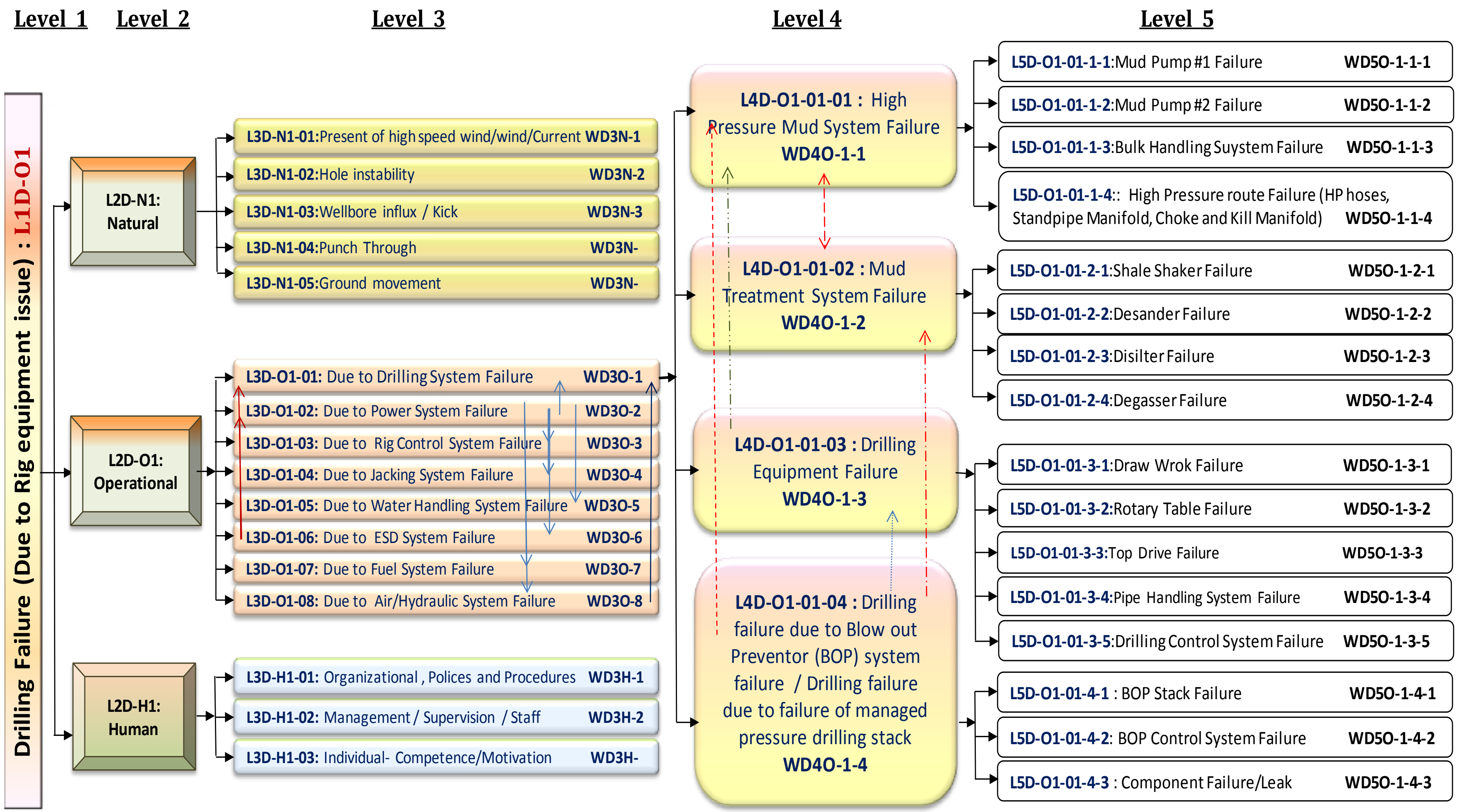

Figure 6.2: Hazard identification and MODU’s operational hierarchy

6.4 The BBN concept and theory

The BBN methodology was introduced in the 1980s and the theory is based on the Bayes rule, proposed by Sir Thomas Bayes (Carlin and Louis, 1997; Cheeseman, 1983; Strauss & Sadler, 1989; Dale, 1999). BBNs have a strong similarity to FTA in many respects. FTA is an effective method in probabilistic failure assessment but is limited to modelling simple static systems. The distinct advantages of BBNs are their capability to explicitly represent the dependencies among the events, updating probabilities, flexible structure compared to FTA and is appropriated for risk assessment and analysis of offshore operation systems (Wang *et al.*, 2011; Ren *et al.*, 2008).

BBNs are increasingly used to model complex domains for which knowledge and data are uncertain (Henriksen *et al.*, 2007). They provide both diagnostic and predictive capabilities and allow for updating the probability distributions when new evidence becomes available (Henriksen and Barlebo, 2008); (Pearl, 2000). However, the calculations involving large numbers of variables are complex and appropriate tools are required (Cheng and Druzdzel, 2000). Bayes' theorem is one that has been proven to be an understandable method of mathematically expressing a decrease in uncertainty gained by an increase in information (Bayes, 1763). A BBN is a directed graph consisting of a set of nodes and links among them. Uncertain variables are associated with each node where the probability of the failure expresses the certainty of the various events consequences and is conditionally subject to the status of the parent nodes at the entering boundaries. BBNs obviously accommodate uncertainty and inconsistency in model predictions because of the probabilistic presentation (Uusitalo, 2007), and they have proven effective for capturing and integrating quantitative and qualitative information from various sources (Smith *et al.*, 2007).

BBNs are excellent tools for managing and understanding complex processes compared to other methods of risk assessment for the reason that they represent the process graphically; each node in the network represents either the prior or conditional probability of the parameter of interest. As mentioned, BBNs offer several advantages over conventional risk assessment techniques (Woodberry *et al.*, 2005):

- A process is presented graphically and the intuitive visual presentation showing causal relationships can be sensibly understood.
- BBN models would be a valuable decision support tool.
- Different sources of information can be employed concurrently in the model.
- Dependent relationships between the events can be described by directing links.
- The data can be simply updated with new knowledge.

6.4.1 BBN theory

Bayes' theorem provides a means for creating probability calculations. In order to generate probability statements about the model's parameters, the analysis must start with providing an initial or prior probability approximation for specific outcomes or events of interest. The objective of this chapter is to apply a probabilistic model for an MODU's risk assessment; this is defined as a translation of information that permits us to evaluate every sophisticated decision in line with the following three axioms as presented in Equation (6.1) (Pearl, 2000):

- $0 \leq P(A) \leq 1$
- P(sure proposition) = 1
- P(A or B) = P(A)+P(B) where A and B are exclusive events (6.1)

Causal BBNs express causal relationships between random variables and involve nodes connected by directed edges. Essentially, it is a relation among conditional and marginal probabilities. Conditional probabilities are essential to a fundamental rule of probability calculus, the product rule. As presented in Equation (6.2), the product rule defines the probability of a conjunction of events (i.e., for two events, A and B):

$$P(A \mid B)P(B) = P(A,B) = P(B \mid A)P(A) \tag{6.2}$$

In Bayesian probability, the concept of inference plays an important role. The rule of updating probabilities is given by Equation (6.3), which is the theorem conventionally known as *Bayes' theorem* (Strauss and Sadler, 1989;, Dale, 1999):

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{6.3}$$

Term P(A|B) in Equation (6.3) is called the posterior probability of A given the assumption that B is known. It is posterior in the sense that it is resulting from or entailed by the specified value of B, and this is called the conditional probability. When P(A|B) = P(A), A and B are said to be independent. In Bayesian probability, conditional probability is not defined in terms of joint events; A|B is rather seen as A in the context specified by B. The term P(B) is the prior or marginal (total) probability of B but also one that provides evidence of interest for the probability update of A. Its inverse is usually regarded as a normalising constant. With this terminology, Figure 6.3 shows a graphical illustration of Bayes' theorem (Press and Press, 1989).

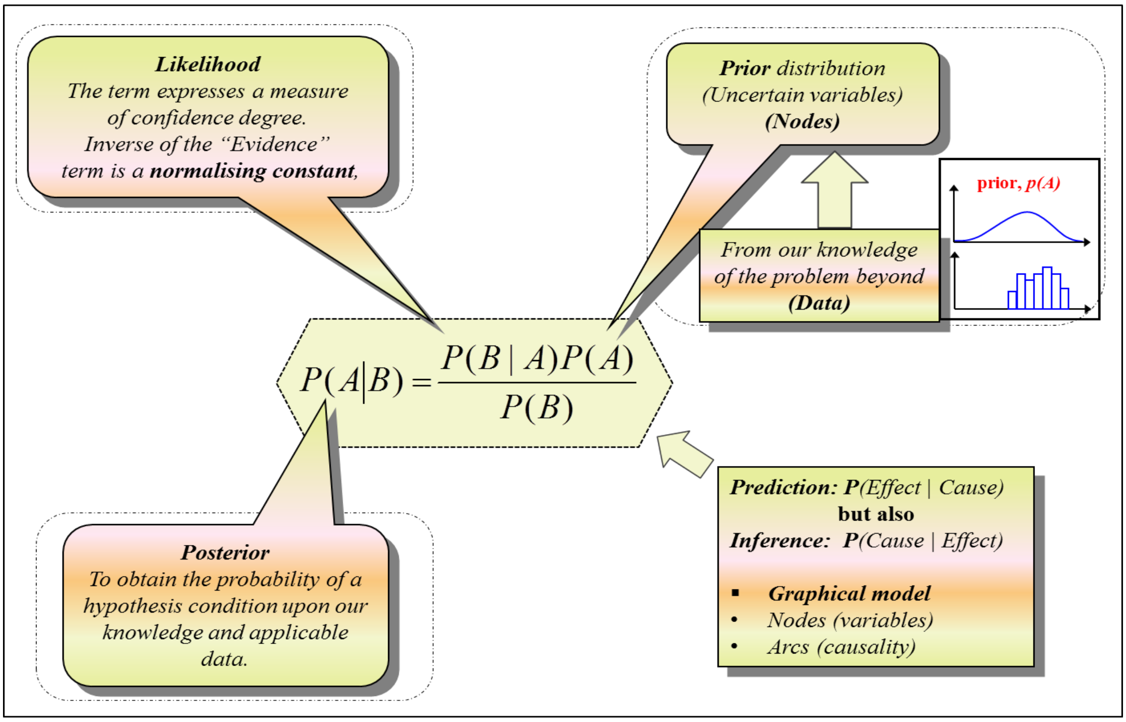

Figure 6.3: A graphical illustration for terms of Bayes' theorem

The term P(A) is named the prior probability of A and is also called the marginal probability of A. It is prior in the sense that it precedes any information or knowledge about B, what is called data, and this is what grounds all the arguments. In light of this new information providing a new data belief, it is desirable to improve the state of knowledge and thus the prior probability values are updated by calculating revised probabilities, referred to as the posterior probabilities. The term P(B|A), for a specific value of B, is called the likelihood function for B given A, where the vertical bar "|" indicates "given that" (Pearl, 2011).

6.4.2 Definition and properties of BBN

The BBN is the common technique used to measure posterior probabilities' distribution given the prior probabilities. This type of inference can use simulation techniques and subjective opinions to obtain fairly accurate probability values. Likelihood estimation is the proportion of occurrence between the various states of the variable. A BBN consists of a set of nodes for representing variables and a set of directed edges representing causal influences between variables (Cowell, 1998; Smyth, 1997). Each variable has a finite set of mutually exclusive states. Figure 6.4 shows a typical BBN or directed acyclic graph where A is the observed variable, because it is a node with no child node. This node A is an uncertain variable; its value is influenced by B, which is the parameter of interest in this problem; we observe A (with n specified), and use this information to infer possible values for B. The dashed region at the top of the graph, labelled Data, clarifies the type of prior distribution used for B that is entered by the analyst.

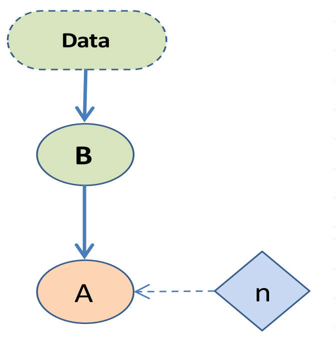

Figure 6.4: Typical BBN (Directed acyclic graph)

As mentioned, a significant benefit of the Bayesian paradigm is that additional parameters can easily be added to a model without seriously adding to the complexity of the statistical analysis, provided that those parameters fit into a conditional independence structure. This means that, provided the dependence of the new parameters on the existing data and parameters can be made explicit, assessing the new parameters is often a simple matter of additional computing time.

6.4.3 Joint probability distribution (JPD)

In the general case, a JPD over a set of variables, $A = [A_1, A_2, \ldots, A_n]$, can be defined recursively using the product rule as presented in Equation (6.4) (Pearl, 1988):

$$\begin{aligned} P(A_1, A_2, \ldots, A_n) &= P(A_1|A_2, \ldots, A_n)P(A_2, \ldots, A_n) \\ &= P(A_1|A_2, \ldots, A_n)P(A_2|A_3, \ldots, A_n)P(A_3, \ldots, A_n) \\ &= P(A_1|A_2, \ldots, A_n)P(A_2|A_3, \ldots, A_n)\ldots P(A_{n-1}|A_n)P(A_n) \end{aligned} \quad (6.4)$$

Equation (6.5) illustrates an application of BBN for (A1, A2, B, C, D) for the graph given in Figure 6.5.

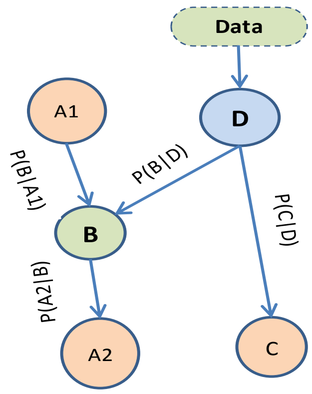

Figure 6.5: Typical BBN (Directed acyclic graph)

$$\begin{aligned} &P(A1, A2, B, C, D) \\ &= P(A1)P(D \mid A1)P(B \mid A1, D)P(C \mid A1, D, B)P(A2 \mid A1, D, B, C) \\ &= P(A1)P(D)P(B \mid A1, D)P(C \mid D)P(A2 \mid B) \end{aligned} \quad (6.5)$$

This factorisation property of JPDs is referred to as the chain rule of probabilities and is one that allows any ordering of variables in the factorisation. Such a rule is especially significant for BBNs because it provides a means of calculating the full JPD from conditional probabilities, which is what a BBN stores. For example, the JPD for three events, a_1, a_2, and a_3, can be expressed more compactly as:

$$P(a_1 \mid a_2, a_3)P(a_2, a_3) = P(a_1, a_2, a_3) = P(a_2 \mid a_1, a_3)P(a_1, a_3) \tag{6.6}$$

Then, in applying Equation (6.7), Bayes' theorem specifies the probability of an event a_1, given the condition that an event a_2 and an event a_3 both occur as:

$$P(a_1 \mid a_2, a_3) = \frac{P(a_2 \mid a_1, a_3)P(a_1 \mid a_3)}{P(a_2 \mid a_3)} \tag{6.7}$$

Thus, risk assessment of events can be carried out on this basis to enhance reasoning that will enable reliable decision-making. Generally, Bayes' rule can be considered for the problem of estimating values of j parameters (causes), $A = [a_1, \ldots, a_j]$, using i observations (effects), $B = [b_1, \ldots, b_i]$. In the rule then, given the observations $B = [b_1, \ldots, bi]$, the posterior probability distribution on A can be computed as:

$$P(A \mid b_1, \ldots, b_i) = \frac{P(b_1, \ldots, b_i \mid A)P(A)}{P(b_1, \ldots, b_i)} \tag{6.8}$$

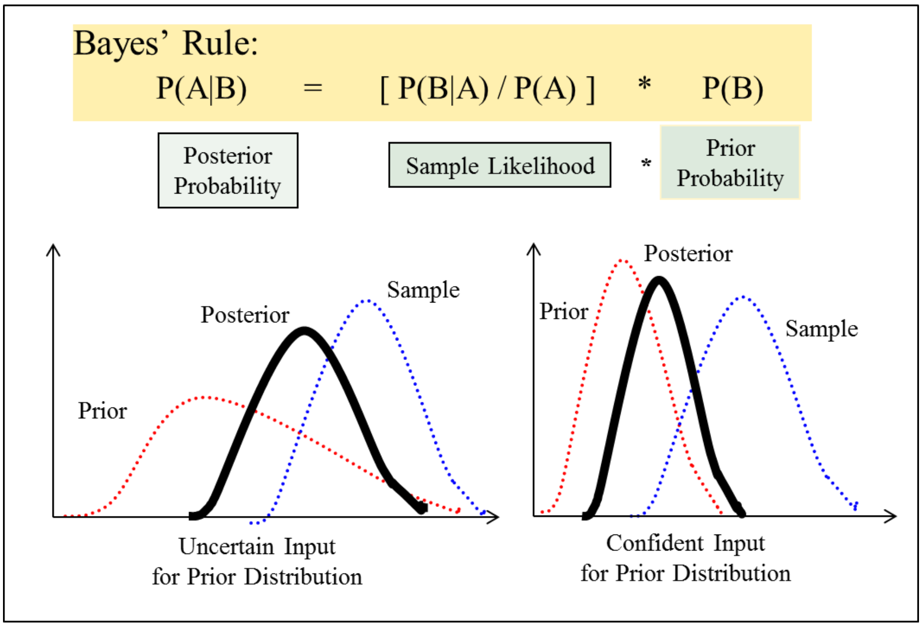

Figure 6.6: An illustration of probability update via Bayes' theorem

Bayesian inference proceeds by summarising the posterior distribution, *P(A|B)*. As depicted in Figure 6.6, after observing the data, the wide prior distribution is converted into the more narrow posterior distribution using Bayes' rule. The process of Bayes' theorem is repeated every time when new or additional information becomes available (Lindley and Smith, 1972). Bayes' theorem has been particularly useful in estimating knowledge about the frequency of rare events or making reliability predictions where there is sparse or no directly applicable data (Hall *et al.*, 2009).

6.4.4 Marginalisation of probabilities

The probability distribution *P(A)* can be calculated from a table *P(A, B)* of probabilities, $P(a_i, b_j)$. Let a_i be a state of *A*. There are exactly *m* different events for which *A* is in state a_i, namely the mutually exclusive events $(a_i, b_1), \ldots, (a_i, b_m)$. Therefore:

$$P(a_i) = \sum_{j=1}^{m} P(a_i, b_j) = \sum_{j=1}^{m} P(a_i \mid b_j) P(b_j) \tag{6.9}$$

In other words:

$$\begin{bmatrix} P(a_1) \\ P(a_2) \\ \vdots \\ P(a_n) \end{bmatrix} = \begin{bmatrix} P(a_1 \mid b_1) & P(a_1 \mid b_2) & \ldots & P(a_1 \mid b_m) \\ P(a_2 \mid b_1) & P(a_2 \mid b_2) & \ldots & P(a_2 \mid b_m) \\ \vdots & \vdots & \vdots & \vdots \\ P(a_n \mid b_1) & P(a_n \mid b_2) & \ldots & P(a_n \mid b_m) \end{bmatrix} . \begin{bmatrix} P(b_1) \\ P(b_2) \\ \vdots \\ P(b_m) \end{bmatrix} \tag{6.10}$$

This calculation is called marginalisation (summing out) and expresses the fact that the variable *B* is marginalised out of the JPD, *P(A, B)* (resulting in *P(A)*) (Sandholm and Suri, 2003; Russell and Norvig, 2003). The notation is:

$$P(A) = \sum_{B} P(A, B) = \sum_{j} P(A \mid B = b_j) P(B = b_j) \tag{6.11}$$

In a similar way, if *P(B, A)* is a CPT over *A* and *B*, then a CPT over the state space of just *B* can be produced by marginalising over *A*, so that, for example:

$$P(b_1) = \sum_{i=1}^{2} P(a_i, b_1) = P(b_1 \mid a_1)\, P(a_1) + P(b_1 \mid a_2)\, P(a_2) \tag{6.12}$$

Marginalisation is of utmost importance for all inference in Bayesian probability: integrating out all superfluous variables derives the information about a subset of the system's variables. Furthermore, the process of marginalisation tackles the problem of decision uncertainty explicitly, by preventing overoptimistic predictions (Vellido and Lisboa, 2001).

6.4.5 Conditional probability distribution

A BBN allows the analytical evaluation of all the probabilities of interest and also represents the quantitative relationships between the modelled variables. It provides us with probabilities information and makes it possible to recognise system failure or weaknesses. The BBN comprises different variables (i.e. independent and dependent), the links represent how the variables are related and each node is described by a probability distribution. Underlying each dependent variable is a conditional probability table that specifies the probability of each state conditional on other variables. A conditional probability is a probability of one event given that another event has occurred, i.e. the conditional probability of a parameter, a_1, given an observed parameter, b_1, would be written as $P(a_1 \mid b_1)$.

There are some differences depending on the level to which the node belongs. As per hazard identification and an MODU's operational hierarchy, shown in Figure 6.2, a framework was chosen to model the system and each dependent node is described by a conditional probability distribution. In level 5, CPT evaluation is reduced to the definition of prior probabilities of occurrence of adverse events. This can be done by relying on historical data and expert opinion; as an example, the conditional probability table associated with the event High-Pressure Mud System Failure (L4D-O1-01-01) being directly dependent on the Mud Pump #1 failure (L5D-O1-01-1-1). Another important characteristic of conditional probability is the nature of failures that can happen within a system and how that may affect other dependent systems or equipment. In this respect, the conditional probability table mainly specifies the logical connection between services or equipment, i.e. the event of Drilling System Failure (L3D-O1-01) in level 3 is conditional on the event of Power System Failure (L3D-O1-02). Principally, a typical conditional probability table is a matrix of conditional probabilities and knowledge of CPT is an integral and essential part in understanding numerical evaluation of probabilities. As illustrated in Table 6.1, a CPT in level 4 is described for four nodes by its matrix format containing two states of each specified event (i.e. Risky & Consistent). Thus, Consistent represents a certain state for each event whilst Risky stands for a failure state. The importance factors which are outputs of the AHP analysis are shown in the second column of each related node and the cumulative states are presented in the last two columns.

Table 6.1: CPT in level 4 of four nodes containing two states of specified events

L4D-01-01-1		L4D-01-01-2		L4D-01-01-3		L4D-01-01-4		**CPT** (Symmetric model)	
States	Importance Factor WD4O-1-1	States	Importance Factor WD4O-1-2	States	Importance Factor WD4O-1-3	States	Importance Factor WD4O-1-4	Risky	Consistent
Risky	0.220	Risky	0.271	Risky	0.175	Risky	0.335	1.000	0.000
Risky	0.220	Risky	0.271	Risky	0.175	Consistent		0.665	0.335
Risky	0.220	Risky	0.271	Consistent		Risky	0.335	0.825	0.175
Risky	0.220	Risky	0.271	Consistent		Consistent		0.490	0.510
Risky	0.220	Consistent		Risky	0.175	Risky	0.335	0.729	0.271
Risky	0.220	Consistent		Risky	0.175	Consistent		0.394	0.606
Risky	0.220	Consistent		Consistent		Risky	0.335	0.555	0.445
Risky	0.220	Consistent		Consistent		Consistent		0.220	0.780
Consistent		Risky	0.271	Risky	0.175	Risky	0.335	0.780	0.220
Consistent		Risky	0.271	Risky	0.175	Consistent		0.445	0.555
Consistent		Risky	0.271	Consistent		Risky	0.335	0.606	0.394
Consistent		Risky	0.271	Consistent		Consistent		0.271	0.729
Consistent		Consistent		Risky	0.175	Risky	0.335	0.510	0.490
Consistent		Consistent		Risky	0.175	Consistent		0.175	0.825
Consistent		Consistent		Consistent		Risky	0.335	0.335	0.665
Consistent		Consistent		Consistent		Consistent		0.000	1.000

An additional class of dependencies that is even harder to identify is associated with the operators' management system and dependencies among the different organisations of the MODU's operation system (i.e. managing different subcontractors for different activities). A failure in one organisation (e.g. Cementing subcontractor) can cascade through dependencies to other parts of the MODU's operation system. A dependency model needs to be flexible enough to capture dependencies at different levels within an operation system.

6.4.6 Conditional independence and dependency

A BBN also represents the quantitative relationship among the modelled variables and it represents the JPD among them. Any probability of interest can be calculated from the JPD of the variables. However, a BBN not only outputs the graphical representation of a joint probability of the variables, but also captures properties of conditional independence (i.e. missing arrows that imply no direct influence) between variables. Conditional independence has the advantage of representing joint probabilities more compactly and efficiently, before the actual conditional probability distributions are numerically specified. Combination of quantitative information with qualitative information of numerical parameters makes probability theory easy to express; the above mixture leads to reduction in complexity of the probability computation and also simplifies probabilistic inference of the network.

Conditional independence also reduces the size of CPTs. As an example, given two events, A and B, A is independent of B if $P(A|B) = P(A)$. Independence is symmetric, and therefore it follows that $P(B|A) = P(B)$. The independence of A and B can also be expressed as $P(A,B) = P(A)P(B)$. Also, A is conditionally independent of B given another event, C, if $P(A|B,C) = P(A|C)$. Conditional independence is symmetric, and therefore it follows that $P(B|A,C) = P(B|C)$. Now, when many variables are conditionally independent, as in the case of Equation (6.6), calculation of joint probabilities using the chain rule can be simplified significantly. As a simple example, if A is conditionally independent of B given C, then $P(A,B,C) = P(A|B,C)P(B|C)P(C) = P(A|C)P(B|C)P(C)$.

6.5 Applications of research methodology for MODU risk assessment

In this section, the application of the BBN is emphasised, in particular, the application of the proposed research methodology for risk assessment of the MODU’s operation system is presented. The BBN technique is used to determine the probability of the MODU’s failure in the course of an offshore operation. The proposed methodology benefits from the inclusion of different complex variables of a hybrid nature in the offshore operation. Application of the BBN method consists of three stages. It starts with hazard identification and construction of the BBN model in line with the MODU's operational hierarchy and is followed by elicitation of probabilities to nodes and, finally, the establishment of calculations. The objective of this chapter is to demonstrate the modelling aspects of the BBN with regard to its ability to update probabilities as well as its various modelling features such as incorporation of variables, dependent failures and expert opinion, which are frequently encountered in risk assessment of operational systems like MODUs.

In spite of the BBN's attraction and widespread attention for modelling complex large-scale marine and offshore operations (i.e. MODU risk assessment), there are a number of concerns in relation to the construction of the hierarchy model and the incorporation of data. The person who creates the models needs to be aware of these concerns, such as distinguishing the variables appropriate to the MODU's operation system, recognising the relationships between these variables and expressing these relations as a conditional probability distribution table. A hierarchy model is regulated by variables and their interactions.

The requirement and guidelines pertaining to well integrity during drilling activities and operations are specified in the Norwegian oil and gas regulations (NORSOK D-010, 2004). According to this standard, all phases of offshore operations must have two separate and independent barriers. Well drilling completion is a good example, in which the mud column is the primary barrier and the secondary barrier is the blow-out preventer BOP, which protects the well from a disaster as the last resort. The primary barrier is the first stumbling block against undesirable flow from the source (Hauge *et al.,* 2011). In overbalanced processes, the mud column is the primary well barrier and should function within the drilling margin pressure (i.e. a pressure greater than the hole pressure and lower than the fracture gradient). Mud control is an operation function and loss of control can lead to an emergency situation. The mud and cementing circulation system is composed of the following: bulk and storage system, high-pressure mud pumping system, mud treatment system and cementing system. The secondary barrier should be active on the detection of an influx and the well should be closed, and this also prevents further unwanted flow in the case of failure of the primary well barrier (PSA, 2008). Macondo (BP, 2010) was planned to be abandoned and left underbalanced, by replacing drilling mud with sea water, and with two cement barriers in place (Commission, 2010b). Well control systems are defined in the NORSOK standard (D-001, 2004) as the mechanical well control and associated equipment and system. This includes BOP, choke & kill system, rise, and the control system for the BOP. As explained previously, the mud system and BOP are the key components of the system to provide the well integrity. Therefore, the simple process diagram of the mud circulation and mixing system as illustrated in Figure 6.7 is considered in levels 4 and 5 of the MODU's operational hierarchy (Figure 6.2). Drilling mud is the primary requirement to start drilling operations and the mud mixing system provides appropriate mud by an adequate combination of dry cement and water (diesel oil or brine may be used to provide viscidity). Drilling mud is made and stored in mud pit(s). Mud pumped through the standpipe manifold into the drill string will pump the prepared mud stored in the mud pit. The standpipe design pressure is in line with the mud pump capacity (typically 7,500 psi). The mud pump provides adequate pressure to overcome the mud column static pressure at the bottom of the drilled hole.

Mud returns through the annular casing, and then the returned mud is directed to the shell shakers via the mud ditch to remove earthen impurities such as sharp rocks. At a later stage, the returned mud will pass through Desander, Desilter and gas separator in order to remove smaller impurities as well as mixed gas trapped in the mud. At the last stage, the treated, returned mud will go back to the mud pits for further circulation. This circulation process is repeated through the course of drilling. The returned mud pressure is continuously measured by BOP sensors and, in the case of over-pressure, the normal circulation line will be blocked and the high-pressure mud will be led to the choke/kill manifold, which is designed for higher pressure (typically 10000 psi), in order to reduce the pressure of the pumped mud on the atmospheric level. In the case of kick (high pressure in the return line because of entry of water, gas, oil, or other formation fluid into the wellbore), the very high-pressure mud (10000 psi) will be injected into the well through the kill line by an additional pump (normally cement pump). The cement pump is also connected to the choke/kill manifold. It should be noted that the "kick" pressure is lower than the "choke" pressure. As the bit "drills ahead", a specially formulated drilling fluid or mud is continually pumped or circulated from the surface to the bottom of the well, and then back to the surface to cool the bit and remove the cuttings, as illustrated in Figure 6.7.(For the system's components description refer to Appendix 2)

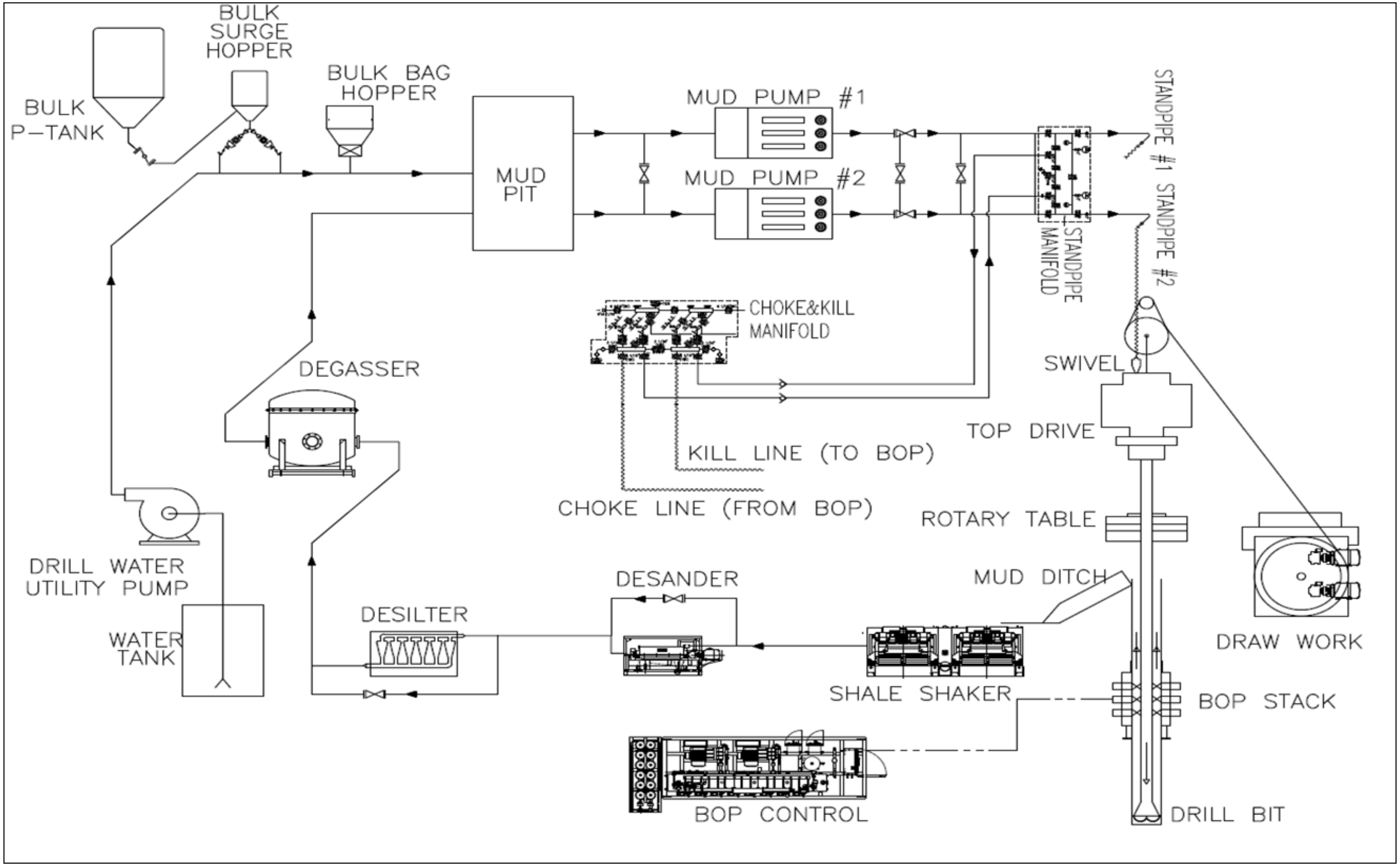

Figure 6.7: Schematic diagram of mud circulation and mixing system/equipment in levels 4 and 5

6.5.1 Hazard identification and potential hazard sources/sub-sources

In the previous chapters (Chapters 4 & 5), the contextual information on the MODU's HGs and the objectives of the application were provided and also a novel methodology was introduced for HG classification with particular emphasis on Drilling Failure (L1D-O1-01). In the hazard identification, the MODU's operational hierarchy is illustrated, beginning with the BEs (root causes) in level 5, followed by the intermediate nodes in levels 3 and 4, also called hinge nodes, and ending up with the target node in level 1. Figure 6.7 illustrated the schematic diagram of the mud system. A model in association with the circulation and mixing system is developed in level 4 with special focus on analysis of failures of the mud system caused by its HGs.

A comprehensive system-level risk analysis is heavily dependent on appropriately identifying the key events of the area of interest. In particular, the identification of potential hazard sources within the structure of the problem domain should be considered as a fundamental step in operational system risk assessment. Within this context, for drilling failure (L1D-O1-01) a HG was developed and, based on its classification and analysis, three main category hazard sources were identified and labelled as: Human (L2D-H1), Operational (L2D-O1) and Natural (L2D-N1). A hierarchy model, represented as a directed graph, as shown in Figure 6.2, is used to assess the goals of L1D-O1-01 (Drilling failure) due to its associated HGs in different levels by disintegration into measurable sub-systems and events.

The analysis starts by identifying the importance of BEs and parent notes in different levels that can influence the goal level (i.e. level 1). In the next step, the exploratory approach is adopted in order to explain the importance of events and their consequences at different levels through application of the AHP technique based on expert judgement. The pairwise comparison scheme in the AHP is an ideal solution to work out the relative importance of an event, providing an explanation for multiple criteria in evaluating important consequences. By employing the pairwise comparison of the AHP technique, the interactive relationships expressed between the risk events through causal and logical dependency and a relative contributions weight factor were introduced. A Fuzzy-AHP is used to determine the importance factors of each event, which interprets their influence on and contributions to the MODU's operational system failure. As an example, in level 4 of the operational hierarchy importance factors (WD4O-1-1 to 4) are considered as the relative weight factors for the nodes L4D-O1-01-01 to 4 respectively. These factors then explain the significance of the event in comparison with the others in a particular process. The corresponding importance factors as a conditional probability are identified and ranked by the Fuzzy-AHP method, as illustrated in Figure 6.8.

The higher levels (i.e. levels 2, 3 and 4) can also affect indirect root causes and consequently their associated hinge nodes from other hazard sources. Several events can exist in parallel or the existence of one event can comprise the existence of another event. As shown in Figure 6.8, there are three HGs of interest, L2D-N1, L2D-O1 and L2D-H1, which belong to level 2 of the operational hierarchy. L2D-N1, L2D-O1 and L2D-H1 can be inferred directly from the BEs in level 3 which include: L3D-N1-01 to 5, L3D-O1-01 to 8 and L3D-H1-01 to 3 respectively. While the event L3D-O1-01 was expanded in two more levels (levels 4 & 5) and is dependent on the existence of lower-level events (i.e. level 4: L4D-O1-01-1 to 4) and BEs in level 5, as listed below:

- L4D-O1-01-01: High-Pressure Mud System Failure
  - L5D-O1-01-1-1: Mud Pump #1 Failure
  - L5D-O1-01-1-2: Mud Pump #2 Failure
  - L5D-O1-01-1-3: Bulk Handling System Failure
  - L5D-O1-01-1-4: High-Pressure Route Failure
    (HP hoses, Standpipe Manifold, Choke and Kill Manifold)
- L4D-O1-01-02: Mud Treatment System Failure
  - L5D-O1-01-2-1: Shale Shaker Failure
  - L5D-O1-01-2-2: Desander Failure
  - L5D-O1-01-2-3: Disilter Failure
  - L5D-O1-01-2-4: Degasser Failure
- L4D-O1-01-03: Drilling Equipment Failure
  - L5D-O1-01-3-1: Draw Work Failure
  - L5D-O1-01-3-2: Rotary Table Failure
  - L5D-O1-01-3-3: Top Drive Failure
  - L5D-O1-01-3-4: Pipe Handling System Failure
  - L5D-O1-01-3-5: Drilling Control System Failure

- L4D-O1-01-04: Drilling Failure due to Blow out Preventer (BOP) System Failure/ Drilling Failure due to Failure of Managed Pressure Drilling Stack
  - L5D-O1-01-4-1: BOP Stack Failure
  - L5D-O1-01-4-2: BOP Control System Failure
  - L5D-O1-01-4-3: Component Failure/Leak

As illustrated in Figure 6.8, a coding system with event importance factors was considered, i.e. in level 3 of the hierarchy model the importance factors WD3N-1 to WD3N-5 are designated to Natural Hazard (L2D-N1) BEs and, similar to that, WD3O-1 to WD3O-8 are designated to the Operational (L2D-O1) BEs. Also the importance factors WD3H-1 to WD3H-3 are designated to the Human (L2D-H-1) BEs. In the same manner, in levels 4 and 5 the importance factors were calculated and are illustrated in Figure 6.8.

6.5.2 Application of AHP for prioritising of risk in the hierarchy

In the real world, events or combinations of events that lead to MODU operation system failure are not well recognised. An integrative model incorporates both failure data and the importance factor of each event based on its contribution to the MODU failure, which is necessary for analyses. When statistical data or expert judgement is presented for prior probabilities, there is a need to identify the consequences and effects of the failure of one system or component on another system. This relation is known as the conditional dependency. The Fuzzy-AHP technique is employed to deal with the importance factor of dependency and ranking of each considered event with its contribution to the failure of the target goal. Table 6.2 shows the pairwise comparison of sub-nodes of L3D-O1-01 and, in a similar way; Table 6.3 presents the pairwise comparison of sub-nodes of node L2D-O1.

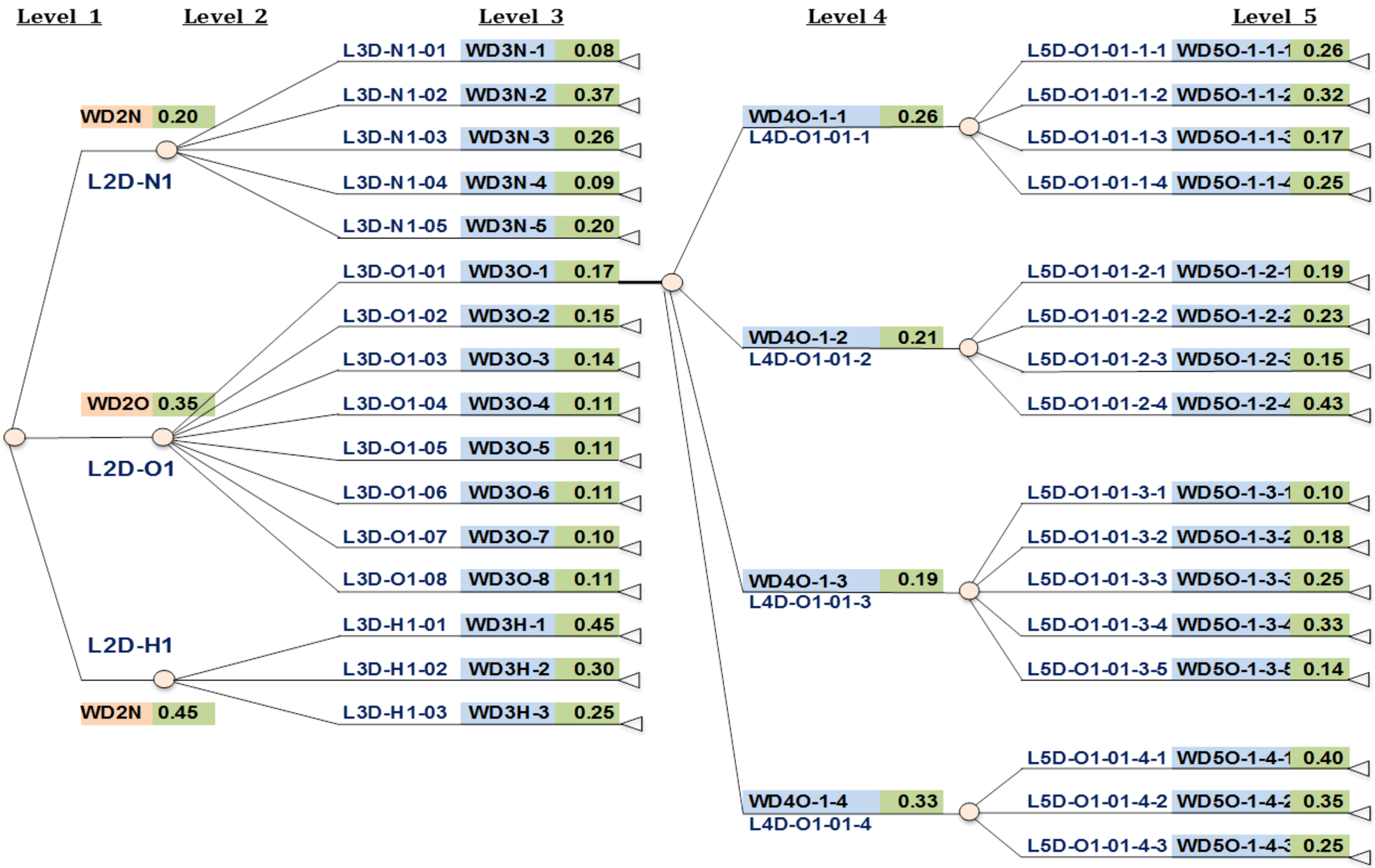

Figure 6.8: A hierarchy model of the MODU system's HG factors

Table 6.2: AHP pairwise comparison for nodes L4D-O1-01-1 to 4

Ranking alternatives for " L3D-O1-01: Drilling System Failure"						
L3D-O1-01	L4D-O1-01-1	L4D-O1-01-2	L4D-O1-01-3	L4D-O1-01-4	**Importance Factor**	
L4D-O1-01-1	1.00	1.30	1.25	0.80	WD4O-1-1	0.26
L4D-O1-01-2	0.77	1.00	1.10	0.65	WD4O-1-2	0.21
L4D-O1-01-3	0.80	0.91	1.00	0.55	WD4O-1-3	0.19
L4D-O1-01-4	1.25	1.54	1.82	1.00	WD4O-1-4	0.33

In Figure 6.8, three categories of HGs at different levels of hierarchy are defined for determination of the relative importance of risk events according to their consequence with respect to other events in view of their contribution to the MODU's failure. Interactive relationships were then expressed between risk events through causal diagrams. Once the risk quantities are inputted by the user, the challenge then is to modify the influence of these inputs towards risk items that need a higher priority as determined by the use of the simultaneous engineering design and operation philosophy, previous management, organisational experiences, and best practices and standards.

Table 6.3: AHP pairwise comparison for nodes L3D-O1-01 to 8

Ranking alternatives for L2D-O1: Operational										
L2D-O1	L3D-O1-01	L3D-O1-02	L3D-O1-03	L3D-O1-04	L3D-O1-05	L3D-O1-06	L3D-O1-07	L3D-O1-08	**Importance Factor**	
L3D-O1-01	1.00	1.26	1.37	1.47	1.53	1.58	1.68	1.63	WD3O-1	0.17
L3D-O1-02	0.79	1.00	1.14	1.29	1.36	1.43	1.57	1.50	WD3O-2	0.15
L3D-O1-03	0.73	0.88	1.00	1.17	1.25	1.33	1.50	1.42	WD3O-3	0.14
L3D-O1-04	0.68	0.78	0.86	1.00	1.10	1.20	0.60	0.80	WD3O-4	0.11
L3D-O1-05	0.66	0.737	0.80	0.91	1.00	1.11	1.33	1.22	WD3O-5	0.11
L3D-O1-06:	0.63	0.70	0.75	0.83	0.9	1.00	1.25	1.13	WD3O-6	0.11
L3D-O1-07	0.59	0.64	0.67	1.67	0.75	0.8	1.00	0.83	WD3O-7	0.10
L3D-O1-08	0.61	0.67	0.71	1.25	0.82	0.89	1.20	1.00	WD3O-8	0.11

This, in turn, leads to highlighting of the relatively high-risk HG (i.e. Drilling Operation failure) and makes up the first pass of risk assessment in a specific phase. The objective form of the BBNs is the same as the causal diagram for that HG.

6.5.3 Node probability data gathering and expert judgement

In the process of developing the risk analysis methodology, the estimation of probability of failure has an important role in correctly prioritising the risks involved and also applying adequate corrective measures. Accurate statistical data are vital to most existing techniques but the statistical data of the system and equipment are hardly available. Therefore, to determine the prior probability of an event, utilisation of Fuzzy set theory may be necessary.

The probability of occurrence of each of the MODU's operation hazards is calculated based on prior probabilities of the BEs and the conditional probabilities of nodes, although the prior probabilities and event relationships are not always obvious and usually require expert knowledge.

Table 6.4: Probabilities of occurrence of BEs (Experts' knowledge) in level 3

BE (Level 3)	Experts judgement																		Crisp No.
	Linguistic terms	Expert 1				Factor	Linguistic terms	Expert 2				Factor	Linguistic terms	Expert 3				Factor	
L3D-N1-01	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-N1-02	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.15**
L3D-N1-03	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.303	**0.13**
L3D-N1-04	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-N1-05	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-O1-01	This event of drilling failure is expanded to its subsystem and events in two lower levels (i.e. Levels 4 and 5)																		
L3D-O1-02	High		0.7	0.8	0.9	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Medium		0.4	0.5	0.6	0.303	**0.25**
L3D-O1-03	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-O1-04	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.15**
L3D-O1-05	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.303	**0.13**
L3D-O1-06	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-O1-07	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L3D-O1-08	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.303	**0.13**
L3D-H1-01	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	High		0.7	0.8	0.9	0.303	**0.37**
L3D-H1-02	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.303	**0.31**
L3D-H1-03	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.25**

As mentioned, the BBN is a tool for risk assessment that can combine quantitative information of different accuracy and qualitative data. Risk assessment of the MODU's operational system is mostly held up by the absence of appropriate and reliable data. In most circumstances, only descriptive information of the offshore operation system and very limited failure data for components become available, but quantitative data about cause-effect relations are still missing. For understanding these cause-effect relationships, expert judgement remains the only available choice. A manageable number of hazards are required in order to have a comprehensive risk assessment for the different operational conditions (i.e. Human error, Operational and Natural hazard). Taking this into account, it is necessary to introduce the probability of BEs in their entirety, so a model with this purpose has been developed using FL. This theory is employed to incorporate expert knowledge, gathered through a questionnaire. As illustrated in Table 6.4 and Table 6.5 in the assessment process, verbal statements are used to describe the occurrence probabilities of BEs. According to these linguistic variables, a value on a numerical scale is assigned to each BE.

Table 6.5: Occurrence probabilities of BEs (Experts' knowledge) in level 5

BE (Level 5)	Experts judgement																	Crisp No.
	Linguistic terms	Expert 1				Factor	Linguistic terms	Expert 2				Factor	Linguistic terms	Expert 3				Factor	
L5D-01-01-1-1	Low		0.1	0.2	0.3	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.303	**0.12**
L5D-01-01-1-2	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.15**
L5D-01-01-1-3	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L5D-01-01-1-4	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.303	**0.11**
L5D-01-01-2-1	Low		0.1	0.2	0.3	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.303	**0.12**
L5D-01-01-2-2	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Mol. Low	0.2	0.3	0.4	0.5	0.303	**0.13**
L5D-01-01-2-3	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L5D-01-01-2-4	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.15**
L5D-01-01-3-1	Low		0.1	0.2	0.3	0.303	Very Low	0	0	0.1	0.2	0.364	Low		0.1	0.2	0.3	0.303	**0.11**
L5D-01-01-3-2	Low		0.1	0.2	0.3	0.303	Low		0.1	0.2	0.3	0.364	Low		0.1	0.2	0.3	0.303	**0.12**
L5D-01-01-3-3	Mol. Low	0.2	0.3	0.4	0.5	0.303	Low		0.1	0.2	0.3	0.364	Medium		0.4	0.5	0.6	0.303	**0.09**
L5D-01-01-3-4	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.303	**0.21**
L5D-01-01-3-5	Low		0.1	0.2	0.3	0.303	Medium		0.4	0.5	0.6	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.15**
L5D-01-01-4-1	High		0.7	0.8	0.9	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Medium		0.4	0.5	0.6	0.303	**0.25**
L5D-01-01-4-2	Medium		0.4	0.5	0.6	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	Mol. High	0.5	0.6	0.7	0.8	0.303	**0.23**
L5D-01-01-4-3	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.303	**0.21**

A common approach to deal with these values is the use of semi-quantitative estimation methods, which rely on linguistic judgements of experts. However, these linguistic terms are related to different kinds of uncertainties (i.e. stochastic, lexical and, informal uncertainty). Various approaches have been developed to decrease the uncertainties in different fields of risk assessment; one popular solution is the use of FL (Darbra and Casal, 2009). If the data for a risk event is sufficient to enable quantitative reasoning, then the form of the information such as frequency of occurrence of the BEs can be converted into a probability distribution for the assessment.

6.5.4 Conditional probability table

A conditional probability table (CPT), which relates states of the parent nodes to those of a child node, includes entries for all possible combinations of the child and parent node states. In a Bayesian network, the number of probability distributions required to aggregate a CPT grows exponentially with the number of parent-nodes associated with that table. The input to the methodology consists of a set of weight factors that quantify the relative strengths and influences of the parent nodes with consideration of their contribution to the MODU’s operation failure by using expert knowledge. A Fuzzy-AHP is used for calculation of the CPTs for the entire parent nodes to determine the degree of influence and importance of factors.

As shown in Figure 6.9, a failure in one system or equipment such as High-Pressure Mud System Failure (L4D-O1-01-01) will affect other systems or equipment like Mud Treatment System Failure (L4D-O1-01-02). Another important characteristic of dependencies is the natures of failure that can occur within a system and how they may spread to other dependent component(s).

The dependencies among an MODU’s components present a major challenge for modelling. Dependencies among components can occur in any part or organisational level of an MODU’s operation system. The probability of the MODU’s drilling failure due to an operational issue is set between 0 and 1 for the Consistent and Risky (hazardous) states, and it is presumed that the situation is initially consistent.

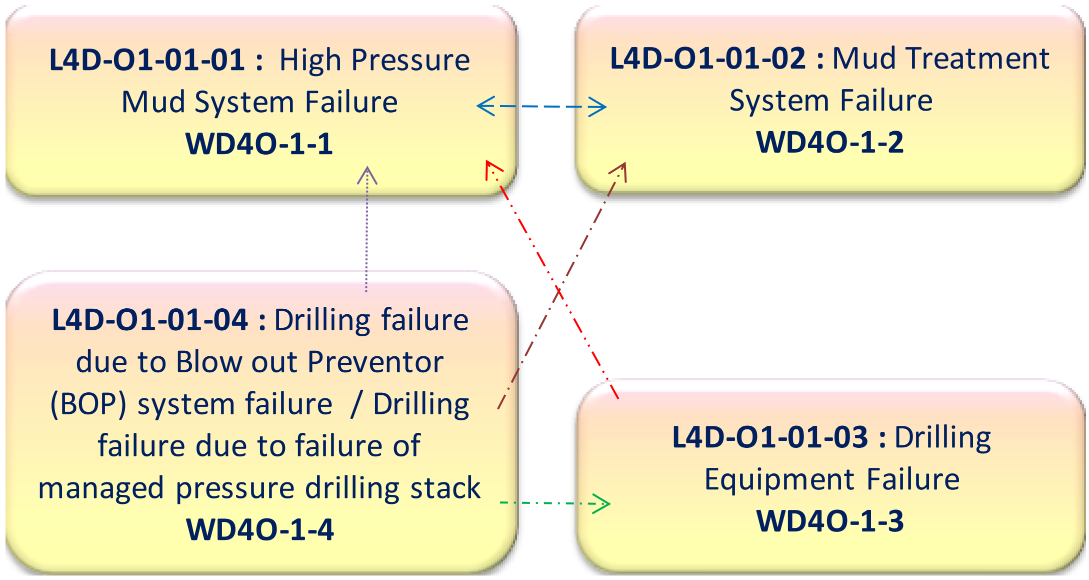

Figure 6.9: Schematic dependency among systems/equipment in level 4

The probable values of importance factor for the Consistent and Risky states are shown in the second column of Table 6.1. As is illustrated in Figure 6.10, Drilling System Failure (L3DO101) is mainly affected by four categories of events (i.e. L4DO1011 to 4). An AHP methodology was used to show the relative importance factor (i.e. WD4O-1-1 to 4) of each parent node for its associated child node. As a result, for each node the conditional probability of that node taking a certain value and the cumulative values of the entire node is presented in the last two columns of Table 6.1. Note that a probability is provided for each combination of events (64 in this case). The CPTs for different levels are established in a similar way and presented in Appendix 3.

Direct dependence of each BE node to its associated node is quantified by assigning each BE node a CPT by using a symmetric model. In the symmetric model, the experts' opinion is distributed by relative importance of each parent node for its associated BEs. The strength of direct dependence of each BE to its associated parents is indicated by their normalised weights (Riahi *et al.*, 2014). This CPT is actually the conditional probability of each event given the other variables or events.

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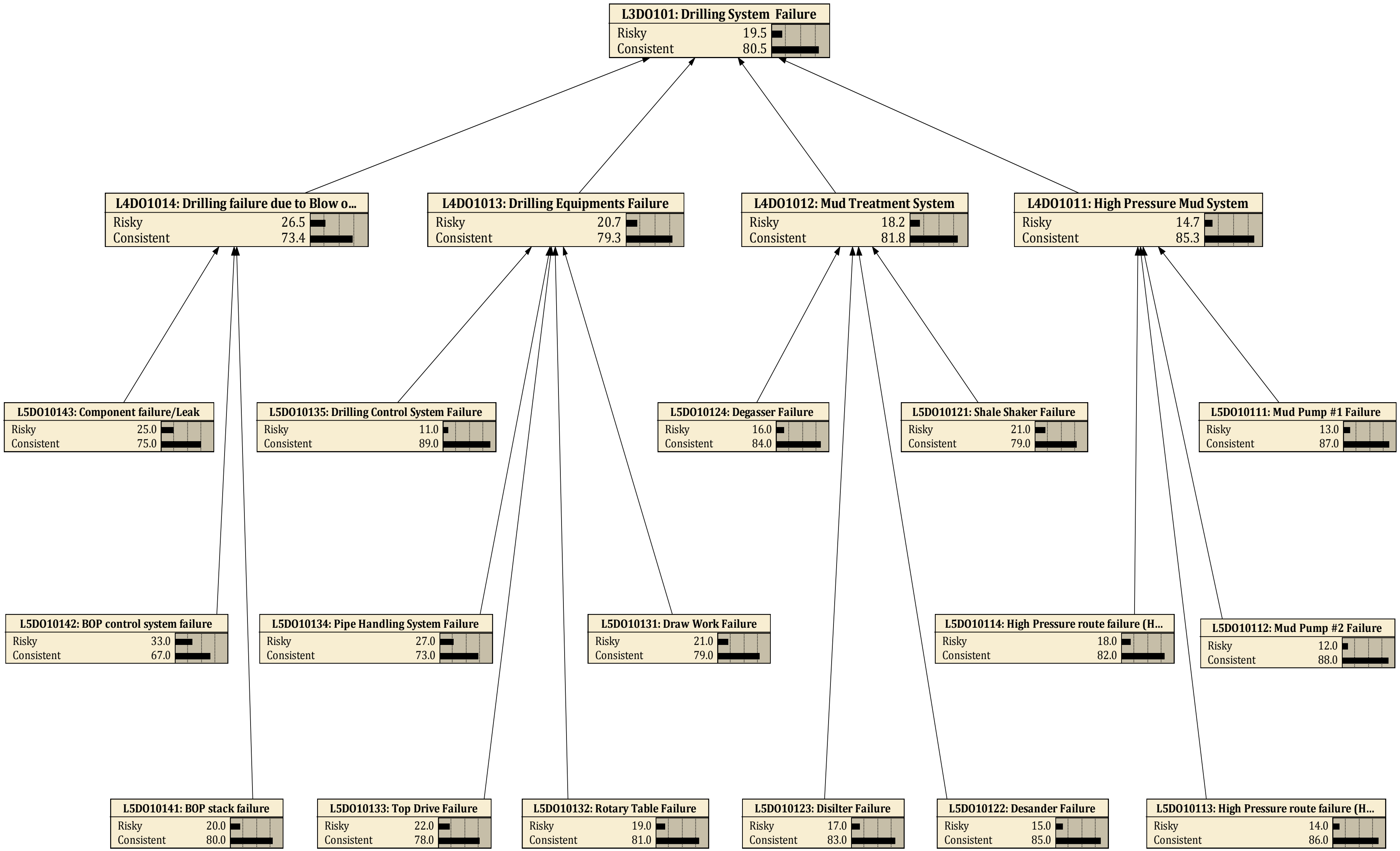


Figure 6.10: BBN model for drilling system failure (L3DO101)

6.5.5 Risk modelling and analysis of the MODU's operation system

Risk modelling and analysis has a fundamental role in the identification of hazard cause potentials, the understanding of the fundamental causal events, the likelihood assessment of these events, the severity evaluation of the potential consequence of catastrophes and the prioritisation of mitigations. The HG hierarchy of the MODU's operation system as illustrated in Figure 6.8 is converted into a BBN. For instance, drilling failure due to Drilling System Failure (L3D-O1-01) is converted into the corresponding parent nodes and the consequence of Mud Pump #1 Failure (L5D-O1-01-1-1) is converted into the corresponding root node. The arc between L4D-O1-01-01 and L5D-O1-01-01-01 is converted into a corresponding link in the BBN. Each category of events consists of some different sub-events that affect the performance of the MODU's operations, as presented in Figure 6.11. For instance, the Pipe Handling System Failure (L5D-O1-01-3-4) is the source of failure of L4D-O1-01-3. Likewise, the L5D-O1-01-4-1 (BOP Stack Failure) and L5D-O1-01-4-2 (BOP control system failure) contribute to L4D-O1-01-04 (Drilling failure due to BOP system failure/drilling failure due to failure of managed pressure drilling stack) to a certain degree.

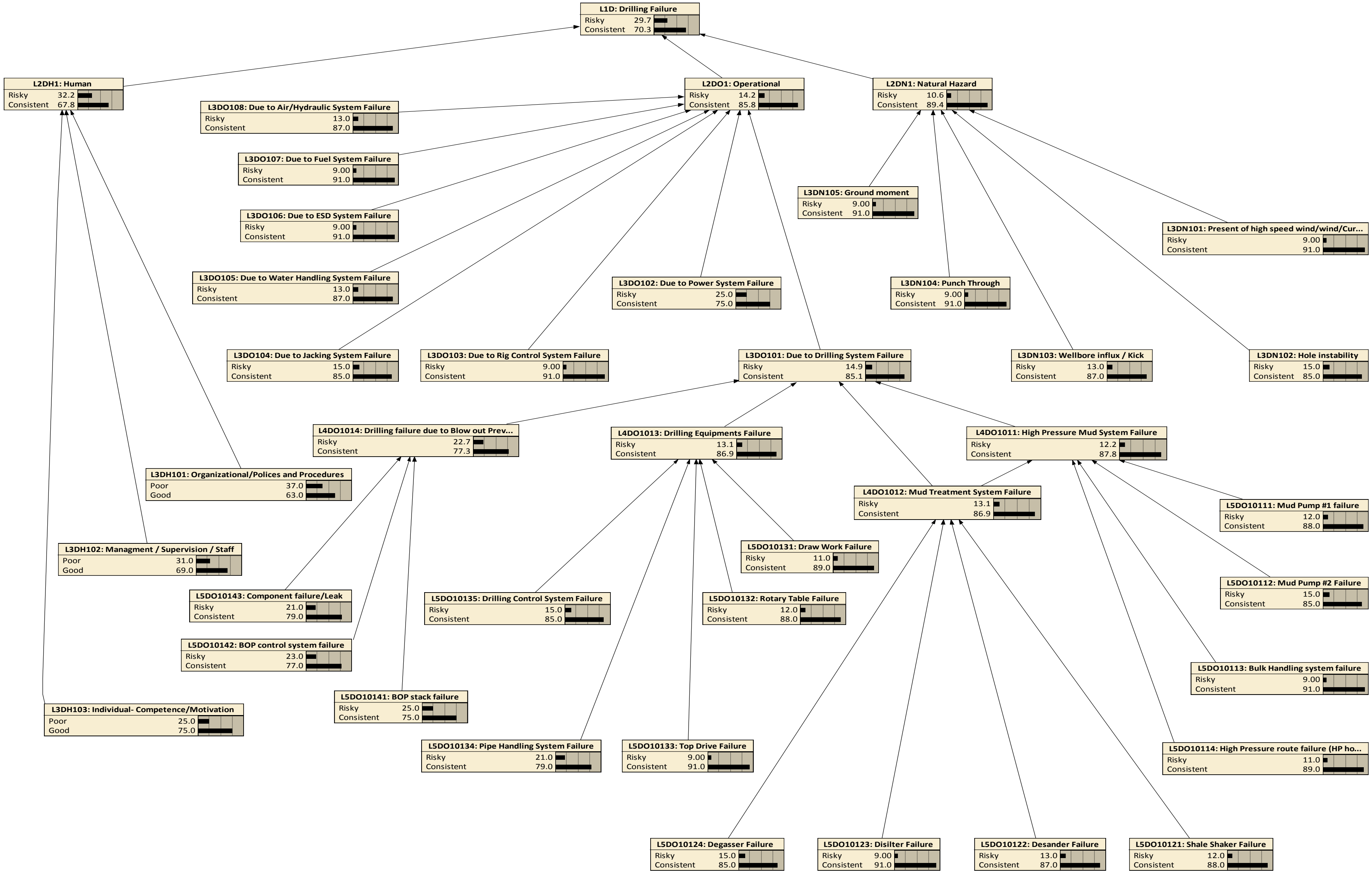


Figure 6.11: BBN model of the MODU's drilling system

Detailed failure statistics for the various BOP systems are presented in the Sintef report, in which the main information source from the study has been the daily drilling reports (Holand, 1999). The probability that there will be L4D-O1-01-4 (BOP control system/stack/component failure) can be calculated as shown in Figure 6.12.

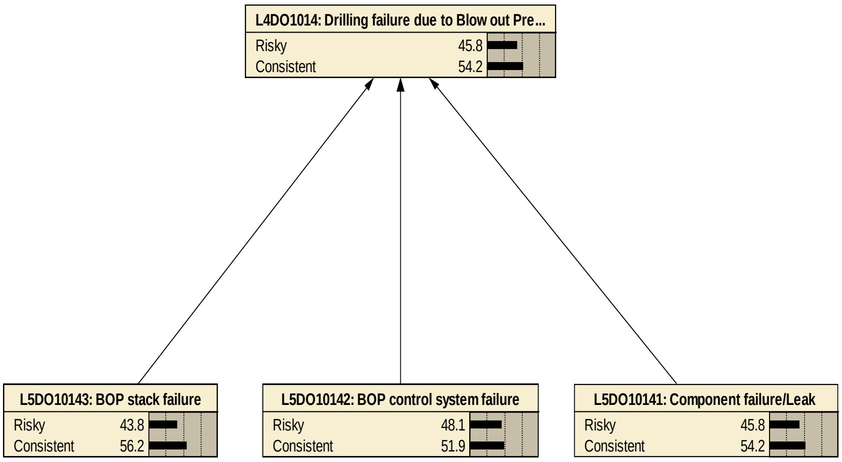


Figure 6.12: BBN model of L4D-O1-01-4 (BOP control system/stack/component failure)

Figure 6.13 illustrates the results for L5D-O1-01-4-1 (BOP stack failure). As would be expected, the probability of drilling failure due to BOP stack failure increases from 45.8% to 68.3%, when BOP stack failure has been observed. This update is due to diagnosis (i.e., bottom-up) inference from the L5D-O1-01-4-1 node to the "evidence" node.

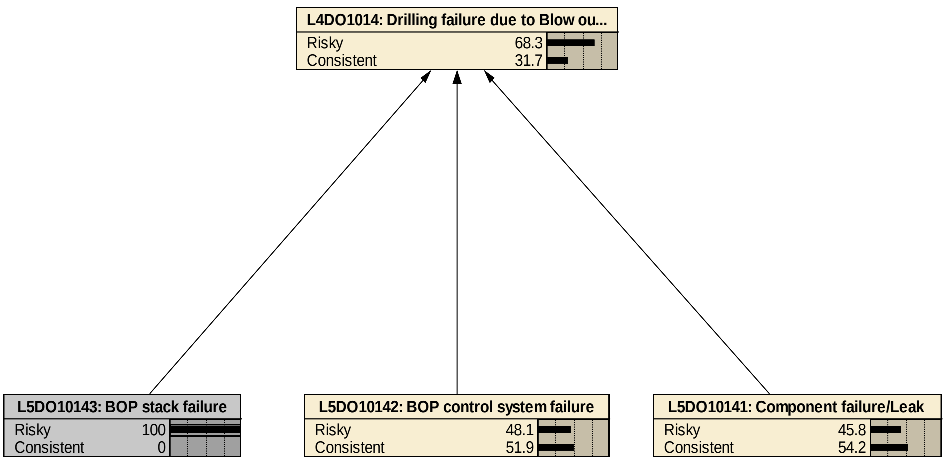


Figure 6.13: Propagated results for BOP control system/stack/component failure when BOP stack failure has been observed)

As illustrated in Figure 6.14 the probability of drilling failure due to BOP stack failure decreases from 68.3% to 28.3%, when BOP stack is 100% consistent.

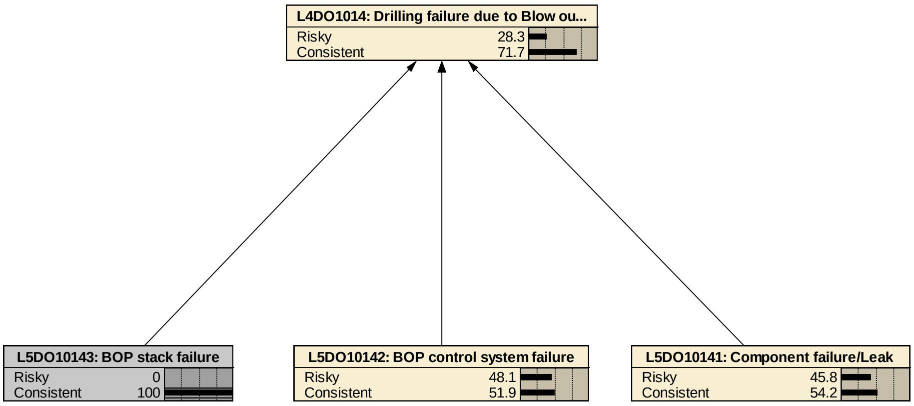


Figure 6.14: Propagated results for BOP control system/stack/component failure, when BOP stack is 100% consistent

6.6 Validation and sensitivity analysis

Validation is an important aspect of a model for the reason that it affords a sensible amount of confidence in the results of the model. It is very useful to be able to compare a model against actual data to verify that the model adequately corresponds to reality and to assess its usefulness as a predictive tool. In this case, in order to carry out a validation of the model, the parameters used need to be closely monitored for a period of time. For MODU system operations, it is obviously an impractical exercise due to the lack of offshore operations data. For validation of the proposed methodology and modelling, three basic principles are considered and should be satisfied. First, a minor oscillation in the prior probability of each parent node should certainly be the result of a relative fluctuation of the posterior probabilities of child nodes. Second, if there is any fluctuation in the probability distributions of an individual parent node, its consequence gradation to child node values should be kept steady. Lastly, the entire effect magnitudes of the probabilities variations from an attribute should constantly be more than that from the set of A-b (b ∈A) features (Cai *et al.*, 2013). Validation is the assignment of representations that the model is a realistic demonstration of a real system and is an important aspect of a methodology, because it provides a reasonable amount of confidence in the model's results. Due to lack of real data, the model should at least satisfy the three basic principles mentioned above. In order to demonstrate the satisfaction of the principles, the BBN for drilling system failure node, L3DO101, is considered, as illustrated in Figure 6.10.

For instance, in the parent nodes of L3DO101 (Drilling system failure), as illustrated in Table 6.6 and also as shown in Figure 6.15, when the risky probability of L5DO1-01-1-4 (High Pressure route failure HP hoses, Standpipe Manifold, Choke and Kill Manifold) is set to 100%, as would be expected, the probability of consistent operations of node L4DO1011 (High-Pressure Mud System Failure) decreases from 87.8% to 70.9%.

Table 6.6: Probability failure of L5DO10114 (High-pressure route failure - HP hoses, standpipe manifold, choke and kill manifold) is set to 100%

Nodes	L5DO10114: High Pressure route failure (HP hoses, Standpipe Manifold, Choke and Kill Manifold)			
	Risky	Consistent	Risky	Consistent
	11%	89%	100%	0%
L1D: Drilling Failure	29.7	70.3	30.1	69.9
L2DO1: Operational	14.2	85.8	15.3	84.7
L3DO101: Due to Drilling System Failure	14.9	85.1	20.7	79.3
L4DO1011: High Pressure Mud System Failure	12.2	87.8	29.1	70.9

Accordingly, as presented in Table 6.7 and illustrated in Figure 6.16, when the risky probability of L5DO10135 (Drilling control system failure) is set to 100%, in the parent nodes of L3DO101 (Drilling System Failure), the probability of operational consistency decreases from 85.1% to 82.7%. Furthermore, in the node of L4DO1013 (Drilling Equipment Failure) the probability of operational consistency decreases from 86.9% to 78.3%.

Table 6.7: Probability failure of L5DO10135 (Drilling control system failure) is set to 100%

Nodes	L5DO10135: Drilling Control System Failure			
	Risky	Consistent	Risky	Consistent
	15.0%	85.0%	100.0%	0.0%
L1D: Drilling Failure	29.7	70.3	29.9	70.1
L2DO1: Operational	14.2	85.8	14.6	85.4
L3DO101: Due to Drilling System Failure	14.9	85.1	17.3	82.7
L4DO1013: Drilling Equipments Failure	13.1	86.9	21.7	78.3

Lastly, in the node of L4DO1014 (Drilling failure due to BOP system failure/Drilling failure due to failure of managed pressure drilling stack), when the node of L5DO10121 (BOP stack failure) is set to 100%, the probability of operational consistency decreases from 77.3% to 58.6%, as presented in Table 6.8 and also illustrated in Figure 6.17.

Table 6.8: Probability failure of L5DO10141: BOP stack failure is set to 100%

Nodes	L5DO10141: BOP stack failure			
	Risky	Consistent	Risky	Consistent
	25%	75%	100%	0%
L1D: Drilling Failure	29.7	70.3	30.0	70.0
L2DO1: Operational	14.2	85.8	15.0	85.0
L3DO101: Due to Drilling System Failure	14.9	85.1	19.0	81.0
L4DO1014: Drilling failure due to Blow out Preventor (BOP) system failure/ Drilling failure due to failure of managed pressure drilling stack	22.7	77.3	41.4	58.6

From the above it can be concluded that increasing each influencing node satisfies the three basic principles, therefore providing a partial validation of the model.

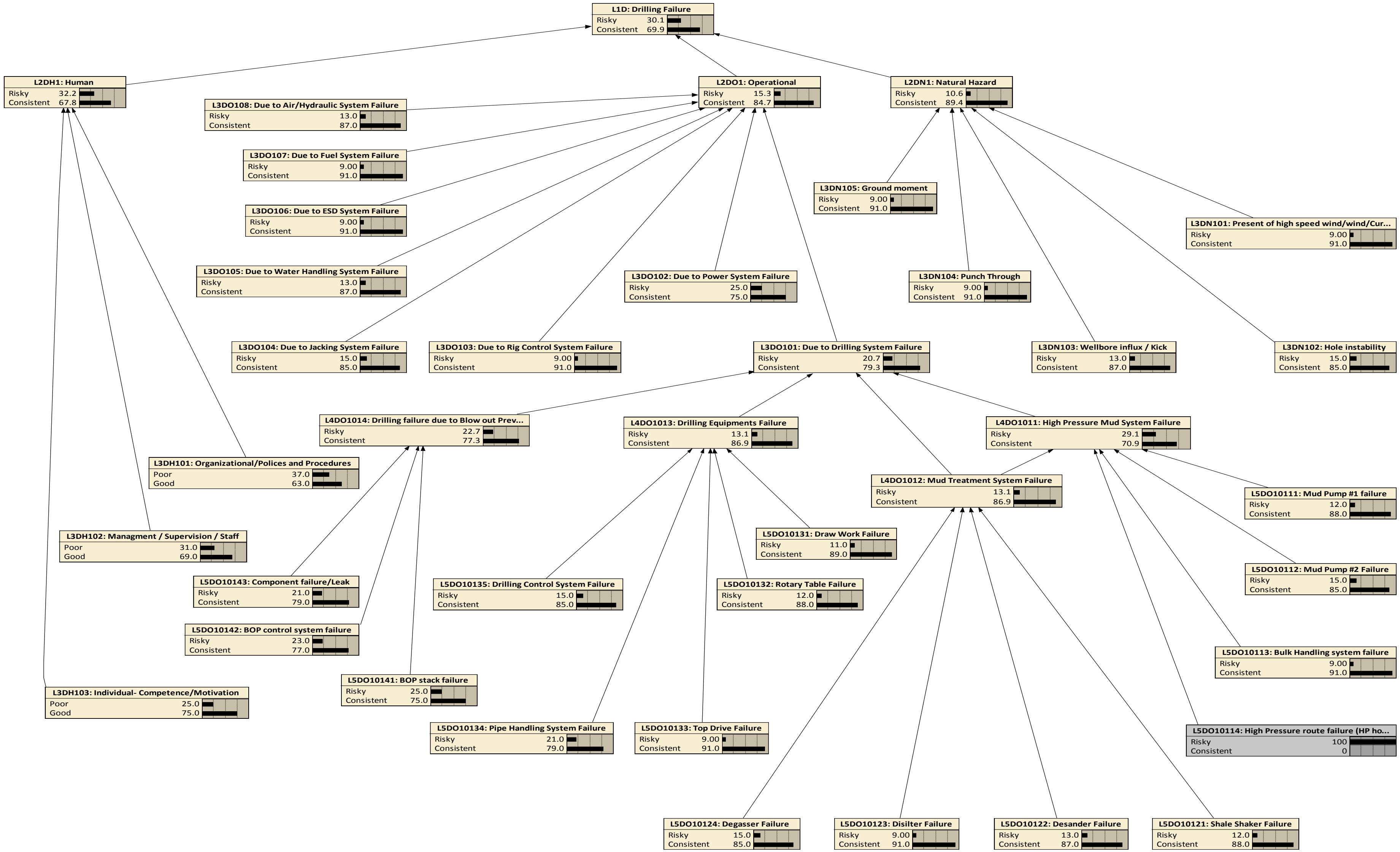


Figure 6.15: BBN of an MODU drilling system failure when the probability failure of L5DO10114 (High-pressure route failure - HP hoses, Standpipe Manifold, Choke and Kill Manifold) is set to 100%

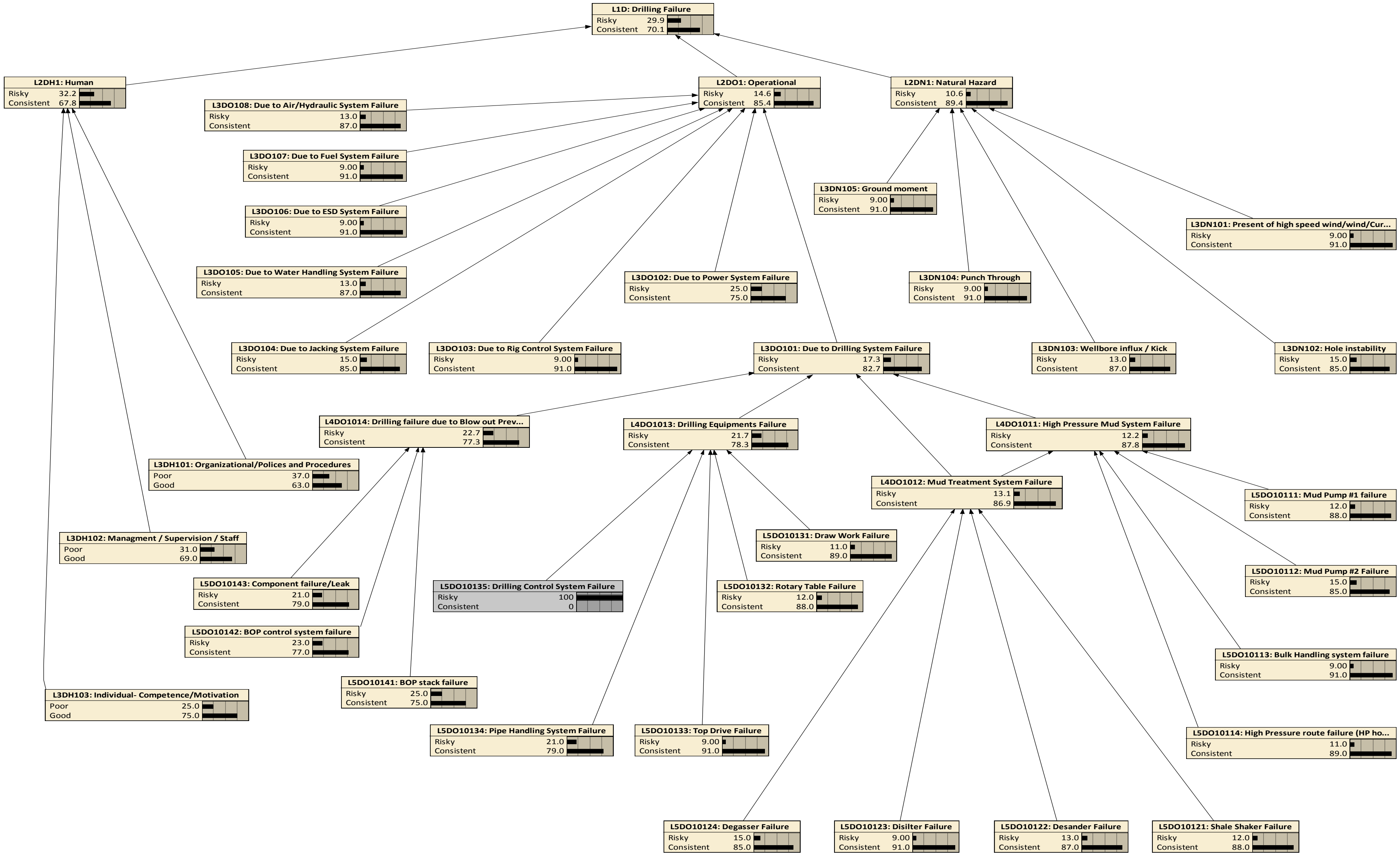


Figure 6.16: BBN of an MODU drilling system failure when the probability failure of L5DO10135 (Drilling control system failure) is set to 100%

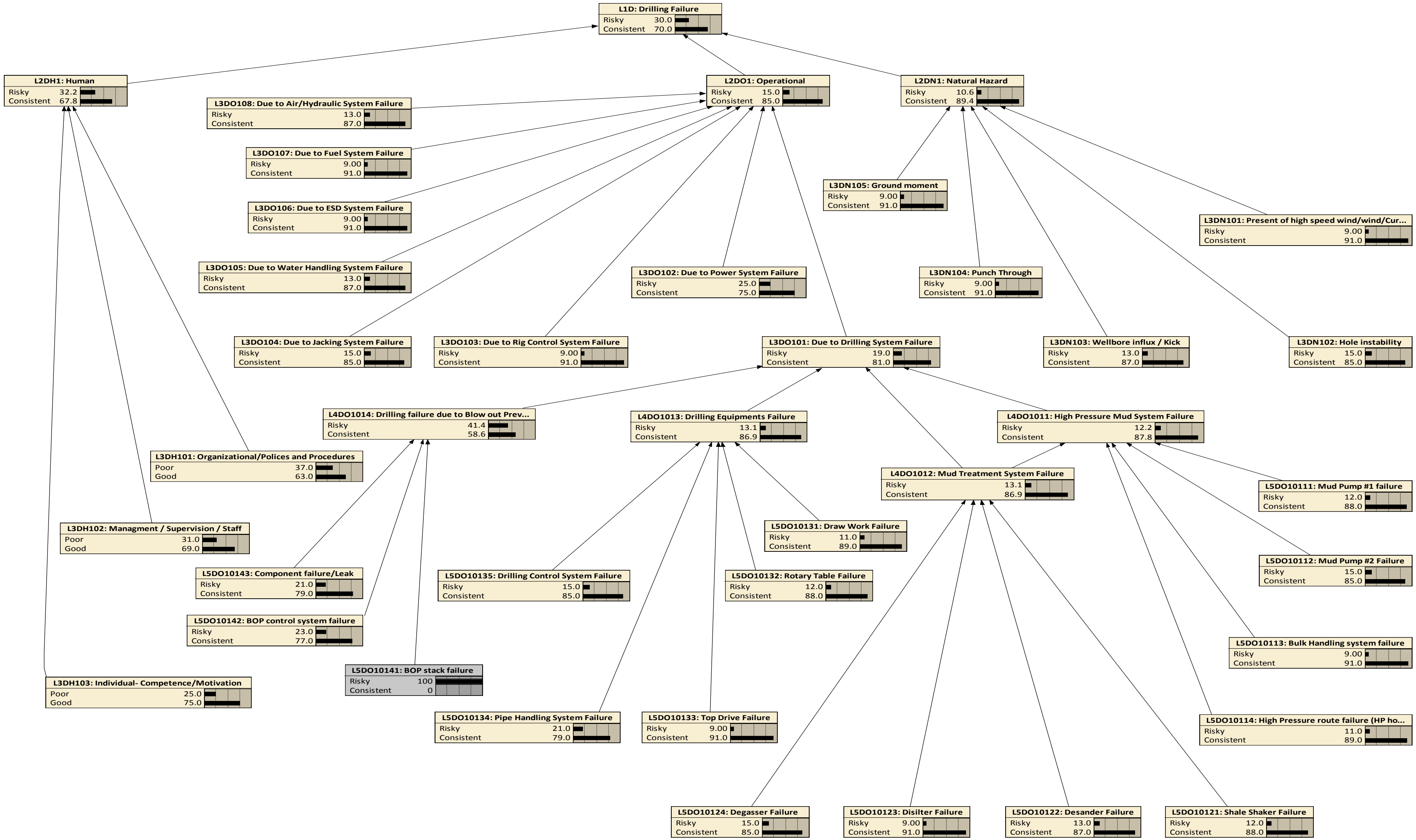


Figure 6.17: BBN of an MODU drilling system failure when the probability failure of L5DO10141 (BOP Stack failure) is set to 100%

The evaluation of the test case shows how change in one or more specific variables would change the belief in the target node L3DO101. This evaluation also revealed the effect of conditional dependence between variables. Further, the test case indicated that Netica is a suitable tool to be used in the calculations of a real-world scenario.

6.7 Results and discussion

MODU risk assessment and probability of failure has made limited improvement compared to analysis methods developed for other offshore structures' probability estimation. Estimation of probability of failure and analysis of the consequences for the MODU operation system can be facilitated by a BBN, as presented in this chapter, allowing modelling with respect to its HG features. This chapter has presented the modelling aspect, including hazard identification and its consequences for MODU failures and offered a methodology for MODU risk assessment, which supports a structured approach to all tasks, involved in the failure of MODUs due to their HGs failure. The Netica Ver (4.16) software is used for propagation of the BBN model and the outcome of assessment offers constructive information in preventing an event's recurrence in the future. The BBN format also allows the establishment of a common model for the entire MODU system, considering all HGs, but in this chapter only a manageable HG is considered. The framework is demonstrated through the assessment of a case study that shows the probability of failure of responses in BBN circumstances and the model is shown in Figure 6.12. Furthermore, many failure-reducing measures influence the risk from other hazards; therefore, for proper risk assessment of an operation system one must consider the risk and associated consequences of those risks from all operation processes.

The presented methodology can easily be extended to include other HGs and the processes should be considered simultaneously; also, it is possible to propagate uncertainties for different HGs and their BEs through modelling and analysis so that the overall system failure can be indicated in a probabilistic approach (i.e. probability distribution or higher and lower confidence limits). This will benefit the decision-maker, who would appreciate the changeability and sensitivity of failure possibility estimates, which would not be so understandable if a risk assessment was offered as single point estimates only. Still, it is then uncertain whether or not the acceptable risk level should be compared with the mean, intermediate levels or some higher confidence limit of the system. Some decision-makers may wish to work this out by using a higher confidence limit, resulting in the conservative use of risk acceptance criteria. Such an approach may not always be usual but it does mean that the decision-maker with consideration of the whole aspect (i.e. environmente issues, cost, time and quality) needs to make a sensible and proper decision.

6.8 Conclusion

This chapter has presented a methodology for risk analysis and decision support and examined the probability of failure of an MODU operation system by using a BBN. This methodology is used for risk assessment through a unique application of Fuzzy-AHP and BBN techniques to assess the consequences of risk events based on prior knowledge and accounting for influences on each other to determine the probability of risk events. The proposed methodology can be used as a process for developing a set of decisions for understanding and identifying the range of consequences and trade-offs of actions within an uncertain atmosphere, which allows representation of offshore operation systems such as MODUs in different levels of detail. Risk analysis is performed by assigning probabilities to a certain event failure or evolution, in which a hierarchical breakdown is used to decompose one single component into a more detailed representation of the component. It is assumed that an MODU's system failure is carried out by a series of simple occurrences, each affecting a different component. An event failure can be seen as a path through the evolutionary graph from a start point to an end point.

Risk assessments are subject to many sources of uncertainty and data limitations that hamper the description of model input and the selection of an appropriate model structure. Conceptual model uncertainty and lack of system understanding is demonstrated to have a great impact on risk assessments. Bayesian networks have the advantage that they are based on a logical framework of cause-effect relations. These relations are based on existing knowledge or experience. As little knowledge is available about the individual relations, many assumptions have to be made. For these assumptions expert knowledge is essential. Risk assessment for an offshore operation system with Bayesian concepts often involves a portion of information in order to achieve a useful BBN model, especially in the case of MODU risk assessment, when a large amount of data is vague and, therefore a combination of various data and information resources is essential. This chapter has proposed a new approach for BBN construction by employing a Fuzzy-AHP and combining domain knowledge from experts where there are limited data. Expert knowledge with Fuzzy set theory was used to estimate the BE failure and conditional probability table. From a theoretical point of view, the methodology has constructed a Fuzzy-AHP of Bayesian learning and a case study is presented showing the practical application.

The quantification and assessment of probability of failures allows an engineered design of MODUs and adjustment of an offshore operation system so that risk is controlled. The largest concern for operators is the disruption of hydrocarbons of delivery to the departure point. MODU failure has previously caused interruptions in drilling; therefore, operators could use the BBN model to quantify loss frequency, mitigation measures, and mitigation to control or to avoid a specified risk of HGs. By doing so, the expected loss of hydrocarbons and expected costs of construction (depending on the acceptable risk level to the operator) can be determined for establishing budgets for design, construction and installation, and also for operations and maintenance.

From this study, it can be concluded that the model has the following advantages:

- The proposed model can take into consideration uncertainty and dependency in different HGs.
- Modelling and simulation are seen as key elements to better understanding of dependencies.
- Assistance in understanding the mitigation process for rare or extreme events.
- It can be useful in the process of MODU risk analysis (i.e. vulnerability assessment).
- Helps the decision-maker as a decision support tool and can be used for what-if analysis by, for example, simulating the consequences of a decision.
- Provides an analysis and decision structure for strategy creation in situations of uncertainty and risky events.

The validation results show that the proposed model calculates the failure probability of MODUs. Furthermore, the BBN model is uniquely capable of directly computing the posterior probabilities of variables which are most valuable for the enhanced system risk assessment. However, in spite of their remarkable power and potential in addressing inferential processes, there are some inherent limitations and liabilities in BBNs such as:

- The elicitation of CPTs to the nodes and edges can be done as a brainstorming exercise by the expert group. In general, this means that, for each node, the expert group has to assess the conditions of probability (i.e. failure of events and the effect of the events on others). They cannot easily incorporate unobserved variables, owing to the fact that the size of the internal CPT for a child node can very quickly become quite large.

- There is computational complexity/difficulty (filling in of details of numerical recipe, computer time, convergence monitoring), which is exponential with the increase in the number of present nodes.

The prior probability is relatively easy to assess. Based on available data or expert judgement, and experience in Netica development and evaluation, it can be done by ranking the importance of the different events, giving them probabilities from a predefined set. The complexity of inference is usually associated with large probabilistic dependencies recorded during inference. However, a large model is preferable to a smaller one only if it provides a sufficiently large improvement of fit to offset the penalty for its additional complexity.

CHAPTER 7: Fuzzy MCDM and Fuzzy TOPSIS for cost-benefit analysis and decision-making

Chapter summary

The main objective of this chapter is to propose a methodology for assessment of the relative importance of criteria and the performance ratings of alternatives of an offshore operation system with respect to the criteria. The proposed methodology offers a quantitative decision model that can help the decision-maker to set priorities, the RCOs, and gain the most benefits for controlling the risk of the MODU's operation system. The purpose is to find the most appropriate alternative(s) from a discrete set of feasible alternatives with respect to a limited set of criteria. A Fuzzy MCDM model based on Fuzzy-AHP and Fuzzy TOPSIS is used for construction of the model and composition of weighting scheme and implementation. In real situations, the decision-makers have to combat curiously vague and conflicting criteria. This controversy increases empirical uncertainties, disputes, and the resulting consequences of these decisions. A Fuzzy MCDM method, which is suitable for treating group decision-making problems in a Fuzzy environment, is proposed for ranking the RCOs from a cost-benefit point of view and to aggregate the conflicting opinions. The proposed methodology with respect to cost and benefit has been implemented in an MODU's operation system intended for decreasing/controlling of the operational risk level of the MODU. A generic model is presented that considers the operational failure of the drilling systems and the focus is on human error and the BOP system that is implemented to propose barriers for reducing the MODU's operational risk. The proposed methodology provides a rational and systematic approach and the main steps in the development of this methodology include: i) Defining and describing the alternatives, ii) Computing the criteria weightings, iii) Evaluating the performing of alternatives against the criteria, iv) Converting the criteria performance values to commensurable units and normalised values, v)Performing the analysis and applying the selected MCDM technique(s), vi) Ranking the RCOs from a cost-benefit point of view, and vii)Evaluating the results and making the final decision.

7.1 Introduction

The main purposes of this chapter are to develop and implement an integrated Fuzzy MCDM model based on Fuzzy-AHP and Fuzzy TOPSIS and construct a composite weighting scheme appropriate to enhance the quality of solving MCDM problems.

The MCDM techniques generally enable a problem to be structured clearly and systematically. With this characteristic, decision-makers have the possibility to easily examine and scale the problem in accordance with their requirements (Isiklar and Buyukozkan, 2006). MADM is a significant part of modern decision-making which can offer a quantitative decision model that can support the decision-maker to set priorities and achieve the most benefits for reducing and controlling the risk level of the system (Shyur and Shih, 2006).

The aim of the MCDM/MADM is to obtain the optimum alternative that has the highest degree of satisfaction for all of the relevant attributes. The decision-maker may express or define a ranking for the attributes in terms of importance/weights. The aim is to obtain the optimum alternative that has the highest degree of satisfaction for all of the relevant attributes (Yang and Huang, 2000). The purpose of this chapter is to suggest and implement an integrated Fuzzy MADM model based on Fuzzy-AHP and Fuzzy TOPSIS and construct a combined weighting scheme composed of appropriate subjective weights, and then present an experimental sample to illustrate the applicability of the proposed methodology. This model is used to improve the current techniques used in assessment of the relative importance of criteria and is applied for the evaluation and ranking of the MODU's operational barriers. The results gained from it show the preference order. MCDM refers to finding the best opinion from all of the feasible alternatives in the presence of multiple, usually conflicting, decision criteria (Torfi *et al.*, 2009)

In the traditional formulation of the TOPSIS, personal judgements are represented with crisp values. However, in many practical cases the human preference model is uncertain and decision-makers might be reluctant or unable to assign crisp values to the comparison judgements (Chan & Kumar, 2007). In many real-world situations, crisp data are not adequate and sufficient to model some decision-making problems (Chen, 2000; Chen & Lu, 2001; Chen *et al.,* 1992). This is because most of the criteria are difficult to measure by crisp values, and so they are frequently neglected during the evaluation course. In the real world, crisp data are not adequate and sufficient to model the decision-making problems in the decision-analysis process (Chen, 2000; Chen & Lu, 2001; Chen *et al.,* 1992). To resolve this problem, Fuzzy set theory has been used and is implemented herein. Fuzzy set theory attempts to select, prioritise or rank a finite number of sequences of action by evaluating a group of pre-set criteria. The proposed methodology is able to handle both Fuzzy and crisp data; in general, each expert's opinion for a given attribute may be different from those of the others, but the proposed model is able to aggregate the conflicting opinions.

Numerous qualitative and quantitative criteria may have an equal effect when assessing alternatives, which may make the selection process difficult and challenging. AHP is a technique often used to model subjective decision-making processes based on multiple attributes, and can be applied to both individual and group decisions (Bolloju, 2001). The Fuzzy-AHP method has been applied in order to identify and measure the relative importance of the barriers, in order to prevent a critical event occurring during the drilling operation of the MODUs. It allows input from experts based on previous experience to determine the degree of importance of each barrier in the model in terms of their contributions to control and reduce the MODU's risk level. The pair-wise comparison scheme used in AHP is ideally suited to estimating the relative importance of an event for multiple criteria. Weighting the criteria and evaluating the performance of alternatives against the criteria are two of the most important and difficult aspects of applying the MCDM methodology and are potential sources of considerable uncertainty (Larichev & Moshkovich, 1995; Roy and Vincke, 1981).

In order to prevent the occurrence of a hazardous situation, it may be necessary to put in place a range of barriers and it cannot be assumed that each barrier is of equal importance and weight in terms of their influence in preventing a hazard. Therefore, it is necessary to consider the contributory factors of an individual barrier in preventing a failure. AHP is used to define the effect of a barrier and its contribution to and influence on other barriers. In the proposed model, a Fuzzy-AHP is used to determine the relative contribution of weight factors of barriers, in terms of their effect in preventing system failure. This overcomes the shortcomings of conventional methods and effectively produces a final decision. The values used throughout the analysis are selected based on their high probability of occurring, and/or the high importance of the potential outcome.

In this chapter, the barriers preventing drilling failure of an MODU have been considered, focusing on the human error and the BOP including the BOP control system. The aim is to prevent a critical event occurring during drilling by assignment of barriers. The study proposes a methodology for developing such an assessment. The decision-maker may express or define a ranking for the attributes in terms of importance/weights. The aim of the MADM/MCDM is to obtain the optimum alternative that has the highest degree of satisfaction for all of the relevant attributes (Yang & Huang, 2000). The purpose is to find the most desirable alternative(s) from a discrete set of feasible alternatives with respect to a finite set of attributes.

Defining the alternatives as well as figuring out the criteria weighting, applying the selected MCDM technique(s), ranking, assessing the result and, as an outcome, making the final decision are the main steps in the development of this methodology. The decision process of selecting an appropriate alternative usually has to take many factors into consideration; for instance, organisational needs and goals, risks, benefits, limited resources, *etc*. Because of the vagueness of human thought, the selection is often based on inadequate information or personal judgements. Decision-makers may find it difficult to identify the best choice due to the lack of systematic methods to deal with multi-criteria problems.

7.2 Literature review

MCDM refers to the problem of selecting among alternatives associated with multiple criteria. The association of weights in multiple criteria problems is a serious step of the entire decision-making process. In conventional MCDM, alternative rating and weights are measured in crisp numbers. Conventional MCDM methods require the determination of alternative ratings and criteria weights are made which are subject to decision-makers' judgements. Crisp values are usually used to represent those ratings and weights. However, in practice, alternative ratings and criteria weights cannot be assessed accurately (Yeh & Deng, 1997). It is shown that calculation of the criteria weights is serious and it may change the ranking results. In a MCDM problem-solving process, weights can practically change the outcome of the whole process. Criteria weighting plays an important role in most MCDM approaches because the evaluation result is often greatly affected by the criteria weights used in the evaluation process. For the reason that the evaluation of criteria entails diverse opinions and meanings, it cannot be assumed that each evaluation criterion is of equal importance (Tzeng & Ding, 2003). Numerous methods for solving MADM problems require definitions of quantitative weights for the attributes (Wang & Chang, 2007; Torfi *et al.*, 2009; Al-Kloub *et al.*, 1997; Gass, 1986; Goh *et al.*, 1996; Srdjevic *et al.*, 2004; Wang & Lee, 2009; Yeh & Deng, 2004; Olson, 2004; Diakoulaki *et al.*, 1995; Deng *et al.*, 2000). Identifying the means by which to measure the weights of decision-makers is a motivating research topic. Each factor has its own contribution to the evaluation. The weight values of evaluation criteria are the most influential coefficients in a system. The higher the weight value, the more significant is the criterion. Usually the weight value depends on the decision-maker's subjectivity, which may result in some errors or mistakes.

Different criteria weight values are used to evaluate a task, which will not lead to the same assessment outcomes (Pilavachi *et al.*, 2006; Afgan *et al.*, 2007). Different criteria weights have an important role in the decision-making process. The way in which to arrange the decision weights should be deliberated in the evaluation process. Many methods have been proposed to determine the weights of decision-makers. Chen and Fan (2007) proposed a factor score method for obtaining a ranking of the assessment levels of experts in group-decision analysis. Ramanathan and Ganesh (1994) proposed a simple and intuitively appealing eigenvector-based method to intrinsically determine the weights of group members by using their own subjective opinions. Xu (2008) gave a direct technique to determine the weights of decision-makers by using the deviation measures between additive linguistic preference relations. Yue (2011a) developed a method for determining weights of decision-makers with interval numbers.

In various circumstances where performance rating and weights cannot be given accurately, the Fuzzy set theory is introduced to deal with the uncertainty of human judgements, and such problems are known as Fuzzy multiple criteria decision-making.

The Fuzzy set theory can make available a decision context that incorporates imprecise judgements in the decision-making process (Dursun & Karsak, 2010).

The use of Fuzzy set theory (Zadeh, 1965) allows the decision-makers to incorporate unquantifiable information, incomplete information, non-obtainable information and partially unknown facts into the decision model (Kahraman, 2005). Bellman and Zadeh (1970) first incorporated Fuzzy set theory into MCDM as an approach to effectively deal with the inherent inaccuracy, vagueness and ambiguity of the human decision-making process. Since then, many researchers have been working on the process with unreliable data. Chen (2000) extended the TOPSIS of Hwang and Yoon (1981) to a Fuzzy environment and developed a technique to calculate the distance between two Fuzzy numbers and defined a closeness coefficient to determine the ranking order of all alternatives by concurrently calculating the distances to both the Fuzzy positive-ideal solution and Fuzzy negative ideal solution.

TOPSIS and its extensions are developed to solve ranking and justification problems. Although it is a popular and simple concept, this method is often complained about for its lack of ability to appropriately handle the inherent uncertainty and imprecision associated with the mapping of the decision-maker's perception to crisp values (Yong, 2006; Chen & Tsao, 2008, Kahraman *et al.*, 2007; Wang & Elhag, 2006; Shyur and Shih, 2006). Yue (2011b) developed a new approach for determining weights of decision-makers in a group decision environment based on an extended TOPSIS by proposing the positive ideal solution as the average of the group decision. The negative ideal solution includes two parts, left and right negative ideal solutions, which are the minimum and maximum matrixes of the group decision, respectively.

7.3 A proposed integrated Fuzzy MCDM and Fuzzy TOPSIS methodology

In this chapter, an approach for multi-criteria recommendation is proposed. The proposed methodology uses the Fuzzy MCDM and Fuzzy TOPSIS techniques to express the causal relationships between a hazard from different sources and its proposed barriers in an offshore operation system. An MODU's operation system is represented by a combination of the various sub-systems and the methodology presented uses a hierarchical model to describe reliance among the hazard and its suggested barriers.

The proposed method concentrates on the assessment of the recommended barriers to prevent the failure of offshore operation systems (i.e. MODUs) posed through the HGs and their root causes (i.e. BEs). The accuracy of assessment in a multi-criteria environment can be improved by a combination of the recommended techniques, FL and MADM methods. Since decision-making in a real MODU's operation system is extremely complicated, the intention of the proposed methodology is to support offshore operators in making sensible decisions through introducing the barriers in order to prevent the occurrence of an event and to decrease the MODUs' risk level. As graphically represented and illustrated in Figure 7.1, the proposed MCDM methodology shows how this method can be applied, and comprises the following stages:

- Performing the analysis and applying the selected MCDM technique(s)
- Calculating the weighting of the criteria
- Defining and describing the alternatives
- Evaluating the performing of alternatives against the criteria
- Construction of a decision matrix
- Establishment of the aggregated weight scheme
- Obtaining the decision matrix to identify the criteria with respect to alternatives
- Evaluating the result and making the final decision (by anyone involved in the decision analysis process)
- Normalising the decision matrix in order to make each criterion comparable
- Calculation of the overall performance evaluation for each alternative
- Finally, determine the positive ideal solution and the negative ideal solution and calculate the closeness coefficient, in order to rank each alternative in descending order

Based on prior discussion on the unavailability of data, FL is used to accumulate the data; the experts were asked to evaluate interrelations between given criteria and provide multi-criteria ratings for selected alternatives. After defining and describing the alternatives and calculation weighting of the criteria, the performance of the alternatives was evaluated against the criteria. Each expert expressed his/her opinion about the identified subjective criteria. The expert opinions are in the form of linguistic terms or verbal statements and this subjective judgements can be demonstrated by a Fuzzy number. The weights of criteria are obtained using Fuzzy-AHP and experts' weights are estimated. Then, a criteria-based aggregation method for grouping experts' judgements is employed. One may conclude that the various experts are not equally important. After assigning a weight for each expert, all ratings are aggregated for each subjective criterion.

In the resulting step, all aggregated Fuzzy numbers are converted into numeric ratings using the centre of gravity method. The result of the last phase is a decision matrix, which contains Fuzzy data. Consequently, the alternatives in hand are ranked by Fuzzy TOPSIS by following these steps:

a) Construct a decision matrix

b) Calculate aggregate weights for each criterion

c) Normalise the Fuzzy decision matrix

d) Calculate overall performance evaluation for each alternative

e) Determine the positive c deal solutions (PIS) and negative ideal solutions (NIS)

f) Calculate distance from Fuzzy PIS and Fuzzy NIS

g) Calculate CC and determine the best alternative

The conceptual model of the proposed method is illustrated in Figure 7.1. This method of assessment can help the operator to carry out the MODU's risk evaluation and to propose the best risk control option in a realistic and methodological way. As demonstrated in Figure 7.1, the decision process in a MADM method contains four main parts, namely: i) alternatives and criteria for evaluating of risk control option, ii) calculating the weights for the criteria, iii) performance measures of alternatives with respect to the criteria, and vi) ranking and decision-making for selection of the best RCOs. The goal of the MCDM is either to design the optimal alternative or to choose the best one from the predefined alternatives, and can be classified in two categories: i.e. MODM and MADM Figure 7.1 describes the features of the two classes.

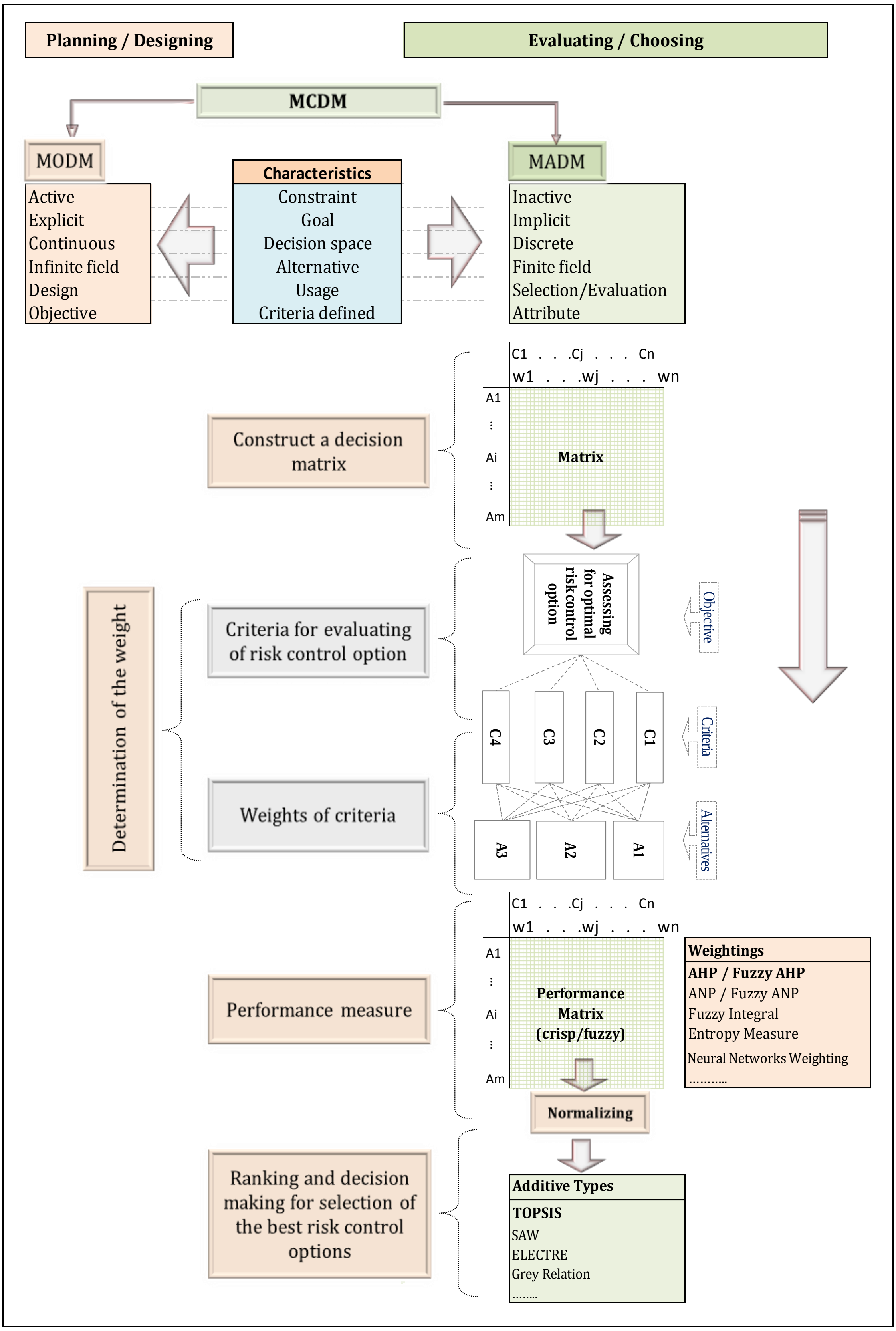


Figure 7.1: Proposed methodology for Fuzzy MCDM and Fuzzy TOPSIS

TOPSIS is a MCDM technique that ranks different alternatives through numerical assessments and this chapter proposes an extension of the Fuzzy TOPSIS approach which integrates subjective weight. The benefit of the proposed methodology is that it not only benefits from decision-makers' know-how, but also involves the offshore operators in the entire decision-making process; moreover, it has the following advantages (Chu and Lin, 2002):

- The method is rational and easy to understand.
- The calculation involved is simple.
- It is capable of finding the best alternatives for each evaluation criterion depicted in a simple mathematical form.
- The concept allows both subjective and objective weights to be aggregated in the decision-making process and the weights can be specified for each criterion, in order to introduce a measure of the relative importance felt by the decision-maker (Gamberini *et al.*, 2006).

7.3.1 Definition and classification of barriers

Based on experience from a literature survey concerning the understanding of the term *barrier* in various industries, it is clear that different terms with similar meanings have been used to define the word (e.g. protection layer, safety barrier, *etc*.). A barrier or protection layer is implemented to protect people/crew, the environment and assets from hazards. In order to properly define the concept of barrier, it is first necessary to define the term barrier function, which is what is needed to assure, increase and/or promote safety and decrease the risk level (De Dianous & Fiévez, 2006)

Sklet (2006b) defines safety barrier function as: a barrier function is a function planned to prevent, control, or mitigate undesired events or accidents. "Prevent" means reduction of the likelihood of an undesired event, control means limiting the extent and/or duration of the event to prevent escalation, and mitigate means reduction of the effects of the undesired event. The classification of barriers (i.e. barrier functions and barrier systems) is shown in figure Figure 7.2. Xue et al. (2013) divide safety barrier functions into proactive and reactive functions depending on whether their service time is before or after a particular undesired event. Barriers that are intended to function before an undesired event are proactive, while barriers that are intended to function after the event are reactive.

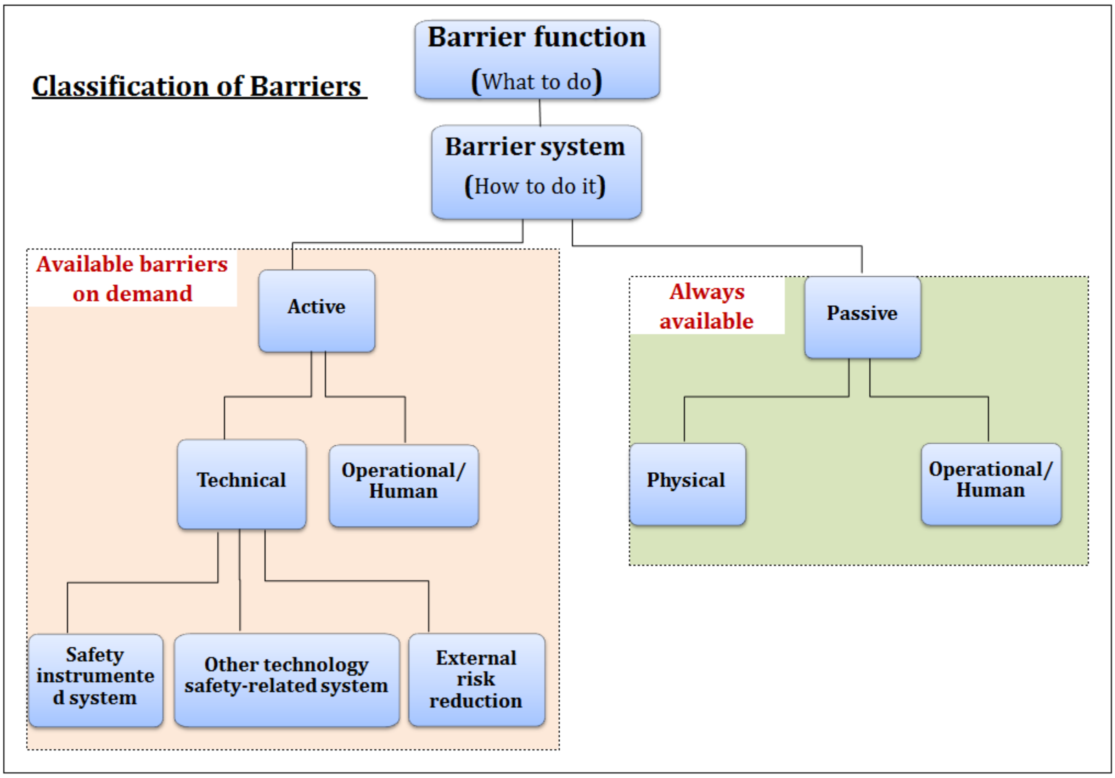


Figure 7.2: Classification of barriers, barrier functions and barrier systems

A passive protection layer (i.e. physical, operational and human) is a protection layer that does not have to take action to achieve its function in reducing risk. An active protection layer is required to move from one state to another in response to a change in a measurable process property (e.g. temperature or pressure), or a signal from another source (such as a push-button or a switch). A well barrier can be viewed as a protection layer whose objective is to prevent flow from the reservoir. A well barrier will, however, be a combination of passive and active protection layer basics.

The requirements and guidelines pertaining to well integrity during drilling activities and operations are specified in the Norwegian oil and gas regulations (NORSOK D-010, 2004). According to this standard, all phases of offshore operations must have two separate and independent barriers. Well-drilling completion is a good example, in which the mud column is the primary barrier and the secondary barrier is the BOP, which protects the well from a disaster as the last resort. In addition to the two well-barrier necessities, it is expected that the primary barrier must continuously be intact. The primary barrier must be intact to allow for isolation of the well in the event of an external event harmful to the oil and gas platform.

A failure is dependent on one or several BEs and a system is functioning if and only if all of its components are functioning. The MODU's operation system is functioning if there is a connection either through the secondary or the primary well barrier, or both.

The BOP system for the Deepwater Horizon, Figure 7.3 (a), was located on the seabed on the wellhead. A riser pipe extended from the top of the system to the drilling rig so that drilling mud could circulate between the well and the drilling unit. As illustrated in Figure 7.3 (b), on top of the five rams of the BOP stack was a blind shear ram. The BOP system also had a spare/emergency cut-off system that would facilitate the drilling unit to move away from the well once the blind shear ram was activated. As a last remedy in a hierarchy of well-control schemes, the two opposing blades of the blind shear ram were designed to cut through the drill pipe and seal the well. At the time of the Macondo blowout, rig personnel could not recapture control of the well by using the BOP because the blind shear ram did not cut the drill pipe and seal the well. In addition, the emergency-disconnect system failed to detach the Deepwater Horizon from the well (NAE-NRC Report, 2011)[9]

The primary barrier is the first stumbling block against undesirable flow from the source (Hauge *et al.*, 2011). In overbalanced processes, the mud column is the primary well barrier and should function within the drilling margin pressure. If the pressure exerted by the drilling mud in the wellbore becomes too great, it can cause a fracture in the exposed rock at any point in the wellbore. Drilling mud would then flow from the wellbore into the fracture and could no longer exert sufficient pressure to prevent an influx of reservoir fluids. Like pore pressure, the pressure at which a fracture occurs

[9] NAE/NRC (National Academy of Engineering/National Research Council). Macondo Well–*Deepwater Horizon* Blowout: Lessons for Improving Offshore Drilling Safety. Washington, D.C.: The National Academies Press. Available online at *http://www.wellintegrity.net/Documents/NAE-NRC%20Report%202011-12-14.pdf.*

usually increases with drilling depth, although actual pressures can be either higher or lower than anticipated (Bommer, 2008).

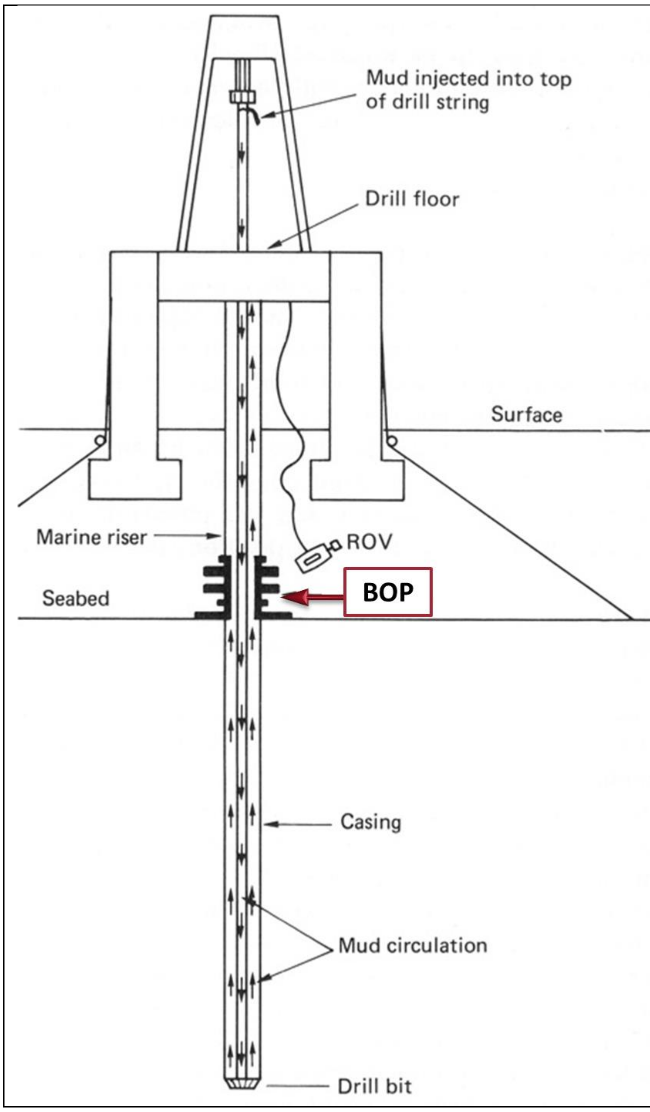


Figure 7.3 (a): An overview of the drilling system for the Deepwater Horizon; BOP was located on the seabed on the wellhead (Source: CSB-FINAL REPORT-MUX(06-02-2014)

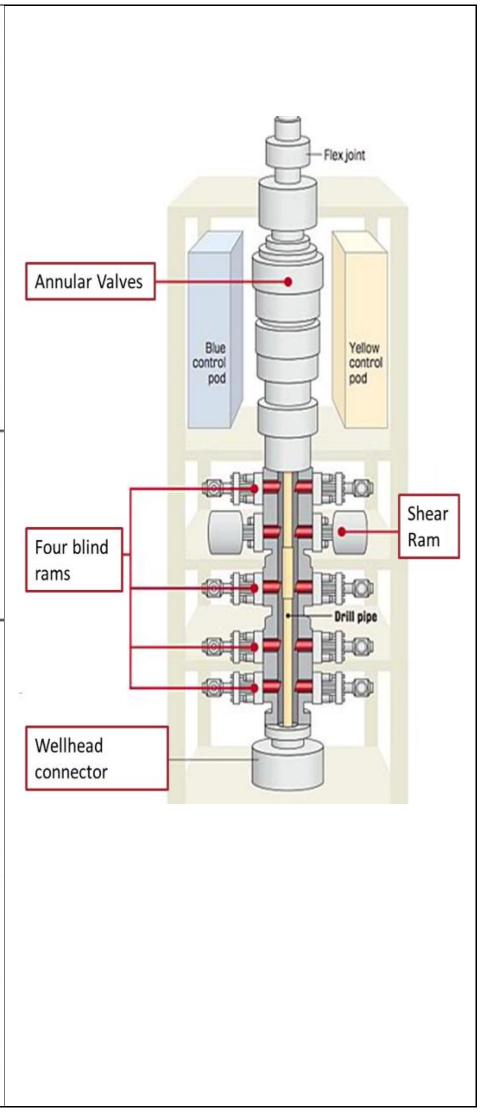


Figure 7.3 (b): Principle indication of BOP stake system with four blind rams and one shear ram

As illustrated in Figure 7.4, another aspect of the definition is whether such a wide-ranging definition undermines the concept. It is essential to distinguish among the barriers that may prevent or mitigate the event, in which the risk influencing factors prompt the barrier performance. In addition, it is vital to specify the barrier function in order to clarify at which level different barriers influence the event. A commonly used categorisation is to distinguish between physical and non-physical barriers (Johnson, 1980; ISO: 17776, 2000; DoE, 1997). As shown in Figure 7.4, the barriers may be physical or non-physical, or a combination thereof (PSA, 2002). Physical barriers are incorporated into the design of a structure or platform, technical barriers are initiated if a hazard is understood, while administrative barriers are integrated into administrative systems and procedures. Svenson (1991) classified barrier systems as physical, technical, or human factors-organisational systems, while Neogy et al. (1996) classified barriers as physical, procedural or administrative, or human action.

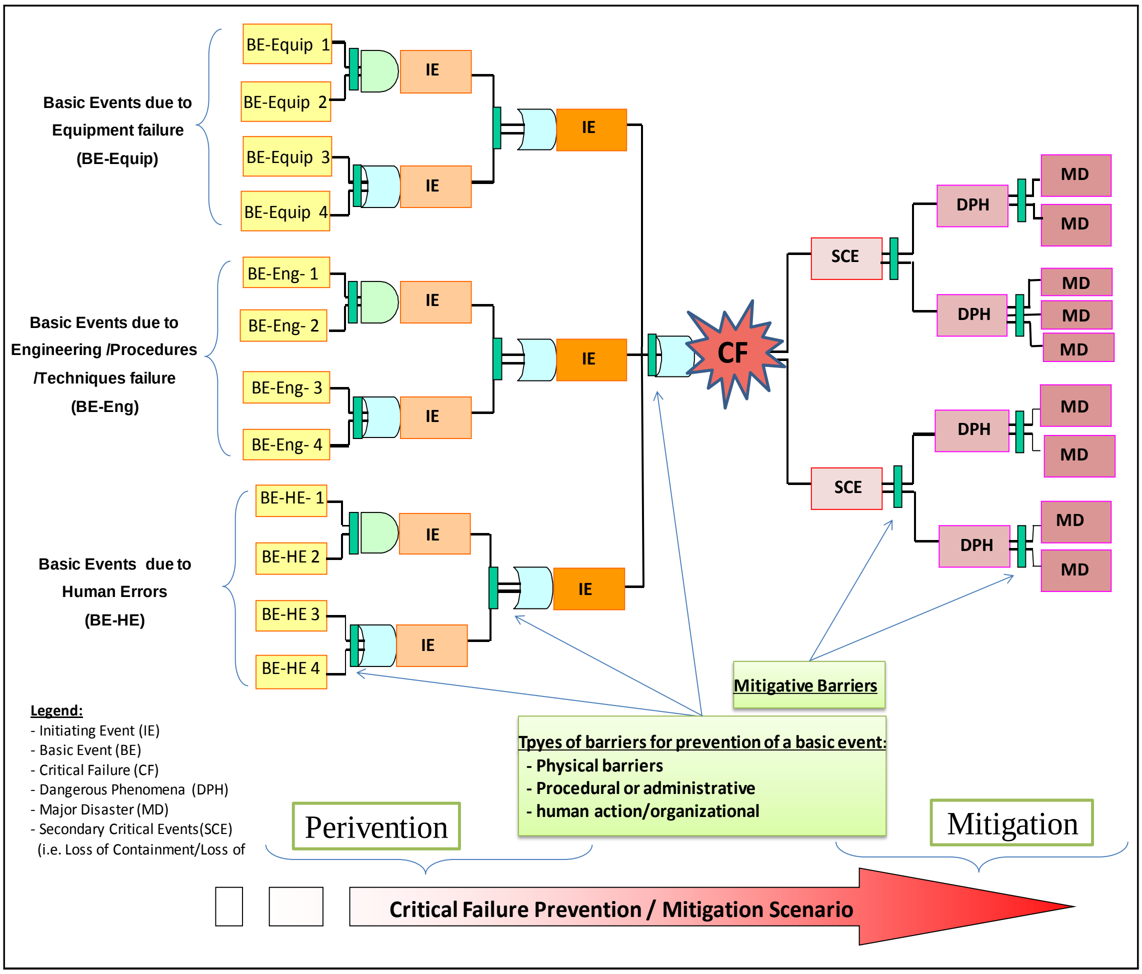


Figure 7.4: Barrier analyses of a combination of physical, procedural or administrative, or human action

Human/organisational barrier functions can be seen as planned into the process but in the end executed by humans with the support of an organised organisation controlling the refuelling work process. The DoE (1997) distinguishes between physical and management barriers. The management barriers may exist at three levels within the organisation, the activity level, the facility level, and the institutional level. Management barriers may be seen as a kind of organisational control.

The typical circumstances and the examples of possible failures in barrier functions and systems are just meant to provide a helpful start for the scenario development. By combining the scenarios with different failures and consequences, most operator assistances can be verified in all of the typical scenarios. In the case of an MODU's operation system, different failure scenarios can be defined and tested in all of the typical situations.

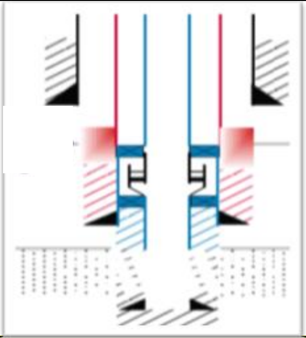
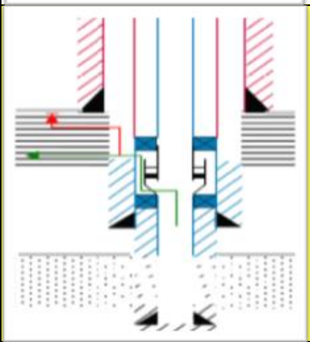
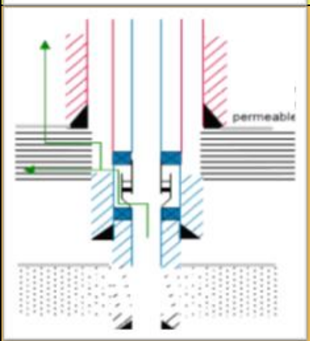
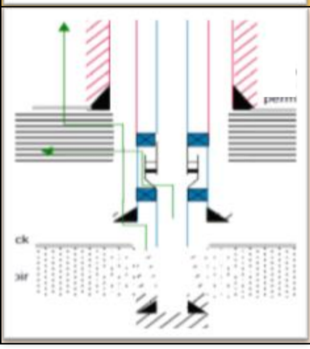
7.3.2 Main well barriers during drilling operations

During drilling operations it must be ensured that hydrocarbons do not migrate from the reservoir into the well. To maintain well control, barriers to prevent influx are therefore implemented. In addition to the static physical components of the well, such as casing and cement, two main barriers are implemented during drilling: the drilling mud column and the BOP. There are colour coding principles for the different categories of barrier failure, and colour designations for the different groups are presented in Table 7.1 and Table 7.2 shows an example of the principles for colour designation and the well barrier element (WBE) as well as the well condition (e.g. the principle of the colour red is for one barrier failure and the other is degraded/not verified, or a leak to the surface and its WBE and condition).

Table 7.1: The principles and colour designations for the different categories

Category	Principle
Red	One barrier failure and the other is degraded/not verified, or a leak to the surface
Orange	One barrier failure and the other is intact, or a single failure may lead to a leak to the surface
Yellow	One barrier degraded, the other is intact
Green	Healthy well – no or only a minor issue

Table 7.2: Principles for colour designation and well barrier element (WBE)

Category	An example sketch	Principle	WBE	Condition
Green		**Healthy well, no or minor issue**	DHSV or deep set plug	Leak rate within acceptance criteria
			Christmas tree ESD valves and annulus valves	Leak rate within acceptance criteria
			Tubing hanger and internal wellhead seals	Leak tight
			Completion and casing string	Leak tight
			Production packer	Leak tight
Yellow		**One barrier degraded, the other is intact**	DHSV or deep set plug	Leak rate within acceptance criteria
			Christmas tree ESD valves and annulus valves	Leak rate within acceptance criteria
			Tubing hanger and internal wellhead seals	Leak rate within acceptance criteria
			Completion and casing string	Leak rate within acceptance criteria
			Production packer	Leak rate within acceptance criteria
Orange		**One barrier failure and the other is intact, or a single failure may lead to leak to surface**	DHSV or deep set plug	Leak rate outside acceptance criteria
			Christmas tree ESD valves and annulus valves	Leak rate outside acceptance criteria
			Tubing hanger and internal wellhead seals	Leak rate outside acceptance criteria
			Completion and casing string	Leak rate outside acceptance criteria
			Production packer	Leak rate outside acceptance criteria
Red		**One barrier failure and the other is degraded/not verified, or leak to surface**	DHSV or deep set plug	Degraded/not verified, or leak to surface
			Christmas tree ESD valves and annulus valves	Degraded/not verified, or leak to surface
			Tubing hanger and internal wellhead seals	Degraded/not verified, or leak to surface
			Completion and casing string	Degraded/not verified, or leak to surface
			Production packer	Degraded/not verified, or leak to surface

7.3.3 MODU's operational hierarchy and proposed barriers

A four-level operational hierarchy of the MODU is used to identify the root causes of a failure. Different methods might be used to identify root causes of operational failure in a specific offshore operation system like an MODU. Because of the complexity of real offshore operations and in order to simplify the assessment processes, a manageable group of hazards and their root causes (i.e. BEs) for the MODU's operation system has been considered. The objective is to propose the best RCOs for offshore drilling failure due to its HGs. As illustrated in Figure 7.5, each HG may be broken down into a number of simpler system components in different levels. Operational hazard: L2D-O1 and Human error: L2D-H1 are the most serious HGs in the offshore operation, in which the system/subsystem and routes describe the MODU's operation system and failure of each system/subsystem may influence and have consequences for drilling failure (L1D-O1-01). Efficient measures to prevent and control the MODUs' operation system failure are important. This section proposes a few new barriers to prevent and control the MODUs' operation failure.

The Macondo blowout accident in the Gulf of Mexico is used and analysed as a case study to show how the proposed methodology can be used to understand the development of the events leading to the failure. The methodology can also be used to support the decision-maker to prevent future failure or to control the escalation of events. With reference to the results of Chapters 5 and 6, literature reviews assessing the Macondo blowout accident, and based on expert judgements for the occurrence probability of failures of each BE, the following barriers are introduced for the three critical BEs, in order to control the MODUs' operation failure and reduce the risk level.

i. Introducing a barrier in level 2 of the operational hierarchy, in order to control the Management/supervision/staff failure (L3D-H1-02).
ii. Introducing a barrier in level 5 of the operational hierarchy, in order to control the BOP stack failure (L5D-O1-01-4-1)
iii. Introducing a barrier in level 5 of the operational hierarchy, in order to control the BOP control system failure (L5D-O1-01-4-2).

The occurrence probability of the BE failures can be used as guidance for the MODUs' operators to become conscious of the vulnerabilities of the safety barrier system, and to analyse and assess the risk associated with the barriers. As mentioned earlier, the barriers can be proposed in different categories such as physical, technical, human/organisational, and regulatory. The Fuzzy TOPSIS technique is used to assess

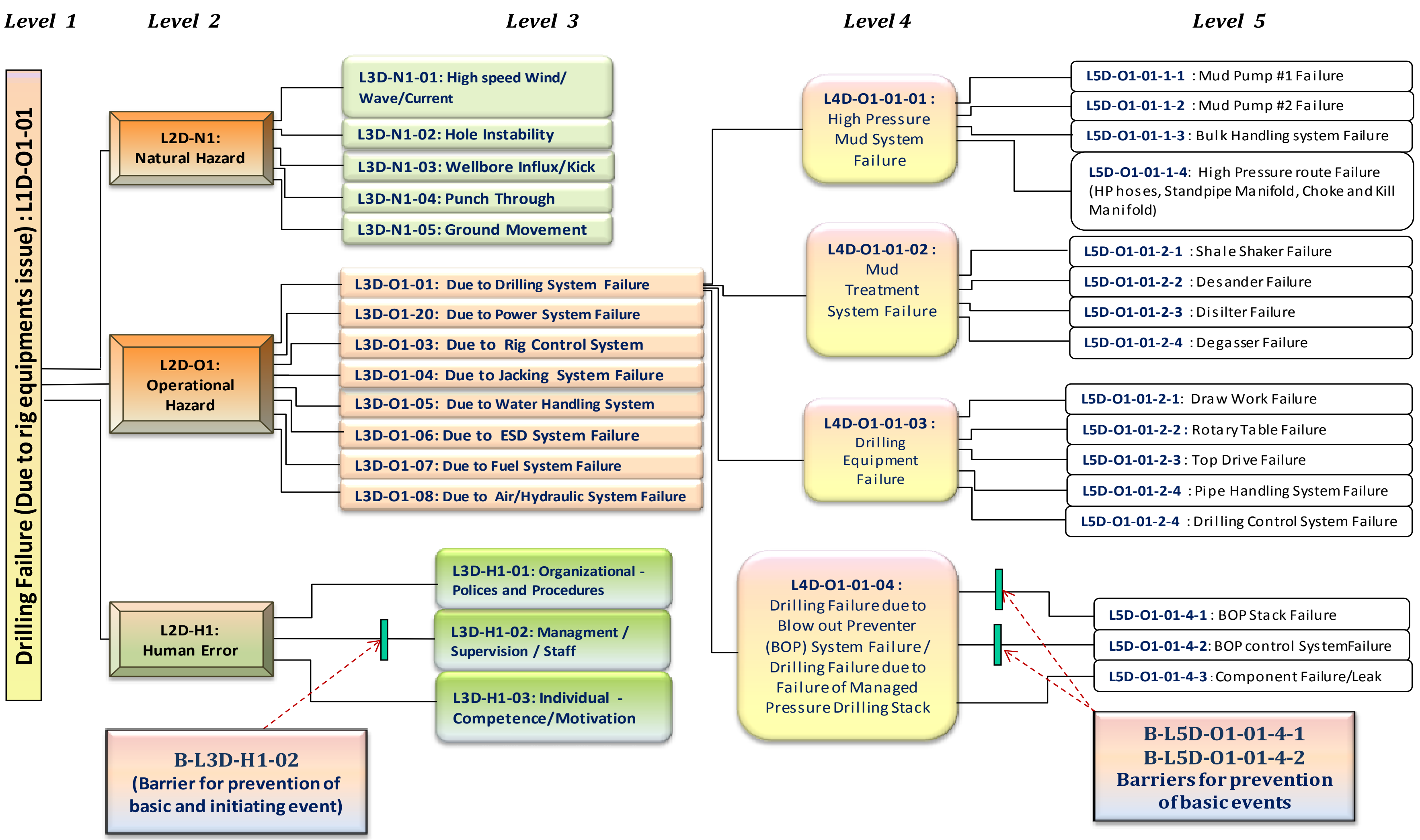


Figure 7.5: Hazard identification and MODU's operational hierarchy

the possible consequences and effects, and to propose the best risk control option. Recommendations for decision-making can be provided based on the level of cost-effectiveness for each risk control measure that is deemed appropriate and feasible on the risk-reduction scale of the ALARP principle framework.

7.3.4 Fuzzy MCDM basic concept

Decision-making with more than one criterion to be considered occurs frequently in our daily lives. Though these MCDM problems are diverse, they share some mutual characteristics (Hwang & Yoon, 1981a). There are two types of weighting approaches: objective and subjective methods (Shemshadi *et al.*, 2011; Wang & Lee, 2009). The techniques developed take into account both the subjective input from the experts and the objective factor resulting from the data that the companies/operators themselves collect (Kao & Hung, 2007). The weights of criteria are determined by the subjective opinion of the decision-makers as well as by the inherent objective properties of the criteria (Zeleny, 1982). The objective weighting approach explains the evaluation in data, but occasionally the weight factors of some indexes disagree slightly on actual significance of these criteria if there are few criteria or data, and moreover it is more difficult to clarify intuitively than the subjective weighting method (Wang *et al.*, 2003). As mentioned in a previous section, the subjective weights are determined entirely according to the preference or judgements of decision-makers. To determine the overall assessment of each decision-maker, a few mathematical techniques can be applied such as: the eigenvector method (Saaty, 1977), the weighted least square method (Chu *et al.*, 1979), and the Delphi method (Hwang & Lin, 1987). Even so, the subjective weighting methods cast serious concerns on the reliability of the outcomes (Triantaphyllou & Sanchez, 1997).

7.3.5 Fuzzy TOPSIS techniques for order preference of the alternatives

Among many well-known MADM methods, TOPSIS is a practical and useful technique for ranking and selection of a number of possible alternatives through measuring Euclidean distances. It has many advantages such as intuitive analytical principle, simple calculation and small sample required and, in practice, TOPSIS has been effectively applied in assessment, selection and evaluation of problems with a limited number of alternatives (Yong, 2006; Teodorović, 1985). Hwang & Yoon (1981a) developed the TOPSIS method based upon the concept that a chosen alternative should have the shortest distance from the PIS (i.e. the solution that maximises the benefit criteria and minimises the cost criteria), and the farthest distance from the NIS (i.e. the solution that maximises the cost criteria and minimises the benefit criteria). This technique ranks alternatives according to their distances from the positive and the negative ideal solutions. The positive ideal solution is identified with a hypothetical alternative that has the best values for all considered criteria, whereas the negative ideal solution is recognised with a hypothetical alternative that has the worst criteria values.

Moreover, TOPSIS is based on a solid logical basis that reflects the rationale of human choice (Sinha and Meller, 2007). A methodology for defining the aggregating function based on a Fuzzy set representation of the distance to the PIS and NIS is proposed. The methodology proposes the aggregating function to be demonstrated as the membership function of the intersection of two Fuzzy sets, the Fuzzy set of the alternative that has the shortest distance from the ideal solution and the Fuzzy set of the alternative that has the farthest distance from the negative ideal solution. Therefore, it provides the mathematical foundation for demonstrating the idea of closeness to the PIS and the NIS and allows a proper explanation of the relationship between the closeness of the PIS and the NIS. It has been demonstrated to be one of the best approaches in addressing the issue of rank problem (Zanakis *et al.*, 1998). However, for the selection of risk control option which is often not crisply defined due to absence of data (Zimmermann, 1986), many scientists have recommended Fuzzy extensions of the TOPSIS method in order to reduce the vagueness that is essential in the corresponding assessment problems (Yong, 2006, Chen, 2001).

As illustrated in Figure 7.6, usually the MCDM problems are considered by *n* attribute (or criteria); however, here the criteria are reduced from *n* dimension problems to two dimensions in order to comprehend the operation of this method. As illustrated in Figure 7.6, a two-dimensional criterion (X_1, X_2) is considered as an example to show the evaluation process for an MCDM problem. As shown in Figure 7.6, alternative A_1 has shorter distances both to the ideal solution A^* and to the negative ideal solution A^- than the other alternative, A_2. Then it is very difficult to justify the selection of A_1. TOPSIS takes an alternative, called the compromise solution, which has the weighted minimum Euclidean distance to the ideal solution in a geometric sense and also has the maximum Euclidean distance to the negative ideal solution. Sometimes the chosen alternative, which has the weighted minimum Euclidean distance to the ideal solution, has the shorter distance to the negative ideal solution than the other alternative(s). Two criteria (X_1, X_2) are considered in order to show the evaluation process of the best performance value, in which, the ideal solution is composed of the best performance value on both criteria, and the negative ideal solution is composed of the worst performance values on both criteria. As illustrated in Figure 7.6, alternative A_1 has shorter distances both to the ideal solution A^* and to the negative ideal solution A^- than the other alternative, A_2. Then it is very difficult to justify the selection of A_1.

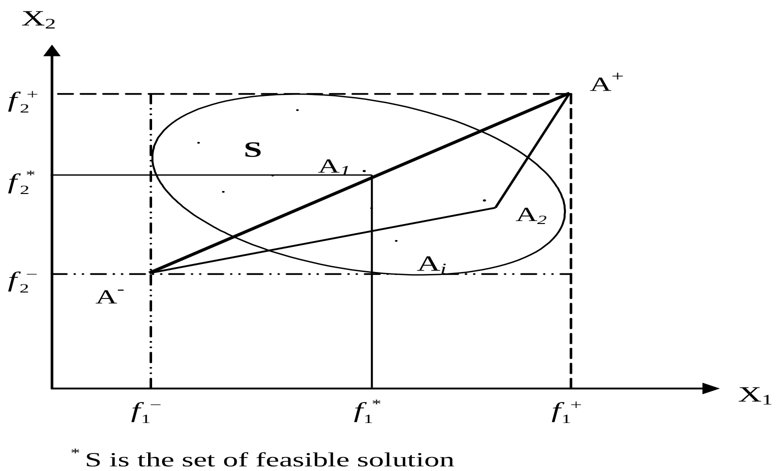


Figure 7.6: TOPSIS to find the compromise solution for a two-dimensional case (Marković, 2010)

7.3.6 Construction of decision matrix and Fuzzy TOPSIS algorithm

The decision matrix in a MADM method with the Fuzzy TOPSIS algorithm comprises different steps; the following steps can express the basic information involved in a MADM model:

a) Construct a decision matrix
b) Determination of the weight
c) Normalisation
d) Calculation of relative significance rate and data collection

- Estimating weights of experts

e) Aggregation
  - Calculation of the degree of similarity
  - Calculation of the AA
  - Calculation of the RA degree
  - Estimation of the consensus coefficient degree
  - Result of aggregation of the experts' judgements

f) Defuzzifying
g) Evaluation, Ranking the alternatives and selection
h) Weights for each normalised criterion
i) The positive ideal and negative ideal solutions
j) Calculate the distance from the positive ideal solution and the negative ideal solution for each alternative
k) Calculation of the CC

7.3.6.1 Construct a decision matrix

Assume there m alternatives $A_i(i=1,2,...,m)$ which decision-makers indicate to be evaluated against n selection criteria $C_j(j=1,2,...,n)$, in which each alternative performance is measured. Assume the aggregation rate of alternative $A_i(i=1,2,...,m)$ for criteria $C_j(j=1,2,...,n)$ is y_{ij} therefore the matrix can be described by Equation (7.1). Subjective assessments are to be made by the decision-maker to conclude the following:

i. The weighting vector $W=(w_1,w_2,...,w_j,...w_n)$

   By using the linguistic terms as presented in Table 4.3 (Chen and Hwang, 1992), the weighting vector W signifies the relative importance of n selection criteria $C_j(j=1,2,...,n)$ for the problem.

ii. The decision matrix $Y=(y_{ij},i=1,2,...,m;j=1,2,..,n)$

The matrix represents the utility ratings of alternative A_i with respect to selection criteria C_j. Given the weighting vector W and decision matrix Y, the objective of the problem is to rank all the alternatives by giving each of them an overall value with respect to all selection criteria. The decision matrix can be expressed as follows.

$$Y = (y_{ij})_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{7.1}$$

$$W = (w_1, w_2, \ldots, w_j, \ldots w_n)$$

7.3.6.2 Determination of the weight

The alternatives in a MADM method are frequently described by qualitative selection criteria. When no selection criteria data exist, the preferred approach is to assign numerical values to qualitative data scaling (i.e. linguistic terms). The weights of various attributes and the ratings of each alternative with respect to each criterion are considered as linguistic variables. A Fuzzy set approach is a sustainable method for dealing with this problem. An expert's opinion can be in the form of linguistic terms such as low, medium or high. The experts express their estimations for each alternative with respect to each criterion. This can be done by asking experts for their opinions for each alternative by considering a subjective criterion. These linguistic variables are expressed in Table 4.3 (Chen and Hwang, 1992). The concept of linguistic variables is very useful in dealing with situations which are too complex or too hard to be defined or to be reasonably described by a conventional quantitative expression (Zadeh, 1965).

7.3.6.3 Normalisation

It is necessary to normalise the decision matrix in order to make each criterion value limited between 0 and 1, so that each criterion is comparable. Criteria ratings are usually normalised to eliminate computational problems caused by different measurement units in a decision matrix. The normalisation procedure attempts to obtain comparable scales, allowing attribute comparisons. The initial data with respect to each criterion will be normalised by dividing the sum of criterion values. For Fuzzy data denoted by trapezoidal/triangular Fuzzy number as $(a_{ij}, b_{ij}, c_{ij}, d_{ij})$, the normalised values for benefit-related criteria and cost-related criteria are calculated as follows.

Linear normalisation: this procedure divides the ratings of a certain criterion by its maximum value. The normalised value of Yij can be obtained by Equation (7.6).

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_{ij}^{+}}, \frac{b_{ij}}{c_{ij}^{+}}, \frac{c_{ij}}{c_{ij}^{+}}, \frac{d_{ij}}{d_{ij}^{+}} \right), j \in B \qquad (7.2)$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_{ij}^{-}}, \frac{b_{ij}}{c_{ij}^{-}}, \frac{c_{ij}}{c_{ij}^{-}}, \frac{d_{ij}}{c_{ij}^{-}} \right), j \in C \qquad (7.3)$$

$$c_j^{+} = \max_i c_{ij} \quad if \quad j \in B \qquad\qquad c_j^{-} = \min_i c_{ij} \quad if \quad j \in C \qquad (7.4)$$

$$r_{ij} = Y_{ij} / Y_{ij}^{*} \quad , \quad , \quad i=1,\dots,m; \; j=1,\dots,n \qquad (7.5)$$

where Y_{ij}^{*} is the maximum value of Y_{ij} and the values of r_{ij} vary between 0 and 1. $(0 \le r_{ij} \le 1)$.

Vector normalisation: this method divides the ratings of each attribute by its norm, so that each normalised rating of Y_{ij} can be obtained by Equation (7.6).

$$r_{ij} = Y_{ij} \Big/ \sqrt{\sum_{i=1}^{m} Y_{ij}^{2}} \quad , \quad i=1,\dots,m; \; j=1,\dots,n \qquad (7.6)$$

The normalised decision matrix can be expressed by Equation (7.7).

$$D = (r_{ij})_{m \times n} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \end{array} \qquad (7.7)$$

7.3.6.4 Calculation of relative significance rate and data collection

Consider $m$experts in a decision-making process. Each element in a Fuzzy pair-wise comparison can be calculated as follows:

$$\tilde{a}_{ij} = (\frac{1}{m}) \otimes (e^{1}_{i,j} \oplus e^{2}_{i,j} \oplus e^{3}_{i,j} \oplus ... e^{l}_{i,j} \oplus ... \oplus e^{m}_{i,j}) \tag{7.8}$$

$$\tilde{a}_{ji} = \frac{1}{\tilde{a}_{ij}} \tag{7.9}$$

Where $\tilde{a}_{i,j}$ is the relative importance by comparing attribute i with attribute j by m experts, and $e^{l}_{i,j}$ is the lth expert's judgements on the comparison of attribute i with attribute j in a Fuzzy number format. The typical trapezoidal Fuzzy number $(\tilde{a}^{l}_{i,1}, \tilde{a}^{m}_{i,1}, \tilde{a}^{u}_{i,1})$ denotes the lower bound (l) , median (m) and upper bound (u) values of $\tilde{a}_{i,1}$. Equation (7.10) presents a $n \times n$ Fuzzy pair-wise comparison matrix where $\tilde{A}$ can be obtained as follows:

$$\tilde{A} = \begin{pmatrix} \tilde{a}_{1,1} & \tilde{a}_{1,2} & \cdots & \tilde{a}_{1,n} \\ \tilde{a}_{2,1} & \tilde{a}_{2,2} & \cdots & \tilde{a}_{2,n} \\ \vdots & \vdots & \tilde{a}_{i,j} & \vdots \\ \tilde{a}_{n,1} & \tilde{a}_{n,2} & \cdots & \tilde{a}_{n,n} \end{pmatrix} \tag{7.10}$$

Weight factors can be estimated by using the geometric mean technique (Saaty, 1990; Tang *et al.*, 2000; Mikhailov, 2004) and can be calculated by Equation (7.12).

$$\tilde{f}_i = \left(\tilde{a}_{i,1} \otimes \tilde{a}_{i,2} \otimes \cdots \tilde{a}_{i,j} \cdots \otimes \tilde{a}_{i,n}\right)^{\frac{1}{n}} \tag{7.11}$$

$$= \left(\left(\tilde{a}^{l}_{i,1} \times \tilde{a}^{l}_{i,2} \times \cdots \times \tilde{a}^{l}_{i,n}\right)^{\frac{1}{n}}, \left(\tilde{a}^{m}_{i,1} \times \tilde{a}^{m}_{i,2} \times \ldots \times \tilde{a}^{m}_{i,n}\right)^{\frac{1}{n}}, \left(\tilde{a}^{u}_{i,1} \times \tilde{a}^{u}_{i,2} \times \cdots \times \tilde{a}^{u}_{i,n}\right)^{\frac{1}{n}} \right)$$

$$\tilde{w}_i = \frac{\tilde{f}_i}{\tilde{f}_1 \oplus \tilde{f}_2 \oplus \cdots \tilde{f}_i \cdots \oplus \tilde{f}_n} = (\sigma, \beta, \delta) \tag{7.12}$$

In Equation (7.12), $\tilde{w}_i$ is the Fuzzy weight factor of the ith criteria and $\tilde{f}_i$ is the geometric mean of the th row in the Fuzzy pair-wise comparison matrix and. As the outputs of the geometric mean method are triangular Fuzzy weight factors, defuzzification is applied in order to convert triangular Fuzzy weight factors into the corresponding crisp weight factors. A defuzzification approach used in Fuzzy-AHP is expressed by Equation (7.13) (Mikhailov, 2004):

$$DF\tilde{w}_i = \frac{1}{3}(\sigma + \beta + \delta) \tag{7.13}$$

where $DF\tilde{w}_i$ is the defuzzified mean value of a Fuzzy weight factor. The normalised weight of attribute *i* (w_i) can then be calculated by using Equation (7.14).

$$w_i = \frac{DF\tilde{w}_i}{\sum_{i=1}^{n} DF\tilde{w}_i} \tag{7.14}$$

- Estimating weights of experts

The weighting of experts is determined according to Table 4.5. Experts' weights are obtained by estimating weight scores and weight factors of experts. Weight scores and weight factors of experts can be obtained by using Equation (4.29) and Equation (4.30) respectively and weight of each expert is presented in Table 4.6.

7.3.6.5 Algorithm for aggregation

Based on the experts' experience and expertise in the relevant field, each expert may have a different opinion. It is necessary to aggregate the experts' opinions to reach a consensus. Presume the experts E_k $(k = 1,2,\ldots,M)$ express their opinions on a specific criterion against a particular situation by a predefined set of linguistic variables. The linguistic terms can be converted into corresponding Fuzzy numbers. Hsu and Chen (1994) presented an algorithm to aggregate the linguistic opinions of a homogeneous/heterogeneous group of experts and the detailed algorithm is explained in the following steps:

- Calculation of the degree of similarity

Where for the calculation of degree of similarity $S_{uv}\left(\tilde{R}_u, \tilde{R}_v\right)$ of the opinions $\tilde{R}_u$ and $\tilde{R}_V$ of a pair of experts, E_u and E_v, and $S_{uv}\left(\tilde{R}_u, \tilde{R}_v\right) \in [0,1]$. According to this method, $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$ are two standard TPFNs. Then the degree of similarity between these two Fuzzy numbers, i.e. $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$, can be obtained by the similarity function of S, which is defined as:

$$S\left(\tilde{A}, \tilde{B}\right) = 1 - \frac{1}{4}\sum_{i=1}^{4}\left|a_i - b_i\right| \tag{7.15}$$

where $S\left(\tilde{A}, \tilde{B}\right) \in [0,1]$. The larger the value of $S\left(\tilde{A}, \tilde{B}\right)$, the greater the similarity between two Fuzzy numbers of $\tilde{A}$ and $\tilde{B}$.

- Calculation of the AA

Calculate the AA degree $AA(E_u)$ of the experts.

$$AA(E_u) = \frac{1}{M-1}\sum_{\substack{u \neq v \\ v=1}}^{M} S(\tilde{R}_u, \tilde{R}_v) \tag{7.16}$$

- Calculation of the Relative Agreement (RA) degree

Calculate the RA degree, $RA(E_u)$ of the experts.

$$E_u\,(u = 1,2,\ldots,M) \quad \text{as} \quad RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)} \tag{7.17}$$

- Estimation of the Consensus Coefficient (CC) degree

Estimate the CC degree, $CC(E_u)$, of expert $E_u(u=1,2,\ldots,M)$:

$$CC(E_u)=\beta\cdot w(E_u)+(1-\beta)\cdot RA(E_u) \tag{7.18}$$

where β $(0\le\beta\le1)$ is a relaxation factor of the proposed method. It shows the importance $w(E_u)$ over $RA(E_u)$. When $\beta=0$, no importance has been given to the weight of an expert and hence a homogeneous group of experts is used. When $\beta=1$, the consensus degree of an expert is the same as its importance weight. The consensus degree coefficient of each expert is a good measure for evaluating the relative worthiness of each expert's opinion. It is the responsibility of the decision-maker to assign an appropriate value to β.

- Result of aggregation of the experts' judgements

Lastly, the aggregated result of the experts' judgements, $\tilde{R}_{AG}$, can be obtained as follows:

$$\tilde{R}_{AG}=CC(E_1)\times\tilde{R}_1+CC(E_2)\times\tilde{R}_2+\cdots+CC(E_M)\times\tilde{R}_M \tag{7.19}$$

7.3.6.6 Defuzzifying

After carrying out the aggregation of different experts' opinions of each alternative under each subjective criteria, these opinions have been aggregated for each alternative under each subjective criterion up to this stage. Therefore, all the aggregated Fuzzy numbers must be defuzzified in order to rank the alternatives of the problem. As a result, all the components of the decision matrix are crisp numbers and any classical method can be used at the selection stage. Each subjective element of matrix $\tilde{x}_{ij}=(a_{ij},b_{ij},c_{ij},d_{ij})$ can be converted to its corresponding crisp value by using Equation (5.10) and (5.11).

7.3.6.7 Evaluation, ranking and selection of the alternatives

- Weights for each normalised criterion

Calculate the overall performance evaluation for each alternative and construct weighted normalised by multiplying the aggregate weights for each normalised criterion, which can be obtained by Equation (7.21).

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times k}, \quad i = 1,2,\cdots,m \quad j = 1,2,\cdots,n \tag{7.20}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_{ij} \tag{7.21}$$

- The positive ideal and negative ideal solutions

Define the positive ideal A^+ and negative ideal A^- solutions, which can be determined in terms of the weighted normalised values by Equations (7.22) and (7.23), where J_1 and J_2 are the set of the benefit and cost attributes respectively.

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \cdots, \tilde{v}_k^+\right), \qquad v_i^+ = \{\max v_{ji}, i \in J_1; \min v_{ji}, i \in J_2\}, \tag{7.22}$$

$$A^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \cdots, \tilde{v}_k^+\right), \qquad v_i^- = \{\min v_{ji}, i \in J_1; \max v_{ji}, i \in J_2\}, \tag{7.23}$$

- Calculate the distance from the positive ideal solution and the negative ideal solution for each alternative

The distance between two Fuzzy numbers $A_1 = (a_1, b_1, c_1, d_1)$ and $A_2 = (a_2, b_2, c_2, d_2)$, and also the distance of each alternative from positive ideal solution d_i^+ and negative ideal solution d_i^-, can be calculated by Equations (7.24) and (7.26) respectively (Bojadziev & Bojadziev, 1995).

$$d(A_1, A_2) = \sqrt{\frac{1}{3}\left[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2 + (d_1 - d_2)^2\right]} \tag{7.24}$$

$$d_i^+ = \sum_{j=1}^{k} d\left(\tilde{v}_{ij}, \tilde{v}_j^+\right),\ i=1,2,\cdots,m \quad \text{where} \quad d_i^+ = \sqrt{\sum_{j=1}^{k} d\left(\tilde{v}_{ij} - \tilde{v}_j^+\right)^2} \tag{7.25}$$

$$d_i^- = \sum_{j=1}^{k} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right),\ i=1,2,\cdots,m \quad \text{where} \quad d_i^- = \sqrt{\sum_{j=1}^{k} d\left(\tilde{v}_{ij} - \tilde{v}_j^-\right)^2} \tag{7.26}$$

- Relative closeness coefficient (RCC)

Calculate the RCC to the ideal solution and rank each RCC of each alternative in descending order. This allows the decision-makers to choose the most rational alternative. The alternative with the highest RCC value will be the best choice and RCC can be calculated by Equation (7.27).

$$RCC_i = \frac{d_i^-}{d_i^+ + d_i^-},\quad i=1,2,\cdots,m \tag{7.27}$$

Since $d_i^+ \geq 0$ and $d_i^- \geq 0$, then $RCC_i \in [0,1]$, and if the alternative reaches A^+, then $d_i^+ = 0$ and RCC_{i} = 1 and if the alternative reaches A^-, then $d_i^- = 0$ and RCC_{i} = 0. It means when the alternative goes towards A^+ or farther from A^-, then RCC_{i} goes towards "1". In addition, if the alternative goes towards A^- or farther from A^+, then RCC_{i} goes towards "0". However, it should be noted that the notion of RCC may lead to inconsistency (Li, 2007). Given two alternatives, *i* and *k*, then alternative *i* is better than k if:

$$RCC_i > RCC_k \quad \text{or} \quad \frac{d_i^-}{d_i^+ + d_i^-} > \frac{d_k^-}{d_k^+ + d_k^-} \tag{7.28}$$

Equation (7.28) holds if one of the following three conditions (i.e. a, b and c) is satisfied:

$$d_i^+ < d_k^+ \quad \text{and} \quad d_i^- > d_k^- \tag{7.29}$$

a) This condition relates to the basic principle of the TOPSIS method that the chosen alternative (i.e. alternative *i*) is better than alternative *k* as it should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution.

$$d_i^+ > d_k^+ \quad \text{and} \quad d_i^- > d_k^- \quad \text{but} \quad d_i^+ < \frac{d_k^+ \times d_i^-}{d_k^-} \tag{7.30}$$

b) Allows alternative *i* to be better than alternative *k* even though alternative *i* is farther from the positive ideal solution than alternative *k*.

$$d_i^+ < d_k^+ \quad \text{and} \quad d_i^- < d_k^- \quad \text{but} \quad d_i^- > \frac{d_k^- \times d_i^+}{d_k^+} \tag{7.31}$$

c) Allows alternative *i* to be superior to alternative *k* even though alternative *i* is closer to the negative ideal solution than alternative *k*.

The normalisation procedure attempts to obtain comparable scales, allowing attribute comparisons. The initial data with respect to each criterion will be normalised by dividing the sum of criterion values. For Fuzzy data denoted by trapezoidal/triangular Fuzzy number as $\left(a_{ij}, b_{ij}, c_{ij}, d_{ij}\right)$, the normalised values for benefit-related criteria and cost-related criteria are calculated as follows.

As stated, TOPSIS ranks the alternatives according to their distances from ideal and negative ideal solutions; in the earlier section, it is presented that this statement is vague in the sense that it does not provide an accurate definition of the relative closeness to the negative and ideal solutions.

In order to overcome this difficulty, a model is proposed to solve the issue. In this circumstance, the model suggested by Zimmermann and Zysno (1985) is used to determine the membership of the alternative that has the shortest distance from the ideal solution and that of the alternative that has the farthest distance from the negative ideal solution. With reference to this model, the membership of the previous set is defined as a function of the distance d_i^+ between a given alternative *i* and the ideal solution, and it is represented by Equation (7.32) and d_i^+ is measured by the Euclidean distance.

$$\mu^{+} = \frac{1}{1+d_i^{+}} \tag{7.32}$$

The membership of the alternative from the negative ideal solution can also be defined as a simple extension of the Zimmermann and Zysno (1985) model. Distance d_i^{-} between the given alternative *i* and the negative ideal solution is given in Equation (7.33):

$$\mu^{-} = 1 - \frac{1}{1+d_i^{-}} = \frac{d_i^{-}}{1+d_i^{-}} \tag{7.33}$$

Yager (1980) proposed a class of intersection connectives as follows. Assume that A and B are subsets of Y with membership values of μ^{A} and μ^{B} respectively. A general class of intersections is defined as follows:

$$A \cap B = C \text{ where } \mu^{c} = 1 - \min[1, (1-\mu^{A})^{P} + (1-\mu^{B})^{P}]^{\frac{1}{P}}, \; P \geq 1. \tag{7.34}$$

The following properties can be concluded from this definition:

i. In Zadeh connective, if $P \rightarrow \infty$, then $\mu^{C} = \min(\mu^{A}, \mu^{B})$

ii. In Lukasiewicz connective, if $P = 1$, then $\mu^{C} = \max[0, (\mu^{A} + \mu^{B} - 1)]$

The parameter P is inversely related to the strength of the "and" operation. P is an inverse measure of how strong the operation is meant. It must be noted that $\mu^{+} \cap \mu^{-}$ is a monotonically decreasing function of P. Thus, as P decreases, the strength of the "and" operation increases (Yager, 1980). According to the intersection connectives suggested by Yager (1980), RCC can be achieved by Equation (7.35).

$$RCC = \mu^{+\cap-} = 1 - \min[1, (1-\mu^{+})^{P} + (1-\mu^{-})^{P}]^{1/P}, P \geq 1 \tag{7.35}$$

where μ^{+} and μ^{-} are defined by Equations (7.32) and (7.33) respectively. Different values of P are associated with different behaviour patterns of decision-makers' uncertainty. In particular, higher values of P correspond to circumstances where decision-makers increasingly take into account the worst characterisation of an alternative, whereas lower values of P correspond to situations where decision-makers consider closeness to the best characterisation of an alternative with increasing strength. As an example, assume the case of two alternatives, *i* and *j*, with membership of $C_i = (0.3, 0.6)$ and $C_j = (0.2, 0.9)$ respectively. Then the ratings that would be produced for different values of parameter *P*, as presented in Table 7.3.

As illustrated in Table 7.3, if $P = \infty$ a decision-maker would rank alternative C_i higher whereas if $P = 1$ a decision-maker would rank alternative C_j higher. Consequently, the proposed class of methods includes an extreme occurrence $(P = \infty)$ corresponding to circumstances where decision-makers take into account only the worst characterisation of an alternative; that means decision-makers have preference alternatives that create as much profit as credible.

Table 7.3: Different values of *P* for illustration of ranking of two alternatives

P	$C_i = (0.3, 0.6)$	$C_j = (0.2, 0.9)$
1	0.000 (2)	0.100 (1)
2	0.194 (1)	0.194 (1)
∞	0.300 (1)	0.200 (2)

7.4 Case study and implementation of the proposed methodology

In this section, a case study is provided to demonstrate how the proposed methodology can be applied to select the best risk control option for an MODU's operation system. As understood, the BOP, which is installed at the seafloor and connected to the marine riser, is the last line of protection against a blowout. The BOP is essentially a system of valves designed to be closed in the event of anomalous wellbore pressure (such pressure is sometimes referred to as a kick). At the depth and pressures encountered by the Deepwater Horizon well, regulations require at least four such valves, or rams, which must be remote controlled and hydraulically operated during offshore operations.

During the Deepwater Horizon blowout, all of the rams on the BOP failed to close properly. In this circumstance, a report was prepared in response to a demand from the Secretary of the Interior by the National Academy of Engineering (NAE) and National Research Council (NRC) and was released in December 2011with the title of: Macondo Well Deepwater Horizon Blowout, Lessons for Improving Offshore Drilling Safety. On the basis of this investigation, the working group/committee perceived that a number of imperfect decisions had led to the blowout and explosions, indicating a lack of effective safety management among the companies involved in the tragedy. Some of the main technical causes of the Deepwater Horizon accident are as follows:

- Well integrity was not established or failed
  - Annulus cement barrier did not isolate hydrocarbons
  - Shoe track barriers did not isolate hydrocarbons
- Hydrocarbons entered the well undetected and well control was lost
  - Negative pressure test was accepted although well integrity had not been established
  - Influx was not recognised until hydrocarbons were in riser
  - Well control response actions failed to regain control of well
- Hydrocarbons ignited on the Deepwater Horizon
  - Diversion to mud gas separator resulted in gas venting onto rig
  - Fire and gas system did not prevent hydrocarbon ignition
- Blowout preventer did not seal the well
  - Blowout preventer emergency mode did not seal well

It is evaluated that approximately five million barrels of hydrocarbons were released into the sea due to the well blowout and consequent explosions and fire on the Deepwater Horizon drilling rig on April 20, 2010, which led to the deaths of 11 workers and 16 serious injuries (Liu *et al.*, 2011). It was felt that a concerted effort by all participants would be necessary to overcome the reputational damage caused by this event. All members in the industry and regulatory communities have an obligation: i) to ensure that such considerations reflect a factual assessment of the risks, and ii) to do all that they can to minimise those risks through technology development, personnel training, and management systems. Neither objective is likely to be achieved if the risks and the responsibility for addressing them are not recognised and accepted. Envisioning failure is key to the safe development and operation of systems, particularly systems that incorporate the complexity of deep water well. Risks must be recognised, quantified, and mitigated. Designers, developers, operators, and regulators must know and understand that the risks are real and conduct themselves accordingly (NAE/NRC, 2011).

Neither industry nor US regulators appear to have foreseen the risks of a Macondo-scale event. The lack of adequate, previously planned capping and containment techniques evidences a failure to foresee an incident of the type or magnitude experienced at Macondo. Nowadays, industry and regulators are both stating their good intentions. Industry is investing significant resources in capping and containment systems, and regulators are making significant organisational and process changes. The question remains as to whether these efforts are a start towards recognition, acceptance, and active management of the risks inherent in offshore operation industry development or whether they represent a transitory response.

7.4.1 Recommendations for controlling and decreasing the risk level of the MODU

The committee developed recommendations for industry and regulators, identifying measures that would decrease the likelihood and mitigate the effects of future blowouts. The following paragraphs summarise some of the committee's major recommendations[10].

- Because operating companies are the only ones that can oversee all aspects of well integrity, they should have ultimate responsibility and accountability for well design and well construction, as well as for assessing the suitability of the drilling rig and safety equipment.
- The companies that share an offshore drilling lease should ensure that the operating company conducts activities in a way that keeps risk as low as is reasonably practicable.

[10] Macondo Well Deepwater Horizon Blowout, Lessons for Improving Offshore Drilling Safety. National Academy of Engineering (NAE) and National Research Council (NRC) December 2011.

- As drilling operations are carried out and wells are made ready for temporary abandonment, there are safety-critical points (e.g. determining the integrity of cemented barriers placed in the well) at which poor decisions are likely to increase hazards.
- Guidelines should be established for incorporating adequate margins of safety into the operating company's approach to well design.
- To improve regulatory effectiveness, the regulatory programme should be expanded to a goal-oriented risk management system that incorporates explicit regulatory review and approval of the safety-critical points in the drilling operation. As offshore drilling operations proceed into deeper waters, the Bureau of safety and environmental enforcement (BSEE) and other regulators should identify the safety-critical points that warrant explicit regulatory review and approval before operations can proceed.
- BOP systems should be redesigned, rigorously tested, and maintained to operate reliably under all foreseeable conditions in which they may be deployed.
- Proper training in the use of these systems in the event of an emergency is also essential.
- Instrumentation and expert system-decision aids should be integrated into the offshore drilling unit to provide personnel with timely warnings of a loss of well control.
- Industry and regulators should significantly increase the formal education and training in implementing safety systems provided to offshore drilling personnel.
- Industry should also increase its research and development on improving the safety of offshore drilling (well design, equipment, human operational failures, and management approaches).

7.4.2 Implementation of recommendations and evaluation for the best RCOs

A well barrier can be viewed as a protection layer whose objective is to prevent flow from the reservoir. A well barrier will, however, be a combination of passive and active protection layers. As mentioned earlier, three barriers are introduced in different levels for the three critical BEs (i.e. L3D-H1-02, L5D-O1-01-4-1 and L5D-O1-01-4-2), as shown in Figure 7.5. Different RCOs and barriers with different purposes could be recommended to improve the safety level of the MODU in the drilling and operational phase. With reference to the committee findings, which are presented in the second column of Table 7.4, three different barriers in the course of the assessment phase are considered in order to prevent the MODU operation drilling failure. The barrier must be intact to prevent the occurrence of an event. With consideration of NAE/NRC's (2011) findings and recommendations, as illustrated in Table 7.4, three different RCOs (i.e. Engineering, Equipment redesign/replace and Regulatory/Human error) for the MODU system are considered. They are named Eng-RCO, Equip-RCO and Regul-RCO, and are presented in the last three columns of Table 7.4. Their purpose is to prevent well leakage and blowout during the operational phase. The objective is to select the best risk control option with respect to cost and benefit.

Table 7.4: Description of findings and recommendations for the RCOs

No.	Basic Event (Level 3 & 5)	**Finding** (Ref. NAE/NRC, 2011)	Recommendation / Risk Control Option (**RCO**) (Ref. NAE/NRC, 2011) Engineering (**Eng-RCO**)	Equipment redesign/Test (**Equip-RCO**)	Regulatory (**Regul-RCO**)
1	**L3D-H1-02** Management / Supervision / Staff	Although data were being transmitted to shore, it appears that no one in authority was required to examine test results and other critical data and render an opinion to the personnel on the rig before operations could continue.	Industry should undertake efforts to expand significantly the formal education and training of industry personnel engaged in offshore drilling to support proper implementation of system safety.	BOP systems should be redesigned to provide robust and reliable cutting, sealing, and separation capabilities for the drilling environment to which they are being applied and under all foreseeable operating conditions.	The regulators should identify and enforce safety-critical points during well construction and abandonment that warrant explicit regulatory review and approval before operations can proceed.
		The decision to proceed to displacement of the drilling mud by seawater was made despite a failure to demonstrate the integrity of the cement job even after .multiple negative pressure tests. This was but one of a series of questionable decisions in the days preceding the blowout that had the effect of reducing the margins of safety, and that evidenced a lack of safety-driven decision making.	Existing codes and standards should review to determine which should be improved regarding requirements for: (a) use of state-of-the art technologies, especially in areas related to well construction, cementing, BOP functionality, and alarm and evacuation systems, among others, and (b) approval and certification incumbent to management of changes in original plans for well construction.	A BOP system with a critical component that is not operating properly, or which loses redundancy in a critical component, should cause drilling operations to cease. Drilling should not resume until the BOP's emergency operation capability is fully cured.	The regulators should undertake efforts to expand significantly the formal education and training of regulatory personnel engaged in offshore drilling roles to support proper implementation of system safety.
2	**L5D-O1-01-4-1** BOP stack failure	The BOP system was neither designed nor tested for the dynamic conditions that most likely existed at the time that attempts were made to recapture well control. Furthermore, the design, test, operation, and maintenance of the BOP system were not consistent with a high-reliability, fail-safe device.	Operator training for emergency BOP operation should be improved to the point that the full capabilities of a more reliable BOP can be competently and correctly employed when needed in the future.	Test and maintenance procedures should be established to ensure operability and reliability appropriate to their environment of application.	The regulators should foster an effective safety culture through consistent training, adherence to principles of human factors, system safety, and continued measurement through leading indicators.
3	**L5D-O1-01-4-2** BOP control system failure	At the time of the Macondo blowout, rig personnel could not regain control of the well by using the BOP because the blind shear ram did not cut the drill pipe and seal the well. In addition, the emergency-disconnect system failed to separate the Deepwater Horizon from the well.	Industry should greatly expand R&D efforts focused on improving the overall safety of offshore drilling in the areas of design, testing, modeling, risk assessment, safety culture, and systems integration. Such efforts should encompass well design, drilling and marine equipment, human factors, and management systems.	BOP systems should be redesigned to provide robust and reliable cutting, sealing, and separation capabilities for the drilling environment to which they are being applied and under all foreseeable operating conditions of the rig on which they are installed.	A single government agency should be designated with responsibility for ensuring an integrated approach for system safety for all offshore drilling activities.

7.4.3 Establishment of decision hierarchy for selection of the best RCOs

Selection of the best RCO is made on the basis of four subjective criteria; three different RCOs (i.e. Engineering (Eng-RCO), Equipment redesign/replace (Equip-RCO) and Regulatory/Human error (Regul-RCO)) are selected, because they are regarded as the most significant attributes associated with the MODU operational barriers based on NAE/NRC's (2011) findings and recommendations. Since it is useful to develop a hierarchical structure showing the overall objective, the criteria and alternatives in such a hierarchy for selection of the best RCO are shown in Figure 7.7. Three alternatives as presented in Figure 7.7 (i.e. Eng-RCO, Equip-RCO and Regul-RCO) are considered and evaluated against four selection criteria (i.e. Crew safety/People, Asset/Resources, Environment and Reputation) with which each alternative performance is measured. Decision hierarchy for selection of the best RCO associated with the MODU operational barriers based on NAE/NRC's (2011) findings and recommendations is illustrated in Figure 7.7.

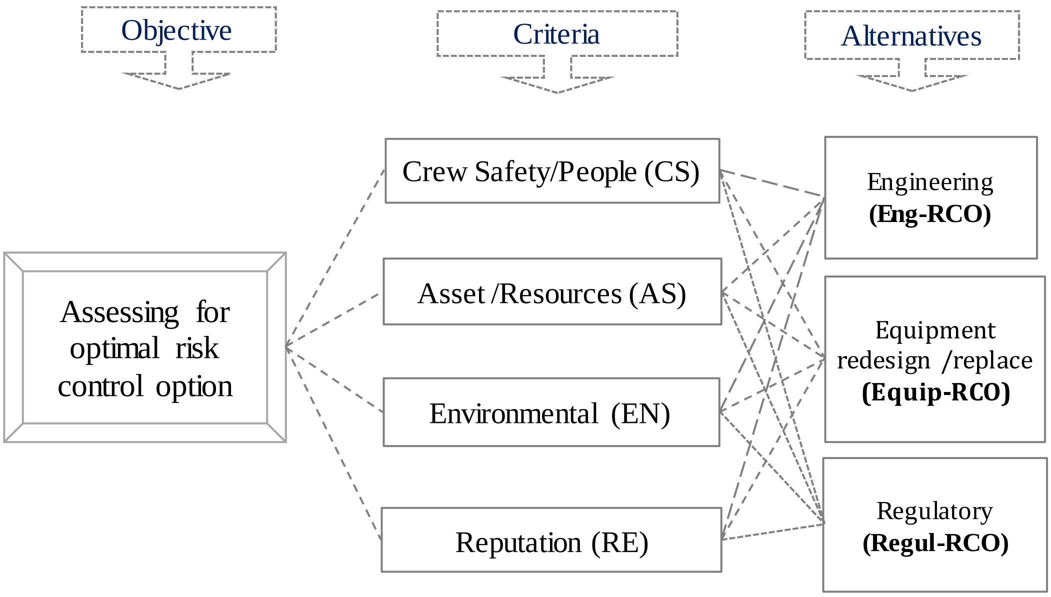


Figure 7.7: Decision hierarchy for selection of the best RCOs associated with the MODU operational barriers based on NAE/NRC's (2011) findings and recommendations.

In an MCDM problem, the attributes can be divided into two categories. The first is cost (the larger, the less preferred) and the second is benefit (the larger, the more preferred).

In Table 7.5, the criteria properties such as the class of criteria and type of assessment are summarised and illustrated.

Table 7.5: Criteria properties and type of assessment of the case study

No.	Description (Criteria)	Class of Criteria	Nature of criteria	Assessment data
1	**CS**	Safety (Benefit)	Safe (the higher more preferable)	Subjective (Expert Judgment)
2	**AS**	Costs	Cost (the lower, the better)	Subjective (Expert Judgment)
3	**EN**	Safety (Benefit)	Safe (the higher more preferable)	Subjective (Expert Judgment)
4	**RE**	Benefit	The higher more preferable	Subjective (Expert Judgment)

As shown in Table 7.5 for the criteria CS, EN and RE, the higher more preferable, for the criteria AS, the lower, the better.

7.4.4 Calculation of relative rate and data collection

With consideration of the unavailability of field data and with respect to the subjective criteria, the alternatives in the case study are evaluated by a group of three experts and the experts' linguistic judgements are transformed into their corresponding Fuzzy numbers by using Table 4.3. It should be noted that the AS must be considered to be the same as the cost of replacing them. For CS, EN and RE, the experts express their opinions with respect to each barrier and they should be considered as benefits; the three experts' judgements are presented for different alternatives (i.e. Eng-RCO, Equip-RCO and Regul-RCO) in Table 7.6 to

Table 7.8 respectively. As presented in Table 7.6, for the basic event of L3D-H1-02, the opinion of Expert 1 for the Eng-RCO risk control option with respect to the CS criterion is "Very High" and is presented in the second column. Likewise, the opinions of Experts 2 and 3 for the same risk control option are "Mol. High" and "High" respectively. In the last column, the three experts' opinions are aggregated and converted to the Crip No. (i.e. 0.235).

Table 7.6: Experts' opinions for Eng-RCO risk control option with respect to CS criteria

Basic Event (Level 3 & 5)	Experts Judgment for **Engineering** risk control option **(Eng-RCO)** with respect to (CS)																		Crisp No.
	Linguistic terms	**Expert 1**				Expert Factor	Linguistic terms	**Expert 2**				Expert Factor	Linguistic terms	**Expert 3**				Expert Factor	
B-L3D-H1-02	Very High	0.8	0.9	1	1	0.303	Mol. High	0.5	0.6	0.7	0.8	0.364	High		0.7	0.8	0.9	0.333	**0.235**
B-L5D-01-01-4-1	High		0.7	0.8	0.9	0.303	Medium		0.4	0.5	0.6	0.364	Very High	0.8	0.9	1	1	0.333	**0.203**
B-L5D-01-01-4-2	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Very High	0.8	0.9	1	1	0.333	**0.207**

Table 7.7: Experts' opinions for Equip-RCO risk control option with respect to CS criteria

Basic Event (Level 3 & 5)	Experts Judgment for **Equipment redesign/Test** risk control option **(Equip-RCO)** with respect to (CS)																		Crisp No.
	Linguistic terms	**Expert 1**				Expert Factor	Linguistic terms	**Expert 2**				Expert Factor	Linguistic terms	**Expert 3**				Expert Factor	
B-L3D-H1-02	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	**0.177**
B-L5D-01-01-4-1	Medium		0.4	0.5	0.6	0.303	Medium		0.4	0.5	0.6	0.364	Very High	0.8	0.9	1	1	0.333	**0.182**
B-L5D-01-01-4-2	Mol. High	0.5	0.6	0.7	0.8	0.303	High		0.7	0.8	0.9	0.364	Medium		0.4	0.5	0.6	0.333	**0.174**

Table 7.8: Experts' opinions for Regul-RCO risk control option with respect to CS criteria

Basic Event (Level 3 & 5)	Experts Judgment for **Regulatory** risk control option **(Regul-RCO)** with respect to (CS)																		Crisp No.
	Linguistic terms	**Expert 1**				Expert Factor	Linguistic terms	**Expert 2**				Expert Factor	Linguistic terms	**Expert 3**				Expert Factor	
B-L3D-H1-02	Very High	0.8	0.9	1	1	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	**0.234**
B-L5D-01-01-4-1	Medium		0.4	0.5	0.6	0.303	High		0.7	0.8	0.9	0.364	Mol. High	0.5	0.6	0.7	0.8	0.333	**0.177**
B-L5D-01-01-4-2	Mol. High	0.5	0.6	0.7	0.8	0.303	Mol. High	0.5	0.6	0.7	0.8	0.333	Medium		0.4	0.5	0.6	0.333	**0.178**

7.4.5 Fuzzy-AHP estimation process and determination of the weight factors

Fuzzy-AHP determines weighting factors by conducting pair-wise comparison. Fuzzy set theory and AHP have been used to estimate the weights of all the criteria by conducting pair-wise comparison. The comparison is based on an estimation scheme, which lists the strength of importance using qualitative descriptors. Table 7.9 has been used to create a pair-wise comparison; five linguistic terms are used fluctuating from equal importance to absolute importance. Each qualitative descriptor has a corresponding Fuzzy number that is employed to transfer experts' judgements into a comparisons matrix, and corresponds to the lower and upper values of a range to describe qualitative. A 4×4 pair-wise comparison matrix is developed to obtain the weights of all the criteria. $\tilde{A}$ is the pair-wise comparison matrix expressing the quantified judgements with regard to the relative importance of the criteria.

Table 7.9: Qualitative descriptions and their corresponding Fuzzy numbers

Qualitative descriptoin (Strength of importance)	Fuzzy numbers (Triangular)	Descriptions
Equal Importance (EI)	(1,1,2)	Two attributes or experts contribute equally to the event.
Weak Importance (WI)	(2,3,4)	Judgment and experience to some extent favour an attribute or expert over another.
Strong Importance (SI)	(4,5,6)	Judgment and experience strongly favour an attribute or expert over another.
Very Strong Importance (VSI)	(6,7,8)	An attribute or expert is favoured strongly over another.
Absolute Importance (AI)	(8,9,9)	The evidence favouring an attribute or expert over another is of the highest order of

As an example, two experts estimated that the criterion of CS compared to the criterion of AS is of "Strong Importance" and their judgements are then translated to a Fuzzy number of (4,5,6). One expert considered that CS is of "Very Strong Importance" in comparison with event AS, which corresponds to Fuzzy number (6,7,8). Using Equation (7.8), elements in $\tilde{a}_{13}$ and $\tilde{a}_{31}$ pair-wise comparison can be obtained as follows:

$$\tilde{r}_{12} = 1/3*((4,5,6) \oplus (4,5,6) \oplus (6,7,8)) = (4.67,5.67,6.67)$$

$$\tilde{r}_{21} = 1/\tilde{r}_{12} = (0.15,018,021)$$

A 4×4 Fuzzy pair-wise comparison matrix $\tilde{A}$ can be constructed as follows:

$$A= \begin{array}{c} \\ \mathbf{CS} \\ \mathbf{AS} \\ \mathbf{EN} \\ \mathbf{RE} \end{array} \begin{array}{c} \begin{array}{cccc} \mathbf{CS} & \mathbf{AS} & \mathbf{EN} & \mathbf{RE} \end{array} \\ \begin{pmatrix} (1.00\ 1.00\ 1.00) & (4.67\ 5.67\ 6.67) & (2.00\ 2.33\ 3.33) & (4.67\ 5.67\ 6.67) \\ (0.15\ 0.18\ 0.21) & (1.00\ 1.00\ 1.00) & (0.17\ 0.20\ 0.25) & (1.00\ 1.00\ 2.00) \\ (0.30\ 0.43\ 0.50) & (0.30\ 0.43\ 0.50) & (1.00\ 1.00\ 1.00) & (4.00\ 5.00\ 6.00) \\ (0.15\ 0.18\ 0.21) & (0.50\ 1.00\ 1.00) & (0.17\ 0.20\ 0.25) & (1.00\ 1.00\ 1.00) \end{pmatrix} \end{array} \tag{7.36}$$

Using the geometric mean technique, each criterion's weight can be calculated by using Equations (7.12) and (7.11) and the weights of all the attributes/criteria are presented in Table 7.10.

$$\tilde{f}_{CS} = ((1,1,1) \otimes (4.67,5.67,6.67) \otimes (2.00,2.33,2.33) \otimes (5.67,5.67,6.67))^{1/4}$$
$$\tilde{f}_{CS} = (2.57,2.94,3.49)$$

$$\tilde{w}_{cs} = \frac{\tilde{f}_{CS}}{\tilde{f}_{CS} + \tilde{f}_{AS} + \tilde{f}_{EN} + \tilde{f}_{RE}}$$
$$\tilde{w}_{cs} = \frac{(2.57,2.94,3.49)}{(2.57,2.94,3.49) + (0.40,0.43,0.57) + (0.77,0.98,1.11) + (0.33,0.43,0.48)}$$
$$\tilde{w}_{cs} = (0.45,0.61,0.86)$$

Table 7.10: Fuzzy weight of attributes/criteria

Fuzzy weight of attributes			
$\tilde{f}_{CS}$	= (2.57, 2.94, 3.49)	$\tilde{w}_{CS}$	= (0.45, 0.61, 0.86)
$\tilde{f}_{AS}$	= (0.40, 0.43, 0.57)	$\tilde{w}_{AS}$	= (0.07, 0.09, 0.14)
$\tilde{f}_{EN}$	= (0.77, 0.98, 1.11)	$\tilde{w}_{EN}$	= (0.14, 0.20, 0.27)
$\tilde{f}_{RE}$	= (0.33, 0.43, 0.48)	$\tilde{w}_{RE}$	= (0.06, 0.09, 0.12)

Table 7.11: Defuzzified and normalised weight of criteria

Defuzzified weight		Normalized weight of criteria	
${}^{DF}w_{CS}$	= 0.642	w_{CS}	= 0.620
${}^{DF}w_{AS}$	= 0.100	w_{AS}	= 0.097
${}^{DF}w_{EN}$	= 0.204	w_{EN}	= 0.197
${}^{DF}w_{RE}$	= 0.089	w_{RE}	= 0.086

7.4.6 Estimating weights of experts

Three experts are selected to make judgements with respect to the subjective attributes. The experts' weights can be obtained by using Table 4.5.and. Table 4.6.

7.4.7 Normalising of data and aggregation

In this step, all the ratings are aggregated for each criterion. As mentioned earlier, the subjective criteria are CS, AS, EN and RE. The aggregation calculations for CS, AS, EN and RE are given in Table 7.12 to Table 7.16 respectively. Aggregation of each risk control option with respect to CS is performed in two stages. The first stage is to obtain rating of judgements of each expert for each RCO, and in the second stage, the aggregation of the three experts' judgements for RCO 1 with respect to criteria needs to be obtained. As an example, in Table 7.12, the judgements of Expert 1 for Eng-RCO for different barriers is given with respect to CS and also the aggregation calculations including degree of similarity, average agreement, relative agreement and closeness coefficient are presented.

Table 7.12: Aggregation of judgements of Expert 1 for Eng-RCO with respect to CS

Basic Event (Level 3 & 5)

Judgment of **Expert 1** for **Eng-RCO** with respect to **(CS)**						Expert weight factor (E_{wf})	
B-L3D-H1-02 **(B1)**	Very High	0.8	0.9	1	1	0.303	
B-L5D-O1-01-4-1 **(B2)**	High		0.7	0.8	0.9	0.303	
B-L5D-O1-01-4-2 **(B3)**	Medium		0.4	0.5	0.6	0.303	
Aggregation calculations							
Degree of similarity		Average agreement		Relative agreement		Consensus coefficient	
S (**B1** & **B2**)	0.675	AA (**B1**)	0.725	RA (**B1**)	0.382	CC (**B1**)	0.342
S (**B2** & **B3**)	0.775	AA (**B2**)	0.613	RA (**B2**)	0.322	CC (**B2**)	0.313
S (**B1** & **B3**)	0.45	AA (**B3**)	0.563	RA (**B3**)	0.296	CC (**B3**)	0.300
Total			1.900		1.000		0.955
Result of aggregation		0.274	0.647	0.742	0.803		

Table 7.13: Aggregation of judgements of Expert 2 for Eng-RCO with respect to CS

Basic Event (Level 3 & 5)

Judgment of **Expert 2** for **Eng-RCO** with respect to **(CS)**						Expert weight factor (E_{wf})	
B-L3D-H1-02 **(B1)**	Mol. High	0.5	0.6	0.7	0.8	0.364	
B-L5D-O1-01-4-1 **(B2)**	Medium		0.4	0.5	0.6	0.364	
B-L5D-O1-01-4-2 **(B3)**	High		0.7	0.8	0.9	0.364	
Aggregation calculations							
Degree of similarity		Average agreement		Relative agreement		Consensus coefficient	
S (**B1** & **B2**)	0.725	AA (**B1**)	0.750	RA (**B1**)	0.326	CC (**B1**)	0.345
S (**B2** & **B3**)	0.775	AA (**B2**)	0.788	RA (**B2**)	0.342	CC (**B2**)	0.353
S (**B1** & **B3**)	0.8	AA (**B3**)	0.763	RA (**B3**)	0.332	CC (**B3**)	0.348
Total			2.300		1.000		1.045
Result of aggregation		0.172	0.591	0.696	0.801		

Table 7.14: Aggregation of judgements of Expert 3 for Eng-RCO with respect to CS

Basic Event (Level 3 & 5)

Judgment of **Expert 3** for **Eng-RCO** with respect to **(CS)**						Expert weight factor (E_{wf})	
B-L3D-H1-02 **(B1)**	High		0.7	0.8	0.9	0.333	
B-L5D-O1-01-4-1 **(B2)**	Very High	0.8	0.9	1.0	1.0	0.333	
B-L5D-O1-01-4-2 **(B3)**	Very High	0.8	0.9	1.0	1.0	0.333	
Aggregation calculations							
Degree of similarity		Average agreement		Relative agreement		Consensus coefficient	
S (**B1** & **B2**)	0.675	AA (**B1**)	0.838	RA (**B1**)	0.356	CC (**B1**)	0.345
S (**B2** & **B3**)	1	AA (**B2**)	0.838	RA (**B2**)	0.356	CC (**B2**)	0.345
S (**B1** & **B3**)	0.675	AA (**B3**)	0.675	RA (**B3**)	0.287	CC (**B3**)	0.310
Total			2.350		1.000		1.000
Result of aggregation		0.524	0.831	0.931	0.966		

The aggregation of the three experts' judgements for Eng-RCO with respect to CS is presented in Table 7.15.

Table 7.15: Aggregation of three experts' ratings for Eng-RCO with respect to CS

Engineering (**Eng-RCO**)-with respect to (**CS**)	Linguistic terms						Expert weight factor (E_{wf})	
	Expert 1 (**E1**)		0.274	0.647	0.742	0.803	0.303	
	Expert 2 (**E2**)		0.172	0.591	0.696	0.801	0.364	
	Expert 3 (**E3**)		0.524	0.831	0.931	0.966	0.333	
	Aggregation calculations							
	Degree of similarity		Average agreement		Relative agreement		Consensus coefficient	
	S (**E1** & **E2**)	0.949	AA (**E1**)	0.850	RA (**E1**)	0.340	CC (**E1**)	0.321
	S (**E2** & **E3**)	0.752	AA (**E2**)	0.778	RA (**E2**)	0.311	CC (**E2**)	0.337
	S (**E1** & **E3**)	0.804	AA (**E3**)	0.876	RA (**E3**)	0.350	CC (**E3**)	0.342
	Total			2.504		1.000		1.000
Result of aggregation for **Eng-RCO**			0.325	0.691	0.791	0.858		

The aggregation of the three experts' judgements for Equip-RCO with respect to CS is presented in Table 7.16.

Table 7.16: Aggregation of three experts' ratings for Equip-RCO with respect to CS

Equipment redesign/Test (**Equip-RCO**) with respect to (**CS**)	Linguistic terms						Expert weight factor (E_{wf})	
	Expert 1 (**E1**)		0.164	0.447	0.543	0.638	0.303	
	Expert 2 (**E2**)			0.625	0.730	0.834	0.364	
	Expert 3 (**E3**)		0.418	0.625	0.725	0.793	0.333	
	Aggregation calculations							
	Degree of similarity		Average agreement		Relative agreement		Consensus coefficient	
	S (**E1** & **E2**)	0.819	AA (**E1**)	0.851	RA (**E1**)	0.339	CC (**E1**)	0.321
	S (**E2** & **E3**)	0.884	AA (**E2**)	0.846	RA (**E2**)	0.337	CC (**E2**)	0.350
	S (**E1** & **E3**)	0.808	AA (**E3**)	0.813	RA (**E3**)	0.324	CC (**E3**)	0.329
	Total			2.511		1.000		1.000
Result of aggregation for **Equip-RCO**			0.190	0.568	0.668	0.758		

The aggregation of the three experts' judgements for Regul-RCO on CS is shown in Table 7.17.

Table 7.17: Aggregation of the three experts' judgements for Regul-RCO with respect to CS

Regulatory (**Regul-RCO**) with respect to (**CS**)	Linguistic terms							Expert weight factor (E_{wf})	
	Expert 1 (**E1**)		0.398	0.596	0.692		0.756	0.303	
	Expert 2 (**E2**)		0.177	0.696	0.801		0.905	0.364	
	Expert 3 (**E3**)		0.329	0.531	0.631		0.731	0.333	
	Aggregation calculations								
	Degree of similarity		Average agreement		Relative agreement			Consensus coefficient	
	S (**E1** & **E2**)	0.855	AA (**E1**)	0.845	RA (**E1**)		0.321	CC (**E1**)	0.312
	S (**E2** & **E3**)	0.835	AA (**E2**)	0.890	RA (**E2**)		0.338	CC (**E2**)	0.351
	S (**E1** & **E3**)	0.945	AA (**E3**)	0.900	RA (**E3**)		0.342	CC (**E3**)	0.337
	Total			2.636			1.000		1.000
Result of aggregation for **Regul-RCO**			0.297	0.609	0.710		0.800		

The decision matrix, aggregation of subjective ratings for each RCO with respect to different criteria, is shown in Table 7.18.

Table 7.18: Decision matrix of subjective ratings

Description	**CS** Safety (Benefit)	**AS** Costs	**EN** Safety (Benefit)	**RE** Benefit
Eng-RCO	(0.325 , 0.691 , 0.791 , 0.858)	(0.133 , 0.400 , 0.500 , 0.600)	(0.202 , 0.634 , 0.734 , 0.823)	(0.062 , 0.456 , 0.556 , 0.657)
Equip-RCO	(0.190 , 0.568 , 0.668 , 0.758)	(0.110 , 0.449 , 0.549 , 0.649)	(0.190 , 0.568 , 0.668 , 0.758)	(0.059 , 0.423 , 0.524 , 0.624)
Regul-RCO)	(0.297 , 0.609 , 0.710 , 0.800)	(0.110 , 0.441 , 0.542 , 0.642)	(0.118 , 0.646 , 0.746 , 0.846)	(0.052 , 0.424 , 0.524 , 0.625)

All the subjective data are converted into crisp values for each RCO, as presented in Table 7.19.

Table 7.19: Crisp value of decision matrix

Description	**CS** Safety (Benefit)	**AS** Costs	**EN** Safety (Benefit)	**RE** Benefit
Eng-RCO	0.649	0.399	0.578	0.415
Equip-RCO	0.529	0.425	0.529	0.392
Regul-RCO)	0.592	0.421	0.562	0.391

7.4.8 Normalisation of the decision matrix

The TOPSIS procedure is applied to the four criteria to obtain the best RCO and ranking orders. In this step, the normalisation is carried out for the decision matrix shown in Table 7.19. The normalised attributes can be obtained using Equation (7.6). The normalised decision matrix is shown in Table 7.20.

Table 7.20: Fuzzy normalised decision matrix

Description	CS Safety (Benefit)	AS Costs	EN Safety (Benefit)	RE Benefit
Eng-RCO	0.633	0.555	0.599	0.600
Equip-RCO	0.516	0.591	0.549	0.567
Regul-RCO)	0.577	0.585	0.583	0.564

The weighted normalised Fuzzy decision matrix can be obtained by employing Equation (7.21). For example, the weighted normalised CS of Eng-RCO is obtained as follows:

$$v_{ij} = 0.633 \times 0.620 = 0.392$$

The weighted normalised Fuzzy decision matrix is shown in Table 7.21.

Table 7.21: Weighted normalised decision matrix

Description	CS Safety (Benefit)	AS Costs	EN Safety (Benefit)	RE Benefit
Eng-RCO	0.392	0.054	0.118	0.052
Equip-RCO	0.320	0.057	0.108	0.049
Regul-RCO)	0.358	0.057	0.115	0.049

<u>Obtaining the distances of an alternative from ideal and negative ideal solutions</u>

Determination of the positive ideal solution can be easily made by taking the largest element for each benefit attribute and the smallest element for each cost attribute. The negative ideal solution is simply the opposite formation of the positive ideal solution. The positive and negative ideal solutions are given in Table 7.22.

Table 7.22: PIS and NIS

Description	PIS	NIS
CS Safety (Benefit)	0.392	0.320
AS Costs	0.054	0.057
EN Safety (Benefit)	0.118	0.108
RE Benefit	0.052	0.049

The distances and closeness membership functions from each RCO to PIS and NIS are calculated for all the alternatives by employing Equations (7.25), (7.26), (7.32) and (7.33). An example highlighting the calculation process for Eng-RCO is given below and the results for all the RCOs are shown in Table 7.23 and Table 7.24.

$$d^{+} = (0.577-0.392)^2 + (0.585-0.054)^2 + (0.583-0.118)^2 + (0.564-0.052)^2$$
$$d^{+} = 0.892$$

$$u^{+} = \frac{1}{1+0.892} = 0.529$$

Table 7.23: Distance and closeness values of each alternative from PIS and NIS

Description	d^{+}	d^{-}	μ^{+}	μ^{-}
Eng-RCO	0.000	0.073	1.000	0.068
Equip-RCO	0.003	0.000	0.997	0.000
Regul-RCO	0.892	0.039	0.529	0.037

Table 7.24: Distance and closeness values of each alternative from PIS and NIS

Description	**Eng-RCO**	**Equip-RCO**	**Regul-RCO**
d^{+}	0.0000	0.003	0.892
d^{-}	0.073	0.000	0.039
μ^{+}	1.000	0.997	0.529
μ^{-}	0.068	0.000	0.037

7.4.9 Computing the RCC of each alternative from the ideal solution

The risk control values of the four RCOs at P =1,2,3,… can be obtained by using Equation (7.34) and the result is shown in Table 7.25.

Table 7.25: RCC values of the RCOs

P	**Eng-RCO**	**Equip-RCO**	**Regul-RCO**
1	0.06842	0.0000	0.0000
2	0.06842	0.00018	0.0000
3	0.06842	0.00019	0.00083
4	0.06842	0.00019	0.02356
5	0.06842	0.00019	0.03174
…	…	…	…
1000	0.0684	0.0002	0.0371

It can be seen from Table 7.25 that each instance of the proposed method yields different values for RCOs corresponding to different behavioural patterns of decision-makers. Indeed, when $P \to \infty$ (e.g. P=1000), Eng-RCO is ranked as the best alternative followed by Regul-RCO and Equip-RCO respectively. Eng-RCO is characterised by the maximum negative membership value of 0.0684, corresponding to decision-makers who prefer alternatives that make not only as much profit as to the extent of practically possible but also as much as risk reduction possible.

7.5 Validation

In the first condition, sensitivity analysis is performed by investigating the values and ranking of the alternatives due to the weight changes. The weights of all the attributes are considered to be of equal importance (i.e. $w_{CS} = w_{AS} = w_{EN} = w_{RE} = 0.250$). Table 7.26 shows that the values of the RCOs are changed due to the weight changes.

Table 7.26: Rating of RCOs by considering equal weights for attributes

P	Eng-RCO	Equip-RCO	Regul-RCO
1	0.07844	0.0000	0.0000
2	0.07844	0.00135	0.0000
3	0.07844	0.00135	0.03268
4	0.07844	0.00135	0.03973
5	0.07844	0.00135	0.04134
…	…	…	…
1000	0.0784	0.0014	0.0419

In the second condition, the weights of 1 and 0 are considered for positive attribute (CS, EN and RE) and negative attribute (AS) respectively. The alternatives (RCOs) with higher Eng-RCO values should have better ranking results. Therefore, the ranking result must be that Eng-RCO is ranked as the best alternative followed by Regul-RCO and Equip-RCO. The results in Table 7.27 confirm the aforementioned expectation.

Table 7.27: Ranking results considering a weight of one for REL and zero for negative attribute

P	Eng-RCO	Equip-RCO	Regul-RCO
1	0.11704	0.0000	0.0000
2	0.11704	0.00215	0.0000
3	0.11704	0.00218	0.04657
4	0.11704	0.00218	0.05989
5	0.11704	0.00218	0.06379
…	…	…	…
1000	0.1170	0.0022	0.0656

In the third condition, model validation is investigated by considering six instances for (1, 1.5, 2.5, 4.5, 7 and 50).Table 7.28 demonstrates that each instance results in different rating values. Six instances are selected randomly.

Table 7.28: Rating value considering different P instances

P	Eng-RCO	Equip-RCO	Regul-RCO
1	0.06842	0.0000	0.0000
1.5	0.06842	0.00010	0.0000
2.5	0.06842	0.00019	0.00000
4.5	0.06842	0.00019	0.02863
7	0.06842	0.00019	0.03617
...	...	…	...
50	0.0684	0.0002	0.0371

RCOs' ranking in Table 7.28can satisfy the expectation.

7.6 Conclusion

The offshore industry should greatly expand research and development efforts focused on improving the overall safety of offshore operation systems in the areas of design, testing, modelling, risk assessment, safety culture, systems integration and regulation. The basic principle of the TOPSIS method is that the chosen alternative should ideally have the farthest distance from the NIS and shortest distance from the PIS. However, such chosen alternative is not always closest to the ideal solution and it may not be the farthest from the NIS either. This chapter presents an effective Fuzzy MCDM method, which is suitable for solving multiple attribute group decision-making problems under a Fuzzy environment where the information available is subjective and imprecise. The proposed method enables a group of decision-makers to incorporate and aggregate subjective opinions. This chapter has identified a set of suggestions for how barriers can be modelled in risk assessment. By using the model developed and presented here, offshore operators can choose the best RCO based on the requirements of multiple criteria. Such a Fuzzy MCDM can be employed as an alternative tool for use in situations where both qualitative and quantitative data have to be synthesised.

CHAPTER 8: Conclusion

Chapter summary

This chapter briefly outlines that the risk assessment and decision-making methodologies and techniques offered in this research would be of support in safe MODU operation and management. Several powerful and efficient tools and techniques were employed in the development of integrative risk assessment analytical models for the offshore operation system application. It is concluded that the developed methodology can be integrated to formulate a platform to facilitate risk assessment of the MODU operations without jeopardising the efficiency and performance of system operations. The development phases for the models that had to be provided with data and uncertainties were handled through inference processes that are based on sound theorems or logic. The proposed methodologies were also enabled via case studies in order to demonstrate their practicality. The areas which require more effort to be paid in order to improve the developed approaches for further work are outlined; also, this chapter reviews the goals achieved in this research.

8.1 Introduction

On the basis of the reviewed different analytical concepts, a proposed framework for the risk-based assessment settings of this research has been developed in a generic sense to be effectively applicable to all offshore operation systems and their components/subsystems. The framework incorporates risk analysis for which data were obtained from industrial databases and/or by expert judgements. Where it is difficult to describe the basic failure events of a system using probabilistic risk analysis methods, subjective reasoning analysis has been deemed more appropriate to assess the safety of the system. FL was utilised as the modelling tool that dealt with the vague/subjective uncertainties in offshore operation systems. In addition, the information from one implemented technique, such as a risk contribution hierarchy, can be used to process the information produced using another technique, such as a FTA. Therefore, the use of well-established risk assessment analytical techniques (e.g., FT and BBN) and the developed risk-based analytical tools (e.g., FL) in an integrated manner may make risk assessment comparatively more efficient and convenient, since the advantages of each method may be more efficiently explored. In this review of the research conducted within this thesis, it can be confirmed that not only has the work followed a logical sequence, but that, most importantly, the aims and objectives of this thesis have been successfully achieved.

8.2 Aims and objectives of this research

The stated aims of this research was to develop a novel QRA methodology for an effective and efficient risk assessment of an offshore operation system. The research has followed and accomplished and the set of following objectives has been achieved:

- Through a review of the literature, the case for the application of the offshore operation system risk assessment principles is examined. This has been achieved by carrying out a review of the available literature as pertaining to cases for the application of risk assessment on the MODU's operation system.
- A novel engineering framework for risk assessment of the MODU is developed, which is also applicable to other offshore operation systems at a similar stage of risk assessment implementation. The framework development was undertaken by representing the MODU's specific operational requirements and the particular stage of risk assessment within the case study was applied to a framework incorporating the wider stages.
- The concept of MCDM as a decision support tools in an MCDM environment is examined, through a review of the literature, the most appropriate techniques is being used for developing the required decision support models. Because of the multitude of factors involved in carrying out of an offshore operation system risk assessment, prioritisation of which barrier schemes to implement is therefore the key instrument for the optimisation of the available resources. MCDA, as the process of analysing, choosing, ranking and sorting appropriate actions, is used effectively in resolving decision problems in an offshore operation system. In this process, it should be

recognised that the decision-making involving prioritisation and optimisation of the available resources is based on balancing conflicting criteria using the practice of trading-off between them to arrive at a decision that is considered most advantageous or optimum.

8.3 Research limitations

The developed risk assessment analytical models provide useful integrative tools for a proactive offshore operation system world but have limitations owing to the complex nature of offshore installations. As with all research, there are limitations within issues affecting the research methodology, the analytical techniques and processes adopted, and the interpretation of the results, particularly when attempting to make generalisations based on the empirical or analytical research. The most significant limitations considered to affect this research are discussed here based on their relevance to each of the research components.

- Eliciting conditional probabilities is more difficult, especially if the probability is conditioned on several states. Besides, many of the probabilities required to quantify a BBN cannot be derived from databases and scientific literature, therfore they may need to be elicited from domain experts, based on their knowledge and experience.
- Lack of industrial failure data.
- Sensitivity analysis is generally deterministic and limited to one- and two-way analyses. Thus, only a partial sensitivity analysis could be conducted for the MODU.
- Although FL is widely used today to solve very complex problems in risk assessment applications in different fields including science, engineering and management, a major limitation of FL is that, for many applications, the information that describes desired system behaviour is held in data sets, and the designer may have to develop the rules (e.g. "IF THEN") from the data sets manually. This is a major task for large data sets.
- Some limitations introduced into the research scope are generally associated with case studies, as discussed in Chapter 4 of this thesis. Such limitations are

related to the complexity of the MODU system, and also that a single case provides little basis for systematic generalisation.

These limitations did not mitigate the efficacy of the conclusions and generalisations of the conducted research. Nonetheless, tackling these limitations should enable the advancement of the integrative risk assessment modelling.

8.4 Conclusion

The thesis has been successful in meeting its aim of developing a novel QRA methodology for an effective and efficient risk assessment and management of an offshore operation system. It is also believed that these methods can be tailored to practical applications of dealing with risk assessment in other industries, especially in situations where a high level of uncertainty exists. The implementation of the defined methodologies could have highly beneficial effects in real life.

The practicality of the developed methodology can be justified for the risk assessment of real-life offshore applications. Envisioning failure is key to the safe development and operation of systems, particularly systems that incorporate the complexity of an MODU. Risks must be recognised, quantified, and mitigated. Designers, developers, operators, and regulators must know and understand that the risks are real and conduct themselves accordingly. Offshore operation safety has evolved in a reactive manner towards a risk-based goal-setting approach recently due to public concern following several catastrophic disasters. Traditional risk assessment techniques are capable of handling risks with confidence on the principle that historical data are obtainable. On the other hand, such techniques may not genuinely reflect risk results in situations where a lack of data exists or the information available consists of a high level of uncertainty. Therefore, it is essential for a study of safe operation in an offshore operation system such as an MODU, to enable the addressing of higher-risk areas where data are scarce. In risk assessment, the issue of uncertainty management is a most important concern. However, the causes of uncertainty are diverse. Thus, regardless of what methodology is to be applied, it is always dependent upon expert judgements to manage such adverse effects. In other words, the deficiencies of risk modelling resulting from the lack of information or a high level of uncertainty must be made up by means of the general evaluation capacity of experts who are able to understand the essence of the system, even if it is vague and unclear. For that reason, the knowledge of experts consulted is very important, since the basis of such uncertainty treatment is the professional judgements of such personnel.

The risk assessment frameworks proposed based on Fuzzy set theory in this study are capable of handling imprecise, ambiguous and qualitative information from experts in a consistent manner. These can be observed as reliable reasoning processes capable of quantifying the judgements from experts who express their opinions qualitatively. In addition, the linguistic terms employed in assessments are developed by consensus. Such harmonious assessments with regard to linguistic terms provide compatibility throughout the risk assessment process.

Following the identification of the research needs, this PhD study has developed analytical models capable of performing risk assessment with confidence under the said circumstances. Such frameworks have been demonstrated by three corresponding test cases with regard to the safe operation of an MODU. The frameworks have been developed in a generic sense to be applicable to deal with both technical and managerial problems. They provide the basis for the generation of the various risk analysis methods and decision-making processes. These methods and techniques can be summarised as follows:

- Using an object-oriented approach to deal with the complexity of MODUs and to provide a hierarchical structure of risk assessment, and using a framework of aggregative risk assessment to represent the relationships of components, subsystems and the overall MODU.
- Applying Fuzzy-AHP to evaluate and rank the risks of the HGs and their subsystems with regard to their capacity to the failure of the MODU.
- Employing Fuzzy FTA to identify critical components in an MODU.
- Employing a BBN to represent the links between unsophisticated available information and to foresee the occurrence likelihood of events that may have consequences in the operation of the MODU systems.
- Using Fuzzy TOPSIS to select the best RCO for an MODU operation system.

Different mathematical theories are combined for assessing the risk frameworks in Chapter 4. Fuzzy set theory is used to represent the characteristics of a hazard such as likelihood of occurrence, consequence severity and vulnerability. AHP is used to rank the risks together with the hierarchical structure to obtain the weight factor to estimate the risk associated with each equipment/component, subsystem and the overall MODU. Risk analysts can use this information to compare risk levels of components and subsystems that contribute to the final aggregated risk. By considering the risk value and weight of each component/equipment and subsystem, the most critical subsystem can be identified. Offshore drilling failure is selected as the most critical HG for further investigation. The next step is to apply Fuzzy FTA to identify the most important MCSs of the most critical subsystem of the Drilling system.

In the absence of precise data, it is necessary to work with subjective probabilities. Under these conditions, it is inappropriate to use conventional FTA. Therefore, Fuzzy FTA is proposed to capture the subjectivity. The results of Fuzzy FTA are the likelihood of occurrence of specific hazards and importance measures of potential contributing factors. Application of Fuzzy FTA in Chapter 5 shows that it is useful to identify critical MCSs for a specific risk ranking.

BBNs are increasingly used to model complex domains for which knowledge and data are uncertain. The proposed methodology uses the BBN technique to express the causal relationships between variables and to combine the evidence from different sources for a QRA of offshore systems. The BBN is used to represent the links between unsophisticated available information and to foresee the occurrence likelihood of events that may have consequences in the operation of the MODU systems. The methodology presented uses a hierarchical model to describe dependencies among the systems or components. The reasons for choosing graphical BBN models are their capability of establishing relationships between hazardous events and capacity to show cause and effect relationships of the events by their directional capability. BBNs have a strong similarity to FTA in many respects. FTA is an effective method in probabilistic failure assessment but is limited to modelling simple static systems. The distinct advantages of BBNs are their capability to explicitly represent the dependencies among the events, their updating probabilities, their flexible structure compared to FTA, and that they are suitable for a comprehensive range of risk assessment and analysis as well as offshore operation systems. Such a technique is also capable of dealing with conditional probability problems.

The results of Chapter 4, Chapter 5 and Chapter 6 can help the analyst to select RCOs for mitigating risk of the most critical subsystem and the overall MODU. However, it is not financially possible to select all the proposed RCOs. Therefore, MADM by using Fuzzy TOPSIS is tailored to select the best RCO from a finite number of RCOs. When dealing with RCO ranking/selecting, decision data available for MADM are usually Fuzzy, crisp, or a combination of the two. Fuzzy TOPSIS is proposed to handle both Fuzzy and crisp data. When evaluating RCOs (i.e. Eng-RCO, Equip-RCO and Regul-RCO) for enhancing the safe performance of an MODU, there are many parameters that need to be considered. On the basis of the test case in Chapter 7 involving the elements of CS, AS, EN and RE, it is reasonable to judge that the decision-making model developed is capable of handling such MADM problems. The proposed method is particularly useful in circumstances where multiple experts are involved in a decision-making process.

Since the case study in this study provides reasonable results, it is felt that the analytical models developed have the potential to improve the safe performance of the MODUs. Such models can be applied individually by the offshore industry, particularly in circumstances where a lack of data exists or the data for use are associated with a high level of uncertainty. More importantly, these frameworks can be integrated to formulate a platform to facilitate risk assessment of MODU operations without jeopardising the efficiency of operations in a variety of situations where traditional techniques may not be applied with confidence.

8.5 Recommendations for further research

While they go a long way to proactively ensuring offshore operation safety and environmental protection at the highest level, it may be beneficial if the novel techniques developed in this research could be further applied to facilitate risk assessment modelling and decision-making. Since the methodologies proposed in this research are generic in nature, such frameworks can be further verified for risk assessment outside the offshore industry. This will provide an added value to the promotion of their use in different industries. Any such practical application can thus be examined through the exploration of a specific case study of relevance to the safety-critical system or component and via the use of the most reliable real-life data and competent expert judgements.

When assessing risks under situations of lack of data, possibly due to the high level of costs associated with conducting a full-scale carrying-out of tests, the use of computer simulation may be hypothetically useful. It is meaningful to note that some computer software enables the data compilation process.

This PhD research formulates a platform for offshore operation systems such as MODUs to improve the risk assessment and risk management of their processes. The principal implication of this is that the offshore operation system will have to collect data for each component with regard to safe operation based on daily operations with the objective of continuous improvement of safe performance and efficiency.

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Appendices

Appendix 1

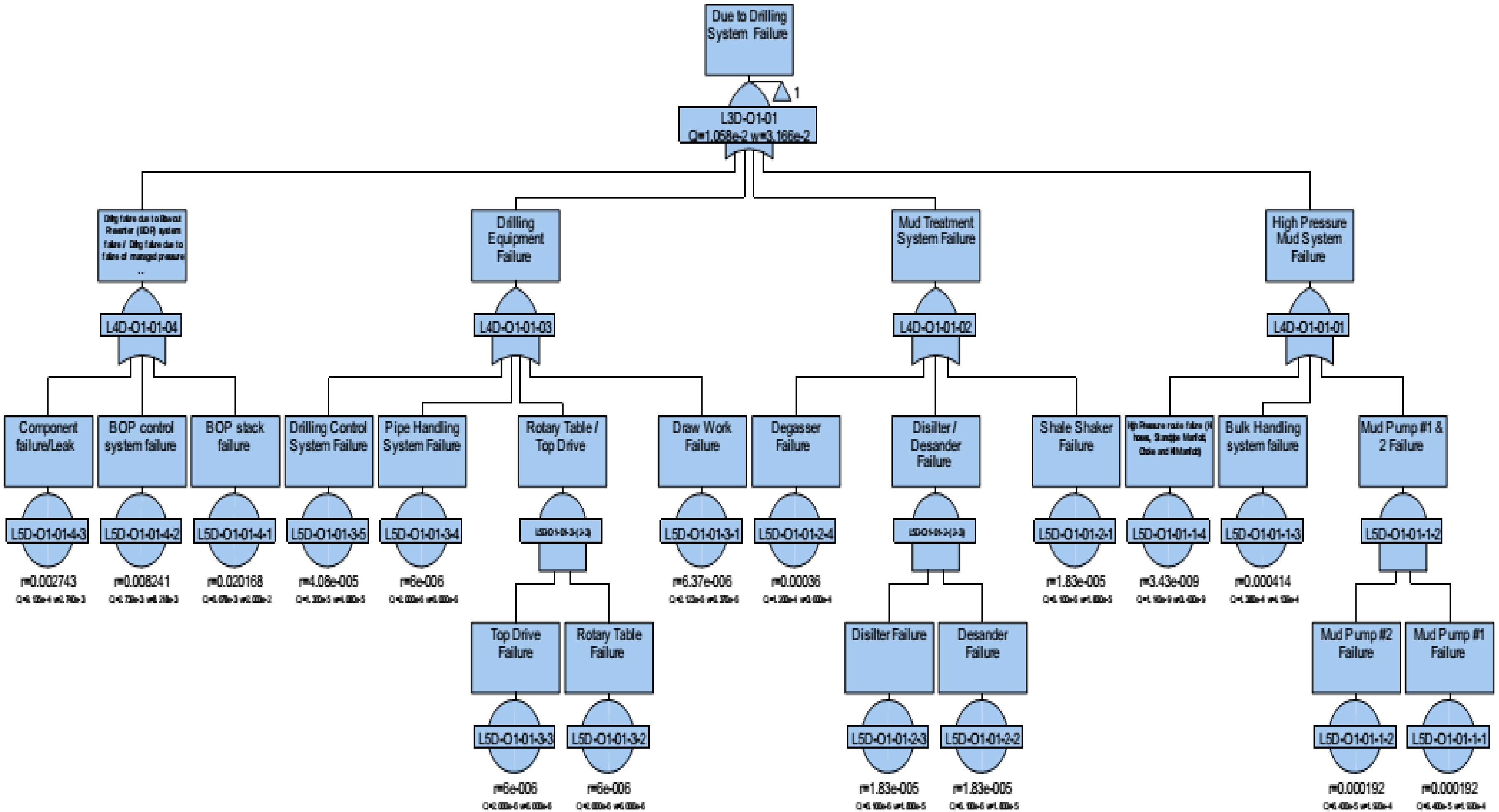

Figure A1: FT model for L3D-O1-01

FaultTree+ V11.2 Event Data

Name	Description	Logic Mode	Generic Model Name	Use Generic Model	CCF Model Name	Unavailability	Failure Frequency
L3D-H1-01	Organizational / Polices and Procedures WD3H-1	Basic		Off		2.999e-4	2.999e-3
L3D-H1-02	Management / Supervision / Staff WD3H-2	Basic		Off		2.499e-4	2.499e-3
L3D-H1-03	Individual - Competence / Motivation WD3H-3	Basic		Off		2.e-4	2.e-3
L3D-N1-01	Present of high speed wind/wind/Current WD3N-1	Basic		Off		4.e-6	4.e-5
L3D-N1-02	Hole instability WD3N-2	Basic		Off		6.995e-4	6.995e-3
L3D-N1-03	Wellbore influx / Kick WD3N-3	Basic		Off		8.992e-4	8.992e-3
L3D-N1-04	Punch Through WD3N-4	Basic		Off		7.e-5	7.e-4
L3D-N1-05	Ground movement WD3N-5	Basic		Off		6.e-6	6.e-5
L3D-O1-02	Due to Power System Failure WD3O-2	Basic		Off		5.e-5	5.e-4
L3D-O1-03	Due to Rig Control System Failure WD3O-3	Basic		Off		8.999e-5	8.999e-4
L3D-O1-04	Due to Jacking System Failure WD3O-4	Basic		Off		4.e-5	4.e-4
L3D-O1-05	Due to Water Handling System Failure WD3O-5	Basic		Off		3.e-5	3.e-4
L3D-O1-06	Due to ESD System Failure WD3O-6	Basic		Off		3.5e-5	3.5e-4
L3D-O1-07	Due to Fuel System Failure WD3O-7	Basic		Off		5.2e-6	5.2e-5
L3D-O1-08	Due to Air/Hydraulic System Failure WD3O-8	Basic		Off		2.3e-7	2.3e-6
L5D-O1-01-1-1	Mud Pump #1 Failure WD5O-1-1-1	Basic		Off		1.92e-5	1.92e-4
L5D-O1-01-1-2	Mud Pump #2 Failure WD5O-1-1-2	Basic		Off		1.92e-5	1.92e-4
L5D-O1-01-1-3	Bulk Handling suystem Failure WD5O-1-1-3	Basic		Off		4.14e-5	4.14e-4
L5D-O1-01-1-4	High Pressure route failure (HP hoses, Standpipe Manifold, Choke and Kill Manifold) WD5O-1-1-4	Basic		Off		3.43e-10	3.43e-9
L5D-O1-01-2-1	Shale Shaker Failure WD5O-1-2-1	Basic		Off		1.83e-6	1.83e-5
L5D-O1-01-2-2	Desander Failure WD5O-1-2-2	Basic		Off		1.83e-6	1.83e-5
L5D-O1-01-2-3	Disilter Failure WD5O-1-2-3	Basic		Off		1.83e-6	1.83e-5
L5D-O1-01-2-4	Degasser Failure WD5O-1-2-4	Basic		Off		3.6e-5	3.6e-4
L5D-O1-01-3-1	Draw Wrok Failure WD5O-1-3-1	Basic		Off		6.37e-7	6.37e-6

FaultTree+ V11.2	Event Data						
Name	**Description**	**Logic Mode**	**Generic Model Name**	**Use Generic Model**	**CCF Model Name**	**Unavailability**	**Failure Frequency**
L5D-O1-01-3-2	Rotary Table Failure WD5O-1-3-2	Basic		Off		6.e-7	6.e-6
L5D-O1-01-3-3	Top Drive Failure WD5O-1-3-3	Basic		Off		6.e-7	6.e-6
L5D-O1-01-3-4	Pipe Handling System Failure WD5O-1-3-4	Basic		Off		6.e-7	6.e-6
L5D-O1-01-3-5	Drilling Control System Failure WD5O-1-3-5	Basic		Off		4.08e-6	4.08e-5
L5D-O1-01-4-1	BOP stack failure WD5O-1-4-1	Basic		Off		1.438e-3	2.014e-2
L5D-O1-01-4-2	BOP control system failure WD5O-1-4-2	Basic		Off		5.883e-4	8.236e-3
L5D-O1-01-4-3	Component failure / Leak WD5O-1-4-3	Basic		Off		1.959e-4	2.742e-3

Appendix 2

Description of drilling equipment and systems:

- Mechanical system - driven by electric motors
  - hoisting system - used for lifting heavy loads; consists of a mechanical winch (drawworks) with a large steel cable spool, a block-and-tackle pulley and a receiving storage reel for the cable
  - turntable - part of the drilling apparatus
- Rotating equipment - used for rotary drilling
  - swivel - large handle that holds the weight of the drill string; allows the string to rotate and makes a pressure-tight seal on the hole
  - kelly - four- or six-sided pipe that transfers rotary motion to the turntable and drill string
  - turntable or rotary table - drives the rotating motion using power from electric motors
  - drill string - consists of drill pipe (connected sections of about 30 ft / 10 m) and drill collars (larger diameter, heavier pipe that fits around the drill pipe and places weight on the drill bit)
  - drill bit(s) - end of the drill that actually cuts up the rock; comes in many shapes and materials (tungsten carbide steel, diamond) that are specialized for various drilling tasks and rock formations
  - turntable - The principal component of a rotary, or rotary machine, used to turn the drill stem and support the drilling assembly.
  - Top Drive - A mechanical device on a drilling rig that provides rotary torque to the drill string to facilitate the process of drilling a borehole.
- Circulation system - pumps drilling mud (mixture of water, clay, weighting material and chemicals, used to lift rock cuttings from the drill bit to the surface) under pressure through the kelly, rotary table, drill pipes and drill collars
  - pump - sucks mud from the mud pits and pumps it to the drilling apparatus
  - pipes and hoses - connects pump to drilling apparatus
  - mud-return line - returns mud from hole
  - shale shaker - shaker/sieve that separates rock cuttings from the mud

  - shale slide - conveys cuttings to the reserve pit
  - reserve pit - collects rock cuttings separated from the mud
  - mud pits - where drilling mud is mixed and recycled
  - mud-mixing hopper - where new mud is mixed and then sent to the mud pits

- Derrick - support structure that holds the drilling apparatus; tall enough to allow new sections of drill pipe to be added to the drilling apparatus as drilling progresses
- Blowout preventer - high-pressure valves (located under the land rig or on the sea floor) that seal the high-pressure drill lines and relieve pressure when necessary to prevent a blowout (uncontrolled gush of gas or oil to the surface, often associated with fire)

Appendix 3

CPT of nodes containing two states of specified events for different nodes in different levels.

Table A3-1: CPT in level 1 of four nodes L1D containing two states of specified events

L2D-N1		L2D-O1		L2D-H1		CPT	
Risky	0.200	Risky	0.350	Risky	0.450	1.000	0.000
Risky	0.200	Risky	0.350	Consistant		0.550	0.450
Risky	0.200	Consistant		Risky	0.450	0.650	0.350
Risky	0.200	Consistant		Consistant		0.200	0.800
Consistant		Risky	0.350	Risky	0.450	0.800	0.200
Consistant		Risky	0.350	Consistant		0.350	0.650
Consistant		Consistant		Risky	0.450	0.450	0.550
Consistant		Consistant		Consistant		0.000	1.000

Table A3-2: CPT in level 4 of four nodes L4DO1011 containing two states events

L5D-O1-01-1-4		L5D-O1-01-1-3		L5D-O1-01-1-2		L5D-O1-01-1-1		CPT	
Risky	0.249	Risky	0.168	Risky	0.325	Risky	0.259	1.000	0.000
Risky	0.249	Risky	0.168	Risky	0.325	Consistant		0.741	0.259
Risky	0.249	Risky	0.168	Consistant		Risky	0.259	0.675	0.325
Risky	0.249	Risky	0.168	Consistant		Consistant		0.417	0.583
Risky	0.249	Consistant		Risky	0.325	Risky	0.259	0.832	0.168
Risky	0.249	Consistant		Risky	0.325	Consistant		0.573	0.427
Risky	0.249	Consistant		Consistant		Risky	0.259	0.508	0.492
Risky	0.249	Consistant		Consistant		Consistant		0.249	0.751
Consistant		Risky	0.168	Risky	0.325	Risky	0.259	0.751	0.249
Consistant		Risky	0.168	Risky	0.325	Consistant		0.492	0.508
Consistant		Risky	0.168	Consistant		Risky	0.259	0.427	0.573
Consistant		Risky	0.168	Consistant		Consistant		0.168	0.832
Consistant		Consistant		Risky	0.325	Risky	0.259	0.583	0.417
Consistant		Consistant		Risky	0.325	Consistant		0.325	0.675
Consistant		Consistant		Consistant		Risky	0.259	0.259	0.741
Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-3: CPT in level 4 of four nodes L4DO1011 containing two states events

L5D-01-01-1-4		L5D-01-01-1-3		L5D-01-01-1-2		L5D-01-01-1-1		L4D-01-01-2		CPT	
Risky	0.190	Risky	0.170	Risky	0.230	Risky	0.200	Risky	0.210	1.000	0.000
Risky	0.190	Risky	0.170	Risky	0.230	Risky	0.200	Consistant		0.790	0.210
Risky	0.190	Risky	0.170	Risky	0.230	Consistant		Risky	0.210	0.800	0.200
Risky	0.190	Risky	0.170	Risky	0.230	Consistant		Consistant		0.590	0.410
Risky	0.190	Risky	0.170	Consistant		Risky	0.200	Risky	0.210	0.770	0.230
Risky	0.190	Risky	0.170	Consistant		Risky	0.200	Consistant		0.560	0.440
Risky	0.190	Risky	0.170	Consistant		Consistant		Risky	0.210	0.570	0.430
Risky	0.190	Risky	0.170	Consistant		Consistant		Consistant		0.360	0.640
Risky	0.190	Consistant		Risky	0.230	Risky	0.200	Risky	0.210	0.830	0.170
Risky	0.190	Consistant		Risky	0.230	Risky	0.200	Consistant		0.620	0.380
Risky	0.190	Consistant		Risky	0.230	Consistant		Risky	0.210	0.630	0.370
Risky	0.190	Consistant		Risky	0.230	Consistant		Consistant		0.420	0.580
Risky	0.190	Consistant		Consistant		Risky	0.200	Risky	0.210	0.600	0.400
Risky	0.190	Consistant		Consistant		Risky	0.200	Consistant		0.390	0.610
Risky	0.190	Consistant		Consistant		Consistant		Risky	0.210	0.400	0.600
Risky	0.190	Consistant		Consistant		Consistant		Consistant		0.190	0.810
Consistant		Risky	0.170	Risky	0.230	Risky	0.200	Risky	0.210	0.810	0.190
Consistant		Risky	0.170	Risky	0.230	Risky	0.200	Consistant		0.600	0.400
Consistant		Risky	0.170	Risky	0.230	Consistant		Risky	0.210	0.610	0.390
Consistant		Risky	0.170	Risky	0.230	Consistant		Consistant		0.400	0.600
Consistant		Risky	0.170	Consistant		Risky	0.200	Risky	0.210	0.580	0.420
Consistant		Risky	0.170	Consistant		Risky	0.200	Consistant		0.370	0.630
Consistant		Risky	0.170	Consistant		Consistant		Risky	0.210	0.380	0.620
Consistant		Risky	0.170	Consistant		Consistant		Consistant		0.170	0.830
Consistant		Consistant		Risky	0.230	Risky	0.200	Risky	0.210	0.640	0.360
Consistant		Consistant		Risky	0.230	Risky	0.200	Consistant		0.430	0.570
Consistant		Consistant		Risky	0.230	Consistant		Risky	0.210	0.440	0.560
Consistant		Consistant		Risky	0.230	Consistant		Consistant		0.230	0.770
Consistant		Consistant		Consistant		Risky	0.200	Risky	0.210	0.410	0.590
Consistant		Consistant		Consistant		Risky	0.200	Consistant		0.200	0.800
Consistant		Consistant		Consistant		Consistant		Risky	0.210	0.210	0.790
Consistant		Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-4: CPT in level 4 of four nodes L4DO1012 containing two states events

L5D-01-01-3-4		**L5D-01-01-2-3**		**L5D-01-01-2-2**		**L5D-01-01-2-1**		**CPT**	
Risky	0.430	Risky	0.150	Risky	0.230	Risky	0.190	1.000	0.000
Risky	0.430	Risky	0.150	Risky	0.230	Consistant		0.810	0.190
Risky	0.430	Risky	0.150	Consistant		Risky	0.190	0.770	0.230
Risky	0.430	Risky	0.150	Consistant		Consistant		0.580	0.420
Risky	0.430	Consistant		Risky	0.230	Risky	0.190	0.850	0.150
Risky	0.430	Consistant		Risky	0.230	Consistant		0.660	0.340
Risky	0.430	Consistant		Consistant		Risky	0.190	0.620	0.380
Risky	0.430	Consistant		Consistant		Consistant		0.430	0.570
Consistant		Risky	0.150	Risky	0.230	Risky	0.190	0.570	0.430
Consistant		Risky	0.150	Risky	0.230	Consistant		0.380	0.620
Consistant		Risky	0.150	Consistant		Risky	0.190	0.340	0.660
Consistant		Risky	0.150	Consistant		Consistant		0.150	0.850
Consistant		Consistant		Risky	0.230	Risky	0.190	0.420	0.580
Consistant		Consistant		Risky	0.230	Consistant		0.230	0.770
Consistant		Consistant		Consistant		Risky	0.190	0.190	0.810
Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-5: CPT in level 4 of four nodes L4DO1013 containing two states events

L5D-01-01-3-5		L5D-01-01-3-4		L5D-01-01-3-3		L5D-01-01-3-2		L5D-01-01-3-1		CPT	
Risky	0.102	Risky	0.183	Risky	0.250	Risky	0.330	Risky	0.136	1.000	0.000
Risky	0.102	Risky	0.183	Risky	0.250	Risky	0.330	Consistant		0.864	0.136
Risky	0.102	Risky	0.183	Risky	0.250	Consistant		Risky	0.136	0.670	0.330
Risky	0.102	Risky	0.183	Risky	0.250	Consistant		Consistant		0.535	0.465
Risky	0.102	Risky	0.183	Consistant		Risky	0.330	Risky	0.136	0.750	0.250
Risky	0.102	Risky	0.183	Consistant		Risky	0.330	Consistant		0.614	0.386
Risky	0.102	Risky	0.183	Consistant		Consistant		Risky	0.136	0.420	0.580
Risky	0.102	Risky	0.183	Consistant		Consistant		Consistant		0.285	0.715
Risky	0.102	Consistant		Risky	0.250	Risky	0.330	Risky	0.136	0.817	0.183
Risky	0.102	Consistant		Risky	0.250	Risky	0.330	Consistant		0.681	0.319
Risky	0.102	Consistant		Risky	0.250	Consistant		Risky	0.136	0.488	0.512
Risky	0.102	Consistant		Risky	0.250	Consistant		Consistant		0.352	0.648
Risky	0.102	Consistant		Consistant		Risky	0.330	Risky	0.136	0.567	0.433
Risky	0.102	Consistant		Consistant		Risky	0.330	Consistant		0.431	0.569
Risky	0.102	Consistant		Consistant		Consistant		Risky	0.136	0.237	0.763
Risky	0.102	Consistant		Consistant		Consistant		Consistant		0.102	0.898
Consistant		Risky	0.183	Risky	0.250	Risky	0.330	Risky	0.136	0.898	0.102
Consistant		Risky	0.183	Risky	0.250	Risky	0.330	Consistant		0.763	0.237
Consistant		Risky	0.183	Risky	0.250	Consistant		Risky	0.136	0.569	0.431
Consistant		Risky	0.183	Risky	0.250	Consistant		Consistant		0.433	0.567
Consistant		Risky	0.183	Consistant		Risky	0.330	Risky	0.136	0.648	0.352
Consistant		Risky	0.183	Consistant		Risky	0.330	Consistant		0.512	0.488
Consistant		Risky	0.183	Consistant		Consistant		Risky	0.136	0.319	0.681
Consistant		Risky	0.183	Consistant		Consistant		Consistant		0.183	0.817
Consistant		Consistant		Risky	0.250	Risky	0.330	Risky	0.136	0.715	0.285
Consistant		Consistant		Risky	0.250	Risky	0.330	Consistant		0.580	0.420
Consistant		Consistant		Risky	0.250	Consistant		Risky	0.136	0.386	0.614
Consistant		Consistant		Risky	0.250	Consistant		Consistant		0.250	0.750
Consistant		Consistant		Consistant		Risky	0.330	Risky	0.136	0.465	0.535
Consistant		Consistant		Consistant		Risky	0.330	Consistant		0.330	0.670
Consistant		Consistant		Consistant		Consistant		Risky	0.136	0.136	0.864
Consistant		Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-6: CPT in level 4 of four nodes L4DO1014 containing two states events

L5D-01-01-4-1		L5D-01-01-4-2		L5D-01-01-4-3		CPT	
Risky	0.400	Risky	0.350	Risky	0.250	1.000	0.000
Risky	0.400	Risky	0.350	Consistant	0.000	0.750	0.250
Risky	0.400	Consistant	0.000	Risky	0.250	0.650	0.350
Risky	0.400	Consistant	0.000	Consistant	0.000	0.400	0.600
Consistant	0.000	Risky	0.350	Risky	0.250	0.600	0.400
Consistant	0.000	Risky	0.350	Consistant	0.000	0.350	0.650
Consistant	0.000	Consistant	0.000	Risky	0.250	0.250	0.750
Consistant	0.000	Consistant	0.000	Consistant	0.000	0.000	1.000

Table A3-7: CPT in level 3 of four nodes L4DO101 containing two states events

L4D-01-01-1		L4D-01-01-2		L4D-01-01-3		L4D-01-01-4		CPT	
Risky	0.220	Risky	0.271	Risky	0.170	Risky	0.340	1.000	0.000
Risky	0.220	Risky	0.271	Risky	0.170	Consistant		0.660	0.340
Risky	0.220	Risky	0.271	Consistant		Risky	0.340	0.830	0.170
Risky	0.220	Risky	0.271	Consistant		Consistant		0.490	0.510
Risky	0.220	Consistant		Risky	0.170	Risky	0.340	0.730	0.270
Risky	0.220	Consistant		Risky	0.170	Consistant		0.390	0.610
Risky	0.220	Consistant		Consistant		Risky	0.340	0.560	0.440
Risky	0.220	Consistant		Consistant		Consistant		0.220	0.780
Consistant		Risky	0.271	Risky	0.170	Risky	0.340	0.781	0.219
Consistant		Risky	0.271	Risky	0.170	Consistant		0.441	0.559
Consistant		Risky	0.271	Consistant		Risky	0.340	0.611	0.389
Consistant		Risky	0.271	Consistant		Consistant		0.271	0.729
Consistant		Consistant		Risky	0.170	Risky	0.340	0.510	0.490
Consistant		Consistant		Risky	0.170	Consistant		0.170	0.830
Consistant		Consistant		Consistant		Risky	0.340	0.340	0.660
Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-8: CPT in level 2 of four nodes L4D1 containing two states events

L3D-N1-05		L3D-N1-04		L3D-N1-03		L3D-N1-02		L3D-N1-01		CPT	
Risky	0.082	Risky	0.368	Risky	0.260	Risky	0.091	Risky	0.199	1.000	0.000
Risky	0.082	Risky	0.368	Risky	0.260	Risky	0.091	Consistant		0.801	0.199
Risky	0.082	Risky	0.368	Risky	0.260	Consistant		Risky	0.199	0.909	0.091
Risky	0.082	Risky	0.368	Risky	0.260	Consistant		Consistant		0.710	0.290
Risky	0.082	Risky	0.368	Consistant		Risky	0.091	Risky	0.199	0.740	0.260
Risky	0.082	Risky	0.368	Consistant		Risky	0.091	Consistant		0.541	0.459
Risky	0.082	Risky	0.368	Consistant		Consistant		Risky	0.199	0.649	0.351
Risky	0.082	Risky	0.368	Consistant		Consistant		Consistant		0.450	0.550
Risky	0.082	Consistant		Risky	0.260	Risky	0.091	Risky	0.199	0.632	0.368
Risky	0.082	Consistant		Risky	0.260	Risky	0.091	Consistant		0.433	0.567
Risky	0.082	Consistant		Risky	0.260	Consistant		Risky	0.199	0.541	0.459
Risky	0.082	Consistant		Risky	0.260	Consistant		Consistant		0.342	0.658
Risky	0.082	Consistant		Consistant		Risky	0.091	Risky	0.199	0.372	0.628
Risky	0.082	Consistant		Consistant		Risky	0.091	Consistant		0.173	0.827
Risky	0.082	Consistant		Consistant		Consistant		Risky	0.199	0.281	0.719
Risky	0.082	Consistant		Consistant		Consistant		Consistant		0.082	0.918
Consistant		Risky	0.368	Risky	0.260	Risky	0.091	Risky	0.199	0.918	0.082
Consistant		Risky	0.368	Risky	0.260	Risky	0.091	Consistant		0.719	0.281
Consistant		Risky	0.368	Risky	0.260	Consistant		Risky	0.199	0.827	0.173
Consistant		Risky	0.368	Risky	0.260	Consistant		Consistant		0.628	0.372
Consistant		Risky	0.368	Consistant		Risky	0.091	Risky	0.199	0.658	0.342
Consistant		Risky	0.368	Consistant		Risky	0.091	Consistant		0.459	0.541
Consistant		Risky	0.368	Consistant		Consistant		Risky	0.199	0.567	0.433
Consistant		Risky	0.368	Consistant		Consistant		Consistant		0.368	0.632
Consistant		Consistant		Risky	0.260	Risky	0.091	Risky	0.199	0.550	0.450
Consistant		Consistant		Risky	0.260	Risky	0.091	Consistant		0.351	0.649
Consistant		Consistant		Risky	0.260	Consistant		Risky	0.199	0.459	0.541
Consistant		Consistant		Risky	0.260	Consistant		Consistant		0.260	0.740
Consistant		Consistant		Consistant		Risky	0.091	Risky	0.199	0.290	0.710
Consistant		Consistant		Consistant		Risky	0.091	Consistant		0.091	0.909
Consistant		Consistant		Consistant		Consistant		Risky	0.199	0.199	0.801
Consistant		Consistant		Consistant		Consistant		Consistant		0.000	1.000

Table A3-9: CPT in level 2 of four nodes L4DO1 containing two states events

L3D-01-08		L3D-01-07		L3D-01-06		L3D-01-05		L3D-01-04		L3D-01-03		L3D-01-02		L3D-01-01		CPT	
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Risky	0.132	Risky	0.140	Risky	0.080	1.000	0.000
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Risky	0.132	Risky	0.140	Consistant		0.920	0.080
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Risky	0.132	Consistant		Risky	0.080	0.860	0.140
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Risky	0.132	Consistant		Consistant		0.780	0.220
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Consistant		Risky	0.140	Risky	0.080	0.868	0.132
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Consistant		Risky	0.140	Consistant		0.788	0.212
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Consistant		Consistant		Risky	0.080	0.728	0.272
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Risky	0.150	Consistant		Consistant		Consistant		0.648	0.352
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Risky	0.132	Risky	0.140	Risky	0.080	0.850	0.150
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Risky	0.132	Risky	0.140	Consistant		0.770	0.230
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Risky	0.132	Consistant		Risky	0.080	0.710	0.290
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Risky	0.132	Consistant		Consistant		0.630	0.370
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Consistant		Risky	0.140	Risky	0.080	0.718	0.282
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Consistant		Risky	0.140	Consistant		0.638	0.362
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Consistant		Consistant		Risky	0.080	0.578	0.422
Risky	0.119	Risky	0.089	Risky	0.110	Risky	0.180	Consistant		Consistant		Consistant		Consistant		0.498	0.502
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Risky	0.132	Risky	0.140	Risky	0.080	0.820	0.180
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Risky	0.132	Risky	0.140	Consistant		0.740	0.260
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Risky	0.132	Consistant		Risky	0.080	0.680	0.320
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Risky	0.132	Consistant		Consistant		0.600	0.400
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Consistant		Risky	0.140	Risky	0.080	0.688	0.312
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Consistant		Risky	0.140	Consistant		0.608	0.392
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Consistant		Consistant		Risky	0.080	0.548	0.452
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Risky	0.150	Consistant		Consistant		Consistant		0.468	0.532
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Risky	0.132	Risky	0.140	Risky	0.080	0.670	0.330
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Risky	0.132	Risky	0.140	Consistant		0.590	0.410
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Risky	0.132	Consistant		Risky	0.080	0.530	0.470
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Risky	0.132	Consistant		Consistant		0.450	0.550
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Consistant		Risky	0.140	Risky	0.080	0.538	0.462
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Consistant		Risky	0.140	Consistant		0.458	0.542
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Consistant		Consistant		Risky	0.080	0.398	0.602
Risky	0.119	Risky	0.089	Risky	0.110	Consistant		Consistant		Consistant		Consistant		Consistant		0.318	0.682